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Differences in perceptions of communication quality between a Twitterbot and human agent for information seeking and learning

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journal homepage: www.elsevier.com/locate/comphumbeh Differences in perceptions of communication quality between a Twitterbot and human agent for information seeking and learning[☆]Chad Edwards^{a,*}, Austin J. Beattie^a, Autumn Edwards^a, Patric R. Spence^b^a School of Communication, Western Michigan University, USA^b Division of Instructional Communication, Department of Communication, University of Kentucky, Lexington, KY, United States

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ABSTRACT

Twitter's design allows the implementation of automated programs that can submit tweets, interact with others, and generate content based on algorithms. Scholars and end-users alike refer to these programs to as "Twitterbots." This two-part study explores the differences in perceptions of communication quality between a human agent and a Twitterbot in the areas of cognitive elaboration, information seeking, and learning outcomes. In accordance with the Computers Are Social Actors (CASA) framework (Reeves & Nass, 1996), results suggest that participants learned the same from either a Twitterbot or a human agent. Results are discussed in light of CASA, as well as implications and directions for future studies.

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1. Introduction

With 320 million active users (Welch & Popper, 2015), Twitter holds a position as one of the largest social networking sites in the world. Its extensive adoption and simplicity make Twitter a prominent medium for distributing a variety of information by individuals and organizations alike. Although Twitter offers a streamlined interface both for content creation and consumption, maintaining relevancy requires more than updating a feed. Tweets often require a significant amount of thought and crafting to be effective. Without the resources of time or funding to hire a human, organizations may enlist the help of automated programs. According to Zhao (2003), automated programs "differ from other types of computer programs in that they are specially designed to communicate with humans in place of humans ... [and] can be grouped into two categories: instrumental or communicative" (p. 448). Instrumental automated programs work in scenarios or applications that require simple automated responses (e.g. Google Maps). Communicative automated programs interact with people

in ways that mirror human communication. (e.g. Microsoft's Cortana, Apple's Siri).

Twitter's design allows automated bots to interface with others in a variety of ways. As a result, organizations frequently employ programs that act in the place of human agents. Some Twitterbots spread useful information, such as Adam Parrish's @everyword, which since 2008 continues to Tweet virtually every word in the English language every 30 seconds. Some bots exist for mischievous purposes and damage Twitter's reputation by sending out spam and promotional hyperlinks. Although useful in many contexts, most Twitterbots exist for communicative task-oriented purposes such as reminders, scheduling, content creation, or information dissemination (Edwards, Edwards, Spence, & Shelton, 2014). Automated Twitterbots allow organizations to possess a social network presence with minimal human input. This "botification" allows computer software effectively to replace the role of a human (Hwang, Pearce, & Nanis, 2012). Research exploring methodologies for differentiating human or automated accounts note that being able to distinguish the difference can be difficult. Although there were some differences, the distinction between human or automated accounts in updating patterns was similar (Chu, Gianvecchio, Wang, & Jajodia, 2010). Though research has given insight into the differences between human or automated accounts, further research is necessary to understand how automated

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programs, or Twitterbots, can impact the social media network. (Edwards et al., 2014; Wagner, Mitter, Körner, & Strohmaier, 2012).

This two-part study explores the differences in perceptions of communication quality between a human agent and a Twitterbot in the areas of cognitive elaboration, information seeking, and learning outcomes. With the growth of both Twitter and the adoption of automated computer systems intended to interact with people, scholars and professionals alike will benefit from a greater understanding of the potential differences in perceptions of human agents versus Twitterbots. This study examines how individuals consume and perceive information through social media, and Twitter's specific role as an information source.

1.1. Twitter as an information source

Social media refers to the computer-mediated tools that allow people to create, share or exchange information about career and personal interests, news stories, and pictures/videos on online networks (Buettner, 2016). Over two billion people worldwide use some form of social media (Kemp, 2015). People use social media for a host of purposes (Jin & Liu, 2010), especially as a source for information (Pepitone, 2010). Presently, Twitter, the third largest social networking website behind Facebook and YouTube (Barnett, 2011; Parmelee & Bichard, 2012; Top Sites, 2016), is among the most used of these social media information sources. (Morris, Teevan, & Panovich, 2010; Sin & Kim, 2013). Twitter holds a top-ten Alexa rank (a website that measures web traffic and reports the most popular sites on the internet) (Top Sites, 2015). As a social media platform, Twitter provides valuable content for information seeking (Lachlan, Spence, Lin, Najarian, & Del Greco, 2016; Spence, Lachlan, Lin, & Del Greco, 2015). Several factors of Twitter interface facilitate the open and prompt flow of information.

