Cyberpsychology, Behavior, and Social Networking
Volume 18, Number 4, 2015

DOI: 10.1089/cyber.2014.0458

Reciprocity in Computer–Human Interaction: Source-Based, Norm-Based, and Affect-Based Explanations

Seungcheol Austin Lee, PhD,[1] and Yuhua (Jake) Liang, PhD[2]

Abstract

Individuals often apply social rules when they interact with computers, and this is known as the Computers Are Social Actors (CASA) effect. Following previous work, one approach to understand the mechanism responsible for CASA is to utilize computer agents and have the agents attempt to gain human compliance (e.g., completing a pattern recognition task). The current study focuses on three key factors frequently cited to influence traditional notions of compliance: evaluations toward the source (competence and warmth), normative influence (reciprocity), and affective influence (mood). Structural equation modeling assessed the effects of these factors on human compliance with computer request. The final model shows that norm-based influence (reciprocity) increased the likelihood of compliance, while evaluations toward the computer agent did not significantly influence compliance.

Introduction

The Computers Are Social Actors (CASA) effect has shown that individuals often respond to computer agents as if they were social beings. This social response appears across a number of different contexts. For example, individuals appear to use traditional gender stereotypes when rating information that comes from male-voiced computers versus female-voiced computers.[1,2] This type of social response extends to attributions of personality; individuals rate computers more favorably when computers use language that mirrors the individuals' own personalities.[3] Individuals even follow politeness norms when they interact with computers.[4] This wide range of application for CASA demonstrates the robustness of the effect.

Indeed, one common thread across this body of work is that interaction with computer agents has the potential to affect individuals socially. The current study focuses on extending the CASA effect to examine situations under which the agents attempt to gain *behavioral compliance* from human partners. In other words, the current research examines if the robustness of the CASA effect allows an agent to take advantage of compliance gaining strategies well established in the social influence literature.

The overarching goal of this research is to examine and compare various mechanisms that may contribute to how individuals respond to an agent's compliance request. The current study extends previous work by testing source-based, norm-based, and affect-based influences on compliance gaining within a CASA context.

Literature Review

Nass and Moon[5(p83)] summarized existing research related to the CASA effect and concluded that the underlying mechanism involved the concept of mindlessness: ''to elicit mindless social responses in [a computer-human interaction] context, individuals must be presented with an object that has enough cues to lead the person to categorize it as worthy of social responses, while also permitting individuals who are sensitive to the entire situation to note that the social behaviors were not clearly appropriate.''

Drawing on this explanation, three focal concepts should trigger mindlessness. First, individuals should view agents as sources, worthy of social responses. Following this logic, how individuals evaluate or perceive the sources, or the agents, should affect how they respond to the agents. An extension of this response may involve how individuals respond to compliance requests from the agents.

Among various dimensions of source evaluations, especially relevant are the two fundamental dimensions of social perception: competence and warmth.[6] Competence refers to the extent to which a source is evaluated as a knowledgeable expert related to a task. Warmth pertains to the general

[1]Department of Communication, Northern Kentucky University, Highland Heights, Kentucky.
[2]Department of Communication Studies, Chapman University, Orange, California.

likeability of a source. Extant literature shows that source evaluations exert a strong, positive effect on the persuasive outcome in traditional interpersonal interactions.[7] If individuals react to agents in a social manner, perceptions of the agents' competence and warmth should directly relate to the likelihood of compliance with the agent's request.

The second concept is that individuals' response to agents may be inherently social. This concept implies that traditional interpersonal compliance gaining mechanisms function similarly in a CASA context.[8] A well-established compliance gaining mechanism in the interpersonal communication literature is the norm of reciprocity, which refers to the inclination to return favors received from others.

