A JOURNAL BY SISSA MEDIALAB

JCOM

ARTICLE

Anthropomorphism and motivating participation in citizen science projects

Zoey Rosen, Marilee Long, Bonne Ford, Eric A. Wendt, Michael Cheeseman, Casey Quinn, Christian L'Orange, John Volckens and Jeffrey R. Pierce

Abstract

Maintaining long-term participation in citizen science projects is challenging; thus, it is important for project developers to use effective techniques to motivate participants. One approach is to incorporate anthropomorphism (ascribing humanlike qualities to a non-human agent) when designing and deploying technology. In a quasi-experimental study conducted as part of the Citizen-Enabled Aerosol Measurements for Satellites (CEAMS) citizen science project, we investigated the relationship between anthropomorphism and motivation to participate in citizen science. Findings showed partial support for the relationship between anthropomorphism and motivation.

Keywords

Citizen science; Public engagement with science and technology; Science communication: theory and models

Received: 26th June 2024
Accepted: 31st October 2024
Published: 25th November 2024

1 ▪ Introduction

Citizen science has been increasingly practiced as an effective way to collect large data sets while engaging the public with the scientific process [Cappa et al., 2018; Palacin et al., 2021]. While most studies employing a citizen science approach have focused on natural science phenomena [Campos et al., 2021; Kullenberg & Kasperowski, 2016], recent work has investigated more participant-based outcomes such as engagement, motivation to participate, and retention [e.g., Pateman et al., 2021; Robinson et al., 2021; Wright et al., 2015]. Such work is vital to the success of citizen science projects, which rely on volunteers [Levontin et al., 2022; Cappa et al., 2018]. Long-term participation is challenging in citizen science projects [Frensley et al., 2017], so efforts to study participant motivation from recruitment to retention are beneficial for future projects.

The use of technologies and digital platforms in citizen science projects [e.g., Jennett & Cox, 2018; Kullenberg & Kasperowski, 2016] provides an opportunity to draw upon the human-robot interaction (HRI) literature to study participant motivation. HRI is a multidisciplinary field that examines the social interactions between humans and robots [Bartneck et al., 2020]. In the HRI domain, psychologists have created models to describe what occurs when people anthropomorphize nonhuman agents, such as technology. The cognitive and emotional drivers people have when anthropomorphizing are similar to key motivations for participating in citizen science projects. In this study, we conduct initial tests of a theoretical framework that connects the Sociality, Effectance, and Elicited Agent Knowledge (SEEK) model of anthropomorphism [Epley et al., 2007] to three common motivations volunteers cite for participating in citizen science projects: building community, perceived competence, and contributing to scientific knowledge [Curtis, 2018; Frensley et al., 2017; Raddick et al., 2010; Tiago et al., 2017]. We investigate the relationship between participants' anthropomorphic behavior toward a backyard air-quality sampler and their motivations to contribute to a longer-term citizen science project.

2 ▪ Literature overview

2.1 ▪ *Motivation to participate in citizen science*

For citizen science projects to succeed, they must attract and retain volunteers [Levontin et al., 2022]. A better understanding of the factors that motivate people to participate in these efforts would aid scientists in designing projects that are more likely to promote successful data collection over longer periods [Frensley et al., 2017]. This understanding is especially important for digital citizen science projects, which can have difficulty sustaining participation over time [Jennett & Cox, 2018; Laut et al., 2017]. For example, Fold-It is a digital citizen science game in which participants help scientists discern the structure of proteins. Launched in 2008, Fold-It has thousands of registered participants, while the number of active participants is much smaller, ranging between 200 and 300 [Curtis, 2015].

Drawing on the work of Humphreys and Revelle [1984], and Robinson et al. [2021], for this study, motivation is defined as the drive to satisfy a need. It is a "primary determinant of performance" [Humphreys & Revelle, 1984]. People can have multiple motivations for participating in an activity, and these motivations are often classified as intrinsic (driven by internal rewards such as enjoyment, curiosity, feelings of belonging) or extrinsic (driven by external rewards such as recognition). This study focuses on intrinsic motivations, though previous work has looked at how encouraging external rewards like credit in publications and announcements can be for participant motivation [Alender, 2016].

