Verbal Disinhibition towards Robots is Associated with General Antisociality

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ABSTRACT
The emergence of agentic technologies (e.g., robots) in increasingly public realms (e.g., social media) has revealed surprising antisocial tendencies in human-agent interactions. In particular, there is growing indication of people’s propensity to act aggressively towards such systems – without provocation and unabashedly so.

Towards understanding whether this aggressive behavior is anomalous or whether it is associated with general antisocial tendencies in people’s broader interactions, we examined people’s verbal disinhibition towards two artificial agents. Using Twitter as a corpus of free-form, unsupervised interactions, we identified 40 independent Twitter users who tweeted abusively or non-abusively at one of two high-profile robots with Twitter accounts (TMi’s Bina48 and Hanson Robotics’ Sophia). Analysis of 50 of each user’s tweets most proximate to their tweet at the respective robot (N = 2,000) shows people’s aggression towards the robots to be associated with more frequent abuse in their general tweeting. The findings thus suggest that disinhibition towards robots is not necessarily a pervasive tendency, but rather one driven by individual differences in antisociality. Nevertheless, such unprovoked abuse highlights a need for attention to the reception of agentic technologies in society, as well as the necessity of corresponding capacities to recognize and respond to antisocial dynamics.

CCS CONCEPTS
• Human-centered computing → User characteristics;
• Social and professional topics → User characteristics;
• Computing methodologies → Artificial intelligence;

KEYWORDS
Aggression, antisociality, human-agent interaction, human-robot interaction, social robotics

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1 INTRODUCTION

Agentic technologies – from disembodied AIs, to virtual agents, to highly humanlike robots – are increasingly pervading public domains. Disembodied AI assistants, such as Apple’s Siri and Amazon’s Alexa, have been available in consumer markets for nearly a decade. Consumer- and enterprise-oriented robotic platforms, particularly those geared towards social engagement (e.g., Anki’s Cozmo, Ugoeb’s Pleo, and Softbank’s Pepper), have already achieved moderate commercial success1 and are beginning to emerge in public spaces around the globe2. Furthermore, although virtual agents remain largely within academic settings, they show substantial potential for widespread public deployment across numerous industries including education (e.g., [10, 15]), medicine (e.g., doctor-patient communications [4]), patient assistance [3]), and therapy (e.g., evaluation [13] and counseling [12]).

1.1 Aggression in Human-Agent Interactions
A natural result of their increased presence is that artificial agents, to highly humanlike robots – are increasingly pervading public domains. Disembodied AI assistants, such as Apple’s Siri and Amazon’s Alexa, have been available in consumer markets for nearly a decade. Consumer- and enterprise-oriented robotic platforms, particularly those geared towards social engagement (e.g., Anki’s Cozmo, Ugoeb’s Pleo, and Softbank’s Pepper), have already achieved moderate commercial success1 and are beginning to emerge in public spaces around the globe2. Furthermore, although virtual agents remain largely within academic settings, they show substantial potential for widespread public deployment across numerous industries including education (e.g., [10, 15]), medicine (e.g., doctor-patient communications [4]), patient assistance [3]), and therapy (e.g., evaluation [13] and counseling [12]).

A natural result of their increased presence is that artificial agents are increasingly available for free-form, unsupervised interactions with the general public. Observation of interactions in these more naturalistic settings have, in turn, brought to light people’s apparent aggression toward agentic technologies. For example:

• Ugoeb’s Pleo: In 2007, DVICE released a video3 of a couple of staff members subjecting a Pleo robot to a series of abusive tests (including hitting the robot, smashing it against a table, and strangling it), which ultimately resulted in the robot’s

1See, for example: goo.gl/icsfYh.
2For example: goo.gl/SwJYBY, goo.gl/UoX7oB, and goo.gl/x3v42f.
3https://youtu.be/pQUCdi6hM0
Verbal abuse comprises a substantial portion of people’s comments toward artificial agents (e.g., “are you a lesbian?”; [28]). Specifically, while there is ample evidence that people treat agentic technologies like they do people (the “media equation” [18]), the treatment is not equivalent. For example, people’s empathy towards a robot monotonically decreases from androids (highly humanlike robots) to robots of more mechanomorphic appearances [19]. That is, the less human an agent seems, the less people empathize. People also exhibit less empathy when observing a robot’s (versus a person’s) abuse [20], more readily engage in the abuse of a robot (versus of a person; [2]), and are generally unmoved by a robot’s pleas for sympathy (e.g., [6, 7, 11, 27]).