Reciprocity involves a norm-based moral code. As Simmel[9] suggested, reciprocity is a fundamental social norm that enables social equilibrium and cohesion. In every society, individuals are taught to return the favor when given. This norm-based code creates a corresponding influence such that it compels individuals to reciprocate. Specifically, individuals tend to return any favors (e.g., receiving objects or help) enacted for them, as the unreturned favor generates a feeling of obligation. Obligation is an aversive feeling that causes the individuals who received an unreturned favor to comply with requests from the favor giver. Previous research offers clear support for the effect of reciprocity on compliance in interpersonal contexts.[10,11]

Following Nass and Moon's[5] contention regarding social responses to agents, reciprocity should lead to higher compliance after individuals receive help from an agent. Fogg and Nass[12] found that participants who received help from computers were likely to return the favor by completing tasks for the computers. Moon[13] also reported that participants were likely to reciprocate self-disclosure from computers by providing deeper and broader information about themselves.

The third concept relates to individuals' affective state. When individuals interact with an agent, a variety of factors in computer–human interaction may divert their attention and lead them to over-apply social scripts from interpersonal interactions. Among the factors, the mood elicited by interactions with the agent may influence individuals' susceptibility to compliance requests. Positive mood elicits an information processing strategy that relies on simple heuristics, while negative mood elicits an analytical mode of information processing. Put differently, individuals may experience more mindlessness or follow scripted behaviors when they are in more positive mood. Therefore, positive mood increases compliance and negative mood decreases compliance in interpersonal interactions.[14,15]

This mechanism may be applicable to computer–human interactions. Previous studies have shown that individuals are more likely to comply with the computer agent's request when the interaction elicits positive mood. For instance, flattery or praise from the agent produces the similar persuasive effects as one that originated from a person.[16,17] In some cases, whether participants actually deserved the praise appears unimportant; even insincere or unwarranted praise paralleled the effectiveness of legitimate positive feedback.[18]

Hypothesized Relationships

Following the CASA literature, the major assumption in the current research is that individuals respond to compliance gaining attempts from a computer agent in a similar fashion as in interpersonal interactions. The current study explores three mechanisms for this effect: source-based, norm-based, and affect-based influences.

First, source evaluations toward a computer agent may affect individuals' compliance with requests from the agent. An agent that helps participants should produce higher perceptions of competence (H1), which lead to higher perceptions of warmth (H2). Research shows that individuals typically view intelligent people as more sociable than less intelligent people.[19,20] This halo effect (i.e., a phenomenon where individuals judge the general personality of a person based on the perception of one salient characteristic)[21] may apply to computer–human interactions if individuals indeed treat computers as social actors. Based on the extant literature related to interpersonal source evaluations and compliance,[7,22] higher evaluations of competence (H3a) and warmth (H3b) are expected to increase the likelihood of compliance.

Second, due to the norm of reciprocity, an agent's helping behavior should directly affect individuals' compliance (H4). Research suggests that when the rule of reciprocity is engaged, individuals feel a sense of obligation to repay the favor, regardless of liking.[8,10] For example, DePaulo et al.[23] reported that the amount of help received predicted the amount of reciprocated behavior. Participants who received more help returned a greater amount of help, even when excessive and inappropriate help created uncomfortable feelings and decreased liking.

Third, relating to individuals' affective state, receiving help from an agent is likely to increase positive mood (H5). In interpersonal contexts, receiving help is associated with positive affect and more liking toward the helper, as long as it does not create an uneasy feeling of obligation or threat to the recipient's self-esteem.[21,24] This positive mood, in turn, enhances an agent's perceived competence (H6a) and warmth (H6b), as demonstrated in previous research.[15,16] Finally, based on the literature on affective states and compliance,[13,25] positive mood should increase the likelihood of compliance to the agent's request (H7).

The hypothesized model (Fig. 1) summarizes previous explanations regarding source-based, norm-based, and affect-based influences.

Methods

Design and procedure

Participants were asked to take part in an online study where they played a trivia game with a computer partner. The ostensible computer partner had an anthropomorphic and gender-neutral name: CHRIS (Computer–Human Retrieval Information System). Participants were told that CHRIS is an automatic information retrieval system, similar to IBM's "Watson" system featured on the popular TV show *JEOPARDY!* To enhance the realism of the experiment, the ostensible mechanism of CHRIS was explained: CHRIS automatically extracts keywords from the questions, retrieves information from a knowledge database, and suggests the answer with the highest relevance. In actuality, however, all of CHRIS's responses were pre-programmed.