Several theories have been used to understand people's motivations, including self-determination theory [Deci & Ryan, 1985; Ryan & Deci, 2000]. This theory identifies three psychological needs essential for a person's motivation and psychological well-being: autonomy (feeling personal agency over one's experiences and actions), competence (feeling able to complete a task), and relatedness (feeling connected to others) [Ryan & Deci, 2017]. Three motivations often identified in studies of participants in citizen science projects — building community, perceived competence, and contributing to scientific knowledge — can be mapped onto self-determination theory's three needs for motivation. Research indicates that these needs are important intrinsic motivations for citizen science participants, which can influence long-term motivation and engagement in a project [Curtis, 2018; Frensley et al., 2017; Raddick et al., 2010; Tiago et al., 2017]. The following sections outline each motivation, using examples from long-term digital and technological citizen science projects.

Building community. According to self-determination theory, a person's desire for relatedness will motivate them to seek opportunities to bond with others. This desire for community has been categorized as an intrinsic motivation, i.e., one that comes from seeking personal fulfillment [Curtis, 2018; Eveleigh et al., 2014; Tiago et al., 2017]. Building community fulfills the social needs of participants, which benefits the participants as well as the overall project goals in citizen science [Curtis, 2018].

While online communities for citizen science projects are generally formed as a communication management strategy between scientists and participants, they can also foster community building among participants [Curtis, 2018; Mankowski et al., 2011]. The Galaxy Zoo project was among the first to determine that building community increases long-term participation in citizen science projects. Galaxy Zoo has volunteers classify images of galaxies from the Sloan Digital Sky Survey using two online interfaces [Raddick et al., 2010]. Forming a sense of community from the project was among participants' top most cited motivations [Raddick et al., 2010, 2013].

Perceived competence. Perceived competence is the extent to which a person feels able to understand and perform the tasks a challenge presents [Tiago et al., 2017]. It is an intrinsic motivation under self-determination theory, and previous psychological studies have shown that people have an inherent need for competence [Deci & Ryan, 1985; White, 1959]. Like a flow state, people experience a sense of enjoyment from feeling that they have the skill to meet a challenge and a sense of control over themselves in that task [Csikszentmihalyi, 1990]. Therefore, citizen science projects should be designed to bolster people's perceived competence, positively affecting their intrinsic motivation to participate.

Some studies have found that the complexity of participation deters citizen contributions [Eveleigh et al., 2014]. If the technology citizen scientists must use to participate is challenging to master, participants tend to drop out of studies [Eveleigh et al., 2014; Frensley et al., 2017]. For example, Tiago et al. [2017] studied intrinsic motivations in citizen science participation in BioDiversity4All, a Portuguese citizen science project where users identify species by taking online fieldnotes and tagging pictures. Perceived competence was positively associated with participation and negatively associated with participant drop-off [Tiago et al., 2017].

Contributing to scientific knowledge. A person's desire to contribute to scientific knowledge is connected to their autonomy, a key psychological need under self-determination theory. When a person volunteers for a citizen science project, they are exerting agency over their actions, which increases their autonomy. Their participation can then lead to increased happiness and empowerment [Mankowski et al., 2011] and feelings of accomplishment when they make discoveries or are part of research that gets published [Curtis, 2018; Frensley et al., 2017; Tiago et al., 2017].

This sense of fulfillment in contributing to the larger body of scientific knowledge has been seen in multiple citizen science projects [e.g., Alender, 2016; Mankowski et al., 2011; Raddick et al., 2013; Tiago et al., 2017]. For example, in a survey of 271 volunteers from eight water quality monitoring organizations in the United States, Alender [2016] found that contributing to scientific knowledge was a key motivator for participation. Participants reported feeling valued when data was shared with them and encouraged when the data was used in a community presentation or a scientific publication [Alender, 2016].