The ability to share previously unknown information proves to be another important consideration in social media as an information source. Sites, such as Twitter, allow users to broadcast their social networks to others (Donath & Boyd, 2004). Users can evaluate and form impressions of other's perceived communication characteristics, such as competence, credibility, or attractiveness. Users may decide to seek additional information, or to be motivated to centrally (or peripherally) process information they read on Twitter based on these factors. Additionally, with the vast ability to create one's online self, being able to discriminate and filter information is a critical skill for people exploring the online world (Haas & Wearden, 2003).

Users form perceptions and impressions of another used based on the various cues within the Twitter pages they observe (Edwards et al., 2014; Lin, Spence, & Lachlan, 2016). Westerman, Spence, and Van Der Heide (2014) found a positive relationship between cues such as update frequency with perceptions of credibility; demonstrating faster updates lead to increased perceptions of credibility. Furthermore, this study found cognitive elaboration mediates the relationship between update speed and information seeking. In another cue system study, Edwards, Spence, Gentile, Edwards, and Edwards (2013) demonstrated that Klout score (the overall influence a user holds over a social network) influenced perceptions of credibility. Cues such as a username, the number of followers, posted links leading to credible sites, the coherence of tweets, the number of retweets, expertise, and reputation of the user all influence source credibility (Morris, Counts, Roseway, Hoff, & Schwarz, 2012).

1.2. Computers are Social Actors (CASA)

The Computers are Social Actors (CASA) framework provides a lens to understand better the potential similarities and differences

between Twitterbots and human agents. CASA provides a practical and valuable paradigm through which to observe communication phenomenon (Nass, Steuer, Tauber, & Reeder, 1993). One of the CASA frameworks strengths lies in its simplicity; a researcher simply replaces a human with a computer in an interaction to test it. Studies indicate that when interacting with a machine possessing anthropomorphic traits similar to a humans, (a) individuals mindlessly interact with machine in a social manner, (b) attribute influence to the artificial human characteristics of the computer, and (c) do not centrally process information as indicative of a computer (Nass & Moon, 2000).

Research over an extensive amount of time has demonstrated that traditional social-science and communication theories hold up in human-computer interaction. According to Reeves & Nass "people's responses to media are fundamentally social in nature" (1996, p. 251). Using CASA as a framework, humans identify and assign personalities such as dominance to computers (Nass, Moon, Fogg, Reeves, & Dryer, 1995), and make mindless attributions to computers such as gender (Lee, Nass, & Brave, 2000). Human-computer interaction reflects significant emotional and behavioral effects similarly to human-human interaction (Brave, Nass, & Hutchinson, 2005; Ferdig & Mishra, 2004). Nass, Moon, and Carney (1999) found that proximity affects human's evaluations of computers in a computer-led tutoring session. People treat computers as teammates in task situations (Nass, Fogg, & Moon, 1996), and evaluate computers differently based on vocal characteristics (Lee, 2010).

Research has recently expanded the conceptualization of a "computer" to include websites (Karr-Wisniewski & Prietula, 2010) and social robots (Lee, Park, & Song, 2005; Stoll et al., 2015). Edwards et al. (2014) found that the use of Twitterbots resulted in similar perceptions of credibility as that of human agents. In demonstrating that humans treat computers in a similar manner to how they treat other humans (even in situations with limited social cues), CASA proves to be a simple theoretical framework to use. Whether commonly acknowledged or not, individuals employ human-human interaction cues when interacting with a machine. With CASA in mind, this study conducted two experiments to examine the similarities and differences between Twitterbots and human agents for cognitive elaboration, information seeking, and learning outcomes.

2. Study One

2.1. Cognitive elaboration and information seeking

Cognitive elaboration involves the process of forming associations between new information and prior knowledge (DeFleur & Ball-Rokeach, 1989; Eveland, 2001). Many studies demonstrate the relationship between cognitive elaboration and persuasion processes (Lachlan, Spence, Edwards, Reno, & Edwards, 2014; Spence, Lachlan, Edwards, & Edwards, 2016). Petty and Cacioppo (1986) found the key to audience persuasion relies on an audience's perception of information as logical, and their willingness to centrally process it. Additionally, people with higher levels of information processing will learn more from media than those with lower levels (Fleming, Thorson, & Zhang, 2006).