Participants were told that CHRIS would assist answering the trivia questions by recommending a choice for every question. During the 10-question trivia game, CHRIS

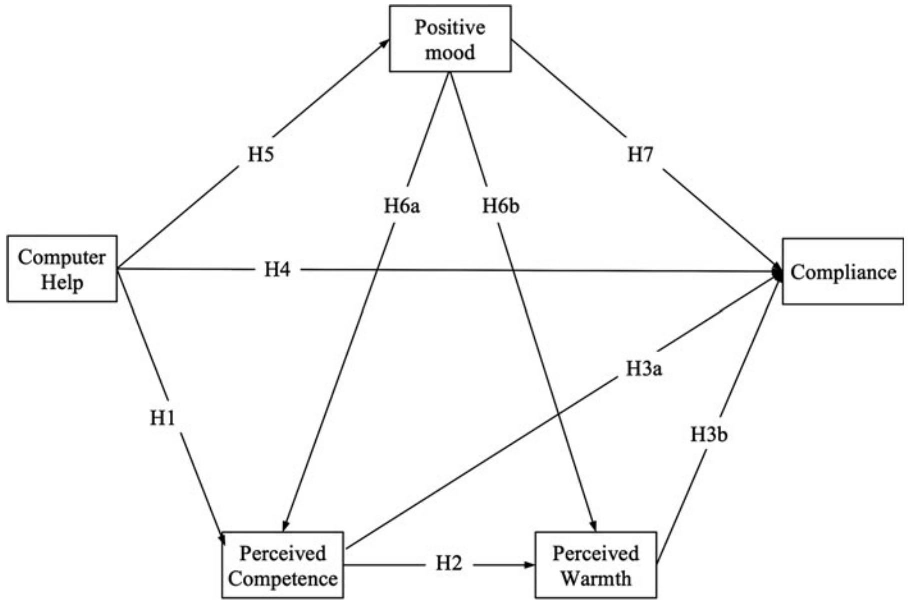

FIG. 1. A path model of the hypothesized relationships.

displayed only a minimal visual cue of an animated smiley face. Most questions (8 out of 10) on the trivia game were designed to be difficult, which meant that participants were less likely to answer the questions correctly without CHRIS's help. To lessen the likelihood of cheating, participants had a time limit of 20 seconds per question.

Participants were randomly assigned to the experimental conditions. In the ''helpful'' condition, CHRIS provided nine correct and one erroneous recommendations to aid the participants in selecting the responses. In the ''unhelpful'' condition, CHRIS provided only two correct responses, six erroneous responses, and two responses where the answers were not retrieved. Figure 2 provides an example of the erroneous response.

After completing the trivia game, participants completed self-report measures of perceptions toward CHRIS, including perceived competence and perceived warmth. Then, the online survey indicated that participants had fully completed the study. Lastly, CHRIS prompted a compliance gaining request, in text form, asking participants whether they would complete pattern recognition tasks.

CHRIS requested participants to complete an average of 30 pattern recognition tasks that would take an average of 15 minutes, respectively. If participants agreed, they were led to conduct a series of Completely Automated Public Turing test to tell Computers and Humans Apart (CAPTCHA) tasks that required typing letters from distorted images that appeared on the screen (Fig. 3). This task was selected because a computer agent cannot resolve it without human assistance. Participants were further instructed that they could discontinue the task at any time. Finally, all participants were debriefed and thanked for their participation.

