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Social Scripts and Expectancy Violations: Evaluating Communication with Human or AI Chatbot Interactants

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ABSTRACT

As artificial intelligence (AI) agents like chatbots play larger roles in daily life, questions arise regarding how people evaluate their communication. Perspectives applying communication scripts to human-AI interactions propose that outcomes are determined by messages and the embedded cues therein. The expectancy violations perspective posits that message characteristics are less important than whether they are expected or unexpected. A pilot study established baseline expectancies about humans' and chatbots' conversational contingency and response latencies. A 2 (contingency: more/less contingent responses) × 2 (latency: fast/slow responses) × 2 (communicator identity: human/chatbot) experiment then tested predictions derived from human-human communication scripts and expectancy violations using textual variations in an e-commerce chat. Communicators showing greater conversational contingency and faster responses were most credible, whether they were human or chatbots, but chatbots were consistently less socially attractive than humans. Results show that humans and chatbots are evaluated similarly regarding the functional, but not the relational aspects of communication. There was greater support for the communication script perspective than the expectancy violations perspective regarding interactions with chatbots.

KEYWORDS

human-AI interaction; expectancy violation; chatbots; communication scripts; credibility; attraction

As more functions formerly performed by humans are allocated to various forms of digital technology, the study of people's reactions to artificial intelligence (AI) has attracted considerable research attention. Of particular interest to the present research are interactions between humans and chatbots – AI ostensibly capable of autonomous agency in sending text-based messages.

This study tested two theoretical perspectives on human-AI interaction. The first is the communication scripts perspective, which focuses on the application of either human-human or human-AI communication scripts to interactions between people and AI. According to Schank and Abelson (1977), "a script is a predetermined, stereotyped sequence of actions that defines a well-known situation"; it describes "appropriate sequences of events in a particular context" (p. 41). A communication scripts perspective makes predictions about communication outcomes by focusing on *what* is communicated as a result of following (or not following) established social scripts.

The second is the expectancy violations perspective, which claims that if pre-interaction expectancies regarding a target's communication behavior are violated, post-interaction evaluations of the target are more extreme than if pre-interaction expectancies regarding a target's communication behavior are met. The expectancy violations perspective focuses on *who* is communicating, in addition to what is said (J. Burgoon & Burgoon, 2001).

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In some ways, the communication scripts perspective and expectancy violations perspectives provide rival explanations for communication phenomenon in human-AI interaction contexts. The expectancy violations perspective puts a premium on the communication source, as the source has implications for whether one's expectancies are violated and how violations are interpreted. The communication scripts perspective prioritizes what is said, as message cues have implications for various outcomes such as whether AI agents are liked. The present study attempts to disentangle the competing arguments from the communication script and the expectancy violations perspectives.

Communication Scripts

Among the script-based approaches, the computers-are-social-actors (CASA) theory (Nass & Moon, 2000) stands out for guiding research on why individuals respond to computers in a social manner. Nass and Moon (2000, p. 83) explained, "individuals are responding mindlessly to computers to the extent that they apply social scripts – scripts for human-human interaction – that are inappropriate for human-computer interaction, essentially ignoring the cues that reveal the essential asocial nature of a computer." The CASA theory also suggests that such mindless responses are more likely if computer agents produce natural language, occupy roles traditionally held by humans, and display messages that are *contingent* with respect to "multiple prior inputs" (p. 84), although it does not specify whether these cues are necessary or sufficient. Empirical research on computers and AI agents have found that agents demonstrating social cues are more likely to be treated as social actors: They are better liked than AI agents that do not demonstrate these characteristics (Gratch et al., 2013; Nass et al., 1994).

A more contemporary approach from Westerman et al. (2020) suggested that as AI communication becomes more sophisticated – and more indistinguishable from human communication – it becomes more appropriate to apply theories from interpersonal communication to human-AI interactions. The challenge is to find out which dynamics from interpersonal communication best apply to communication between humans and AI agents. Westerman et al.'s (2020) approach is, overall, similar to traditional CASA approaches (e.g., Nass et al., 1994) in its application of human-human interaction scripts to human-AI interactions, although it places greater emphasis on the mutual exchange of text-based messages (as opposed to, e.g., anthropomorphic cues).

Another script-based perspective by Gambino et al. (2020, p. 78) proposed "extending CASA to incorporate scripts derived from human-media agent interaction" as opposed to relying solely on human-human interaction scripts as in traditional CASA research. The argument, essentially, was that human-machine interaction should be judged on its own standard, and need not always take reference from human-human interaction (see also Spence, 2019). However, Gambino et al. did not provide examples as to how differences between human-human interaction scripts and human-media agent interaction scripts (or human-machine interaction scripts) can be tested, operationalized, or measured in a study.

Foci of Evaluation in the Present Study

Studying how people's perceptions of AI agents can be influenced by human-human interaction scripts or by the violation of expectancies regarding AI agents (discussed in detail later) requires the selection of communication characteristics that have the potential to prompt similar reactions based on interpersonal communication scripts, yet have dissimilar expectancies for humans and for AI agents. As such, the present research considers two communication factors. The first factor is message contingency (Sundar et al., 2016; also known as interactivity in Rafaeli, 1988), which is mentioned by Nass and Moon (2000) as an important characteristic that may trigger social responses toward AI agents. A second factor is response latency, a quality of communication with a substantial history of empirical research in human-to-human conversation and computer-mediated human communication (e.g., Walther & Tidwell, 1995).

