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How Chatbot Language Shapes Consumer Perceptions: The Role of Concreteness and Shared Competence

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Abstract:	In service settings, chatbots frequently are associated with substandard care, depersonalization, and linguistic misunderstandings. Drawing on assemblage theory (i.e., the examination of how heterogeneous parts, through their ongoing interaction, create an emergent whole with new capacities that the parts themselves do not have), this paper investigates how chatbots' language concreteness––the specificity of words used during interactions with consumers––can help improve satisfaction, willingness to use the chatbot, and perceived shopping efficiency. Across three experiments, the findings revealed a psychological mechanism driven by concrete chatbot language that makes chatbots seem competent and reinforces consumer self-competence, in turn boosting satisfaction, willingness to use the chatbot, and perceived shopping efficiency. This pattern of results contributes to consumer behavior by providing evidence of the chatbot language concreteness effect on consumer-chatbot interactions. For practitioners, we outline conversational designs that could help optimize implementation of chatbots in customer service.

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Abstract

In service settings, chatbots frequently are associated with substandard care, depersonalization, and linguistic misunderstandings. Drawing on assemblage theory (i.e., the examination of how heterogeneous parts, through their ongoing interaction, create an emergent whole with new capacities that the parts themselves do not have), this paper investigates how chatbots' language concreteness—the specificity of words used during interactions with consumers—can help improve satisfaction, willingness to use the chatbot, and perceived shopping efficiency. Across three experiments, the findings revealed a psychological mechanism driven by concrete chatbot language that makes chatbots seem competent and reinforces consumer self-competence, in turn boosting satisfaction, willingness to use the chatbot, and perceived shopping efficiency. This pattern of results contributes to consumer behavior by providing evidence of the chatbot language concreteness effect on consumer-chatbot interactions. For practitioners, we outline conversational designs that could help optimize implementation of chatbots in customer service.

Keywords: language concreteness; assemblage theory; competence; satisfaction; chatbot; shopping efficiency

INTRODUCTION

An adequate response to consumers' needs is imperative to generate satisfactory customer service. Recurring consumer complaints concern issues related to erratic attention, substandard care, miscommunication, and reduced listening capacity from firms' service agents (Berger et al. 2022; Packard and Berger 2021). As services become automated, artificially intelligent (AI) agents also can demonstrate lack of care and erratic attention to consumers (Hoffman et al. 2022; Kaneshige and Hong 2018). For practitioners, the subsequent questions are whether these AI agents can minimize erratic attention and miscommunication, and what linguistic strategies can help them enhance consumer satisfaction in interactions (e.g., Crolic et al. 2022; Ramesh and Chawla 2022)?

Among current AI applications in customer service, chatbots represent one of the most commonly adopted technologies (Fotheringham and Wiles 2022; Ciechanowski et al. 2019). Companies implement chatbots as responsive computer programs to address multiple consumer needs through text, voice, or both. Companies in sectors such as retail, healthcare, entertainment, financial services, and hospitality use chatbots to address consumers' queries and help them search for information and make purchases (Hoyer et al. 2020; Kull et al. 2021).

A dual perspective coexists in the academic marketing discourse on chatbot implementation (Crolic et al. 2021). Whereas one perspective emphasizes reductions in operating costs (e.g., De 2018; Jovic 2020), a contrary perspective focuses on problematic issues that consumers perceive in their interactions with this technology, such as dehumanized interactions and perceived low service quality (e.g., Kaneshige and Hong 2018; Van den Broeck et al. 2019). This disjunction between positive and negative perspectives when implementing chatbots has elicited explorative research on how to improve chatbots by minimizing their negative aspects and reinforcing their strengths (e.g., Hoyer et al. 2020; Ramesh and Chawla 2022).

Language is a central characteristic of chatbots' functioning, driving interactions with humans (Morrissey and Kirakwski 2013). For this reason, companies need to know which language configurations and word structures can be incorporated into chatbots' functioning to serve consumers satisfactorily (Crolic et al. 2022; Ramesh and Chawla 2022). Interestingly, the marketing literature has been examining how human employees and consumers' language—in terms of concreteness, use of verbs/nouns/adjectives, or verb tense—shapes persuasion and affects consumer behavior (e.g., Packard and Berger 2021; Packard et al. 2023). Therefore, research on the implications of language structures, such as language concreteness, on consumer-chatbot interactions remains relatively scant (Park et al. 2021; Shumanov and Johnson 2021). The present study aims to fill this gap.

In this paper, we examine whether using more concrete language in chatbots' responses to consumers enhances satisfaction, willingness to use the chatbot for more than just one task/situation, and perceived shopping efficiency. We propose that concrete chatbot language's influence on satisfaction, willingness to use the chatbot, and perceived shopping efficiency is a consequence of a perceptual mechanism that involves perceived chatbot and consumer competence to achieve an informational or transactional goal during the interaction. We root this perceptual mechanism in assemblage theory (DeLanda 2006; Deleuze and Guattari 1988), which assigns equal agency (i.e., the capacity to affect and be affected by interactions) to consumers and chatbots that contribute with their capacities during searching and buying processes (Hoffman and Novak 2018; Novak and Hoffman 2019, 2022).

We contend that when chatbots use concrete language, it induces in consumers the perception that chatbots can help them. In an optimal consumer-chatbot assemblage (Novak and Hoffman 2019), the whole interaction would make the consumer perceive self-competence in obtaining an efficient outcome that ultimately enhances satisfaction with the chatbot, drives willingness to use the chatbot in multiple situations, and implies perceived shopping efficiency. We describe the effect of this shared chatbot-consumer competence as a consequence of a self-expansion experience (e.g., Aron et al. 2004, 2013; Novak and Hoffman 2019) in which consumers treat the assemblage's emergent capacities (perceived chatbot competence) as their own (consumer competence).

Across three experiments, we provide evidence that concrete chatbot language is crucial to enhancing consumer satisfaction, willingness to use the chatbot, and perceived shopping efficiency. We also demonstrate how the shared chatbot-consumer competence mechanism helps companies improve strategies for replacing humans with AI agents when necessary. Study 1 examines the influence of language concreteness on consumers' satisfaction and opinions about using chatbots while shopping. Study 2 determines whether concrete chatbot language elicits a perceptual mechanism that affects perceived chatbot competence, perceived consumer competence, satisfaction, and willingness to use the chatbot. Study 3 evaluates whether the chatbot-consumer competence mechanism's influence on satisfaction and perceived shopping efficiency elicits strategies that compensate for the use of more concrete language by chatbots as an alternative to human agents who use less concrete language. In this third study, we also test the theoretical proposition that consumers penalize chatbots that use less concrete language more severely than human employees who also use less concrete language.

In sum, these studies respond to recent calls for a deeper understanding of how service agents' language shapes consumer satisfaction, willingness to use chatbots, and perceived shopping efficiency (e.g., Crolic et al. 2022; Ramesh and Chawla 2022). Our investigation offers several contributions to prior consumer behavior and new technology marketing research (e.g., Crolic et al. 2022; Hoffman et al. 2022; Hoyer et al. 2020). First, we demonstrate that programming chatbots with concrete language to satisfy immediate shopping needs (i.e., searching for information and ordering a product/service) benefits consumer-AI service agent relationships, positively influencing satisfaction, willingness to use the chatbot, and perceived shopping efficiency. Second, to improve companies' strategies, we found that chatbots using more concrete language can compensate for human agents who use less concrete language.

CHATBOTS IN CUSTOMER SERVICE

Chatbots represent one of the most adopted AI agent technologies in customer service, with a market size expected to reach $1.25 billion by 2025 (Statista 2022). Chatbots are computer programs that use natural language to respond to consumers' questions in real time (Luo et al. 2019). Their benefits include reducing operating costs by up to 30% and fulfilling consumers' utilitarian needs when chatbots work well and consumers use them properly (Jovic 2020). One of the first operative goals attributed to chatbots is the attention paid to consumers' problems that are relatively easy to solve without human assistance (Chen et al. 2022). However, a more ambitious goal is proposed for the development of future service chatbots, namely to improve this technology's ability to amplify consumers' capability to search for information, shop, or develop a planning task (Crolic et al. 2022; Hoyer et al. 2020). For example, a consumer can complement their knowledge about a service by asking a firm's chatbot to supplement prior information, thereby improving the quality of the consumer's decisions.

As with any other technological advances in customer service, multiple questions arise about how to design a better chatbot that responds to consumers' needs appropriately. These questions have fueled research on attributes and functions that a chatbot should provide as part of a firm's marketing strategy (Chen et al. 2022; Ramesh and Chawla 2022). Whereas some studies focus on the level of anthropomorphism (i.e., human-like qualities) that consumers should perceive in their interactions with chatbots (e.g., Crolic et al. 2022; Go and Sundar 2019; Sheehan et al. 2020; Sivaramakrishnan et al. 2007), other studies have investigated the impact from chatbots' communication signals on consumers' attitudinal and behavioral responses (Kull et al. 2021; Luo et al. 2019; Roy and Naidoo 2021)—for example, the conversation style (more vs. less warmth) or the need for constant clarification of meaning during communication.

In this regard, past research on chatbot implementation has taken a unidirectional approach, emphasizing consumers' responses to technological assistants, known as the consumer-centric approach (Novak and Hoffman 2019). What is examined through this perspective is whether chatbots' characteristics (e.g., profile aesthetics, anthropomorphism level, or conversational style) enhance consumers' attitudinal and behavioral responses (Hoffman and Novak 2018). This consumer-centric focus has been criticized for its narrow approach to determining what both parts of the interaction contribute as a whole during a search for or purchase of products/services (Jiménez-Barreto et al. 2021; Novak and Hoffman 2019, 2022).

In building a more cohesive comprehension of consumer-chatbot interactions, some authors have proposed analyzing this interactive experience as an assemblage phenomenon—also called the interaction-centric perspective (Hoffman and Novak 2018, see Table 1). This perspective observes whether the combination of consumers and AI agents' capacities (i.e., what the parts of an assemblage can do) and properties (i.e., the conformed assemblage's measured characteristics) helps achieve a goal in a consumption context. Hoffman and Novak (2018) introduced the consumer-smart technology assemblage perspective as a theoretical implementation of prior theories on social sciences, such as assemblage theory (DeLanda 2006; Deleuze and Guattari 1988) and actor-network theory (Latour 1996). The consumer-smart technology assemblage perspective proposes that interaction between smart objects and consumers is a dual process that affects individuals and technology, with both influencing what is created as a whole during the interaction (Hoffman and Novak 2018). In this exchange of "affections," it is believed that AI assistants and consumers can have the same level of agency (i.e., the capacity to affect and be affected). Therefore, this philosophical idea implies a paradigm change that ranges from examining how technology influences consumers' attitudinal and behavioral responses to examining how the assemblage of humans and technologies facilitates (vs. limits) attainment of consumption goals.

Building on assemblage theory (DeLanda 2006) and the consumer-AI assemblage orientation (Hoffman and Novak 2018), we examine how both parts of the assemblage (chatbots and consumers) contribute as a whole while searching for or buying a product/service. In line with Hoffman and Novak (2022), we propose that the analysis of natural language strategies from the assemblage perspective (e.g., chatbots' linguistic concreteness) can generate new insight into how consumer and chatbot competence (i.e., what consumers and chatbots can do as a result of an interaction) is enhanced, shared, or limited, ultimately improving managerial implementation of chatbots.