Participants

Participants were 664 undergraduate students (64% female). Participants' average age was 20.5 years ($SD = 2.44$ years). European Americans composed the majority of the

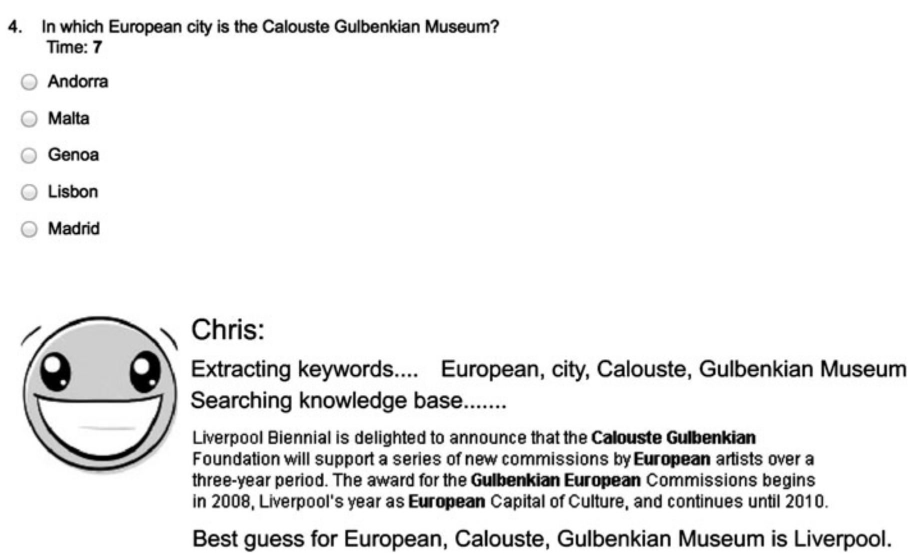

FIG. 2. Example of trivia question (erroneous answer).

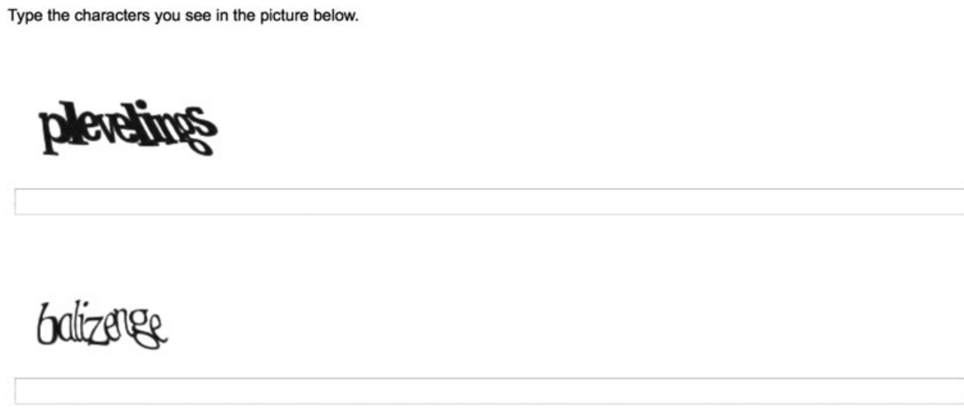

FIG. 3. Example of Completely Automated Public Turing test to tell Computers and Humans Apart (CAPTCHA) task.

participants (73.6%), followed by African Americans (9.6%), Asians (8.7%), Hispanic (2.6%), and others or mixed (2.6%).

Measures

Source evaluations. The current study examined two universal dimensions of source evaluation: competence and warmth.[6] The 7-point Likert scale measuring perceived competence included ''CHRIS is intelligent,'' ''CHRIS is knowledgeable,'' and ''CHRIS is competent.'' The items assessing perceived warmth included ''CHRIS is likable,'' ''CHRIS is sociable,'' ''CHRIS is friendly,'' and ''CHRIS is personal.'' A confirmatory factor analysis of the 7-item scale yielded a good fit for the two-factor model, $\chi^2(9) = 21.26$, $p = 0.01$, comparative fit index (CFI) = 0.99, Tucker–Lewis index (TLI) = 0.99, and root mean square error of approximation (RMSEA) = 0.05. Reliabilities (Cronbach's α) were 0.85 for competence and 0.90 for warmth.