Message contingency

Message contingency refers to the extent to which messages that occur later in a conversation are related to or acquire meaning in reference to earlier messages (Rafaeli, 1988; Rafaeli & Sudweeks, 1997). Contingency occurs when people's messages respond to others' earlier messages; messages address the information-level semantic meaning of earlier messages as well as their implied, connotative meaning in a way that shows situational or contextual awareness. When a conversation is contingent, subsequent utterances (beyond adjacency pairs such as *question/answer*) derive meaning from their explicit or implicit reference to prior utterances (J. Burgoon et al., 1999).

Various scholars have argued that contingency generates several positive effects, both generally and with respect to online conversations. For example, Rafaeli (1988) proposes that contingency leads to greater satisfaction with a conversation, and when conversations are part of tasks, greater motivation, higher performance quality, and increased cooperation. Sundar et al. (2015) also argue that contingency can enhance engagement, which may subsequently lead to more favorable attitudes toward the discussed content or toward the discussants.

Several empirical studies show that a verbally contingent communicator begets more positive evaluations than a verbally non-contingent communicator. For example, people engaged in contingent face-to-face interactions were rated as having relatively greater expertise compared to people engaged in non-contingent face-to-face interactions, who were also rated as being less receptive and as having less understanding (J. Burgoon et al., 1999). In online chat, as well, people who provided contingent responses were also rated as having greater social attractiveness and task attractiveness than people who gave non-contingent responses (Lew et al., 2018).

Unlike the expectancy violations perspective, perspectives based on human-human/human-AI communication scripts suggest that if chatbots reply to messages in a contingent manner, communicator identity – whether one's interaction partner is a robot or a human – should not matter as much as contingency – whether one's interaction partner's messages are contingent or non-contingent with respect to prior messages within a conversation (Nass & Moon, 2000; Westerman et al., 2020). Communicators displaying greater contingency should be more credible (J. Burgoon et al., 1999; Sundar, 2008; Sundar et al., 2015) and more attractive (Kang et al., 2008; Sundar et al., 2008; Lew et al., 2018).

Response latency

Response latency, defined as the time between the sending of a message and receiving a reply, is one aspect of chronemics, a cue related to the perception of and reaction to time. Response latency as a cue in human-computer interaction is ironic: It could be disadvantageous for a digital agent to resemble humans, who are relatively slow in responding (Shiwa et al., 2008).

Research shows that communicators who provide faster responses are evaluated more positively than communicators with slower responses. For example, fictitious e-commerce customer service representatives produced greater co-presence and better customer service perceptions when they responded via a text-messaging app immediately than when they responded several hours later (Park & Sundar, 2015). Participants in a text-based dyadic interaction task also rated their partners as more trustworthy if a partner's response was faster than if it was slower (Kalman et al., 2013).

However, the notion that a faster response is better is not always supported. Intentional response delays by chatbots can foster greater perceptions of humanness and social presence than immediate responses (Gnewuch et al., 2018). In research on texting (Döring & Pöschl, 2009) and dyadic e-mail, a slower response can signal more intimacy than a faster response, because "partners who are comfortable with one another do not need to reply to each other quickly" (Walther & Tidwell, 1995, p. 362). In an e-commerce context, responding to text messages in a fast but non-contingent manner reduces one's satisfaction with an interaction as it may signal a lack of concern for either the interaction or for one's interaction partner (Lew et al., 2018).

Hypotheses from a Communication Scripts Perspective

With regard to conversational contingency, and if human-AI interactions are viewed through the lenses of human-human interaction scripts, following the perspectives of Westerman et al. (2020) or the CASA theory (Nass & Moon, 2000):

H1: Highly contingent AI agents (chatbots) are perceived as (**a**) more credible and (**b**) more attractive than less-contingent AI agents.

For the outcome of credibility, the present study utilized a three-dimensional conceptualization by McCroskey and Teven (1999), comprising competence (expertise), trustworthiness (honesty), and goodwill (concern toward others). As for attraction, one important dimension frequently studied by researchers of human-AI interaction is social attraction (e.g., Croes & Antheunis, 2021; A. Edwards et al., 2019; C. Edwards et al., 2016), which indicates how friendly people perceive a target to be. Due to the present context of an e-commerce chat (see Method section of main study), another dimension of attraction – task attraction, which measures perceptions of how well a target can accomplish a task – was crucial for capturing more functional perceptions of AI agents' attractiveness. As such, McCroskey and McCain's (1974) dimensions of social attraction and task attraction were utilized.

With regard to response latency, however, it is unclear whether agents with faster responses or agents with slower responses are preferable. From the perspective of human-human interaction scripts:

RQ1: Do faster or slower responses lead to perceptions of an AI agent (a chatbot) as (**a**) more credible or (**b**) more attractive?

Expectancy Violations

People have expectancies (used interchangeably with *expectations*) for a variety of communication phenomena. Expectancies are "cognitions about the anticipated communicative behavior of specific others, as embedded within and shaped by the social norms for the contemporaneous roles, relationships, and context" (J. Burgoon & Walther, 1990, p. 236). The concept of expectancy violations is featured prominently in several communication theories, such as expectancy violations theory (EVT; J. Burgoon, 1993) and language expectancy theory (LET; M. Burgoon et al., 2002). Although these theories include additional constructs and qualifiers (e.g., communicator reward valence in EVT), they both offer clear and compelling arguments for the prediction of expectancy violations that can extend to the context of interactions between humans and AI agents.