2.2 ▪ *Anthropomorphism*

Anthropomorphism describes the assigning of human characteristics to real or imagined nonhuman objects [Connell, 2013; Epley, Waytz et al., 2008]. Attributions can range from physical traits, such as perceiving a smile on an animal's face, to emotional states, such as crediting a computer as being angry when it is not working as expected [Epley et al., 2007; Epley, Waytz et al., 2008]. This phenomenon has been studied in many areas including consumer behavior in marketing [Connell, 2013; MacInnis & Folkes, 2017], the psychology behind religion [Epley, Akalis et al., 2008], and in human-robotic interaction (HRI) [Epley et al., 2007; de Kleijn et al., 2019]. In the HRI domain, researchers have used Epley et al.'s [2007] three-factor model — the sociality, effectance, and elicited agent knowledge (SEEK) model — to explain why people anthropomorphize nonhuman agents, such as unfamiliar technology. The SEEK model is based on research in social cognition [Epley, Waytz et al., 2008]. Its three factors are described in the following paragraphs.

Sociality. People may anthropomorphize nonhuman objects to fulfill a need for social connection [Epley et al., 2007]. Loneliness is uncomfortable; thus, people may try to alleviate it by anthropomorphizing objects [Bartz et al., 2016; Gardner et al., 2005]. Several studies have investigated the relationship between sociality and nonhuman agents [e.g., Waytz, Epley & Cacioppo, 2010; Waytz, Morewedge et al., 2010; Blut et al., 2021; Christoforakos & Diefenbach, 2023]. For example, Epley, Akalis et al. [2008] had participants read descriptions of technological gadgets, such as Clocky (a wheeled alarm clock that "runs" from the user when it goes off). The researchers found that loneliness was positively correlated with beliefs in gadgets' human-like characteristics. In 2016, Bartz et al. replicated the findings of Epley, Akalis et al. [2008] using a much larger sample, and they further found that reminding participants of a close, supportive relationship reduced their anthropomorphic tendencies.

Effectance. According to the SEEK model, people are motivated to anthropomorphize non-human objects they do not understand [Wiese et al., 2017]. Termed "effectance", this motivation encourages people to anthropomorphize to reduce uncertainty and help cope with the unknown [Epley et al., 2007]. For example, people have anthropomorphized severe weather when they do not understand why a storm is destructive [Epley et al., 2007; Waytz, Cacioppo & Epley, 2010]. Effectance has also been experimentally tested in HRI studies. For example, Eyssel et al. [2011] hypothesized that participants' acceptance of Flobi, an anthropomorphized robot head with facial features that move to express different emotions, would be higher when they anticipated interacting with the robot and the robot's behavior was predictable than when they did not expect to interact with the robot. Results indicated that participants who anticipated that they would need to interact with Flobi anthropomorphized more than those who did not [Eyssel et al., 2011].

Elicited agent knowledge. People understand non-human agents, such as animals and objects, by humanizing what they perceive the others' realities to be [Epley et al., 2007]. This result occurs because most interactions people have are with other humans [Epley et al., 2007]. Thus, when people lack knowledge of a nonhuman agent, such as an unfamiliar animal, they initially process that agent's behaviors in light of their own experiences, i.e., in anthropomorphic terms, because it is easier to do so [Epley et al., 2007]. The need for an easy way to explain nonhuman behavior is also seen in robotics. For example, after observing a robot that was gesturing using unfamiliar movements, people were motivated to anthropomorphize the robot's features to explain its behaviors [Higgins, 1996]. A perceived similarity between people and a robot drives people to anthropomorphize further [Epley et al., 2007]. Having human-like physical characteristics, like eyes and a mouth, help to make a robot more familiar [DiSalvo et al., 2002].