Positive mood. A modified version of the Positive and Negative Affect Schedule (PANAS[26]) measured positive mood. Participants received each of the mood descriptors on a 7-point Likert scale. The seven items measuring positive mood included: interested, excited, strong, enthusiastic, proud, inspired, and active. A confirmatory factor analysis of the 7-item scale showed a good fit for a one-factor model, $\chi^2(14) = 111.41$, $p < 0.001$, CFI = 0.96, TLI = 0.95, and RMSEA = 0.12. Reliability was 0.93.

Compliance. Initially, three methods assessed participant compliance: likelihood of agreeing to complete the pattern recognition tasks, percentage of actual pattern recognition tasks completed, and percentage of correct pattern recognition responses. Participants who complied with the task request completed more than 95% of the pattern recognition tasks and responded correctly more than 90% of the time. As a result, the final measure of compliance included only the dichotomous response of agreement or disagreement to the request.

Results

A path analysis examined both the direct and mediated relationships within the hypothesized model and identified the importance of each predictor. In addition, this approach allowed an assessment of the data fit to the hypothesized model.

Before conducting analysis, the data were screened for outliers, missing observations, and multicollinearity. First, if a case significantly exceeded the critical value ($p < 0.001$) for the Mahalanobis distance, it was considered as an outlier and excluded from the analysis. Second, missing observations, which comprised < 2% of the data, were estimated based on the expectation-maximization algorithm. Finally, variance inflation factor (VIF) statistics ranged from 1.03 to 1.38, indicating no threats of multicollinearity.

Table 1 reports zero-order correlations among all study variables. Path analysis was performed using Mplus,[27] which provides robust weighted least squares estimation for categorical dependent variables. The paths in the model were evaluated in terms of statistical significance and standardized path coefficients (i.e., standardized beta weights), which represented the direct effect of variables. Goodness of overall model fit was assessed by Hu and Bentler's[28] criteria. After testing an initial model with the hypothesized relationships, nonsignificant paths were eliminated and additional paths were included to improve the model. The additional paths were considered only when modification indices were > 5.0.[29]

The initial model with the hypothesized relationships did not yield a good fit, $\chi^2(1) = 14.76$, $p < 0.001$, CFI = 0.98, TLI = 0.80, and RMSEA = 0.14. The path between competence and compliance (H3a) was not statistically significant, $\beta = -0.03$, $p = 0.67$.

After excluding this path, the modified model produced an acceptable fit, $\chi^2(2) = 13.04$, $p = 0.002$, CFI = 0.98, TLI = 0.92, and RMSEA = 0.09. Figure 4 presents the model with standardized path coefficients. All the paths in the model

Table 1. Zero-Order Correlation Matrix of Variables

	1	*2*	*3*	*4*	*5*
1. Computer help	1.00	0.63**	0.22**	0.33**	0.18**
2. Perceived competence		1.00	0.46**	0.37**	0.09*
3. Perceived warmth			1.00	0.41**	−0.02
4. Positive mood				1.00	0.11**
5. Compliance					1.00
M	0.78	5.33	4.19	4.02	0.36
SD	0.42	1.62	1.54	1.45	0.48

*$p < 0.05$; **$p < 0.01$.
Variables were dummy-coded as follows:
Computer help: 0 = unhelpful; 1 = helpful.
Compliance: 0 = no compliance; 1 = compliance.