The theories converge when it comes to sources who communicate only through language, offering application to chatbots and humans using text-based online chats. Specifically, positive expectancy violations occur when enacted behavior is more immediate and pleasant than a conversation partner anticipated, and negative expectancy violations occur when enacted behavior is less immediate and more unpleasant than anticipated (J. Burgoon & Burgoon, 2001). In both approaches, expectancy violations are theorized to have an intensification effect relative to meeting expectations. According to J. Burgoon and Burgoon (2001, p. 84), "receivers do have shared expectations about the behaviors a communicator *should* exhibit. When these expectations are violated, receivers overreact to the behaviors *actually* exhibited" (italics in original). As a result, all other things being equal, positive expectancy violations result in the most favorable outcomes, followed by positive behavior that meet expectations, then negative behavior that meets expectations, and lastly, negative expectancy violations, which have the least favorable outcomes (J. Burgoon, 1993).

Critical to the application of the expectancy violations approach is to have baseline knowledge of what normative expectancies are, as well as whether there are different expectancies for different sources. There is often a "shortage of empirically based knowledge about what constitute expected and unexpected interpersonal behaviors and how they are evaluated" (J. Burgoon & Walther, 1990, p. 232), even for humans. The question of what behaviors are expected for AI agents, then, is critical to the exploration and application of the expectancy violations framework.

Expectancies of AI Agents

Recent theorizing on how AI interacts with humans or how AI mediates human-human interactions have highlighted the dynamic relationship between people's expectations of AI agents and the improving capabilities of those agents. For example, Sundar (2020) described a "machine heuristic" based on common stereotypical perceptions that AI is "rule-governed, precise, accurate, objective, neutral, infallible, and when entrusted with private information, do not gossip like some humans . . . . [but also] mechanistic, unyielding, unemotional, cold, transactional and prone to being hacked" (pp. 79–80). Depending on what machine heuristics people use in different situations, people's expectancies of AI agents may be met or violated, potentially influencing people's perceptions of the AI agents (Sundar, 2020). Additionally, with the growing prominence of AI capable of smart replies or auto-completion (e.g., in Gmail) as well as the prevalence of real-time video filters (see Hancock et al., 2020), people may come to expect AI to be more contingent and faster, respectively.

Despite technological advances that enable AI to approximate human communication, people appear to have different expectancies for interaction with AI agents than they do for humans across a variety of foci. The expectancies can influence people's attitudes or behaviors toward AI agents at various stages of a communication process: pre-interaction, during interaction, and post-interaction.

Prior to any interaction, people expect their future communication with AI agents to have greater uncertainty, less presence, and less social attraction, as compared to their expectations of future communication with other humans (C. Edwards et al., 2016; Spence et al., 2014). During social interaction, people expect that other humans can potentially be persuaded, but not AI agents. During cooperation tasks, people therefore make more utterances to AI agents than to other humans, and get more annoyed at noncooperative humans than noncooperative robots (Orcutt & Anderson, 1977; Shechtman & Horowitz, 2003). After a social interaction, people evaluate AI agents more positively if their expectations of the AI agents were explicitly set at the start of the interaction and met during the interaction, but evaluate AI agents more negatively if their expectations of the AI agents were never set in the beginning (Groom et al., 2011). In contrast, whether expectations of humans were explicitly set or not at the start of a social interaction does not affect post-interaction evaluations of a human interaction partner (Groom et al., 2011).

As a whole, research shows that people have different expectations for AI agents than humans. When those expectations are violated, the violation can influence post-interaction evaluations of a communicator. The AI agent featured in the present study was a chatbot. In terms of expectancy violations, as applied to conversational variations in message contingency and response latency between human and chatbot conversation partners, the following assumptions are made. *Assumption 1a*: Chatbots are not expected to exhibit message contingency in text-based chats. *Assumption 1b*: Humans are expected to exhibit message contingency in text-based chats. *Assumption 2a*: Chatbots are expected to exhibit fast responses in text-based chats. *Assumption 2b*: Humans are not expected to exhibit fast responses in text-based chats. A positive expectancy violation occurs if chatbots exhibit contingency, and a negative expectancy violation occurs if chatbots exhibit slow response latencies.

Pilot Study on Expectancies

By testing the above assumptions, a pilot test provided empirical benchmarks for people's expectancies for humans' and chatbots' latency and contingency in online text-based interactions. MTurk participants from the U.S. received \$1 to complete a self-administered questionnaire that measured these expectancies. A total of $N = 97$ participants ranged in age from 21 to 70 years old ($M = 39.0$, $SD = 12.0$);

49 identified as male, 47 identified as female and 1 identified as non-binary. White participants made up 70.1% of the sample, Black participants 10.3%, Asian participants 5.2%, Hispanic/Latino participants 5.2%, and the remainder indicated they have mixed backgrounds.

Measures

Expectations about message contingency reflected several conceptual principles, including adapting one's answers to specific questions rather than giving generic replies, responding to one's conversation partners as unique individuals, and the amount of cognitive effort one puts into the conversation (see Rafaeli, 1988). Expectations for response latency were conceptualized unidimensionally: how long it should take for a conversation partner to reply to a message from another partner (Walther & Tidwell, 1995) in a real-time discussion.

Twenty scale items measured expectancies of human partners' contingency and response latency. The same twenty items, re-worded and repeated, measured expectancies of chatbots. The order of presentation for questions about humans or chatbots was randomized and counterbalanced. The question stem for human expectancies read, "Imagine you are having an online chat with a salesperson on an online shopping website. On a scale of 1 (not at all) to 7 (a great deal), to what extent do you expect the salesperson to . . . ." The question stem for chatbot expectancies replaced the word "salesperson" with "chatbot," and was otherwise the same. See Table 1.