1.2 Implications & Considerations
These antisocial tendencies (aggression toward, and limited empathy for, agentic technologies) are especially problematic for two reasons in particular. First, while aggression may not necessarily pose harm to a nonhuman target, aggression in the context of multiparty interactions negatively impacts bystanders who are witness to the abuse [29]. Second, aggression toward humanlike robots—which embody identity characteristics (e.g., gender)—may facilitate subsequent aggression toward people who share identity characteristics with the abused robots. For example, stereotypic abuse of a female-bodied robot (e.g., via sexualization) may reinforce stereotypes the aggressor has of women, resulting in greater expression of bias in subsequent interactions with women.

It is thus critical for artificial agents to be able to respond to manifestations of aggression if and when it arises. To respond, however, requires that the agent has the capacity to recognize aggression. And to accurately and reliably recognize aggression requires, first, identification of the relevant information channels and cues that communicate aggression. To that end, recent work has identified a range of associated factors (e.g., the agent’s gendering [5], racialization [25], and size [14]).

Not all people, however, exhibit aggressive tendencies toward robots. For example, deployment of a delivery robot in medical settings showed that while some staff treated the robot poorly and locked it away when they could, others treated the robot relatively well, using the robot to make their daily routine more efficient [17]. Indeed, the majority do not condone [27] nor exhibit aggression, with estimates as to the prevalence ranging from 8% (explicit physical abuse; [7]) to just under 50% (verbal aggression; [24]).

1.3 Present Work
Thus, towards better understanding differences amongst individual engagement in the aggressive treatment of agentic technologies, we examined the relationship between people’s verbal abuse towards two robots – TMI’s Bina48 and Hanson Robotics’ Sophia (see Figure 2) – and verbally aggressive tendencies in their interactions with other people. Specifically, we sought to determine whether people’s aggression toward the given robots is spontaneous or whether it is consistent with a broader pattern of aggression. That is, is this a general phenomenon or does it align with individuals’ prosociality (or rather, lack thereof).

To acquire data representative of more naturalistic (free-form, unsupervised) interactions with robots than what is available in controlled laboratory settings, we elected to scrape Twitter for commentary directed towards two robots with active accounts on Twitter. For greater comparability to recent literature (e.g., [23–25]), we utilized robot targets (versus other categories of agentic systems). Towards mitigating associations stemming from any particular embodiment, we utilized two targets.

From people’s tweets at the two robots, we identified 40 distinct Twitter users (20 per robot) who tweeted abusively or non-abusively at the given robot. We effected a quasi-manipulation of user type (two levels: abusive versus non-abusive towards robots) via identification of users (with $N_{abusive} = 10$ and $N_{non-abusive} = 10$ per robot). We then scraped 50 of each user’s tweets closest (in time) to their originating tweet ($N = 2000$) in order to evaluate the association between aggression towards the robots and the prevalence of abuse in users’ broader tweeting.

\footnote{https://goo.gl/nFEfS1}
2 METHOD
We conducted an online, quasi-experimental evaluation \((N = 40)\) of the association between aggression in HRI and in human-human social dynamics.

2.1 Design
Given indications from existing literature that abusive human-agent interactions more frequently manifest in free-form, unsupervised contexts, we utilized Twitter (which hosts accounts for several publicized robot platforms such as Hanson Robotics’ Sophia) as a source of similar interaction data. Specifically, given greater disinhibition in online spaces [26], we expected to better capture abusive interactions that may not arise in more controlled contexts. Furthermore, the interaction modality enables more naturalistic human-robot interactions than traditional laboratory settings [21], which may better capture the public’s perceptions of emergent platforms.