2.3 ▪ *Role of anthropomorphism in motivating citizen science participation*

This study addresses the challenge of maintaining participation in longer-term citizen science projects by testing relationships between anthropomorphism and motivation to participate. To our knowledge, anthropomorphism has not been tested with factors like participant motivation in citizen science. The proposed relationships are based on the SEEK model of anthropomorphism [Epley et al., 2007] and key elements of motivation according to self-determination theory [Deci & Ryan, 1985; Ryan & Deci, 2000]. As Figure 1 shows, anthropomorphizing nonhuman agents to meet sociality needs can be paired with desire to build community, as people seek interaction and form relationships in both. Likewise, effectance and perceived competence explain why people feel a need to operate effectively within their environments [Deci & Ryan, 1985; White, 1959]. Lastly, elicited agent knowledge and the motivation to contribute to scientific knowledge both describe people's motivations for understanding how things work.

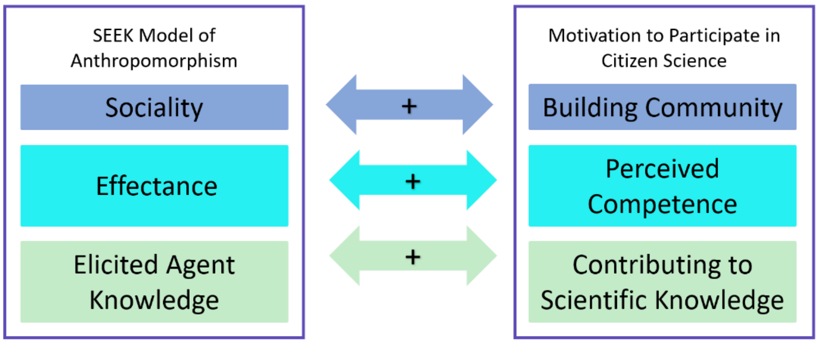

Figure 1. Conceptual model showing connections between the SEEK model of anthropomorphism and motivation to participate in citizen science.

2.4 ▪ *Encouraging anthropomorphic responses in human-robot interactions*

In HRI, anthropomorphism can be encouraged through design. Humanlike movement in robots without human-like physical features has been shown to activate mirror neuron responses in research participants [Gazzola et al., 2007]. For example, programming social movements like stretching or lifting to happen when a person turns on a robotic instrument could simulate "waking up", activating a person's cognitive familiarity between the machine and the human. Physical characteristics, like movement or structure, are some of the greatest drivers of anthropomorphism with technology [Darling, 2015; DiSalvo et al., 2002].

Language is another social element that can stimulate a human-robot interaction. Using anthropomorphic language to describe robots (e.g., giving them a name or a backstory) affects people's perceptions of and interactions with them. Through interviews with people who interacted with robots as part of their work, Darling [2015] found that anthropomorphically portraying the robot, such as calling it a companion or giving it a personified name, increased users' tolerance for malfunctions and altered emotionally how people approached the machine. Encouraging anthropomorphism through description can boost the social function of a technology and encourage human interactions with a nonhuman agent [Darling, 2015].

3 ▪ Objective

Based on the theoretical framework presented in Figure 1, we make the following predictions about the relationships between the SEEK model and motivations to participate in citizen science projects:

H1: Sociality and building community will be positively correlated.

H2: Effectance and perceived competence will be positively correlated.

H3: Elicited agent knowledge of air quality sampling and contributing to scientific knowledge will be positively correlated.

Longer-term citizen science projects where participants use novel technological instruments provide a prime opportunity to test our hypotheses about the relationships between anthropomorphism and motivation to participate. For this study, we recruited participants in the Citizen-Enabled Aerosol Measurements for Satellites (CEAMS) citizen science project. CEAMS was a longer-term citizen science project that used novel technology [Ford et al., 2019; Wendt et al., 2019, 2021]. The goal of CEAMS was to design a low-cost air quality sampler that accurately measured regional air quality [Wendt et al., 2019; Ford et al., 2019].[1] In this project, citizen scientists set up aerosol mass and optical depth (AMOD) samplers in their backyards to measure local air quality for several weeks. The AMOD sampler, seen in Figure 2, can be classified as a robot, as its programming carries out certain functions, the sampler displays movements, and it functions automatically [Bartneck et al., 2020; Darling, 2015; DiSalvo et al., 2002].