Results and Discussion: Pilot Study

Two sets of exploratory factor analysis – one for human "salesperson" and one for "chatbot" – employed maximum likelihood estimation and direct oblimin rotation. Both analyses resulted in solutions with three factors: individuated contingency, scripted replies, and response latency (see Table 1). Items that loaded on individuated contingency were about treating communication partners as unique individuals and the interrelatedness of messages. Items that loaded on scripted replies were about not giving canned replies, but all these items were reverse-coded, suggesting that method artifact may be responsible for this factor. Items that loaded on response latency were related to reply speed.

Table 1. Factor Loadings for Two Exploratory Factor Analyses (H & CB) Using Direct Oblimin Rotation.

	Individuated Contingency		Scripted Replies		Response Latency	
Items	H	CB	H	CB	H	CB
Be able to find personalized solutions for you	**.89**	**.71**	−.03	−.18	−.06	.05
Treat you as an individual, distinct from other people	**.86**	**.83**	−.13	−.11	−.04	−.11
Provide responses tailored to your specific questions	**.85**	**.80**	< −.01	−.09	−.01	.11
Understand your individual wants/needs	**.84**	**.88**	−.02	−.03	−.02	−.13
Regard you as a unique individual	**.76**	**.79**	−.21	−.19	−.14	−.06
Think about your question before answering it	**.73**	**.71**	< −.01	−.15	−.07	−.21
Pay attention to the details in your messages	**.73**	**.85**	−.11	.02	.17	.08
Carefully process what you typed before replying	**.67**	**.81**	−.07	−.06	.03	.05
Search for information extensively before replying	**.66**	**.75**	.18	−.01	.04	−.06
Listen to what you say/type	**.65**	**.78**	−.14	.01	.19	.01
Adapt answers to your specific questions	**.64**	**.86**	−.18	.07	< .01	.01
Remember what you said at the beginning of a conversation	**.56**	**.65**	.03	−.05	.21	.27
Give replies that are tangential to what you are saying (R)	−.32	−.42	−.11	−.06	−.11	−.10
Use prepackaged responses to respond to customers (R)	.06	.14	**−.93**	**−.79**	.04	.01
Provide customers with scripted responses (R)	.03	.07	**−.76**	**−.89**	.22	−.01
Respond in generic fashion (R)	.25	.28	**−.66**	**−.68**	−.05	.05
Give a prompt reply	−.04	.11	.01	.02	**.78**	**.93**
Answer my questions in a short amount of time	.23	.14	.04	.12	**.68**	**.83**
Respond quickly	.12	.11	.04	.14	**.65**	**.78**
Take a long time to respond (R)	−.07	−.18	−.29	−.24	**.65**	**.75**
Eigenvalues	9.44	10.28	1.87	1.24	1.81	3.12
Percentage of variance explained	47.20	51.42	9.33	6.17	9.04	15.59

Note. H = human, CB = chatbot, R = reverse coded. Items that loaded on a factor are in bold.

The factor loading patterns were very similar across the "salesperson" analysis and the "chatbot" analysis. Following that, scales of participants' expectancies toward salespersons and chatbots were created based on the factor analysis results: Individuated Contingency$_{salesperson}$ (Cronbach's α = .94), Individuated Contingency$_{chatbot}$ (α = .96), Scripted Replies$_{salesperson}$ (α = .88), Scripted Replies$_{chatbot}$ (α = .92), Response Latency$_{salesperson}$ (α = .81), and Response Latency$_{chatbot}$ (α = .88).

A series of paired-samples *t*-tests compared expectancies for human salespeople with expectancies for chatbots. Participants expected chatbots (M = 4.26, SD = 1.66) to be less oriented toward their chat partners in a contingent-individuated manner than humans (M = 5.76, SD = 1.02), $t(96) = 8.60$, $p <$ .001, Cohen's d = .87; and relatedly, expected chatbots (M = 2.70, SD = 1.70) to reply in a less contingent, more scripted fashion than humans (M = 4.54, SD = 1.71), $t(96) = 8.70$, $p < .001$, d = .88. Participants also expected faster replies from chatbots (M = 5.63, SD = 1.24) than from humans (M = 5.17, SD = 1.16), $t(96) = 3.20$, $p = .002$, $d = .33$.

The results showed that in online text chats, people expect chatbots to reply faster than humans, and expect chatbots to reply in a less contingent and individualized way than humans. These results support the assumptions made about differences in expectancies for chatbots in relation to humans. It may be that when chatbots communicate similarly to humans with respect to contingency and/or latency, these expectancy violations trigger different evaluations for the chatbots, with the violation itself producing the most pronounced effects.

Hypotheses from an Expectancy Violations Perspective

Based on the pilot test results, chatbots are not expected to be contingent in text-based chats. Therefore, a positive expectancy violation could occur if chatbots are contingent, leading to the prediction:

H2[1]: There is an interaction between communicator identity (i.e., human or chatbot) and contingency such that highly contingent chatbots are perceived as (**a**) more credible and (**b**) more attractive than equally highly contingent humans, but with no difference between chatbots and humans that are equally less-contingent.

Again from an expectancy violations perspective, the pilot test results showed that chatbots are expected to have fast response latencies in text-based chats. Therefore, a negative expectancy violation occurs if chatbots have slow response latencies, leading to the prediction:

H3: There is an interaction between communicator identity and response latency such that chatbots with slow response latencies are perceived as (**a**) less credible and (**b**) less attractive than humans with equally slow latencies, but with no difference between chatbots and humans that have equally fast response latencies.

Finally, responses to variations in latency may differ depending on other message qualities. In particular, contingency effects have been shown to outweigh latency effects in research examining online human conversation partners (Lew et al., 2018). Analyses must explore whether there is a higher-order interaction among the tested factors:

RQ2: Is there an interaction between contingency, response latency, and communicator identity that affects perceptions of (**a**) credibility or (**b**) attraction?