Here we defined “abusive” as any content that is dehumanizing in nature. Specifically, if a tweet contained content that was objectifying (including overt sexualization, [16] and ambivalent and benevolent sexism [9]), racist (e.g., evocative of race-based stereotypes [1]), generally offensive (e.g., such as calling the robot stupid [7]), and/or violent (verbally hostile or threatening of physical violence) towards the given agent – it was coded as abusive.

2.2 Manipulation
We effected a quasi-manipulation of user type (abusive versus non-abusive) via selection of the 40 users (20 per robot, with 10 abusive and 10 non-abusive each). To identify the 40 users, we scraped all available Twitter mentions at Bina48 and Sophia (on March 22, 2018). A total of 9,497 tweets \((N_{\text{Bina}} = 648; N_{\text{Sophia}} = 8,849)\) were returned – a subset of which \((N_{\text{Bina}} = 648; N_{\text{Sophia}} = 1,000)\) were then coded by a research assistant blind to the research questions on a single, binary dimension: whether a given tweet contains abusive content (1) or not (0).

A threshold of 1,000 tweets for coding was set a priori based on existing literature (using the lowest frequency of abuse reported in online contexts – 10% of commentary [8]). Although the expected proportion of abusive commentary (100) exceeds the number of abusive users needed (10), we set a higher threshold in anticipation of a lower frequency of abusive commentary (e.g., due to content moderation by the account managers) and loss of data (e.g., discarding of repeat tweets from the same user). The criteria for retention were as follows:

- Independence: We aimed to identify independent users; thus, multiple tweets from a single user were excluded (except for one randomly selected tweet of the user’s tweets). In addition, tweets which were replies to other users were excluded.
- Decipherability: Any tweets that were indecipherable (e.g., due to lack of context) were excluded. For example, the tweet – “iBina48: Cyber space” #pii2013 – was excluded.

From the tweets remaining post-coding \((N_{\text{Bina}} = 253; N_{\text{Sophia}} = 631)\), we randomly selected 20 users (10 with an abusive and 10 with a non-abusive tweet at the given robot) for each robot.

2.3 Data Acquisition & Annotation
For each of the 40 users selected (to effect the quasi-manipulation of user type), we scraped the user’s 50 tweets most proximate to and centered around (i.e., 25 pre- and 25 post-) the user’s originating tweet at one of the robots. This scraping was completed between February 22 and March 02, 2018 and yielded a total of 2,000 tweets for analysis. Each of the 2,000 tweets were coded on a binary dimension (0 or 1) for the presence of abusive content – which was then used to compute an overall frequency of abuse for each of the 40 users. As verification of the coding reliability, a second coder independently coded 10% of the 2,000 tweets. Calculation of Cohen’s \(k\) confirmed high inter-rater reliability \((k = .86)\).

3 RESULTS
Similar to rates reported in literature on verbal disinhibition towards chatbots (e.g., [8]), the overall frequency of dehumanizing content across users comprised approximately 10% of the Twitter-based interactions \((M = .09, SD = .12)\).

To evaluate the association between user type (abusive versus non-abusive towards robots) and the frequency of abusive content in a user’s general tweeting, we conducted an analysis of variance (ANOVA) with significance evaluated at a standard \(\alpha\)-level of .05. Due to different racializations of the two robots (Bina48 is racialized as Black, Sophia is racialized as White), we included robot racialization as a covariate in the statistical model.

The results of the ANOVA showed a main effect of user type (abusive versus non-abusive towards robots) on the frequency of dehumanizing content in users’ broader Twitter communications: \(F = 11.67, p < .01, \eta^2_p = .25\). Specifically, the users identified in the

Table 1: Source information from which the quasi-manipulation of user type (abusive versus non-abusive) was effected. “Mentions”, “coded”, and “retained” refers to the number of tweets scraped, analyzed, and retained for selection of the 40 users.

| Source           | Mentions | Coded | Retained |
|------------------|----------|-------|----------|
| @iBina48         | 648      | 648   | 253      |
| @RealSophiaRobot | 8,849    | 1000  | 631      |

Figure 2: The two robots involved – TMI’s Bina48 (left) and Hanson Robotics’ Sophia (right).
coding process as abusive were much more frequently abusive in their general tweeting \((M = .15, SD = .15)\) than were non-abusive users \((M = .03, SD = .05;\) Cohen’s \(d = 1.07\)). We additionally confirmed, via a post-hoc power analysis using the found effect size, that the study was adequately powered \((1 - \beta = .9532)\) to capture the given differences.