Table 1. Extant Research Focused on Consumer-Chatbot Interactions and Contributions of This Research

Research perspective	Research focus	Source	Methods	Findings
Consumer-centric approach	Chatbot anthropomorphism	Sivaramakrishnan et al. (2007)	Experimental design: 2 (gist vs. detailed product information) x 2 (anthropomorphic information agents [AIA] vs. No AIA); 2 (utilitarian vs. experiential consumption motive) x 2 (AIA vs. No AIA).	• The anthropomorphic agent exerts a positive effect when static product information on the website is limited. • When detailed product information is readily available, the anthropomorphic agent can prove detrimental when the consumer has a utilitarian consumption motive.
		Go and Sundar (2019)	Experimental design: 2 (anthropomorphic visual cues: high vs. low) × 2 (message interactivity: high vs. low) × 2 (identity cue: chatbot vs. human).	• High message interactivity compensates for the impersonal nature of a chatbot low on anthropomorphic visual cues. Moreover, identifying the agent as a human raises user expectations on interactivity.
		Sheehan et al. (2020)	Two experiments compared the perceived humanness and adoption scores for an error-free chatbot, a chatbot seeking clarification regarding a consumer input, and a chatbot that failed to discern the context.	• Unresolved errors are sufficient to reduce anthropomorphism and adoption intent. However, no perceptual difference was found between an error-free chatbot and one that seeks clarification.
		Crolic et al. (2021)	Analysis of a real-world data set from an international telecommunications company and four experiments.	• When customers enter a chatbot-led service interaction in an angry emotional state, chatbot anthropomorphism exerts a negative effect on customer satisfaction, overall firm evaluation, and subsequent purchase intentions. However, this is not the case for customers in non-angry emotional states.
		Roy and Naidoo (2021)	Two laboratory experiments and a field experiment.	• Present-oriented subjects prefer a warm vs. competent chatbot conversation, leading to favorable product decisions. Future-oriented subjects prefer a competent vs. warm conversation.
	Consumers' responses to chatbot stimuli	Ho et al. (2018)	Experimental design that examined downstream effects after emotional vs. factual disclosures in conversations with a supposed chatbot or person.	• The effects of emotional disclosure corresponded to whether participants thought they were communicating with a chatbot or a person.
		Luo et al. (2019)	Field experiment data on more than 6,200 customers randomized to receive highly structured outbound sales calls from chatbots or human workers.	• Undisclosed chatbots are as effective as proficient human workers and four times more effective than inexperienced human workers in engendering customer purchases. • When customers know that their conversational partner is not a human, they are curt and purchase less because they perceive the disclosed bot as less knowledgeable and less empathetic.
		Van den Broeck et al. (2019)	Survey research with an online panel of Facebook users.	• Chatbots' helpfulness and usefulness negatively affect chatbot ads' perceived intrusiveness. • Facebook chatbot ads' perceived intrusiveness predicts patronage intentions.
		Chung et al. (2020)	Survey research with Korean students.	• Chatbot e-service provides interactive and engaging brand/customer service encounters.
		Kull et al. (2021)	Text analysis and two experiments	• When chatbots initiate a conversation using a warm (vs. competent) message, brand engagement increases. Brand-self distance mediates this effect, such that a warm (vs. competent) initial chatbot message makes consumers feel closer to the brand.
Interaction-centric approach	Language concreteness and shared competence between chatbots and consumers	This research	Three experiments examined the downstream effects of language concreteness in chatbots on consumer competence, satisfaction, and perceived shopping efficiency.	• High chatbot language concreteness enhances perceived chatbot and consumer competence, satisfaction, and perceived shopping efficiency. • High language concreteness can compensate when using chatbots (vs. a human agent that uses less concrete language) and further enhances satisfaction and perceived shopping efficiency. Chatbots that use less concrete language are penalized more severely than human service agents who also use less concrete language.

Note. The literature review is not intended to be exhaustive, but includes influential articles in each categorized research perspective.

CONSUMER-CHATBOT ASSEMBLAGE

From assemblage theory (DeLanda 2006), Novak and Hoffman (2018, 2022) suggested that consumers and AI assistants can be described through agentic and communal roles. In consumer-chatbot interactions, the agentic role involves observing behavior on behalf of consumers/chatbots, such as proactively asking questions, requesting information, or complementing feedback received from the other interaction part. The communal role indicates that consumers/chatbots can develop cooperative capacities in searching for information or buying products/services. As a result of this combination of roles, the interaction may reveal amplified (or reduced) capacities for properly developing an adequate search/buying process (Novak and Hoffman 2019). Therefore, in some cases, consumers and chatbots may contribute with their capacities and properties during interactions, while in other cases, limitations in human knowledge or technological functioning may cause distortions that reduce such interactions' capabilities in the process of searching for or buying products/services.

Although Hoffman and Novak introduced the assemblage perspective to understand consumer-smart technology interactions, its application to understanding consumers' conversations with chatbots remains unexamined (Jiménez-Barreto et al. 2021). We propose that the assemblage perspective, which focuses on studying consumers' perceived capacities in interactions with chatbots, can help delineate whether consumer-chatbot interactions elicit efficient attitudinal and behavioral outcomes. In this context, language is central to communication with service chatbots (Park et al. 2021; Shumanov and Johnson 2021). That is, the assemblage perspective's contribution to analyzing consumer-chatbot interactions is represented mainly by what is communicated in text and/or orally.

The focus on consumer-chatbot communication raises multiple questions about how to design effective chatbots—for example, which communication style the chatbot should use to enhance consumer satisfaction and whether more concrete (vs. less concrete) chatbot language could amplify consumer and chatbot capabilities to search for and buy products/services.

Recent investigations of consumer behavior have focused on human employees to determine which kind of language (more concrete vs. less concrete) elicits more satisfactory interactions with consumers (e.g., Berger et al. 2022; Packard and Berger 2021). These studies outlined how human employees can use more specific communication with consumers to improve their responses and increase consumer satisfaction. For instance, when a frontline service employee tells consumers that their package will be arriving "*there*" [less concrete] vs. "*at their door*" [more concrete]. In this case, language concreteness is the degree to which a situation/object/component denoted by words refers to a perceptible entity (Brysbaert et al. 2014). That is, language concreteness is not a directly attributable characteristic of a source, such as warmth or competence; it represents an antecedent that can reinforce/limit a source's attributable perceptual characteristics, such as warmth, competence, or even power (see Wakslak et al. 2014).

Given that consumer behavior research still is examining human employees' language concreteness, the role of language concreteness in consumer-chatbot interactions remains relatively unknown. Pivoting on this research gap, we propose that a company may benefit from implementing a chatbot that uses concrete language. We also contend that chatbot language concreteness entails a psychological mechanism that can be observed using assemblage theory (DeLanda 2006). Specifically, we expect concrete chatbot language to increase consumers' perceptions that the chatbot is competent when replying to their queries. Perceived chatbot competence is related to chatbots' capabilities, skillfulness, and efficacy demonstrated during consumer-chatbot interactions (Li et al. 2019). Therefore, a chatbot that uses concrete language may imply to consumers that the chatbot can provide personalized responses to their queries due to its capacity to process and provide precise information.

Based on social cognition research, when a source uses concrete language, it signals knowledgeability and activates the idea of high competence in the audience (Hansen and Wänke 2010). If an interaction with a chatbot elicits knowledge activation through concrete language that signals knowledgeability, thereby implying high chatbot competence, then the role of technology competence in helping the consumer emerges as an inherent element of a satisfactory interaction. Therefore, individuals may view chatbot language concreteness and its association with a characteristic that can define the technological source (e.g., chatbot competence) as valuable enough to help them (Loersh and Payne 2011), as well as assimilate chatbot competence into their own competence traits (Bargh et al. 1996; Higgins et al. 1977).

In this context, assemblage theory contributes by explaining the positive effects of consumer assimilation vs. contrast of a chatbot's capabilities. When assimilation occurs via chatbot concrete language, the chatbot and consumer share their competence, enhancing the consumer self-expansion experience (Aron et al. 2004, 2013).

More specifically, from Hoffman and Novak's (2018) perspective, language concreteness can represent a driver of a self-expansion experience while interacting with the chatbot (Aron et al. 2004, 2013). During interactions with a chatbot that uses concrete language (i.e., a chatbot with a high communal role), consumers could perceive that the chatbot efficiently transfers its capacities to the whole interaction, ultimately making consumers feel more capable of searching for information or buying products/services (i.e., consumers with a high communal role).

Overall, a self-expansion experience in consumer-chatbot interactions means that consumers treat a close other's resources and capabilities (i.e., chatbot competence) as their own (consumer competence).

Furthermore, we propose that if consumers perceive that the chatbot is competent in attending to their needs, the overall interaction will empower consumers to obtain/convey the information/task desired, thereby enhancing the perception that they are also competent enough to resolve the consumption situation. That is, individuals may identify opportunities to express and demonstrate their capabilities to learn about something or complete a task using the chatbot (Gilal et al. 2019). The combination of perceived high competence (in the chatbot and the consumer) may generate satisfaction with the chatbot (Li et al. 2019), thereby implying the idea that the chatbot could be useful in more than one situation (e.g., searching for information and communicating service issues) and that consumers can use it efficiently without perceiving a loss of information and/or time (i.e., perceived shopping efficiency; Gensler et al. 2012).

CONCRETE LANGUAGE

In interpersonal communication, whether the speaker uses more or less concrete language may elicit a distinct reaction in the audience (Berger et al. 2022). Concrete language refers to using words that help create specific mental images about tangible entities while decoding the information transmitted (Brysbaert et al. 2014; Kroll and Merves 1986). Nonconcrete language is articulated using nonspecific qualities or ideas (Hansen and Wänke 2010).

Prior research on social psychology has revealed multiple effects from language concreteness on individuals' judgment about a source, depending on the interaction context and goal. Whereas abstract language indicates a power cue of the source, particularly in interactions in which the source wants to convey a hierarchical role (Wakslak et al. 2014), concrete language serves as a signal of the source's knowledgeability because the communication process focuses on highlighting specific details (Hansen and Wänke 2010).

In service settings, in which consumers normally interact with a firm's agent to satisfy task-oriented needs (e.g., to find products/services easily), it is plausible to consider that concrete language (vs. nonconcrete language) may elicit more favorable effects on consumer downstream attitudes and behavior (Berger et al. 2022; Packard and Berger 2021). For example, a service agent might use concrete language to ask a customer "*Are you looking for blue jeans?*" vs. nonconcrete communication, e.g., "*Are you looking for something?*" Comparing language concreteness levels implies that more concrete expressions increase vividness and frame the communication (Kroll and Merves 1986; Semin and Fiedler 1988).

Social science and computational linguistic studies have approached language concreteness from multiple perspectives. These include differentiating between language categories (descriptive action verbs [*to push, to phone*]; interpretative verbs [*to help, to support*]; state verbs [*to love, to hate*]; Semin and Fiedler 1988), assigning concreteness scores to words (e.g., Brysbaert et al. 2014), using attributive adjectives (e.g., Lazaridou et al. 2015), and observing psychological functions of language (e.g., Johnson-Grey et al. 2019).

In a consumption context, language concreteness has been analyzed as a main factor in consumer-human agent interactions, in which human service agents who employ concrete language are associated with more tailored attention to consumers (Packard and Berger 2021). The linguistic strategies that promote service agents' concrete language use product/service-related adjectives that are part of the conversation, combined with words (mainly descriptive action verbs [e.g., *to look, to process, to deliver, to place*]) that describe the company's service processes. In consumer-human agent interactions, using words that make agents' communications more concrete (e.g., "*I'll go look for that T-shirt in gray*" vs. "*I'll go look for that*") tends to increase the perception that agents possess better listening capacity, thereby enhancing consumer satisfaction (Berger et al. 2022; Packard and Berger 2021).

Although language concreteness has been investigated in consumer-human employee interactions, the communication process with chatbots may represent a different context. That is, communicating with a chatbot requires a set of prior capacities from the consumer (Hoyer et al. 2020). Thus, the need for a minimum ability to use chatbots may result in a less-familiar context than interactions with humans. In such a process, some consumers may know how to interact with chatbots, while others could perceive difficulties in developing a valuable conversation with them.

The limited research that has analyzed chatbot language in customer service emphasizes that elements, such as emotional conversation types (Roy and Naidoo 2021) and chatbots expressing personality through language (Shumanov and Johnson 2021), may hold consequences for consumers' downstream attitudes and behavioral intentions. These investigations found that chatbots that use a warm conversation style (i.e., friendly and social expressions) or match the consumer's personality through the language used enhance consumer attitudes, patronage intentions, and engagement with chatbots. However, missing from these studies is a specific way to determine which linguistic model and word structures used by chatbots (e.g., selecting words that indicate high [low] language concreteness) could shape consumer satisfaction, willingness to use the chatbot for more than just one situation/task, and perceived shopping efficiency.

Language Concreteness for Chatbots vs. Human Service Agents

The strategic implications of using chatbots for customer service are typically contra-positioned by determining how a human agent would convey the task assigned to the chatbot and at which efficiency level (Luo et al. 2019). In this sense, as part of the context of service agents' linguistic concreteness, an unresolved question entails whether a chatbot or human agent can benefit from being more (less) concrete.

Prior investigations have found that chatbots may suffer from a perceptual penalization compared with human employees while attending to consumers' requests (see Crolic et al. 2022; Ho et al. 2018; Luo et al. 2019; Mou and Xu 2017). This effect is elicited because consumers expect chatbots to provide less utilitarian (e.g., knowing how to solve the problem) and emotional (e.g., empathizing with consumers' needs) outcomes. This effect is observed even when the chatbot is objectively more efficient than human employees in completing a customer service task (Luo et al. 2019).

In line with these arguments, we aim to understand how companies can improve perceptions of chatbots compared with human employees through language concreteness. We suggest that companies that use chatbots programmed to display more concrete language can replace human agents who use less concrete language. Simultaneously, we expect that consumers will respond much more negatively in encounters with chatbots that use less concrete language compared with human agents that use less concrete language. This is because any preconceived negative notions about chatbots that the consumers possess will be reinforced by perceived miscommunication or lack of attention to their needs derived from low language concreteness (Luo et al. 2019; Mou and Xu 2017).

A complementary understanding of why consumers would penalize chatbots that use less concrete language may be explained by the relevance of the source priming the interaction with concrete (vs. nonconcrete) language (LeBoeuf and Estes 2014). Chatbots—being less familiar and more distant agents (Henderson and Wakslak 2010; LeBoeuf and Estes 2014) and, therefore, less relevant to consumers than human employees—may limit the mechanism through which consumers experience a self-expansion via the assimilation of chatbots' competence, further reducing satisfaction, willingness to use the chatbot, and perceived shopping efficiency. In this context, language concreteness may compensate for consumers perceiving a chatbot as less relevant, thereby increasing perceptions of the chatbot's high competence and further reinforcing consumer competence, ultimately enhancing satisfaction, willingness to use the chatbot, and perceived shopping efficiency.