Main Study

The main study involved a 2 (more/less contingent responses) × 2 (fast/slow response latency) × 2 (communicator identity: human/chatbot) between-subjects experiment. Research participants watched one of eight simulated text-based chat conversations between a potential customer and a communicator – presented either as a human or a chatbot customer service representative – on an online shoe store website mocked up for this study. After that, participants rated the customer service representative's (i.e., the communicator's) credibility and attractiveness.

Participants first read that a potential customer was interacting with either a "customer service employee" or a "customer service chatbot." Participants then observed a conversation between the prospective customer and the customer service representative regarding the company's products, from the customer's perspective. Stimuli employed HTML and Javascript, and appeared just like an online chat system embedded in a web page. The chat simulation displayed in real-time. As newer messages appeared, older messages scrolled up in the chat window.

The customer service representative either replied to the customer in a more contingent or less contingent manner, and with a fast or slow response latency. Using the estimated fast/slow latencies for humans (following Lew et al., 2018) as benchmarks with which to test expectancy violations when chatbots communicated like humans, the representative in the fast response condition replied 8s after each statement the customer completed, while the representative in the slow response latency condition took 40s. Participants were exposed to the stimuli for about 2 min 15s in the fast response condition and about 6 min in the slow response condition. A timer on the questionnaire prevented participants from skipping ahead before the chats finished playing.

The message contingency manipulation featured differences in the extent to which later messages during the chat explicitly or implicitly referred to elements expressed in earlier messages (see Rafaeli & Sudweeks, 1997; Sundar et al., 2016). For example, the customer told the customer service representative that his company transferred him to Singapore, and that he is having difficulty finding size 10E shoes. In the less contingent condition, the representative replied, "Different countries have different sizes and items. I cannot see the inventory for every region. Try contacting your local team." In the more contingent condition, the representative replied, "Different countries have different sizes and items. I cannot see the inventory for Singapore, so I don't know about a 10E," the latter response more explicit referencing elements in earlier messages by specifically mentioning the location and shoe size that appeared previously. More contingent representatives also made statements that referenced the customer's disappointment, unlike less contingent representatives. See online supplementary materials for full chat transcripts.

Sample

Participants were Amazon MTurk workers from the United States who did not participate in the pilot test. Each participant was paid $2. Data were screened for errors in attention check questions and for duplicate IP addresses or geolocation. The attention checks required participants to select a particular response if they were paying attention. Responses were further screened using another attention check that asked participants if they could recall whether the customer interacted with a human or a chatbot. Data from those who could not recall, or who recalled incorrectly, were removed from further analysis. After excluding participants,[2] the final sample had a size of $N = 258$. Participants' ages ranged from 20 to 70 ($M = 36.77$, $SD = 11.07$). There were 167 male participants, 89 female participants, and 2 participants who declined to state their sex. White participants made up 76.7% of the sample, Black participants 9.7%, Hispanic/Latinx participants 6.6%, Asian participants 4.3%, and the remainder indicated mixed ethnicity.

Measures

The customer service representative's credibility was measured using McCroskey and Teven's (1999) scales, which have three dimensions: competence, trustworthiness, and goodwill. Each dimension is comprised of six items on a 7-point semantic differential scale. Competence included items such as *competent/incompetent* and *intelligent/unintelligent*, α = .94. Trustworthiness included items such as *trustworthy/untrustworthy* and *honest/dishonest*, α = .92. Goodwill included items such as *cares about me/doesn't care about me* and *has my interests at heart/doesn't have my interests at heart*, α = .92.

Attraction toward the customer service representative, who was named "Ro," was measured with two dimensions from McCroskey and McCain (1974). Social attraction consisted of items like "I think Ro could be a friend of mine" and "Ro would be pleasant to be with," α = .91. Task attraction consisted of items like "I have confidence in Ro's ability to get the job done" and "If I wanted to get things done, I could probably count on Ro," α = .91. Responses for both attraction dimensions were scored on a Likert-type scale from 1 (*strongly disagree*) to 7 (*strongly agree*).

Perceived contingency – used as a manipulation check – was measured with seven items adapted from Sundar et al. (2016), e.g., "The messages the customer received from the agent were based on his previous inputs" and "The customer's interaction with the agent felt like a continuous thread or a loop" on a 1 (*strongly disagree*) to 7 (*strongly agree*) scale, α = .86. Perceived contingency was greater for participants in the more contingent responses condition ($M = 4.96$, $SD = 1.12$) than participants in the less contingent responses condition ($M = 4.42$, $SD = 1.12$), $t(256) = 3.91$, $p < .001$, Cohen's $d = .49$.

Results: Main Study

A multivariate analysis of variance (MANOVA) tested the combined influence of contingency, response latency, and communicator identity on the three dimensions of credibility: competence, trustworthiness, and goodwill. There was a significant two-way interaction between contingency and response latency, Wilks's $\lambda = .96$, $F(3, 248) = 3.89$, $p = .010$, partial $\eta^2 = .045$.

Univariate follow-up tests commenced employing the Holm (1979) correction, in which p-values for each factor or interaction term, when arranged from smallest to largest, must be below .017, .025, and .050 respectively. There were significant univariate interaction effects between contingency and response latency for competence, $F(1, 250) = 9.59$, $p = .002$, partial $\eta^2 = .037$; trustworthiness, $F(1, 250) = 10.17$, $p = .002$, partial $\eta^2 = .039$; and goodwill $F(1, 250) = 6.80$, $p = .010$, partial $\eta^2 = .026$. Tukey HSD tests revealed that the interaction effects were driven by the fast and more contingent condition, which yielded ratings on competence, trustworthiness, and goodwill that were significantly greater than all the other conditions (see Table 2). The other conditions did not significantly differ from each other. There were no significant main or interaction effects involving communicator identity.