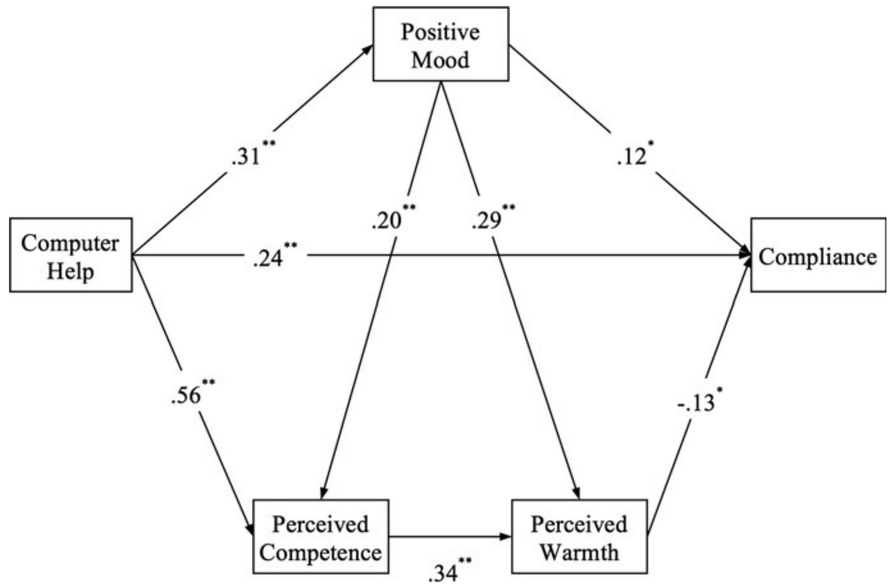

FIG. 4. Modified model with standardized path coefficients (*$p < 0.05$; **$p < 0.01$).

were significant. The modification indices did not suggest any additional paths that would improve the model fit.

Agent help (helpful/unhelpful conditions) was a strong predictor of perceived competence (H1; $\beta = 0.56$, $p < 0.001$), which in turn affected perceived warmth (H2; $\beta = 0.34$, $p < 0.001$). There was no direct path between perceived competence and compliance. In addition, inconsistently with the hypothesis, the path coefficient from perceived warmth to compliance was negative (H3b; $\beta = -0.13$, $p = 0.03$). Therefore, the hypotheses regarding source-based explanations received no support.

The model provided stronger evidence for norm-based explanations. The direct effect of computer help, without the mediation of perceived competence or perceived warmth, was significant for compliance (H4; $\beta = 0.24$, $p < 0.001$). After receiving help from an agent, 40.2% of participants agreed to help the agent in return. When the agent was not helpful, only 20.1% of participants agreed to help. This difference was significant, $\chi^2(1) = 20.26$, $p < 0.001$, $\phi = 0.18$, odds ratio (OR) = 2.67.

Positive mood partially mediated the relationships between computer help and source evaluations. Computer help significantly impacted positive mood (H5; $\beta = 0.31$, $p < 0.001$), which in turn influenced both perceived competence (H6a; $\beta = 0.20$, $p < 0.001$) and perceived warmth (H6b; $\beta = 0.29$, $p < 0.001$). In addition, positive mood had a direct effect on compliance (H7; $\beta = 0.12$, $p = 0.02$), albeit weak compared to the direct effect of computer help.

Table 2 presents the significant direct, indirect, and total effects. The direct effect of computer help on compliance ($\beta = 0.23$, $p < 0.001$) was the same as its total effect. The mediated paths through perceived competence, perceived warmth, and positive mood were statistically significant with the bootstrapping method with 1,000 replications. Nevertheless, those indirect effects were trivial and in different directions, cancelling out the effects of each other. Consequently, the indirect effects did not contribute to the total effect at all.

TABLE 2. SIGNIFICANT DIRECT, INDIRECT, AND TOTAL EFFECTS

Parameters	*Standardized estimate*	p-*Value*
Direct effect		
Computer help → compliance	0.23	0.001
Indirect effect		
Computer help → competence → warmth → compliance	−0.02	0.04
Computer help → positive mood → compliance	0.04	0.03
Computer help → positive mood → warmth → compliance	−0.01	0.03
Computer help → positive mood → competence → warmth → compliance	−0.003	0.04
Total effect		
Computer help → compliance	0.23	0.001

Discussion

The current study examined mechanisms that influence individuals' compliance with requests from a computer agent by testing source-based, norm-based, and affect-based explanations. The structural equation model showed that participants' evaluations toward the agent were not associated with compliance. Participants' positive mood, elicited by receiving help from the agent, was minimally related. By contrast, the agent's helping behavior was the main predictor of compliance, supporting the norm-based explanation.