Related to cognitive elaboration, information seeking refers to the tendency for individuals to search for additional knowledge based on messages they encounter (Lachlan, Spence, Lin, & Del Greco, 2014; Spence et al., 2016). Creators of messages that wish to be effective must consider an individual's orientation to engage in this behavior. Times of risk and crises heighten this desire for information, resulting in many positive outcomes (Spence, Westerman, Skalak, et al., 2006). With increases in automation

on Twitter and the widespread adaptation of social media as an information source, the ability to determine an individual's likelihood to seek information depending on source becomes more important than ever. Although many studies demonstrate people use Twitter as a primary source of information, few studies have shown if significant differences in these behaviors exist between human or Twitterbot agent feeds.

In consideration of Edwards et al.'s (2014) findings that indicated people may perceive Twitterbots as credible sources of information, the current study will examine the predicted similarities between Twitterbots and human agents. CASA contends that individuals treat computers (and programs) similar to other individuals. Results of many studies demonstrate that humans apply similar social scripts with computers as they do other humans (See Nass et al., 1995). It then becomes reasonable to assume that humans evaluate and interact with Twitterbots using similar scripts as they would with a human Twitter user. Taking this into account and in line with the CASA framework, the following is posed:

H. The mean scores in individuals' cognitive elaboration and information seeking tendencies will not vary as a function of the type of Twitter agent (Twitterbot or human).

2.2. Methods

2.2.1. Participants

The convenience sample comprised of 230 undergraduate students enrolled in communication courses at a large Midwestern research university. Participants included 148 females (70%) and 62 males (30%). The majority of participants identified as White/Caucasian (70.0% $n = 146$), and Black/African American (19% $n = 39$). Participants' ages ranged from 18 to 51 years with a mean of 21.05 ($SD = 4.10$). Participants received course credit in return for participating in the study.

2.2.2. Procedure

In order to test the hypothesis, a two-treatment experimental design that featured a human agent and a Twitterbot agent was employed. Following the receipt of IRB approval, the researchers informed the participants about the study through a secure online system. Participants received a link to the secure website containing the study. In both conditions, after informed consent was provided, the participants were randomly assigned to either the Twitterbot or human agent Twitter feed condition. Both the Twitterbot and human condition featured a Center for Disease Control (CDC) Twitter feed informing readers about information regarding sexually transmitted diseases. Each page contained the same written information, background pictures, and the number of followers, with the exception of the description section, which described the author as a CDC Twitterbot or a CDC scientist. Participants were led to believe that they viewed an actual CDC Twitter feed to help reduce random effects in the experimental setting.

2.2.3. Instruments

After viewing the Twitter page updated by either a human or a Twitterbot, participants responded to two standard measures. The measure of cognitive elaboration used a version of Perse's (1990) 5-item measure modified to reflect the previously visited Twitter page. Using a 5-point response scale (5 = strongly agree, 1 = strongly disagree), people reported their level of agreement with each item (e.g., "When I looked at this page, I thought about it over and over again"). This study obtained an acceptable reliability coefficient of 0.76 ($Item M = 3.04$, $SD = 3.68$).

The 11-item information seeking measure used a 5-point response scale (1 = not interested at all, 5 = very interested).

This item asked the respondents how interested they were in obtaining information regarding the following (e.g., "How sick can STDs make me?" or "What can I do to keep from getting STDs?" or "What foods or vitamins should I take?"). This scale achieved a reliability coefficient of 0.91 ($Item M = 3.58$, $Item SD = 0.85$). Additionally, participants responded to a small demographic section.

2.3. Results

To examine this hypothesis, a test of equivalence was applied to the data. This test was done for two reasons. First, CASA theory predicts that there will not be a difference between the conditions. Second, "equivalence tests are the correct tests to use when the goal is to find statistical support for the null hypothesis" (Weber & Popova, 2012, p. 192). To utilize equivalence testing, effect sizes must be determined from the current research (Levine, Weber, Park, & Hullett, 2008). While a meta-analysis of this area of research is not possible to determine the effect sizes for this type of test, the current study utilized Weber and Popova's (2012) effect size suggestions. Their work examined 112 meta-analyses in the field of communication studies and set up communication specific effect sizes. Because of the nature of this test, the effect size for consideration will be set at a medium size of 0.20.

An independent-samples *t*-test of equivalence was conducted to evaluate the hypothesis that the mean scores in individuals' cognitive elaboration and information seeking tendencies will not vary as a function of the type of Twitter agent (Twitterbot or human). The test was significant for cognitive elaboration, $t(198) = 0.05$, $p < 0.01$, $\Delta = 0.20$. In other words, the mean scores were not significantly different from each other at a medium (0.20) effect size. The test was significant for information seeking, $t(193) = 0.46$, $p < 0.05$, $\Delta = 0.20$. Again, the mean scores were not significantly different for each condition at a medium (0.20) effect size. The hypothesis is supported. See Table 1 for means and standard deviations.