The results are more consistent with H1a, which predicted that credibility evaluations of chatbots would be affected similarly by variations in contingency (alone): Evaluations were a result of an interaction of greater contingency by faster latency. The results do not reflect the expectancy violation predictions of different credibility assessments for human vs. chatbots in H2a and H3a. The answer to RQ1a, whether response latency affects credibility of chatbots, is that it depends on contingency (but not, apparently, communicator identity).

The next analysis employed a MANOVA to test the effects of contingency, response latency, and communicator identity on social attraction and task attraction. There was, again, a significant multivariate interaction effect between contingency and latency on the two forms of attraction, Wilks's $\lambda = .95$, $F(2, 249) = 6.32$, $p = .002$, partial $\eta^2 = .048$. Unlike the previous MANOVA, there was also a

Table 2. Means (and SDs) for univariate effects on competence, trustworthiness, and goodwill.

	More Contingent		Less Contingent			
	Fast	Slow	Fast	Slow	Human	Chatbot
Competence	5.13^a (1.12)	3.92^b (1.57)	4.13^b (1.31)	3.96^b (1.34)	4.35 (1.42)	4.24 (1.44)
Trustworthiness	5.73^a (.97)	4.86^b (1.20)	4.54^b (1.21)	4.54^b (.99)	5.01 (1.29)	4.85 (1.10)
Goodwill	5.21^a (1.08)	4.12^b (1.47)	3.91^b (1.38)	3.67^b (1.34)	4.27 (1.49)	4.21 (1.41)

*Note. SD*s are in parentheses. For the Contingency × Response Latency interaction, different superscripts indicate significant differences using the Tukey HSD test, $p < .001$. Descriptive statistics for communicator identity (human/chatbot) are not broken down due to non-significant main and interaction effects.

Table 3. Means (and SDs) for Univariate Effects on Social Attraction and Task Attraction.

	More Contingent		Less Contingent			
	Fast	Slow	Fast	Slow	Human	Chatbot
Social attraction	4.48[a] (1.35)	3.40[b] (1.53)	3.56[b] (1.45)	3.19[b] (1.31)	4.06[c] (1.40)	3.30[d] (1.48)
Task attraction	5.19[a] (1.09)	3.79[b] (1.60)	3.89[b] (1.34)	3.72[b] (1.53)	4.24[c] (1.60)	4.09[c] (1.45)

Note. *SD*s are in parentheses. For the Contingency × Response Latency interaction, different superscripts indicate significant differences using the Tukey HSD test, $p < .01$. For the main effect of communicator identity (human/chatbot), different superscripts indicate significant differences using the univariate *F* test, $p < .001$. Descriptive statistics for communicator identity are not broken down due to non-significant interaction effects.

multivariate main effect of communicator identity (human vs. chatbot) on attraction, Wilks's $\lambda = .89$, $F(2, 249) = 14.96$, $p < .001$, partial $\eta^2 = .107$. There were no interaction effects involving communicator identity and any other factor.

A univariate follow-up test commenced for communicator identity effects. Using the Holm correction, *p*-values for each effect of communicator identity on task and social attraction, when arranged from smallest to largest, had to be below .025 and .050, respectively. There was a significant univariate main effect of communicator identity on social attraction: Humans ($M = 4.06$, $SD = 1.40$) were more socially attractive than chatbots ($M = 3.30$, $SD = 1.48$), $F(1, 250) = 18.86$, $p < .001$, partial $\eta^2 = .070$. The effect of communicator identity on task attraction was not significant, $F(1, 250) = .56$, $p = .453$. These results are inconsistent with predictions derived from either the expectancy violations perspective or the application of human-human scripts to human-AI interactions. They suggest a difference in attraction toward humans versus chatbots, independent of their communication behaviors. The results did not support predictions from expectancy violations as humans were rated more socially attractive than chatbots regardless whether the communicators violated or conformed to expectancies. Results suggest the persistence of *ontological* rather than behaviorally-based preferences.

There were significant univariate interaction effects for contingency by response latency on social attraction, $F(1, 250) = 4.32$, $p = .039$, partial $\eta^2 = .017$; and on task attraction, $F(1, 250) = 12.33$, $p = .001$, partial $\eta^2 = .047$. Tukey HSD post-hoc tests revealed that the effects were again driven by the faster and more contingent condition, for which social attractiveness and task attractiveness means were significantly greater than all other conditions, the latter of which did not significantly differ from each other (see Table 3).

Results for task attraction partially supported H1b. Chatbot agents that were more contingent were perceived as more attractive task partners than chatbot agents that were less contingent, although the hypothesized effects of contingent replies were conditional upon fast response latencies. Results for social attraction did not support any of the hypotheses as humans were rated as more socially attractive than chatbots across all conditions.

Discussion

This study compared the evaluation of humans' vs. chatbots' communication using several perspectives from human-AI interaction and expectancy violations. A pilot study established differential expectancies for humans and chatbots with regard to text message contingency and response latency. A separate study tested the combined effects of contingency, response latency, and communicator identity on credibility and attraction.