THE CURRENT RESEARCH

In contributing to prior research on how language shapes consumers' satisfaction (Berger et al. 2022; Packard and Berger 2021), we propose that when chatbots use more concrete (vs. less concrete) language, they will elicit more satisfactory interactions with consumers because concrete language facilitates a more specific and vivid mental composition, leading to perceived competence while understanding what is communicated (Hansen and Wänke 2010). In particular, we adopt an assemblage perspective to determine that when chatbots use concrete language, a psychological mechanism exists in which consumers may infer that the chatbot is more competent in the interaction, thereby leading to consumers perceiving themselves as more competent as a self-expansion effect (Aron et al. 2004; Novak and Hoffman 2019). We expect that language concreteness will make the chatbot seem more attentive (Berger et al. 2022), thereby enhancing consumer satisfaction with the chatbot and consumer willingness to use the chatbot in multiple situations. Furthermore, as language concreteness may facilitate consumers' mental materialization of their needs (Hansen and Wänke 2010), we also propose that chatbot language concreteness and perceived chatbot and consumer competence while searching for information or shopping will boost perceived shopping efficiency. Therefore, if a chatbot uses concrete language while responding to consumer queries, the consumer may infer that using a chatbot is an efficient way to manage their time during service experiences (Puntoni et al. 2020).

In designing interactive consumer-chatbot scenarios, we manipulated the chatbot language concreteness (high vs. low) in all parts of a conversation. To establish a conversational structure in our experiments, we defined consumer-chatbot interaction as a sequential interpersonal communication process (Skjuve and Brandzaeg 2018) comprising opening, query/response, and closing phases (De Vito 2018).

During the opening phase, the chatbot could present itself using either a more concrete (e.g., "*Hello, I'm Oscar, the chatbot of X brand*") or less concrete (e.g., "*Hello, I'm your virtual assistant*") language. Similarly, in response to a consumer query, the chatbot could use words that facilitate a specific representation of the circumstances driving the conversation (e.g., more concrete language: "*Can I help you with bookings, requests, or services?*" vs. less concrete language: "*Can I help you?*"). Finally, the chatbot also could use more concrete words to end the conversation (e.g., more concrete language: "*You're welcome. Thank you for booking a double room in X hotel. See you next Friday*" vs. less concrete language: "*You're welcome. Thank you for your booking.*").

Across three studies, we investigate these relationships using a scenario-based experimental approach. Study 1 examines chatbot language concreteness during each conversation stage (opening, query/response, and closing), its effects on satisfaction with the chatbot, and whether language concreteness drives more positive consumer evaluations concerning the idea of using a chatbot during shopping experiences.

Study 2 aims to determine whether a chatbot's concrete language in a complete conversation elicits a significant perceptual mechanism that drives perceived chatbot and consumer competence, satisfaction, and willingness to use the chatbot in multiple situations. Study 2 also tests two alternatives to our proposed psychological mechanism. One is that language concreteness effects may arise from consumers' perceptions that the chatbot is mimicking their language in a concrete language scenario, ultimately generating the perception of more personalized attention (Moore and McFerran 2017; Packard and Berger 2021). Another alternative is that concrete language entails using more words to provide details about what is communicated. Thus, we control whether the perceived quantity of information drives the effects in our experiments.

Finally, Study 3 tests the contentions that (a) chatbots that use concrete language can compensate for human agents that also use less concrete language and (b) chatbots that use less concrete language will be penalized more severely than human employees who also use less concrete language in the perceptual formation of service agent and consumer competence, satisfaction, and perceived shopping efficiency (see Table 2 for an overview of the studies).

Table 2. Overview of Studies

Study	Data and methods	Findings
Study 1 Chatbot language concreteness, satisfaction with the chatbot, and evaluations of using a chatbot during shopping experiences in different conversation phases (opening, query/response, closing).	• Experiment with 288 consumers: 2 chatbot language concreteness (high vs. low) x 3 conversation phases (opening, query/response, closing) between-subjects design. • Grounded theory and psycholinguistic analyses.	• High chatbot language concreteness enhances consumers' satisfaction with the chatbot and implies positive evaluations from using a chatbot during shopping experiences.
Study 2 Chatbot language concreteness, chatbot-consumer competence, satisfaction and willingness to use the chatbot in multiple situations (complete conversation).	• Experiment with 385 consumers: two-group experimental design; chatbot language concreteness (high vs. low). • Sequential mediation analysis (Process Model 6).	• Chatbot competence and consumer competence are sequential mediators between concrete chatbot language and consumers' satisfaction and willingness to use the chatbot in multiple situations.
Study 3 Chatbot vs. human service agent, language concreteness, chatbot-consumer competence, satisfaction, and perceived shopping efficiency in a complete conversation.	• Experiment with 478 consumers: 2 (concreteness: high vs. low) x 2 (service agent type: chatbot, human) between-subjects design. • Moderated-mediation analysis (Process Model 83).	• High language concreteness can compensate for using a chatbot (vs. a human agent that uses less concrete language) and further enhances satisfaction and perceived shopping efficiency. • Chatbots that use less concrete language are penalized more severely than human service agents who also use less concrete language.

STUDY 1: CONCRETE CHATBOT LANGUAGE AND CONSUMER SATISFACTION

In Study 1, we began by examining consumers' perceptions of chatbots' concrete language and their implications for consumer satisfaction. Concurrently, we examined consumers' opinions about using chatbots while shopping. Considering that conversations with chatbots traditionally have been structured in a narrative composition similar to interpersonal communication—comprising opening, query/response, and closing (Skjuve and Brandzaeg 2018)—during each phase, we analyzed and compared consumers' perceptions of a chatbot that used either more or less concrete language. In line with prior research on (human) service agents' language concreteness, we expected that concrete chatbot language would enhance consumer satisfaction with the chatbot during each conversation stage because language concreteness would make the chatbot seem more attentive to consumers' queries (Packard and Berger 2021). We tested this proposition in the following experiment.

Method. A total of 300 U.S. consumers were recruited from Academic Prolific online panels (12 participants did not pass attention checks; final sample = 288; 34.72% between 25 and 34 years old; 57.50% female; 78.22% had interacted with a chatbot before). They were distributed in a 2 chatbot language concreteness (high vs. low) by 3 conversation stage (opening, query/response, closing) between-subjects design. For the experimental stimuli, we designed a conversation between a consumer and a chatbot concerning a fictitious jeans brand (see Web Appendix A). The participants were asked to read the conversation between the chatbot and the consumer. The conversation's phases were manipulated using more concrete vs. less concrete language in the chatbot responses. During the opening phase, the chatbot offered its support. During the query/response phase, the consumer requested information, and the chatbot responded. During the closing phase, the chatbot offered its support again, the consumer indicated the end of the interaction, and the chatbot conveyed a final "thank you" to the consumer.

Following prior research on consumer behavior that outlines strategies to manipulate language concreteness (Packard and Berger 2021), we designed a stimulus for each conversational phase intended to achieve analytical (vs. holistic) cognitive processing of the displayed information. During the concrete introduction phase, the chatbot used specific words (i.e., mainly descriptive action verbs referring to specific behaviors in specific situations) to present itself and functionalities that consumers could use during the interaction. During the concrete query/response phase, the chatbot described actions and specific options to the consumer. During the concrete closing phase, the chatbot highlighted information that the consumer obtained during the interaction and indicated its availability to help the consumer with future queries.

In contrast with previous studies that manipulated gist (vs. detailed) information from a chatbot (e.g., Sivaramakrishnan et al. 2007), we contextualized the manipulation of language concreteness within a conversation. That is, whereas Sivaramakrishnan et al. (2007) focused on providing product characteristics before an interactive experience, we manipulated all text sections during a conversation that can infer more (vs. less) concreteness using expressions, words, adjectives, and both verbs centered and not centered on product/service descriptions.

We tested these manipulations of language concreteness using the Linguistic Inquiry and Word Count (LIWC) program, which can identify the intensity of words that refer to a more analytical and contextualized (vs. holistic and decontextualized) cognition on a word-by-word basis (Pennebaker et al. 2014). LIWC's analytical dimension captures the degree to which a chatbot uses words that suggest formal, logical, and hierarchical thinking patterns. During the text analysis, this dimension is computed as (articles) + (prepositions) - (total pronouns) - (auxiliary words) - (negations) - (conjunctions) - (adverbs) (Monzani et al. 2021). Values approximating a score of 100 indicate a high level of analytical processing of the information. In this regard, concrete language stimuli are expected to elicit higher scores on the analytical cognitive processing dimension (Johnson-Grey et al. 2019; Packard and Berger 2021).

As expected, for the conversation's opening, query/response, and closing phases, the scores from LIWC's analytical dimension were higher in the high concreteness condition (opening = 18.82; query/response = 78.98; closing = 51.42) than in the low concreteness condition (opening = 8.69; query/response = 31.30; closing = 8.69). Therefore, we ensured that the manipulation reflected the desired level of concreteness in the chatbot's responses and the subsequently analytical (holistic) processing of each part of the conversation. To test language concreteness manipulations further, the participants indicated the level at which they perceived that the chatbot's replies were concrete using a measure from Packard and Berger (2021): "How concrete were the chatbot's replies?" (1 = not at all concrete; 7 = very much concrete). The scores were higher for the high concreteness condition (M = 5.78; SD = .81) than for the low concreteness condition (M = 5.30; SD = 1.34; $F(1, 287) = 12.96$; $p < .001$; $\eta^2 = .04$). Perceived chatbot language concreteness did not vary across conversational phases (opening, query/response, closing) in both linguistic conditions (high concreteness: $F(2, 139) = 1.26$; $p > .05$; $\eta^2 = .01$; low concreteness: $F(2, 147) = 1.20$; $p > .05$; $\eta^2 = .01$).

After reading the stimuli, the participants rated their satisfaction with the chatbot (three items adapted from Rosen et al. 2013; α =.85) on a seven-point Likert scale (1= strongly disagree; 7 = strongly agree; see Web Appendix B). Next, to enrich the experimental approach, we presented the participants with an open-ended question that asked for their opinions about using a chatbot for shopping experiences. We analyzed the participants' written narratives using a combination of methods, including the grounded theory approach (Strauss and Corbin 1990) and a psycholinguistic examination of the texts. In the grounded theory approach, we extracted the main themes from the participants' narratives. In the psycholinguistic analysis, we examined whether each experimental condition affected how the participants expressed general opinions in their evaluations of using chatbots during shopping experiences.

Preferences for more concrete vs. less concrete language. ANOVA results revealed a significant main effect from concreteness ($F(1, 287) = 13.66$; $p < .001$; $\eta_p^2 = .04$) and conversational phases ($F(2, 287) = 4.63$, $p < .01$; $\eta_p^2 = .03$) on satisfaction. Conversely, no significant interactions were found between language concreteness and conversation phases for satisfaction (F(2, 287) = 1.53, p > .05; η_p^2 = .01). A planned contrast analysis indicated that when the chatbot used more concrete responses, this enhanced consumer satisfaction with the chatbot ($M_{\text{high concreteness}}$ = 4.94; SD = 1.10; $M_{low\ concreteness}$ = 4.40; SD = 1.33; F(1, 287) = 13.99; p < .001; η^2 = .04). Among the conversational phases, greater satisfaction was found with the query/response (M = 4.80; SD = 1.37) and closing phases of the conversation (M = 4.86; SD = 1.07) compared with the opening phase (M = 4.35; SD = 1.24; F(1, 191) = 5.69; p < .05; η^2 = .03; F(1, 195) = 9.35; p < .01; η^2 = .04). Satisfaction did not vary between the conversation's query/response and closing phases (F(1, 187) = .09; p > .05; η^2 = .001).

Next, we analyzed the qualitative data obtained from participants' opinions about using a chatbot for shopping experiences. First, through the grounded theory approach, we processed the participants' texts through open, axial, and selective coding (see Table 3). With open coding, we emphasized the participants' quotes line by line. With axial coding, we examined concepts and abstract ideas for links with theoretical concepts representing the value of using chatbots for shopping experiences. With selective coding, we outlined the final subthemes extracted.

The analysis indicated that the participants expressed main themes in a duality representing positive and negative concerns about using chatbots for shopping. From the participants' perspective, the positive aspects of using chatbots were represented mainly by the capability of obtaining quick responses (i.e., responsiveness), high convenience while addressing less complex queries (i.e., convenience), and direct and helpful support (i.e., direct support). The negative aspects of chatbots included a perceived lack of personalization and adaptability to unique queries (i.e., depersonalization), limited abilities to address complex consumer queries, and the feeling that humans lost their jobs to these AI agents. This duality concerning chatbots' pros and cons corresponds with discussions in the marketing literature that also separate what can be expected (positively and negatively) from chatbots integrated into customer service (e.g., Crolic et al. 2022; Hoyer et al. 2020; Miao et al. 2021; Ramesh and Chawla 2022).