2.4. Summary of study one

Study One explored whether cognitive elaboration and information seeking scores would vary by condition (Twitterbot or human agent). The data demonstrated findings consistent with the CASA framework in that the scores for each condition were equivalent to each. In short, participants reported having the same cognitive elaboration and information seeking for either the Twitterbot or the CDC scientist, demonstrating as CASA predicted that individuals employ the same social scripts with computers that they use with humans.

Individuals and organizations use Twitter for multiple reasons (Jin & Liu, 2010), especially information seeking (Morris et al., 2010; Pepitone, 2010). Many organizations, such as CDC, World Health Organization (WHO), and the National Institutes of Health (NIH) all employ Twitter to spread health-related information to large

Table 1
Means and standard deviations for the two conditions on the dependent variables.

Variable	Twitterbot Agent		Human Agent	
	<i>M</i>	(<i>SD</i>)	<i>M</i>	(<i>SD</i>)
Cognitive Elaboration	15.22 _a	(3.81)	15.24 _a	(3.58)
Information Seeking	39.16 _a	(10.29)	39.77 _a	(8.41)
Affective Learning	37.51 _a	(9.03)	37.24 _a	(9.25)
Motivation to Learn	46.51 _a	(14.89)	47.51 _a	(15.72)

Note. Means in a row with same subscripts are equivalent at $p < 0.05$

audiences (Lee & Sundar, 2012). Because Twitter reaches millions of people, individuals and organizations will likely continue utilizing it as a tool for communication with their respective audiences. With the results of Study One and previous research (Edwards et al., 2014) supporting the predictions of CASA on Twitter; it is reasonable for organizations to accept the viability of using Twitterbots to disseminate information, considering that doing so should result in similar perceptions as employing a human agent at least for cognitive elaboration and information seeking.

3. Study two

3.1. Learning and motivation

An important factor to consider when exploring Twitter as an information source is to what degree people learn and are motivated to learn. Kearney (1994) defined affective learning as “an increasing internalization of positive attitudes toward the content or subject matter” (p. 81). Affective learning has positively related with motivation to learn (Christensen & Menzel, 1998; Frymier & Houser, 2000) and serves as a forerunner to cognitive learning (Rodriguez, Plax, & Kearney, 1996). Learning from the media or specifically, social media, is likely a result of the combination of direct instructions, observations, repetition or vicarious learning (McIntyre, Spence, & Lachlan, 2012; Nelson, Spence, & Lachlan, 2009).

Determining which impressions lead to higher amounts of motivation to learn broadens the understanding of Twitterbots' effectiveness in informative or communicative contexts. Examined in the instructional communication literature, state motivation “refers to a specific learning situation such as a particular class, task, or content area” (Myers & Rocca, 2000, p. 291). Christophel (1990) demonstrated the positive relationship between state motivation and learning. Hall (1966) argued that motivation is one of the most important elements that contribute to learning. This research shows perceptions of source influence motivation to learn. Therefore, to advance understanding of Twitter's likelihood to inspire learning and motivation behaviors, research must continue to explore people's perception of what they encounter. Following the logic of Study One, Twitterbots and human agents should not vary regarding reported affective learning or motivation to learn. Furthermore, CASA would predict that there should be little to no difference between conditions. Therefore, the following hypothesis is offered:

H. The mean scores in individuals' affective learning and motivation to learn scores will not vary as a function of the type of Twitter agent (Twitterbot or human).

3.2. Method

3.2.1. Participants

The convenience sample comprised of 181 undergraduate students enrolled in communication courses at a large Midwestern research university. Participants included 128 females (66.8%), 58 males (31.5%), and three not identified. The majority of participants identified as White/Caucasian (70.1% $n = 129$), and Black/African American (19.6% $n = 36$). Participants' ages ranged from 18 to 51 years with a mean of 20.85 ($SD = 3.68$). Participants received course credit in return for participating in the study. Study One and Study Two took place in different classes over different semesters and students did not have an opportunity to participate in both studies.

3.2.2. Procedure

To explore the hypothesis, the same experimental design as

used in Study One was utilized for the current study. The only changes were to the instruments.

3.2.3. Instruments

After participants had viewed the Twitter page updated by either a human or a Twitterbot agent, participants responded to two standard measures. McCroskey's (1994) modified Affective Learning Measure is an 8-item instrument designed to assess a person's affect for subject matter along a series of 7-point semantic differential scales. The items address affect toward the content (e.g., “I feel that the content on this Twitter feed is: valuable/worthless”). Past studies have reported reliability coefficients exceeding 0.90 (McCroskey, 1994). In this study, a reliability coefficient of 0.89 ($Item M = 4.68$; $Item SD = 1.14$) was obtained for affective learning.