Communication Scripts, with Functional and Relational Aspects

Although none of the expected effects were supported, the study provided insight into how chatbots are evaluated in several important ways. First, although unhypothesized, the interaction between contingency and response latency (a combination of H1 and RQ1) was commensurate with the communication scripts perspective. Independent of people's expectancies, chatbots and humans that were contingent in replying and were relatively fast (by human standards) were rated as more credible and attractive than all other permutations of contingency (more/less contingent) and response latency (fast/slow). The result that more contingent chatbots were preferred over less contingent chatbots shows that the implicit rules of interpersonal communication can be applied to interaction with chatbots (Westerman et al., 2020) – especially given that contingency has been proposed as a construct cardinal to the essence of what interpersonal communication is (Walther, 2019). Yet, results for response latency show that human characteristics are not necessarily the benchmarks that AI agents should emulate (see Gambino et al., 2020; Spence, 2019). Using human response latencies as benchmarks, participants in this study rated communicators exhibiting slow responses as less credible and less attractive as task partners than communicators that exhibit fast responses in a contingent manner, even though slow responses are more typical of humans than chatbots. Future studies can explore how chatbots are evaluated based on response latencies set to chatbot standards rather than to human standards like in the present study. Relatedly, the "fast" latency of 8s could be too slow for chatbot standards or the "slow" latency of 40s could be unacceptable in an e-commerce context, opening the possibility that the present results for latency may be influenced by a methodological artifact. Future research should be sensitive to experimental manipulations not only in a relative sense (e.g., is 8s faster than 40s?), but also in an absolute sense (e.g., is 8s – on its own – considered fast?), while also considering the context.

Second, the unhypothesized finding that humans were consistently more socially attractive than chatbots, above and beyond contingency or response latency, warranted a reconsideration of the *a priori* theoretical lens through which the present study framed communication phenomena regarding chatbots. To this end, Guzman and Lewis's (2020) typology of the ways in which an AI can elicit different human responses is useful in explaining the ontologically-based evaluations participants seemed to have made when they rated humans as more socially attractive than chatbots regardless of contingency or response latency. Guzman and Lewis (2020) identified three aspects of AI as communicator: *Functional* aspects pertain to how people perceive AI within its intended roles. *Relational* aspects deal with how people perceive AI in relation to themselves (and vice versa). *Metaphysical* aspects are about the ontological nature of what constitutes AI or AI communication.

In particular, the distinction between the functional and the relational aspects of an AI agent is important for understanding the present set of results: It is one thing to claim that an AI agent is credible/non-credible with regard to the information it was designed to provide *functionally*, and another to claim that an AI agent is social/asocial in terms of its ability to communicate as a human-like entity *relationally*. *Functional* concerns appeared to drive the way people evaluated the chatbots, to the extent that providing trustworthy information can be considered the primary role/function of customer service chatbots. With regard to the *relational* aspects of AI as communicator, humans were found to be more socially attractive than robots, suggesting that robots are not desirable as potential friends. Although the task-oriented encounter in the present study is not especially conducive to burgeoning friendship, it was nevertheless the case that ostensibly human communicators, whose utterances were no different from the chatbots', received significantly higher social attraction ratings.

For functional assessments of human-AI interactions, such as when a human obtains information from a chatbot, the most salient aspect of the interaction may be the information being exchanged. If the information makes sense, then there is no reason to think about whether the source of the information is a chatbot or a human, and therefore chatbots and humans are not perceived differently. But for social assessments, when individuals are asked to evaluate the social attractiveness of a communicator or whether the communicator can potentially be a friend, the identity of the communicator can be more potent than aspects of the interaction with that communicator. The possibility that participants made ontological, rather than behavioral, discriminations cannot be ruled out.

Although ontological explanations for the evaluation of chatbots are somewhat tangential to the original research goals of this study, they deserve greater mention than a mere passing remark given their plausible influence on the present results, and more importantly, due to their potential to act as a theoretical boundary to the communication scripts perspective. Within the communication scripts perspective, CASA theory in particular proposes that people *initially* respond to chatbots in a social manner if conditions are conducive to mindless responses. However, the extent to which social responses to chatbots persist *over time* is still ambiguous at a theoretical level from script-based perspectives. Empirically, there is evidence indicating that although people may respond socially to chatbots in initial interactions, they eventually become more aware of the fact that chatbots are non-human, and therefore decrease their amount of self-disclosure toward a chatbot over time (Croes & Antheunis, 2021). In another study based on the analysis of actual chat transcripts, people were found to be more agreeable and to have self-disclosed more when interacting with humans than with chatbots (Mou & Xu, 2017). What could explain these results? One plausible reason is that chatbots fail to respond in a sufficiently contingent manner (i.e., lack of conversational contingency gets more obvious as an interaction goes on). Another plausible reason is that people eventually start to make ontological discriminations between chatbots and humans. Future research can study the adequacy of these explanations or formally introduce them as boundary conditions to the communication scripts perspective (i.e., explicitly stating what researchers currently acknowledge implicitly).

Expectancy Violations

The expectancy violations perspective was not supported. No evidence was found for a positive chatbot expectancy violation for message contingency or for a negative chatbot expectancy violation for response latency. There are several plausible explanations for the lack of support for expectancy violations. Some of these reasons are theoretical while others have to do with the limitations of the study.

Theoretical explanations

In the present study, H2 and H3 were motivated by the *concept* of expectancy violations, which is a feature in several social science theories (see J. Burgoon & Burgoon, 2001), rather than by a *specific theory* that deals with the violation of expectations. Therefore, H2 and H3 contained predictions that depended solely on whether an inferred expectancy violation caused an intensification effect, that is, whether positive expectancy violations led to more favorable outcomes than positively meeting expectations or negative expectancy violations led to less favorable outcomes than negatively meeting expectations.