Finally, the psycholinguistic analysis of the participants' narratives focused on the directionality of emotions (positive vs. negative) elicited while expressing their general opinions about using chatbots while shopping. We used LIWC to compute an index of participants' emotional tone on a word-by-word basis for each experimental condition (low vs. high chatbot language concreteness and conversational phases). The higher the score for this emotional aspect, the more positive the emotional tone of participants' opinions about chatbots (Pennebaker et al. 2014). Interestingly, and in line with our experiment's results, although the participants expressed positive and negative opinions about chatbots in both conditions, in the concrete chatbot language condition, they conveyed a more positive emotional tone when expressing opinions about the idea of using chatbots while shopping ($M = 68.13$; SD = 33.38) than in the less concrete chatbot language condition ($M = 57.33$; SD = 36.66; $F(1, 287) = 6.80$; $p < .05$; $\eta^2 = .02$). Across the conversational phases, we did not find differences in the participants' emotional tone related to LIWC's emotional tone dimension.

Discussion. In line with prior research on human employees (Berger et al. 2022; Packard and Berger 2021), we found that concrete chatbot language enhances consumers' satisfaction with the chatbot. We also found that each manipulated conversational phase with the chatbot could induce high (low) language concreteness perceptions as separate informational units. Thus, we validated our conversational phases as being stimuli that can be presented in future experiments as a whole (i.e., without separating each phase of the conversation). Furthermore, our qualitative and psycholinguistic analyses indicated that more concrete (vs. less concrete) chatbot language imbues consumers with more positive evaluations of chatbots' capabilities.

Table 3. Study 1: Coding of Participants' Narratives about Using a Chatbot for Shopping Experiences

Experimental scenario	Narrative directionality	Examples of open coding extracted from participants' quotes (line-by-line coding)	Subthemes (axial coding)	Theme mentioned (frequency counts % of participants per condition)	Main themes (selective themes)
More concrete chatbot language	Positive aspects	"It can be useful for quick questions with concrete factual answers"; "I don't feel pressured when asking a question"; "You feel like you are getting instant attention"; "It is quick and easy for the most part."	Responsiveness	21.6%	(a) Responsiveness, convenience, and direct support are the main positive aspects of using a chatbot for shopping. (b) Depersonalized support, limited ability to address complex queries, and perceived replacement of humans' jobs are the main negative aspects of using a chatbot for shopping.
		"It's really fast and convenient"; "They're available without having to wait in a long queue"; "They are a convenient way to get information."	Convenience	21.6%	
		"The chatbot understands exactly what you want to purchase"; "Chatbots can be helpful with most things"; "When you have simple questions, they're very helpful!"	Direct support and helpfulness	35.1%	
	Negative aspects	"Generic and don't understand what I want to accomplish"; "Sometimes they don't understand what you are trying to say."	Depersonalized support	14.2%	
		"If I get too detailed on clothes, chatbots don't help me much"; "It's also a problem for more complex situations."	Limits in addressing complex queries	8.1%	
		"Hire qualified people, pay them a living wage, and adequately train them"; "I think companies should hire real people to do this work."	Perceived replacement of humans' jobs	24.3%	
Less concrete chatbot language	Positive aspects	"It may be faster than using other features like the menu or the search bar"; "Great time saver"; "When it is quick and able to answer my question, I like the service."	Responsiveness	25.7%	
		"They can sometimes be helpful if you have a general problem"; "They are a convenient way to get information."	Convenience	29.3%	
		"The chatbot can be good for certain straightforward things"; "I like it when the chatbot is able to be really effective"; "I like using a chatbot when I have a basic question"; "They are able to help me and get the information I need."	Direct support and helpfulness	39.3%	
	Negative aspects	"I doubt it can really understand the nuances of my questions"; "I don't think they usually have the answers to my unique questions"; "It's very impersonal"; "[People] want real human beings to talk to."	Depersonalized support	17.1%	
		"It doesn't know the answer to my question, and it redirects me to an FAQ"; "Some questions are a little too complex and require a live person to answer"; "Chatbots provide [efficient interactions] just when there is a simple question."	Limits in addressing complex queries	6.4%	
		"A human should be given a job role instead of a chatbot"; "Chatbots should not take the place of a person in a job"; "Chatbots, like robots, take away jobs from real human beings."	Perceived replacement of humans' jobs	25%	

Note. Theme frequency counts did not vary across conditions (all *p-values* > .05).

STUDY 2: CHATBOT LANGUAGE AND SHARED COMPETENCE

Study 2 tested the idea that language concreteness in chatbots' responses elicits a sequential mechanism that boosts both perceived chatbot and consumer competence during the interaction, in turn enhancing satisfaction with the chatbot and consumer willingness to use the chatbot in more than just one situation. Similar to communication processes with human employees (Packard and Berger 2021), a chatbot that uses more concrete language may influence consumer perceptions that the technological agent is addressing queries appropriately, leading to consumers feeling more competent in searching for information or shopping.

In this context, chatbot-consumer shared competence is a capability that contributes to useful interactions for consumers. Following assemblage theory (DeLanda 2006) and consumer-smart object experience conceptualization (Hoffman and Novak 2018), we expected that when the chatbot and consumer express high competence, it would elicit more satisfactory encounters via consumer self-expansion experience, in which the consumer treats the assemblage's emergent capacities as their own (Hoffman and Novak 2018). Additionally, when the chatbot-consumer assemblage is characterized by a high competence of both parts of the interaction, consumers may perceive that the chatbot can be used in more than just one situation during shopping experiences (Jiménez-Barreto et al. 2021). Therefore, apart from the satisfaction, we expect a downstream consequence from chatbot language concreteness and shared chatbot-consumer competence on consumer willingness to use the chatbot in multiple situations (e.g., asking for information, communicating service issues, and asking for a recommendation).

In the following experiment, we manipulated the context to analyze whether high or low language concreteness in a service chatbot influenced consumer satisfaction and willingness to use the chatbot in multiple situations through the simultaneous mediation of perceived chatbot competence and consumer competence. We also tested an alternative explanation for perceived chatbot competence, such as chatbots' mimicking capacities during interactions with consumers. Considering that more concrete language has been related to linguistic mimicry (i.e., imitating what is said; Moore and McFerran 2017; Packard and Berger 2021), one could speculate that perceived chatbot competence is driven by chatbots' capacity to mimic consumers' words, creating the perception of providing more personal attention to consumers' needs and subsequently enhancing consumers' perceived self-competence, satisfaction, and willingness to use the chatbot. Furthermore, as more concrete language is characterized as providing more details than less concrete language (Packard and Berger 2021), we also examined whether participants perceived that the chatbot gives more (less) information across conditions.

Method. 400 U.S. consumers were recruited from Academic Prolific online panels (15 participants did not pass attention checks; final sample = 385; 39% between 25 and 34 years old; 48.5% female; 83% had interacted with a chatbot before). They were distributed into two main experimental conditions that varied in chatbot language concreteness (high vs. low). We manipulated two types of conversations between a hypothetical consumer and a service chatbot from a fictitious hotel chain (see Web Appendix C). The conversation included three main communication phases (i.e., opening, query/response, and closing).

We conducted two analyses to test the manipulations. First, we processed all the chatbot responses per condition using LIWC. The scores obtained per condition indicated more analytical and contextualized psychological processing when the chatbot used high concrete language (high concreteness = 75.90; low concreteness = 52.71). Second, the participants also indicated the level of concreteness that they perceived in the chatbots' responses after reading the conversations ("How concrete were the chatbot's replies?"; 1 = not at all concrete; 7 = very much concrete). The high concreteness condition (M = 6.21; SD = .71) was perceived as more concrete than the low concreteness condition (M = 6.03; SD = .72; $F(1, 384) = 6.08$; $p < .05$; $\eta^2 = .01$).

Finally, the participants were asked to indicate satisfaction with the chatbot (three items; α =.82), chatbot competence (two items; composite reliability = .81), and consumer competence (two items; composite reliability = .80) adapted from Jiménez-Barreto et al. (2021) on a seven-point Likert scale (1= strongly disagree; 7 = strongly agree; see items in Web Appendix B and the measures' validity in Web Appendix D). As a proxy for willingness to use the chatbot for multiple shopping situations (Morales et al. 2017), we used a behavioral choice task in which participants could select one or multiple situations in which they would use the chatbot displayed from a choice set ranging from one to seven cases (i.e., asking for room type, prices, hotel location, attractions near the hotel, comments from prior customers, hotel facilities, and booking confirmation).

Preferences for more concrete vs. less concrete language. MANOVA results indicated that when the chatbot used more concrete language (Wilks' lambda = .95; $F(2, 382) = 9.64$; $p < .001$; $\eta_p^2 = .04$), it enhanced satisfaction ($F(1, 384) = 15.60$; $p < .001$; $\eta_p^2 = .04$) and willingness to use the chatbot in multiple situations ($F(1, 384) = 6.58$; $p < .05$; $\eta_p^2 = .01$; see Web Appendix E for details).

Chatbot and consumer competence. MANOVA analysis demonstrated that language concreteness (Wilks' lambda = .96; $F(2, 382) = 7.94$; $p < .001$; $\eta_p^2 = .04$) significantly influenced chatbot ($F(1, 384) = 15.80$; $p < .001$; $\eta_p^2 = .04$) and consumer ($F(1, 384) = 5.72$; $p < .05$; $\eta_p^2 = .01$) competence. A planned contrast analysis indicated that more concrete chatbot language reinforced chatbot (M = 5.05; SD = 1.22) and consumer (M = 3.97; SD = .55) competence more strongly than less concrete language ($M_{chatbot\ competence}$ = 4.55; SD = 1.26; $F(1, 384) = 15.80$; $p < .001$; $\eta^2 = .04$; $M_{consumer\ competence}$ = 3.83; SD = .56; $F(1, 384) = 5.72$; $p < .05$; $\eta^2 = .01$).

Testing the process. To test our proposal that when a chatbot uses concrete language, it increases perceived chatbot and consumer competence, thereby enhancing satisfaction and willingness to use the chatbot, we ran a sequential mediation model (PROCESS Model 6; Hayes et al. 2018; see Figure 1). Variance inflation factors (VIFs) indicated no multicollinearity issues for the mediation model (VIFs range from 1.04 to 1.43). The findings indicated a sequential indirect mechanism activated by high language concreteness that increased chatbot and consumer competence (self-expansion effect), thereby enhancing satisfaction with the chatbot (language concreteness → chatbot competence → consumer competence →satisfaction; $b = .08$; SE = .02; 95% CI = .03 to .13) and consumer willingness to use the chatbot in multiple situations (language concreteness → chatbot competence → consumer competence → willingness to use the chatbot; $b = .05$; SE = .02; 95% CI = .005 to .11).

The sequential mediation obtained was reinforced by a significant indirect effect between concrete chatbot language and consumer competence through chatbot competence (language concreteness → chatbot competence → consumer competence; $b = .12$; SE = .03; 95% CI = .06 to .18), with the direct effect of concrete chatbot language on consumer competence being nonsignificant (language concreteness → consumer competence; $b = .01$; SE = .04; 95% CI = -.08 to .11). This finding indicates that concrete chatbot language's effect on consumer competence is elicited indirectly through perceived chatbot competence.

We also ran the model with the mediators in reverse order (i.e., consumer competence first and chatbot competence second). The indirect effects were not significant when the mediators were reversed for satisfaction (language concreteness → consumer competence →