The CASA paradigm assumes that individuals would evaluate computer agents differently as a result of their interactions.[5] Consistent with this paradigm, this research showed that whether the agent helped the participants affected perceived competence, which in turn impacted perceived warmth. This result suggests that the halo effect may apply to computer–human interactions. Indeed, the correlation between perceived competence and perceived warmth of the agent in this study ($r = 0.46$) was similar to those found by Rosenberg et al.[19] ($r = 0.42$) and Judd et al.[18] ($r = 0.52$) in interpersonal interactions.

In this study, however, the agent failed to gain compliance in light of more positive source evaluations. Positive mood also had only a limited effect. Instead, norm-based influence, or reciprocity, affected participants' compliance. These findings are consistent with Regan's[10] classic experiment where pre-giving a can of coke increased the likelihood of compliance for donation; meanwhile, the likability or pleasantness of the giver did not affect compliance. As Gouldner[30] explained, reciprocity is a moral sense of returning the benefits to those who give benefits. The findings of the current study demonstrate that such a sense still occurs when individuals interact with computer agents.

Taken together, the results offer some interesting directions for managers and designers to develop and implement agents, especially if the agents' aim involves influencing individuals' actual behavior to compliance requests. First, practitioners typically focus on ways to increase anthropomorphism or other creative characteristics related to the agents. These practitioners may do so in hopes of making the agents more personable and likable in an effort to gain compliance. However, the findings of the current study show that this source-based focus will not significantly affect compliance. Instead, practitioners may direct their efforts more on taking advantage of more robust norm-based mechanisms in interpersonal communication, such as reciprocity, to gain compliance from users.

One way of implementing reciprocity may involve a collaborative task or game where computer agents clearly assist the human partners. Conceivably, these types of tasks and games may be built in to interactive robots such as the *Autom* Robot, which aims to help individuals to lose weight; message designers may utilize an interactive game with the ultimate aim of gaining individuals' compliance toward completing a weight loss task.[31] Future practitioners may also harness the compliance gaining ability of agents to promote other health or prosocial behaviors in novel applications.

The implications should be taken in light of the current study's limitations. The unique experimental context employed demands additional research to establish stronger support for external validity. Also, participants were primarily European Americans, potentially limiting the generalizability of the findings to different cultural contexts. In addition, the order of measurements was fixed (i.e., measuring liking before compliance) rather than counterbalanced. This design was selected to ensure that participants knew they completed the study when responding to the agent's request and that compliance was completely voluntary. As Regan[10] suggested, however, reversing the order (i.e., measuring compliance before liking) may create differences in the liking–compliance correlation. Finally, participants' cognitive processing during the interaction with the agent was not measured. As a result, the current study can only infer that the mechanism associated with reciprocity functioned via obligation. Future research may focus on examining additional mechanisms of compliance gaining that are applicable in CASA contexts.

Author Disclosure Statement

No competing financial interests exist.