Yet, readers familiar with the concept of expectancy violations would be aware of J. Burgoon's (1993) expectancy violations theory (EVT), which of course also features the concept of expectancy violations but also contains other qualifiers, such as communicator reward valence. In EVT, communicator reward valence moderates the influence of expectancy violations on interaction outcomes. For example, people might be more forgiving if a communicator with high reward valence engages in a behavior that results in negative expectancy violations, but people might be more hesitant to show approval if a communicator with low reward valence engages in a behavior that results in positive expectancy violations. If communicator reward valence is indeed critical for observing expectancy violations effects, it is possible that the seemingly low levels of communicator reward valence in the present context – an online chat with a customer service representative is relatively impersonal – could have stymied efforts to find empirical support for the expectancy violations perspective.[3]

A second plausible theoretical explanation why the expectancy violations perspective was unsupported has to do with the types of phenomena covered by the perspective. In both EVT (J. Burgoon, 1993) and language expectancy theory (M. Burgoon et al., 2002), expectancies refer to the anticipated communication behaviors of specific communicators. However, the possibility that the expectancies of *outcomes* influenced the results cannot be ruled out. In the present study, the chats had a slightly disappointing outcome (i.e., the customer did not buy anything) to facilitate the scripting of contingency, as opportunities for nuanced conversational contingency are fewer if the customer service representative replied affirmatively for all the customer's requests. Although theories of expectancy violations are conceptually about the difference between enacted and expected behavior by a communicator, the somewhat negative outcome in the present study may also influence credibility or attraction to the extent that outcomes fall under the purview of expectancy violations in a broader sense (that goes beyond the scope of expectancy-based theories). For example, could expectancies for chatbots be positively violated only if chatbots reply contingently *and* produce favorable outcomes? Future research can investigate the notion that expected behaviors and expected outcomes may interact with each other to produce moderation effects or reveal boundary conditions.

Limitations

Notwithstanding the theoretical reasons mentioned above, it is also possible that several limitations led to the lack of empirical support for the expectancy violations perspective. One limitation of this study is that pre-interaction expectancies were measured only in the pilot test and not in the main study. However, measuring pre-interaction expectancies of the main study participants could potentially make participants too conscious of communicator identity, potentially producing demand characteristics. While we are still able to infer, based on the pilot study results, that people have different expectancies in the main study, we are unable to definitively claim that the absence of expectancy violations effects was not because main study participants did not have their expectancies violated in the first place.

Another limitation pertains to the experimental treatment. Although having participants watch the chats (vs. actually chatting) ensured consistency of treatment, participants did not have a genuine chat experience. Observation may not be a problem *per se*, as past research has found that evaluations made by actual participants and observers of a social interaction can be very similar (e.g., J. Burgoon & Le Poire, 1999), showing that theoretical relationships can still be demonstrated via observation. Yet, actually participating in a chat could make participants more cognitively involved in the study than observation. With greater cognitive involvement, participants could be more likely to reevaluate chatbots/humans in relation to their prior expectancies (as opposed to passively observing), potentially producing greater expectancy violations that influence the outcome measures. If future research were to enact procedures involving actual chats, the sample size[4] should be greater than that of the present study (N = 258) to compensate for the greater variance that may accompany the lesser degree of standardization across experimental trials, as the chats will no longer be identical.

Conclusion

Functionally, chatbots in the present customer service context are evaluated for their ability to meet the communication demands of their intended roles. Relationally, there also seems to be an ontological bias rather than a behavioral bias. Yet, efforts to enable chatbots to respond with great contingency, even reflecting specific partners' unique conversational contents and their reactions, over time – perhaps the *sine qua non* of interpersonal social relationships (Walther, 2022) – are already emerging (Hakim et al., 2018). Future studies will continue to explore the various communication qualities and attributes by which a digital agent can be (perceived as being) superior, inferior, or equal to human conversation partners.

Notes

1. Reversed effects of expectancy violations for humans were not predicted because the aim was to examine the effects of expectancy violations when a chatbot replies like/unlike an individual engaged in interpersonal communication using human-human scripts (Nass & Moon, 2000; Westerman et al., 2020). To this end, the contingency and latency manipulations described in the main study were operationalized according to what would be considered more/less contingent and fast/slow according to human standards.

2. A total of 485 participants were originally recruited, out of which $n = 74$ dropped out on their own volition. Participants' data were excluded from further analysis if they gave incorrect responses to the attention check questions ($n = 39$) or if they incorrectly recalled whether the customer service representative was a human or a chatbot, or admitted they could not recall ($n = 115$). If duplicate IP addresses or geolocation information appeared in the data ($n = 104$), analyses retained only the earliest instance. Inattentive participants and duplicate IP addresses (doing the same study multiple times) are known threats to MTurk data quality, and should be checked (Cheung et al., 2017). The number of eliminated participants should not be summed up as eliminated participants can fail multiple checks.
3. Note that J. Burgoon's (1993) EVT is but one theory that deals with expectancy violations. In M. Burgoon et al.'s (2002) language expectancy theory, for example, communicator reward valence does not feature at all.
4. Relatedly, there is the question of whether expectancy violations effects were not found because the present study was underpowered. This seems unlikely, considering that (a) there was a significant main effect of communicator identity on social attraction and (b) there was a consistent significant interaction effect between contingency and latency on the three dimensions of credibility and the two dimensions of attraction. The hypotheses for the expectancy violations perspective, H2 and H3, require the same degrees of freedom as the interaction effect between contingency and latency (and they were all two-way interactions). As such, if sample size was a big problem, the significant contingency by latency effect is unlikely to be as consistent across various measures.

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Data Availability

The data underlying this article will be shared on reasonable request to the corresponding author.

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