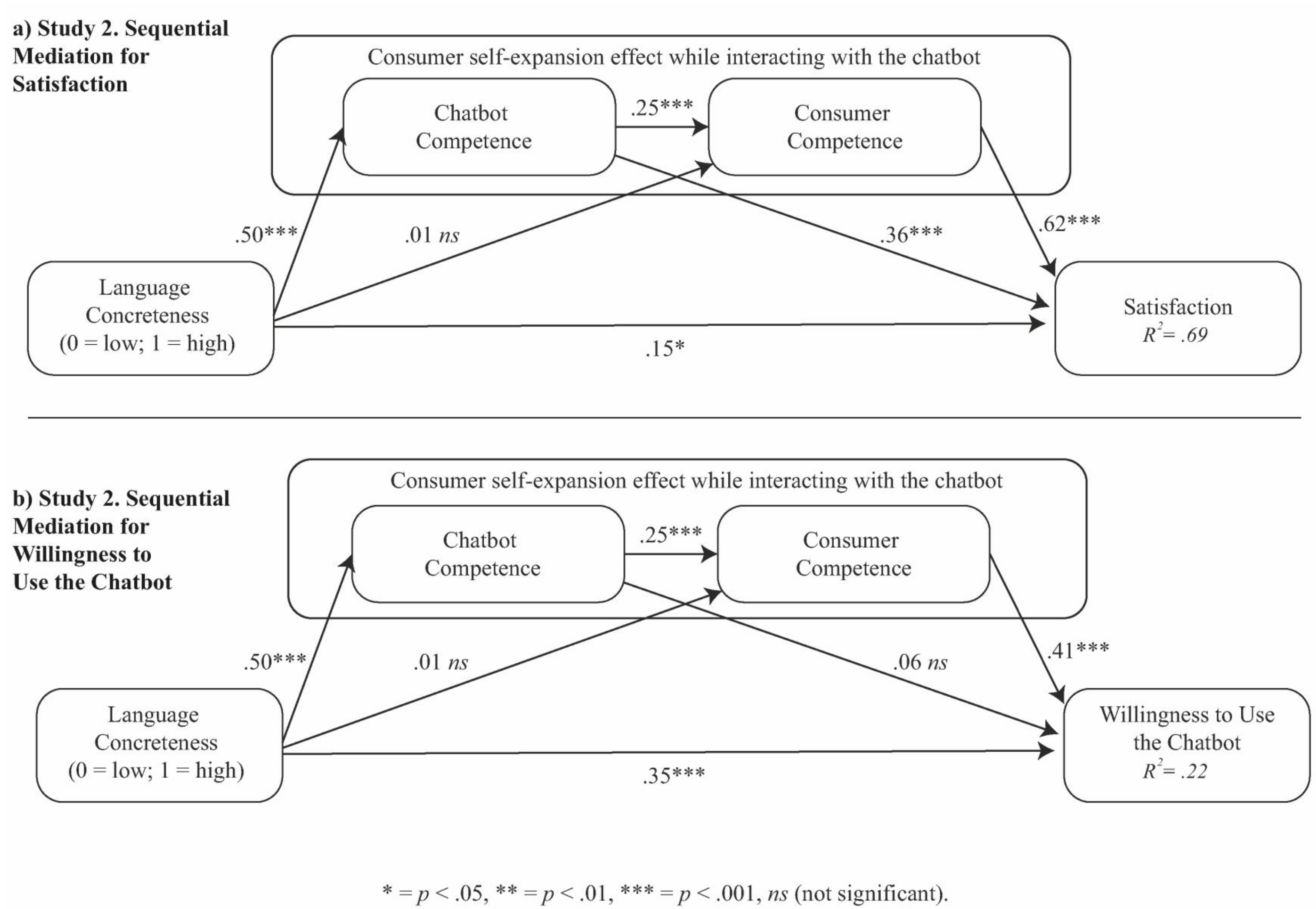
chatbot competence → satisfaction = .04; 95% CI from –.001 to .10) and willingness to use the chatbot (language concreteness → consumer competence → chatbot competence → willingness to use the chatbot = .01; 95% CI from –.01 to .07).

Alternative explanations. To test the idea that mimicking may be an alternative to the proposed chatbot-consumer competence mechanism, the participants were asked to rate "To what extent was the chatbot mimicking what you said in its replies?" (1 = not at all mimicking; 7 = very much mimicking; measure extracted from Packard and Berger 2021). The results indicated that mimicry did not offer an alternative explanation, as it did not vary by level of chatbot language concreteness ($F(1, 384) = 2.79$; $p > .05$; $\eta^2 = .007$).

Second, it is plausible to consider that the concrete language condition provides more information due to an ample use of words detailing what is communicated. To test this possibility, participants rated "To what extent information the chatbot gave was" 1 = far too little; 7 = far too much (see similar implementation in Sivaramakrishnan et al. 2007). The results indicate that perceived quantity of information did not vary across conditions ($M_{high\_concreteness} = 4.12$; $SD = .49$; $M_{low\_concreteness} = 4.05$; SD = .35; $F(1, 384) = 2.87$; $p > .05$; $\eta^2 = .007$).

Discussion. Study 2 demonstrated that chatbot and consumer competence were sequential mediators between concrete chatbot language, consumers' satisfaction, and willingness to use the chatbot in multiple shopping situations. Thus, concrete language makes the chatbot seem more competent and enhances consumers' perceived self-competence during the interaction (i.e., self-expansion experience). Ultimately, this positive and shared chatbot-consumer competence enhances satisfaction and willingness to use the chatbot in multiple shopping situations.

Figure 1. Study 2: Sequential Mediation



STUDY 3: LANGUAGE CONCRETENESS: CHATBOT VS. HUMAN SERVICE AGENTS

Study 3 sought to determine whether the chatbot-consumer competence mechanism's influence on satisfaction and perceived shopping efficiency could elicit strategies that compensate for the use of more concrete language in chatbots as an alternative to human agents who use less concrete language. Although chatbots could boost companies' efficiency while attending to consumer-firm communication (Hoyer et al. 2020), critical challenges remain for companies that aim to realize consumer satisfaction. For example, some consumers have expressed distrust and uncomfortable feelings while interacting with nonhuman agents (Luo et al. 2019). This perceptual problem is observed when chatbots fall short of consumers' expectations. For instance, when the AI agent does not properly interpret/understand consumers' queries, leading to consumers having an aversion to these technologies (e.g., Crolic et al. 2022; Luo et al. 2019).

Drawing on these arguments, we propose that more concrete chatbot language may help minimize consumers' aversion to chatbot assistance by eliciting at least the same effects on consumer perceptions and satisfaction as human service agents who use less concrete language. Simultaneously, we suggest that consumers may penalize chatbots that use less concrete language more severely than human agents who also use less concrete language. This is because a perceived lack of attention to consumers' needs derived from less concrete language could reinforce existing aversions to chatbots (Ciechanowski et al. 2019; Kestenbaum 2018; Luo et al. 2019; Mou and Xu 2017).

To test our propositions, we compared whether chatbot vs. human language concreteness affected satisfaction through the mechanism related to service agent-consumer competence observed in Study 2. Furthermore, as the concrete language of chatbots and human service agents is related to higher perceived efficiency in the attention and use of time while searching for information or buying products/services (Kull et al. 2021; Roy and Naidoo 2021), we also examined whether concrete language shapes perceived shopping efficiency.

Method. We recruited 500 U.S. consumers from Qualtrics panels (22 participants did not pass attention checks; final sample = 478; 39% between 25 and 34 years old; 51.2% female; 86.75% had interacted with a chatbot before). The participants were asked to imagine ordering coffee online that they would pick up a few minutes later from a fictitious coffee shop. Study 3 used a 2 (concreteness: low, high) by 2 (service agent type: chatbot, human) between-subjects design. The conversations presented to the participants were identical for the human and chatbot service agents, and included three sequential phases as a whole (i.e., opening, query/response, closing). The differences were in concreteness levels. The high (low) service agent language concreteness conditions used more (less) concrete words (i.e., the presence of descriptive action verbs, e.g., *to process* and *to place*, + detailed descriptions) across the conversation's opening, query, and closing narrative phases (see Web Appendix F).

To test the manipulations, we processed all the service agents' texts displayed per condition (high vs. low concreteness) using LIWC. The scores obtained per condition confirmed more analytical and contextualized words in the high concreteness condition (high concreteness = 65.46; low concreteness = 59.32). The participants then rated the concreteness levels that they perceived in the (chatbot or human) agents' responses on a Likert-type scale after being asked "How concrete were the chatbot/human agent's replies?" (1 = not at all concrete; 7 = very much concrete). The high concreteness condition (M = 6.39; SD = .64) was perceived as more concrete than the low concreteness condition (M = 5.75; SD = 1.19; $F(1, 477) = 54.28$; $p < .001$; $\eta^2 = .10$).

Next, the participants were asked to indicate satisfaction with the chatbot (three items; α =.85), perceived shopping efficiency (three items adapted from Mathwick et al. 2002; α = .93), and chatbot (two items; composite reliability = .85) and consumer (two items; composite reliability = .87) competence on a seven-point Likert scale (1= strongly disagree; 7 = strongly agree; see items in Web Appendix B and the measures' validity in Web Appendix G).

Preferences for more concrete vs. less concrete language. MANOVA results (see Web Appendix H) revealed significant main effects of concreteness (Wilks' lambda = .85; $F(2, 473) = 43.36$, $p < .001$; $\eta_p^2 = .16$) and service agent typology (Wilks' lambda = .94; $F(2, 473) = 16.11$, $p < .001$; $\eta_p^2 = .06$) for satisfaction ($F(1, 477) = 86.79$; $p < .001$; $\eta_p^2 = .15$; $F(1, 477) = 27.10$; $p < .001$; $\eta_p^2 = .05$) and perceived shopping efficiency ($F(1, 477) = 30.49$; $p < .001$; $\eta_p^2 = .06$; $F(1, 477) = 25.15$; $p < .001$; $\eta_p^2 = .05$). Interestingly, significant interactions were found between language concreteness and service agent type (Wilks' lambda = .97; $F(2, 473) = 5.43$, $p < .01$; $\eta_p^2 = .02$) for satisfaction ($F(1, 477) = 8.06$, $p < .01$; $\eta_p^2 = .01$) and perceived shopping efficiency ($F(1, 477) = 9.50$, $p < .01$; $\eta_p^2 = .02$).

The planned contrasts indicated that more concrete chatbot language led to higher evaluations of satisfaction ($M = 6.07$, SD = .74) than when the human agent used less concrete language ($M = 5.69$, SD = 1.23, $F(1, 240) = 8.63$, $p < .01$; $\eta^2 = .03$). For perceived shopping efficiency, the chatbot's more concrete language ($M_{Shopping\_efficiency} = 5.98$, SD = 1.06) indicated a similar effect compared with human agents' less concrete language ($M_{Shopping\_efficiency} = 5.93$, $SD = .96$, $F(1, 240) = .15$, $p > .05$; $\eta^2 = .001$). Furthermore, less concrete chatbot language led to evaluations that conveyed low satisfaction ($M_{Satisfaction} = 4.96$, SD = 1.20) and perceived shopping efficiency ($M_{Shopping\_efficiency} = 5.11$, SD = 1.36) compared with less concrete human language

($M_{Satisfaction}$ = 5.69, SD = 1.23, $F(1, 223) = 20.39$; $p < .001$; $\eta^2 = .08$; $M_{Shopping\_efficiency}$ = 5.93, SD = .96, $F(1, 223) = 26.58$, $p < .001$; $\eta^2 = .10$).

Chatbot and consumer competence. MANOVA analysis revealed a main effect of language concreteness (Wilks' lambda = .91; $F(2, 473) = 21.96$, $p < .001$; $\eta_p^2 = .09$) on service agent competence ($F(1, 477) = 38.19$, $p < .001$, $\eta_p^2 = .08$) and consumer competence ($F(1, 477) = 34.61$, $p < .001$, $\eta_p^2 = .07$). For service agent typology (Wilks' lambda = .90; $F(2, 473) = 27.25$, $p < .001$; $\eta_p^2 = .10$), the effects on service agent competence ($F(1, 477) = 49.11$, $p < .001$; $\eta_p^2 = .09$) and consumer competence ($F(1, 477) = 40.70$, $p < .001$; $\eta_p^2 = .08$) also were significant. Importantly, the analysis found a significant interaction effect of concreteness and type of service agent (Wilks' lambda = .98; $F(2, 473) = 5.56$, $p < .01$; $\eta_p^2 = .02$) on service agent competence ($F(1, 477) = 9.43$, $p < .01$; $\eta_p^2 = .02$) and consumer competence ($F(1, 477) = 9.03$, $p < .01$; $\eta_p^2 = .02$).