1. The AMOD sampler was designed to provide high-quality, surface-based PM2.5 and aerosol optical depth (AOD) measurements both in real-time, as well as time-averaged by using a traditional filter [Ford et al., 2019]. PM2.5 is a measure of the mass of small aerosols at "breathing-level", measuring 2.5 microns in diameter, and AOD is a measure of how much light does not pass through the atmosphere due to the presence of aerosols. More technical information about the sampler is available in Ford et al. [2019] and Wendt et al. [2019].

Figure 2. Photo of AMOD sampler.

4 ▪ Methods

4.1 ▪ *Anthropomorphizing the AMOD sampler*

To study the relationship between anthropomorphism and participants' motivation to participate in CEAMS, we anthropomorphized the AMOD sampler. Some anthropomorphism design elements were inspired by Frayer [2010]; for example, each AMOD sampler had a "Hello My Name is ________" sticker, to encourage participants to name their AMOD samplers and make the sampler personal to them, which can encourage participants to develop an attachment to their sampler [Frayer, 2010]. A second component of the anthropomorphism prime included having the sampler perform a "wake up" sequence to show that it was ready to take a sample. The AMOD's wake-up sequence went as follows: the AMOD "rested" when its indicator light was orange; the light turned green when the AMOD was ready to sample the air, i.e. "wake up". In addition, when the light turned green, the long, black turret on top of the AMOD (Figure 2) rose to find the sun and the sampler spun around until it located the sun. Once it found the sun, the AMOD stopped spinning, took measurements, lowered the turret, and the indicator light turned orange to indicate the sampler was resting again.

A third component of the prime was the anthropomorphic language we used in the training session when participants learned to operate their samplers and in the sampler user manuals. During the session, we described the AMOD as a *partner* in data collection. For example, we used phrases like "you are working together with the sampler to measure the air", and "make sure you remember to charge your partner so they can be ready to go for the next week of measurements". The user manuals with anthropomorphic language used similar phrasing as in the training.

4.2 ▪ *Variables*

To measure the motivation to participate in citizen science variables in our hypotheses, we adapted questions from the Motivation to Participate in Citizen Science Scale [Phillips et al., 2017]. *Perceived competence* was measured using nine items, such as "I think I am pretty good at taking air quality samples" and "It is important to me to feel that I took air quality samples as well as or better than other participants". *Contributing to scientific* *knowledge* was measured using four items, such as "I want to contribute to science" and "I want to help scientists understand more about air quality". *Building community* was measured using one item ("I want to help my community). All items had a seven-point Likert scale response set (1 = strongly disagree, 7 = strongly agree).

To measure the three SEEK variables in our hypotheses, we used items employed in other studies that used the SEEK model [Epley et al., 2007; Epley, Waytz et al., 2008]. *Effectance* was measured using two items ("I have a good idea of what I must do to participate" and "The project's goals have been clearly explained"). *Elicited agent knowledge* was measured using seven items, such as "I understand how ground-level air quality is measured" and "I understand how satellites measure air quality". *Sociality* was measured using one item ("I want to interact with research team members". All items had a seven-point Likert scale response set (1 = strongly disagree, 7 = strongly agree).

4.3 ▪ *Pilot study*

We conducted a pilot study for five weeks in Spring 2021 to determine whether our approach to encouraging participants to anthropomorphize their AMOD samplers was effective and to test the reliability of the scales used to measure the variables in our hypotheses.

The pilot study used a pre-test/post-test control group quasi-experimental design, where the treatment group was encouraged to anthropomorphize their AMOD samplers while the control group was not. We recruited 24 participants from the Community Collaborative Rain, Hail and Snow Network (CoCoRaHS), a citizen science project that has been running since 1998. The sample consisted of 16 males and 8 females, with an average age of 61 years (SD = 15 years, range: 54 years). The sample was 87.50% White, 4.17% Hispanic/Latino, and 8.33% preferred not to report.