References

1. Lee EJ. Gender stereotyping of computers: resource depletion or reduced attention? Journal of Communication 2008; 58:301–320.
2. Nass C, Moon Y, Green N. Are computers gender-neutral? Gender stereotypic responses to computers with voices. Journal of Applied Social Psychology 1997; 27:864–876.
3. Nass C, Moon Y, Fogg BJ, et al. Can computer personalities be human personalities? International Journal of Human–Computer Studies 1995; 43:223–239.
4. Nass C, Moon Y, Carney P. Are respondents polite to computers? Social desirability and direct responses to computers. Journal of Applied Social Psychology 1999; 29:1093–1110.
5. Nass C, Moon Y. Machines and mindlessness: social responses to computers. Journal of Social Issues 2000; 56:81–103.
6. Fiske ST, Cuddy AJ, Glick P. Universal dimensions of social cognition: warmth and competence. TRENDS in Cognitive Sciences 2006; 11:77–83.
7. Cialdini RB. (1993) *Influence: science and practice*. New York: Harper Collins.
8. Liang Y, Lee SA, Jang JW. Mindlessness and gaining compliance in computer–human interaction. Computers in Human Behavior 2013; 29:1572–1579.
9. Simmel G. (1950) *The sociology of Georg Simmel*. Trans. KH Wolff KH. Glencoe, IL: Free Press.
10. Boster FJ, Rodriguez JI, Cruz MG, et al. The relative effectiveness of a direct request message and a pregiving message on friends and strangers. Communication Research 1995; 22:475–484.
11. Regan DT. Effects of a favor and liking on compliance. Journal of Experimental Social Psychology 1971; 7:627–639.
12. Fogg BJ, Nass C. (1997) How users reciprocate to computers: an experiment that demonstrates behavior change. In: *CHI'97 extended abstracts on human factors in computing systems: looking to the future*. New York: Association of the Computing Machinery, pp. 331–332.
13. Moon Y. Intimate exchanges: using computers to elicit self-disclosure from consumers. Journal of Consumer Research 2000; 26:323–339.
14. Milberg S, Clark MS. Moods and compliance. British Journal of Social Psychology 1988; 27:79–90.
15. Schwarz N, Bless H. (1991) Happy and mindless, but sad and smart? The impact of affective states on analytic reasoning. In Forgas JH, ed. *Emotion and social judgments*. London: Pergamon, pp. 55–71.
16. Fogg BJ, Nass, C. Silicon sycophants: the effects of computers that flatter. International Journal of Human–Computer Studies 1997; 46:551–561.
17. Johnson D, Gardner J, Wiles J. Experience as a moderator of the media equation: the impact of flattery and praise. International Journal of Human–Computer Studies 2004; 61:237–258.
18. Reeves B, Nass C. (1996) *The media equation: how people treat computers, televisions, and new media like real people and places*. New York: Cambridge University Press.
19. Judd CM, James-Hawkins L, Yzerbyt V, et al. Fundamental dimensions of social judgment: understanding the relations between judgments of competence and warmth. Journal of Personality & Social Psychology 2005; 89:899–913.

20. Rosenberg S, Nelson C, Vivekananthan PS. A multidimensional approach to the structure of personality impressions. Journal of Personality & Social Psychology 1968; 9:283–294.
21. Thorndike EL. A constant error on psychological rating. Journal of Applied Psychology 1920; 4:25–29.
22. Wilson EJ, Sherrell DL. Source effects in communication and persuasion research: a meta-analysis of effect size. Journal of the Academy of Marketing Sciences 1993; 21:101–112.
23. DePaulo BM, Brittingham GL, Kaiser MK. Receiving competence-relevant help: effects on reciprocity, affect, and sensitivity to the helper's nonverbally expressed needs. Journal of Personality & Social Psychology 1983; 45:1045–1060.
24. Nadler A, Mayseless O. (1983) Recipient self-esteem and reactions to help. In Fisher JD, Nadler A, DePaulo BM, eds. *New directions in helping: recipient reactions to aid*. New York: Academic Press, pp. 167–188.
25. Petty RE, Schumann DW, Richman SA, et al. Positive mood and persuasion: different roles for affect under high- and low-elaboration conditions. Journal of Personality & Social Psychology 1993; 64:5–20.
26. Watson D, Clark LA, Tellegen A. Development and validation of brief measures of positive and negative affect: the PANAS scales. Journal of Personality & Social Psychology 1988; 54:1063–1070.
27. Muthén LK, Muthén BO. (2011) *Mplus user's guide*. 6th ed. Los Angeles, CA: Muthén & Muthén.
28. Hu LT, Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. Structural Equation Modeling 1999; 6:1–55.
29. Jöreskog KG. (1993) Testing structural equation models. In Bollen KA, Lang JS, eds. *Testing structural equation models*. Newbury Park, CA: Sage, pp. 294–316.
30. Gouldner AW. The norm of reciprocity: a preliminary statement. American Sociological Review 1960; 25:161–178.
31. Kidd CD, Breazeal C. (2008) Robots at home: understanding long-term human–robot interaction. *IEEE/RSJ International Conference on Intelligent Robots and Systems 2008*. Nice, France: IROS, pp. 3230–3235.

Address correspondence to:
Dr. S. Austin Lee
Department of Communication
Northern Kentucky University
434 Griffin Hall
Highland Heights, KY 41099

E-mail: austin.lee@nku.edu