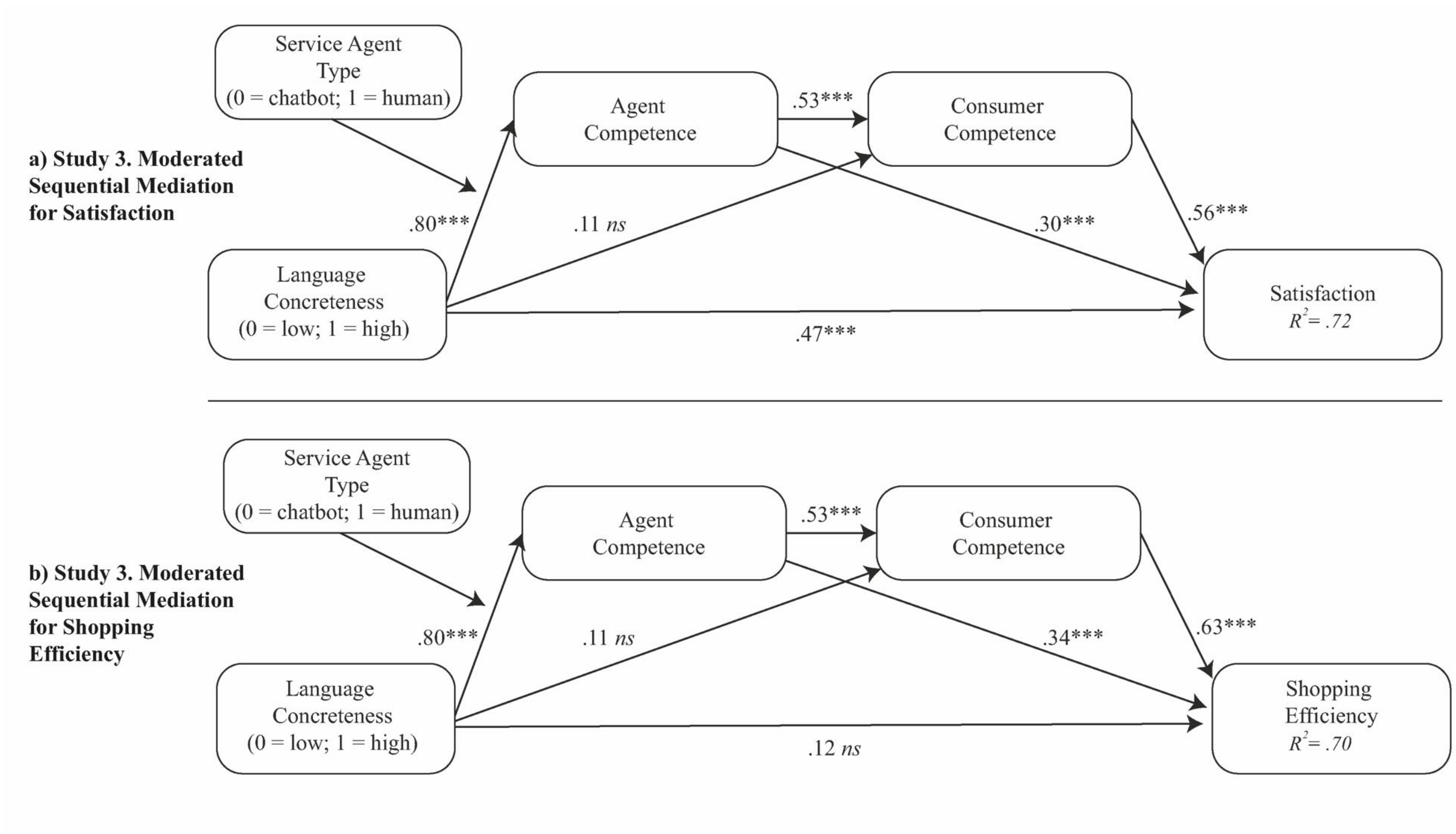
A planned contrast indicated that concrete chatbot language elicited positive effects on chatbot competence and consumer competence ($M_{\text{chatbot agent competence}}$ = 6.04, SD = .83; $M_{\text{consumer competence}}$ = 3.84, SD = .68) that were similar to less concrete human language ($M_{\text{human agent competence}}$ = 6.11, SD = .95, $F(1, 240) = .38$, $p > .05$; $\eta^2 = .002$; $M_{\text{consumer competence}}$ = 3.88, SD = .74, $F(1, 240) = .13$, $p > .05$; $\eta^2 = .001$). Furthermore, when the agent used less concrete language, chatbot and consumer competence were penalized more ($M_{\text{chatbot agent competence}}$ = 5.23, SD = 1.25; $M_{\text{consumer competence}}$ = 3.25, SD = .87) than when in the presence of the human agent ($M_{\text{human agent competence}}$ = 6.11, SD = .95, $F(1, 223) = 34.23$, $p < .001$; $\eta^2 = .13$; $M_{\text{consumer competence}}$ = 3.88, SD = .74, $F(1, 223) = 33.41$, $p < .001$; $\eta^2 = .13$).[1]

[1]MANOVA analysis, including mediators and dependent variables, supported the significance of interactions for concreteness and type of service agent (Wilks' lambda = .97; $F(4, 471) = 3.22$, $p < .05$; $\eta_p^2 = .02$).

Moderated sequential mediation. We evaluated whether the type of service agent (human vs. chatbot) moderated the sequential indirect effect between language concreteness, satisfaction, and perceived shopping efficiency through service agent competence and consumer competence (Model 83, Hayes 2018; see Figure 2). VIF diagnostics of the proposed model showed no multicollinearity issues (VIFs range from 1.09 to 2.37). The results revealed that the total sequential indirect effects of concrete language elicited between service agent competence and consumer competence were stronger in the presence of a chatbot for satisfaction (agent type$_{chatbot}$ b = .24; SE = .05; 95% CI = .14 to .35; agent type$_{human}$ b =.08; SE = .03; 95% CI = .01 to .16; index of moderated mediation = -.16; SE = .05; 95 % CI = -.28 to -.05) and perceived shopping efficiency (agent type$_{chatbot}$ b = .26; SE = .06; 95% CI = .15 to .39; agent type$_{human}$ b =.09; SE = .04; 95% CI = .01 to .17; index of moderated mediation = -.18; SE = .06; 95 % CI = -.31 to -.05).

In line with Study 2, the sequential mediation outlined the shared competence mechanism's importance as a self-expansion effect in consumer-chatbot interactions because a significant indirect effect was elicited between concrete chatbot language and consumer competence through chatbot competence that was stronger in the presence of a chatbot (agent type$_{chatbot}$ b = .42; SE = .07; 95% CI = .27 to .58; agent type$_{human}$ b = .14; SE = .06; 95% CI = .03 to .26; index of moderated mediation = -.28; SE = .09; 95 % CI = -.47 to -.09). These results indicate that more concrete language can compensate for negative consumer perceptions of chatbots (vs. human agents who use less concrete language) and further enhance satisfaction and perceived shopping efficiency. These effects are explained by an underlying mechanism that involves an increase in perceived chatbot competence that consequently boosts consumers' perceived self-competence while searching for information or buying a product/service.

Figure 2. Study 3: Moderated Sequential Mediation



* = $p < .05$, ** = $p < .01$, *** = $p < .001$, *ns* (not significant).

GENERAL DISCUSSION

Although implementing well-programmed and -trained chatbots can benefit firms in terms of efficiency, multiple aspects of consumer-chatbot interactions can go wrong. Like human agents, chatbots can be unprepared to use appropriate language during conversations, thereby reducing the probability of producing satisfactory service experiences. Whereas prior research on consumer behavior has examined how human employees' language shapes consumer satisfaction (e.g., Berger et al. 2022; Packard et al. 2023; Packard and Berger 2021), we shifted the discussion toward the consumer-chatbot interaction paradigm. Our research focuses on determining whether concrete chatbot language enhances satisfaction, willingness to use the chatbot, and perceived shopping efficiency in the process of attending to consumers' shopping needs.

First, we examined chatbot language concreteness differentiation during conversational phases in consumer-chatbot interactions (i.e., opening, query/response, and closing). In each scenario, we tested the influence of language concreteness on satisfaction with the chatbot and consumers' opinions about using chatbots while shopping (Study 1). Second, we determined whether a perceptual mechanism is elicited from concrete chatbot language that affects perceived chatbot and consumer competence, satisfaction, and willingness to use the chatbot (Study 2). Finally, we tested the theoretical propositions that chatbots that use more concrete language can compensate for human agents who use less concrete language in terms of satisfaction and perceived shopping efficiency, and that chatbots which use less concrete language are penalized more severely than human agents who also use less concrete language (Study 3).

Theoretical Contributions

Our research poses multiple implications for consumer behavior (e.g., Berger et al. 2022; Packard et al. 2023; Packard and Berger 2021) and new marketing technology research (e.g., Hoffman et al. 2022; Hoyer et al. 2020; Ramesh and Chawla 2022). First, our findings extend Packard and Berger's (2021) research on human agent language into the consumer-chatbot conversational context by supporting the idea that concrete language enhances consumer satisfaction while interacting with human and AI-based service agents (i.e., chatbots). In this regard, we confirmed that chatbot language can make a differential impact on consumer satisfaction, willingness to use chatbots, and perceived shopping efficiency. The results presented in this paper indicate that the optimal chatbot design for customer service should be based on linguistic patterns that include the use of concrete words during all conversational phases (opening, query/response, and closing) while addressing consumers' queries.

Second, unlike prior research on AI agents that focused on anthropomorphism or consumers' responses to chatbots' stimuli, we proposed an interaction-centric approach based on assemblage theory (DeLanda 2006; Hoffman and Novak 2018). By focusing on what the chatbot and consumer contributed to the interaction, we found that language concreteness makes consumers perceive chatbots and themselves as being more competent while searching for information or buying products/services.

Third, the present research sheds light on social cognitive literature regarding the role of language concreteness in signaling the competence of a source that communicates a piece of information (Hansen and Wänke 2010; Wakslak et al. 2014). In a consumption context, in which consumers seek immediate help from a chatbot, our results indicate that concrete chatbot language initiates a sequential mechanism that subsequently assigns attributable characteristics to the chatbot's knowledgeability and, therefore, high competence, which the consumer ultimately assimilates into their own competence traits. In this regard, we contend that concrete chatbot language gives consumers the idea that the chatbot can help them. Consequently, consumers may perceive themselves as more competent after interacting with the chatbot. We framed this shared chatbot-consumer perceived competence effect on satisfaction, willingness to use the chatbot, and perceived shopping efficiency as elements of a self-expansion experience (Hoffman and Novak 2018; Novak and Hoffman 2019; 2022), in which the consumer treats the assemblage's emergent capacities (i.e., perceived chatbot competence) as their own (i.e., consumer competence).

Methodologically, we first determined that chatbot language concreteness boosts consumer satisfaction with the chatbot. Concurrently, through a qualitative approach combined with a psycholinguistic technique, we found that participants evaluated the use of a chatbot during shopping experiences through a duality representing positive and negative aspects. Positive aspects of using chatbots were characterized mainly as obtaining quick responses (i.e., responsiveness), high convenience while addressing less complex queries (i.e., convenience), and receiving direct support. For the participants, the chatbots' negative aspects comprised a perceived lack of personalization and adaptability to individual queries (i.e., depersonalization), an inability to address complex queries, and the perception that these AI agents eliminate humans' jobs. The psycholinguistic analysis revealed that the participants presented with more concrete (vs. less concrete) chatbot language expressed more positive emotions while describing the attractiveness of using chatbots during shopping experiences.

We considered that this particular effect could be elicited by chatbot language concreteness while communicating with a consumer. These preliminary findings provided enough evidence to examine whether perceived chatbot and consumer competence could explain the effects of language concreteness on satisfaction with the chatbot.

Guided by assemblage theory (DeLanda 2006), we continued to examine whether chatbots and consumers' exchange of high agency during interactions, which elicits perceived competence in both actors, creates a fundamental element that ultimately enhances consumer satisfaction with the chatbot. The results indicate that concrete chatbot language directly affects perceived chatbot competence and indirectly influences consumers' perceived self-competence. Thus, we emphasized a sequential mediation mechanism elicited first by perceived chatbot competence, then by consumer-perceived self-competence between concrete chatbot language, satisfaction, willingness to use the chatbot, and perceived shopping efficiency.

Furthermore, we tested whether a concrete chatbot could generate a similarly satisfactory and efficient service compared with human employees. The findings revealed that more concrete chatbot language can compensate for less concrete human language in terms of satisfaction and perceived shopping efficiency. This result is crystallized through our proposed perceptual mechanism that entails an increase in perceived chatbot competence, consequently affecting consumers' perceived self-competence while searching for information or buying a product/service.

We also found that consumers penalized chatbots that use less concrete language more severely than human agents who also use less concrete language. This could occur because less concrete language from chatbots may be interpreted as a lack of attention paid to consumers' needs, thereby reinforcing consumers' pre-conceived notions about chatbots and eliciting avoidance and mistrust in this customer service technology (Crolic et al. 2022; Luo et al. 2019).

Finally, we validated conversational designs of chatbots that are intended to be concrete by eliciting analytical psycholinguistic processing of the information produced for consumers. The study participants perceived concrete conversations containing descriptive action verbs and detailed descriptions linked with expressions of specific behaviors in specific situations throughout the conversation. This manipulation of language concreteness extends prior approaches in consumer behavior that used concreteness scores for words in isolated sentences that human employees produced (Packard and Berger 2021).

Managerial Implications

Although companies are implementing chatbots for customer service (e.g., Air New Zealand, Mastercard, or H&M), practitioners' knowledge of the benefits of concrete language in chatbots and human agents is still limited (Packard and Berger 2021). In line with our findings, chatbot language concreteness emerges as an essential characteristic of fruitful and satisfactory interactions when consumers need information to satisfy an immediate shopping need. Indeed, language models trained on massive amounts of data tend to use more concrete descriptions of situations and actions as they evolve (See et al. 2019). However, not all service companies can afford massively pretrained language models; therefore, more affordable chatbots could compensate for this by using predesigned concrete expressions throughout conversations to meet immediate consumer needs. To shed light on the benefits of chatbot language concreteness, we emphasized three communication phases (opening, query/response, and closing) during which it is possible to introduce concrete language to influence consumers' perceptions about chatbot competence. These language compositions can be expressed by including detailed descriptions of the chatbot at the beginning of the conversation (e.g., "*Hello, I'm Oscar, the chatbot of X brand*"), providing specific options that companies can employ to satisfy consumers' needs (e.g., "*Can I help you with bookings, requests, or services?*"), and concretizing which aspects the chatbot has helped with during the interaction at the end of the conversation (e.g., "*You're welcome. Thank you for your booking; see you next Friday.*").

Although our research suggests that using chatbots for customer service can provide strategic benefits, these benefits are conditioned by human agents' ability to attend to consumers' queries. This implies that consumers generally prefer human support in customer service, but we demonstrated that human employees who use less concrete language are as effective as chatbots that use concrete language to enhance consumers' perceived competence, satisfaction, and perceived shopping efficiency. Thus, chatbots should be implemented in service settings with more concrete language when human employees are not well-trained in the use of concrete language, in turn allowing companies to increase efficiency derived from the application of AI-based agents.