Participants were randomly assigned to the control group (n = 12) or the treatment group (anthropomorphized condition) (n = 12). Treatment group participants received AMOD samplers that had the name stickers, while control group participants received samplers that did not have these stickers. All participants attended a virtual training session where they learned to operate their AMOD sampler, use the phone app to start sample collection, and recharge their sampler; they also learned other project logistics. In treatment group training sessions, project personnel used anthropomorphic language to describe and refer to the sampler as outlined in the Anthropomorphizing the AMOD Sampler section. In the control group training sessions, project personnel did not use anthropomorphic language. Training sessions for all participants lasted 45 minutes to 1 hour; they were hosted on the virtual meeting platform Zoom. After training sessions, all participants were emailed the PowerPoint slides from their group's session, PDF copies of their respective operation manuals (i.e., anthropomorphized language or control), and links to videos on how to operate the sampler and interact with their air quality data.

Testing the anthropomorphism prime. To determine whether we were successful in encouraging participants in the treatment group to anthropomorphize the AMOD sampler, participants in both groups kept a weekly log about their sampling experiences. We conducted a quantitative content analysis of the log entries. Log entries were coded for presence/absence of participants indicating that the samplers (a) showed lifelikeness, (b) had emotional states, (c) displayed intentions, (d) were referred to a name instead of as a machine (e.g., "Andy") and (e) were referred to using gendered pronouns (e.g., he/him or she/her). These five anthropomorphic language types have been used in previous content analytic studies of anthropomorphism [Dorion, 2011; Fink et al., 2012; Sah & Peng, 2015; Sealey & Oakley, 2013].

Lifelikeness was defined as language that depicted the sampler as being alive or having (parts of) a body [Fink et al., 2012]. For example, participants referenced the AMODs as having an arm, eyes, feet, "waking up", or being alive/dead. *Emotional states* were defined as writing that indicated the sampler had a feeling [Fink et al., 2012] such as sadness, excitement, and anger. *Displaying intention* was defined as explanations for a process where the machine could be perceived as having sentience for its actions [Dorion, 2011]. Examples of intention included the use of verbs such as "wants", "prefers", "needs", "gives", "seems to like", or "trying" on behalf of the AMOD. The *use of a name* (besides "AMOD" or "sampler") was coded; examples included Optical Prime, WALL-E, Sunny, Dennis, Snoop Dogg, and Nova. Last, the use of *gendered pronouns* (e.g., he/him or she/her) instead of neuter pronouns like "it" was coded [Sah & Peng, 2015; Sealey & Oakley, 2013]. Two coders independently coded 15 entries from the weekly logs to test intercoder reliability for the anthropomorphic language types. These entries were chosen randomly and they represented 15% of the log entries (N = 98 log entries). To determine intercoder reliability for each anthropomorphic language type, Krippendorff's alpha (α) coefficients were calculated to measure the levels of chance-adjusted agreement between the coders. As seen in Table 1, acceptable levels of reliability were attained for all five language categories [Krippendorff, 2019].

Table 1. Intercoder reliability for pilot logs.

Anthropomorphic language type	*Alpha* (α)
Lifelikeness	0.81
Emotion	1.00
Personality/Intention	0.79
Name	1.00
Pronouns	1.00

Once intercoder reliability was established, the rest of the weekly log entries for both the control and treatment groups were coded. Once all the log entries were coded, then a score was calculated for each log entry, and that score was based on the number of types of anthropomorphic language that were in each log entry. A score could range from 0 to 5 each week. These scores were averaged across all the log entries each participant had.
A comparison of the anthropomorphic language levels in the control group logs and the treatment group logs indicates that the anthropomorphism primes worked. The level of anthropomorphic language was significantly higher in the experimental group logs ($M = 1.54$, $SD = 1.25$) than in the control group logs ($M = 0.15$, $SD = 0.36$), based on the results of a Mann-Whitney test, $U(N_{experimental} = 50, N_{control} = 48) = 355.00$, $z = -6.57$, $p < 0.01$.