Christophel's (1990) Motivation Scale is a 12-item instrument designed to assess motivation to learn in a particular course. This scale was modified to represent a user reading a Twitter feed. Items are rated using 7-point semantic differential scales (e.g., “motivated/unmotivated,” “inspired/uninspired”). Past studies have reported reliability coefficients consistently higher than 0.90 (Christophel, 1990). A reliability coefficient of 0.96 ($Item M = 3.90$, $Item SD = 1.27$) was obtained in the present study.

3.3. Results

To examine this hypothesis, a test of equivalence was applied to the data in Study Two. Similar as in Study One, the effect size for consideration will be set at a medium size of 0.20. An independent-samples *t*-test of equivalence was conducted to evaluate the hypothesis that the mean scores in individuals' affective learning and motivation to learn will not vary as a function of the type of Twitter agent (Twitterbot or human). The test was significant for affective learning, $t(176) = 0.19$, $p < 0.05$, $\Delta = 0.20$. Additionally, the test was significant for motivation to learn, $t(175) = -0.35$, $p < 0.05$, $\Delta = 0.20$. The hypothesis was supported. Refer to Table 1 for means and standard deviations. In summary, the mean scores were not significantly different from each other at a medium (0.20) effect size for each of the dependent variables.

4. Discussion

This study directly compared two types of agents found on Twitter. The findings of both Study One and Study Two demonstrate that people report similar levels of information seeking, cognitive elaboration, affective learning, and motivation behaviors when receiving information from a Twitterbot when compared to a human agent. Furthermore, these findings are consistent with the CASA framework that maintains people will use the same basic social rules when interacting with computers (or automated agents) as people would when interacting with others. (Reeves & Nass, 1996). Each of the variables under study has practical uses for social media applications.

Future research should continue to explore how Twitterbots can influence perceptions of communication. Among them, the organizational affiliation of the Twitterbot is one that may produce different impressions. In the current study, participants were led to believe that the Twitterbot and scientist were from the CDC. The findings may be due in part to existing impressions of the CDC organization itself as credible. A Twitterbot associated with a lesser-known organization communicating the same information might not produce the same impressions. Overall, the current study suggests that organizations might be able to utilize an automated agent to enhance their social media feeds without much loss regarding information seeking or learning.

The nature of the information itself is another aspect that could

influence perceptions of a Twitterbot. While many studies support CASA, machines do not possess human emotions. However, machines do possess the ability to influence the emotions of people with whom they interact (Stoll, Edwards, & Edwards, 2015). The ability to understand and share the feelings of another is an important quality of effective communicators (Frymier & Thompson, 1992; Nadler & Nadler, 2001). The human emotional response is an important factor to consider with the growth of Twitterbots of automated programs. Because of this, research should explore Twitterbots that, for example, distribute cooking tips and recommendations to test if people trust culinary advice from an entity with no sense of smell or taste. Twitter's uncensored and publicly available design (Johnson, 2011) positions it to be a frequented source of communication for years to come. Its popularity and multifunctional nature (Jin & Liu, 2010) make it an important medium in which to study human interaction and that of automated agents.

4.1. Limitations and future directions

This study was not without limitations, perhaps most apparent of which was the design of the independent variable conditions. Available resources required the usage of screen-shot manipulated images of a Twitter feed as the best option to represent internal validity of the experiment. However, not using "live" pages risked participants not fully engaging in the actual Twitter experience, and resulted in a few limitations. Twitter updates in real-time. Individuals using it do not need to refresh the page or interact with it in any way for the viewed content to change. Similarly, Twitter feeds may contain video, animated GIFs, advertisements, or other elements that add movement to the page. The static nature of the screenshots may have failed to represent adequately the "busy" or "connected" feel of a Twitter page which in recent years is hallmarked by notifications, advertisements, animated graphics, and embedded videos. Future Twitter studies must continue working on this limitation and examine the feasibility of creating conditions that more closely resemble the actual Twitter experience.

5. Conclusion

This study forwards our understanding in the largely unexplored territory of understanding human interaction with automated entities over social media (Edwards et al., 2014). The findings were predicted by CASA in that people treat both computers and others similarly. While this study is among few to experimentally test the perceptions of individuals on communication qualities of a Twitterbot, the results indicate the viability of organizations and individuals utilizing a Twitterbot to be effective in the social media space on several important variables. Seeking more information and knowing this information could potentially help someone in a crisis. A Twitterbot appears to be as effective as a human agent for some types of information.

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