Limitations and Directions for Future Research

Chatbot language concreteness and its effects on consumer satisfaction and behavior are a novel approach in marketing literature; therefore, future studies should investigate multiple elements implicit in chatbot language and their repercussions on consumer behavior.

First, we manipulate chatbot language concreteness in online experiments. Although this approach permits confirmation of causal evidence concerning the impact of language concreteness on competence, satisfaction, willingness to use the chatbot, and perceived shopping efficiency, future research should use field experiments with established service chatbots that support our results' generalizability. Future research also should propose behavioral measures to control the shared competence mechanism between chatbots and consumers with real interaction scenarios. For example, measuring the effect of chatbot language concreteness on time spent and the number of actions needed to satisfy a shopping need. This behavioral procedure may reduce potentially illusory correlational evidence (Armstrong 2012).

Second, although we used different product and service firms in our experiments, all these firms were fictitious to avoid brand-related bias. Future research should employ real firms and test whether consumer familiarity with each firm, purchase frequency, or level of consumer technology adoption moderates the effects on satisfaction, willingness to use the chatbot, and perceived shopping efficiency. Alternatively, as we focused the experiments on immediate shopping needs, future research might test whether the effect of language concreteness on consumer satisfaction and behavior varies with a long-term or future consumption focus.

Third, we based the analysis on a communication modality represented by writing text. Today's chatbots also can communicate with consumers through voice interactions; thus, future research should examine whether interactions with chatbots, whether written or oral, exert similar/dissimilar effects on consumer downstream attitudes and behavior. Furthermore, our manipulations were based on variations in chatbot language, rather than on whether consumers use more (less) concrete language during the conversation. Future research could clarify whether chatbots should modulate their language depending on how concrete consumer language is.

Finally, although we focused our research on chatbots, our conceptual and experimental models can help support future research while analyzing other types of AI agents. That is, language concreteness also can be tested on voice assistants, such as Siri, Alexa, Cortana, and Google Assistant, among others. Therefore, the present study provides the foundation for future research on how language concreteness shapes consumers' attitudes and behavior while interacting with different types of AI agents in customer service.

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WEB APPENDIX

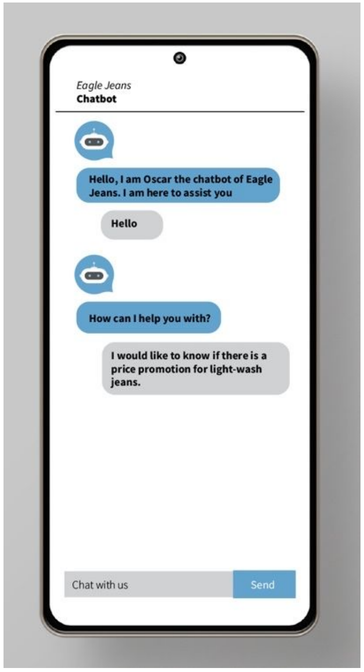
How Chatbot Language Shapes Consumer Perceptions: The Role of Concreteness and Shared Competence

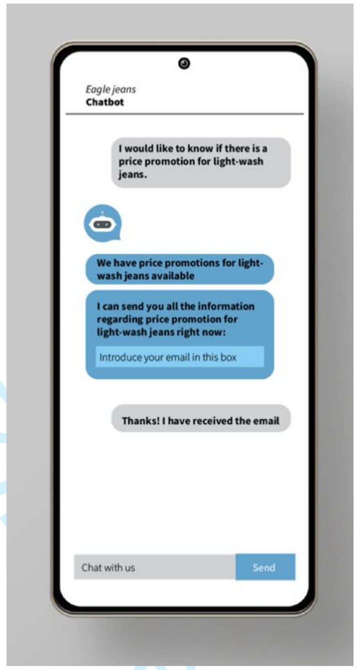
Table of contents

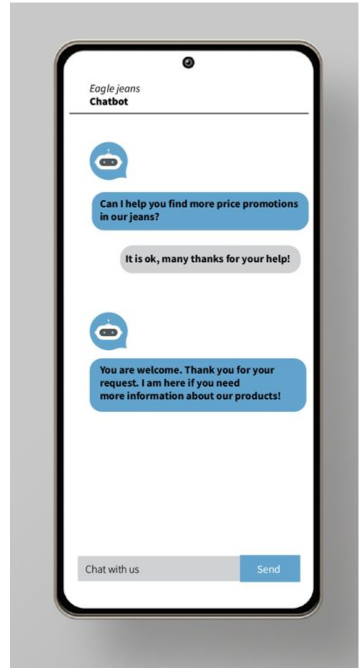
These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

Web Appendix A. Study 1 Stimuli

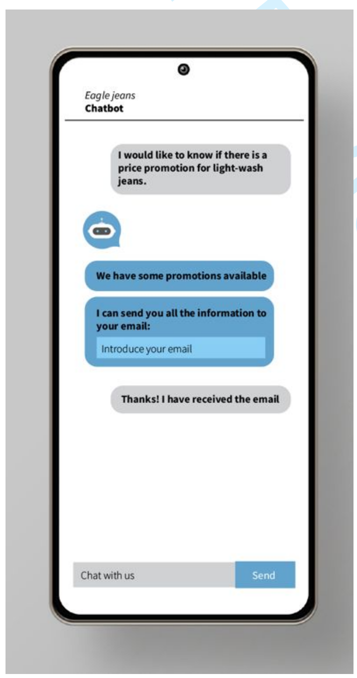
Opening (high language concreteness)	Query/response (high language concreteness)	Closing (high language concreteness)







Opening (low language concreteness)	Query/response (low language concreteness)	Closing (low language concreteness)

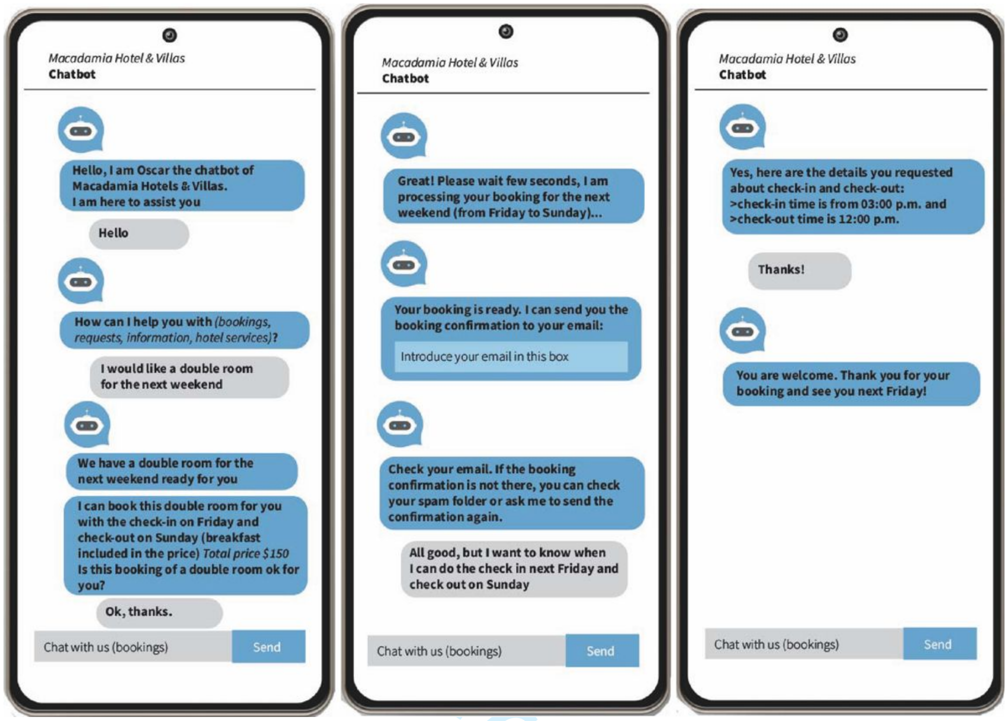


Web Appendix B. Measures used in Studies 1, 2, and 3

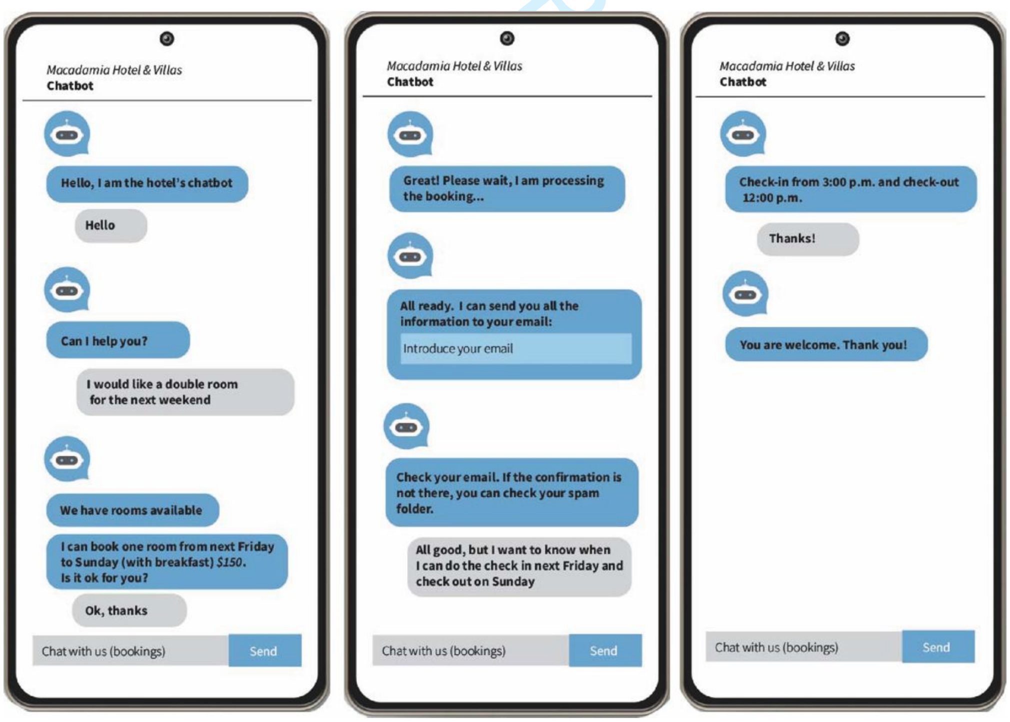
Construct level	Item	Source
Satisfaction		
Satisfaction_1	Overall, I am satisfied with the chatbot's responses.	
Satisfaction_2	The chatbot exceeds my expectations.	Rosen et al. (2013)
Satisfaction_3	The chatbot is close to my ideal customer service technology.	
Chatbot Competence		
Chatbot competence_1	I feel that this chatbot can take on and master complex queries.	
Chatbot competence_2	I feel that this chatbot is competent in attending to consumer queries.	
Consumer Competence		Jiménez-Barreto et al. (2021)
Consumer competence_1	I feel that I can take on and master complex queries with this chatbot.	
Consumer competence_2	I feel that I am competent in generating queries with this chatbot.	
Shopping Efficiency		
Shopping efficiency_1	Shopping from this company's chatbot is an efficient way to manage my time.	
Shopping efficiency_2	Shopping from this company's chatbot makes my time more efficient.	Mathwick et al. (2002)
Shopping efficiency_3	Shopping from this company's chatbot fits with my schedule.	