4 DISCUSSION

4.1 Summary of Findings

The present study served as a preliminary investigation into individual differences in aggression towards agentic technologies. Via an analysis of public tweet data, we found a significant association between people’s antisociality and their abuse of two robots.

Given the methods used (wherein we evaluated the prevalence of aggression in each user’s 50 surrounding tweets), there are two possible interpretations of this association: (1) A person’s aggression towards the robots is associated with an antisocial personality (i.e., relatively unchanging demeanor). (2) Or, it may be that a person’s aggression towards the robots resulted during a period of general negative affect (i.e., temporally-constrained aggression).

4.2 Implications

Assuming the first interpretation (aggression towards robots is associated with antisocial personality), then manifestations of aggression might be predicted by tracking of indicative personality characteristics and averted by proactive avoidance of interlocutors identified as generally antisocial. Assuming the aggression resulted from negative affect, then tracking interlocutors’ general affect (e.g., positive, neutral, or negative) may facilitate prediction of potential aggression. In this case, manifestations of aggression might be mitigated via targeted intervention to regulate the aggressor’s emotional state.

Assuming either interpretation, the findings indicate, in particular, that in addition to linguistic content analysis, construction and maintenance of models of interlocutors encountered may be important to the prediction and recognition of aggression in HAIs.

For example, if an interlocutor shows general aggressive tendencies, this may be a valuable heuristic toward deciding, subsequently, whether given data (e.g., linguistic utterance) is likely aggressive or not. Or, if an interlocutor exhibits emotional agitation, recognition by the agent could cue an intervention such as an exercise in emotion regulation.

More generally, the findings underscore a need for respective agent capacities (to recognize and respond to aggression). This is especially relevant in multi-party contexts, wherein aggressive treatment of an artificial agent may have broader impacts both on immediate bystanders and on subsequent interactions involving the aggressor (e.g., facilitation of the dehumanization of people sharing identity characteristics with the targeted agent). However, responding to aggression requires, first, that the agent can reliably detect it when it manifests. And the present findings indicate that detection may be significantly facilitated by modeling individual interlocutors in addition to explicit conversational content.

4.3 Limitations & Avenues for Future Research

There are a number of limitations to the present study, which serve to highlight avenues for future research. In particular, we conducted an online evaluation of the association between people’s general degree of aggression and their aggression towards two robots. However, more representative interaction settings (i.e., ecological validity), as well as broader sampling across platforms (i.e., more than two robots) and agent types (i.e., chatbots, virtual agents, and robots), is needed to understand how the findings extend to actual human-robot interactions and more generally, to human-agent interactions. In addition, given the two possible interpretations to the present findings (association with personality and/or affect), further research is needed to determine which interpretation – and corresponding, which approach to responding – is appropriate (if not both).

5 CONCLUSIONS

Towards understanding individual differences in aggressive tendencies in human-agent interactions, we examined people’s verbal disinhibition in their tweeting at two robots and in their broader interactions. Using Twitter as a corpus of free-form, unsupervised interactions, we identified 40 independent Twitter users who tweeting abusively or non-abusively at one of two robots with Twitter accounts (TMU’s Bina48 and Hanson Robotics’ Sophia). Analysis of each user’s 50 tweets most proximate to their tweet at the robot shows people’s abuse of the robots aligns with more frequent abuse in their general tweeting. The findings thus suggest that disinhibition towards robots is not necessarily a pervasive tendency, as it is significantly associated with general antisocial behavior. While interpretation of the findings is constrained by methodological limitations, such unprovoked abuse nevertheless highlights a need for particular attention to the social capacities of agentic systems and suggests that maintenance of a user-specific model may facilitate predication and interpretation of aggression in HAIs.

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