Web Appendix C. Study 2 Stimuli

Conversation (high language concreteness)



Conversation (low language concreteness)

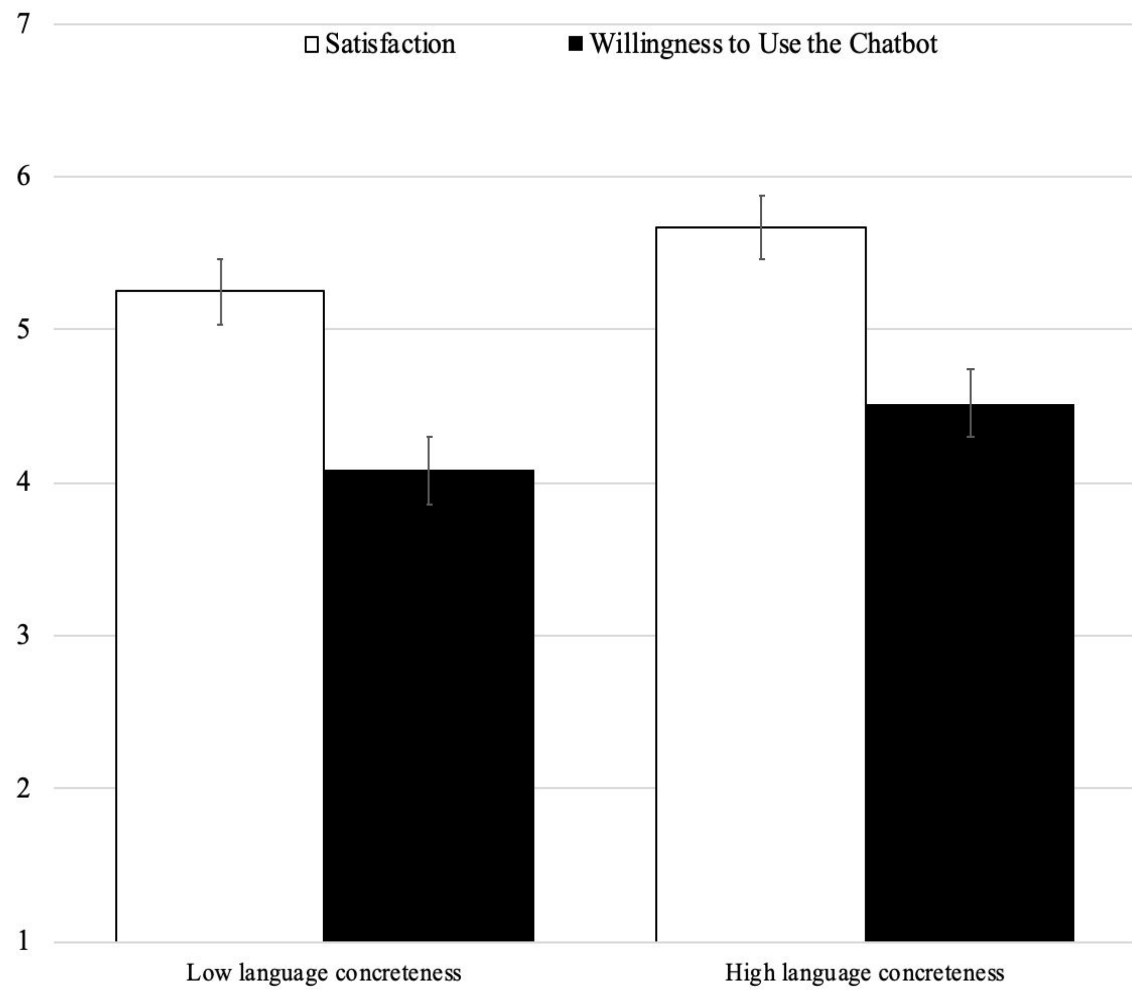


Web Appendix D. Study 2: Convergent and Discriminant Validity of Measures.

Construct level	Construct category	(α); CR; AVE			(1)	(2)	(3)
Study 2							
(1) Chatbot Competence	Sequential mediators	.81; .68			***.83***		
(2) Consumer Competence		.80; .67			.66 [.66]	***.82***	
(3) Satisfaction with the Chatbot	Dependent variable	(.82); .84; .64			.76 [.76]	.72 [.71]	***.80***
Item level		Cross-loadings (oblique rotation)			Cross-loadings (orthogonal rotation)		
		(1)	(2)	(3)	(1)	(2)	(3)
Item_1 Chatbot competence		**.94**	.45	.51	**.89**	.19	.23
Item_2 Chatbot competence		**.88**	.52	.61	**.77**	.27	.35
Item_1 Consumer competence		.42	**.92**	.55	.15	**.86**	.29
Item_2 Consumer competence		.51	**.90**	.47	.29	**.84**	.18
Item_1 Satisfaction		.47	.63	**.86**	.17	.41	**.75**
Item_2 Satisfaction		.51	.38	**.89**	.26	.11	**.85**
Item_3 Satisfaction		.58	.52	**.86**	.33	.26	**.76**

Notes. Main diagonals in bold and italics are the square roots of AVEs (average variance extracted). CR = Composite reliability. For oblique rotation, Promax with Kaiser Normalization and principal component analysis were used to estimate cross-loading rotation and extraction, respectively. For orthogonal rotation, Varimax with Kaiser Normalization and principal component analysis were used to estimate cross-loading rotation and extraction, respectively. In brackets are the heterotrait–monotrait ratio of correlations (Henseler et al. 2015).

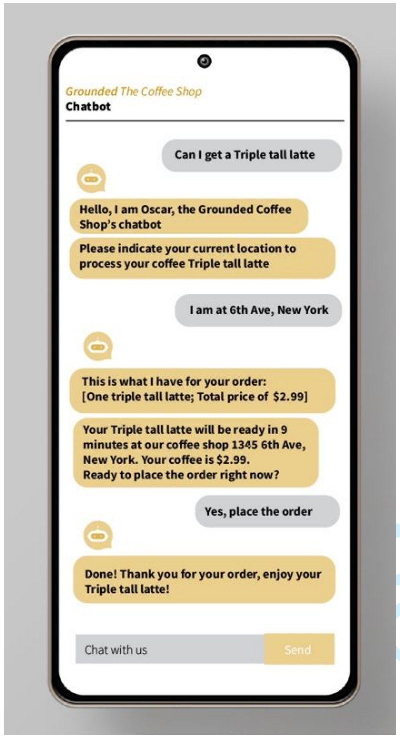
Web Appendix E. Study 2: Study 2: Effect of Language Concreteness on Satisfaction and Willingness to Use the Chatbot



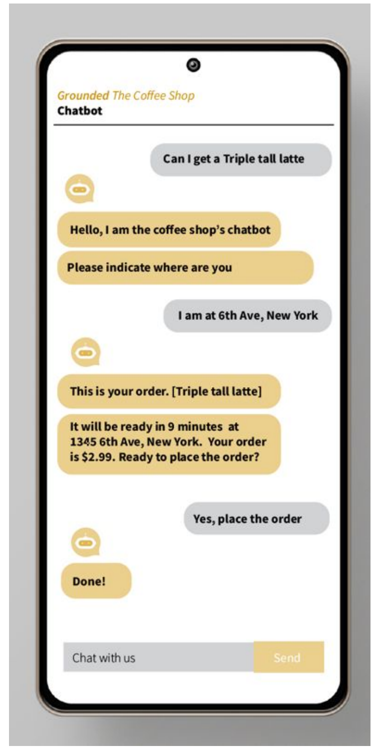
Note. Error bars represent standard errors of the means

Web Appendix F. Study 3 Stimuli

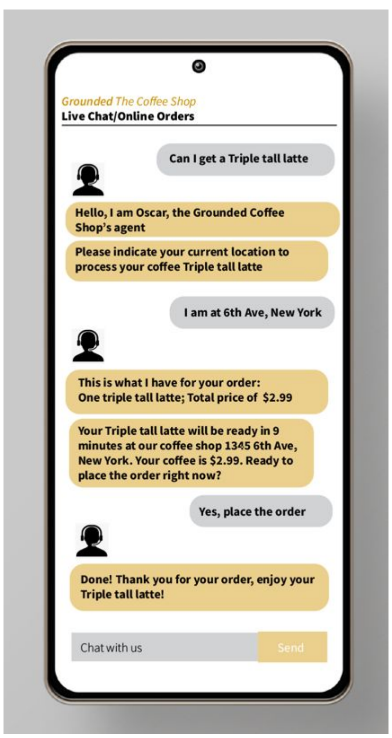
Chatbot (high language concreteness)



Chatbot (low language concreteness)



Human (high language concreteness)



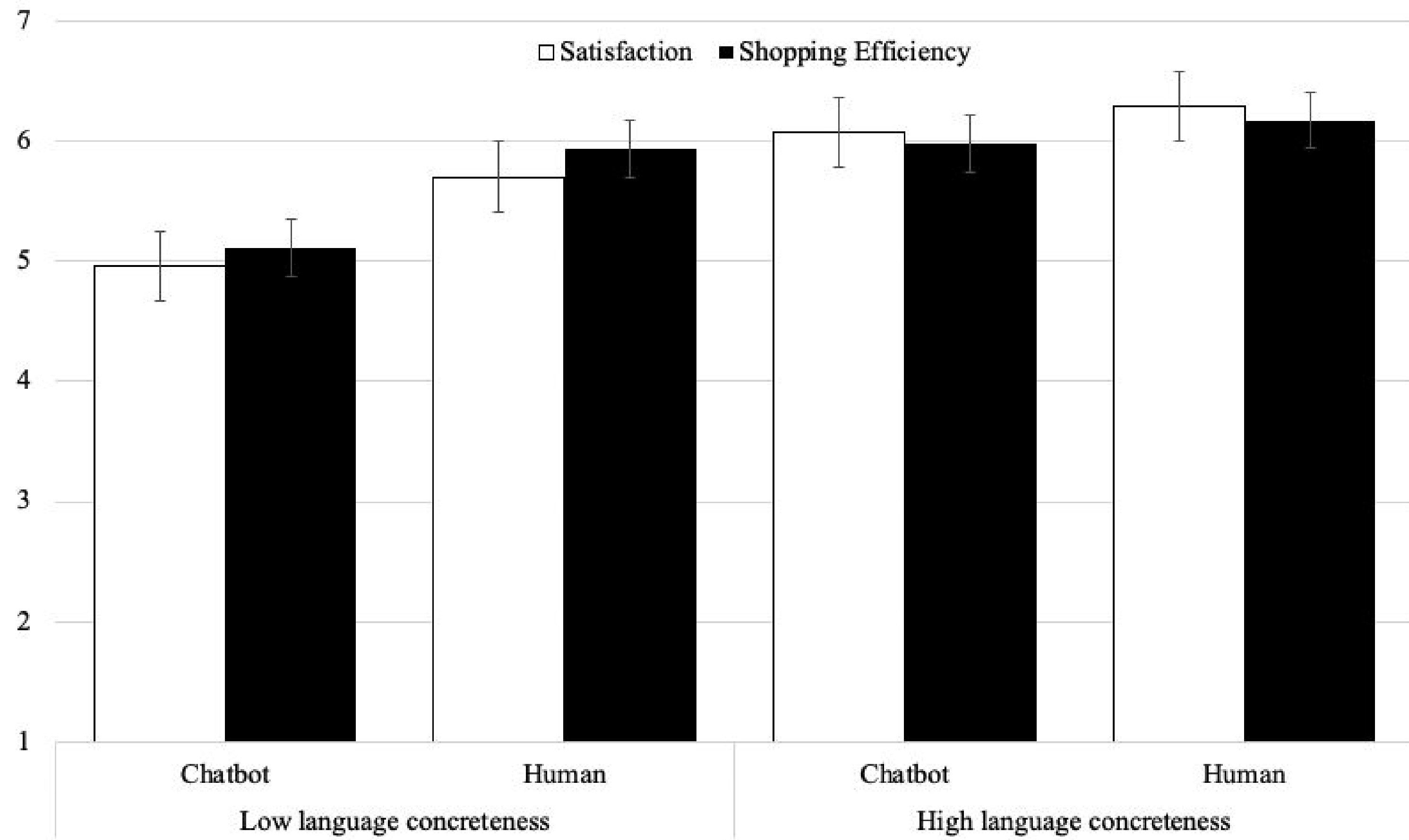
Human (low language concreteness)

Web Appendix G. Study 3. Convergent and Discriminant Validity of Measures

Construct level	Construct category	(α); CR; AVE				(1)	(2)	(3)	(4)
Study 3									
(1) Chatbot Competence	Sequential mediators	.85; .74				***.86***			
(2) Consumer Competence		.87; .76				.81 [.81]	***.87***		
(3) Satisfaction with the Chatbot	Dependent variables	(.85); .86; .67				.72 [.72]	.75 [.75]	***.81***	
(4) Shopping Efficiency		(.93); .93; .82				.70 [.70]	.73 [.73]	.74 [.75]	***.90***
Item level		Cross-loadings (oblique rotation)				Cross-loadings (orthogonal rotation)			
		(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Item_1 Chatbot competence		**.90**	.66	.62	.63	**.73**	.33	.30	.32
Item_2 Chatbot competence		**.94**	.58	.49	.52	**.85**	.28	.18	.22
Item_1 Consumer competence		.61	**.94**	.58	.59	.30	**.81**	.26	.28
Item_2 Consumer competence		.63	**.91**	.59	.63	.33	**.74**	.27	.33
Item_1 Satisfaction		.61	.40	**.86**	.59	.38	.02	**.75**	.30
Item_2 Satisfaction		.46	.58	**.90**	.52	.14	.31	**.81**	.19
Item_3 Satisfaction		.46	.61	**.88**	.65	.12	.32	**.75**	.37
Item_1 Shopping Efficiency		.57	.57	.61	**.95**	.25	.22	.26	**.84**
Item_2 Shopping Efficiency		.56	.59	.60	**.94**	.23	.24	.26	**.84**
Item_3 Shopping Efficiency		.52	.57	.60	**.92**	.19	.24	.28	**.82**

Notes. Main diagonals in bold and italics are the square roots of AVEs (average variance extracted). CR = Composite reliability. For oblique rotation, Promax with Kaiser Normalization and principal component analysis were used to estimate cross-loading rotation and extraction, respectively. For orthogonal rotation, Varimax with Kaiser Normalization and principal component analysis were used to estimate cross-loading rotation and extraction, respectively. In brackets are the heterotrait–monotrait ratio of correlations (Henseler et al. 2015).

Web Appendix H. Study 3. Effect of Language Concreteness and Service Agent Type on Satisfaction and Perceived Shopping Efficiency



Note. Error bars represent standard errors of the means

Web Appendix References

Henseler, J., Ringle, C.M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modelling. *Journal of the Academy of Marketing Science, 43*(1), 115-135.