Testing measurement scale reliabilities. Four variables were measured using multiple Likert scale questions. To test the reliability of the scales used to measure these four variables, participants completed two questionnaires: before they attended their training session, and at the end of the study (at the end of the fifth week). Each questionnaire took 10 to 15 minutes to complete and was administered via Qualtrics.

Table 2. Cronbach's alpha values and scale descriptive statistics for pilot study.

Scale	*Cronbach's alpha*	*Scale mean*	*Standard deviation*
Effectance	0.74	6.50	0.51
Perceived Competence	0.85	5.20	1.00
Elicited Agent Knowledge	0.82	5.76	0.66
Contributing to Scientific Knowledge	0.85	6.71	0.72

Due to the small sample size for the pilot, the entire group (n = 24) was combined to analyze scale reliability. Cronbach's alpha values and scale descriptive statistics from post-test of the pilot study are presented in Table 2 since this questionnaire had every scale included.

To summarize, the results of the pilot study indicated that the anthropomorphism primes were effective and that all scales used to measure four of the variables in the hypotheses were reliable.

4.4 ▪ *Main study*

During Summer 2021, we recruited 30 participants from NASA's Student Airborne Research Program (SARP) to participate in the CEAMS citizen science project, which ran for eight weeks. SARP is an eight-week program for college students interested in earth-systems science. Normally, SARP participants spend eight weeks at one or more NASA Airborne Science Program flying science laboratories at the Ames Research Center. However, because of the COVID-19 pandemic, the program was conducted virtually during Summer 2021. An advantage of SARP's virtual status that summer was that we had the opportunity to recruit participants from across the United States. In addition to the 28 students who agreed to participate in CEAMS, two faculty members from SARP also participated. The sample consisted of 10 males and 20 females with an average age of 22 years (SD = 5 years, range = 36 years). The sample was 70% White/Caucasian, 10% Hispanic/Latino, 10% Asian, and 10% Black/African American.[2]

Due to the collaborative nature of citizen science projects, especially longer-term projects like CEAMS, having a classic control group can be operationally difficult. Consequently, we used a within-subjects, pre-test/post-test, quasi-experimental design for the main study. In the main study, all participants received AMOD samplers that had "Hello, my name is ________" stickers, and they attended virtual training sessions where project personnel used anthropomorphic language to describe and refer to the sampler, as outlined in the "Anthropomorphizing the AMOD Sampler" section. Training sessions for the main study covered the same topics as those in the pilot study.

Virtual training sessions lasted between 45 minutes to 1 hour and were hosted on Zoom. After the session, participants were emailed the PowerPoint slides from the session, PDF copies of the operation manual, and links to videos on how to operate the sampler and interact with their air quality data.

Participants completed three questionnaires: a pre-questionnaire before they underwent training, a midpoint questionnaire at the end of the fourth week, and a post-test

2. While participants could select multiple ethnicities when filling out the questionnaires, they all chose one selection.

questionnaire at the end of the eighth week.[3] The questionnaires took 10 to 15 minutes to complete and were administered through Qualtrics. The items measuring sociality, building community, perceived competence, and contributing to scientific knowledge appeared on each questionnaire; the items measuring effectance and elicited agent knowledge appeared on the midpoint and post-test questionnaires because participants had no knowledge of the sampler or how to interact with it at the pre-test. In the main study, 25 entries from the weekly logs were coded to establish intercoder reliability ($N = 164$). The Cronbach's alphas were reliable in the main study as well, which were calculated as the mean alpha across the three times the variable was measured (Table 3). Variables measured by a single item did not have an alpha value calculated.

Table 3. Cronbach's alpha values and scale descriptive statistics for main study.

Scale	*Cronbach's alpha*	*Scale mean*	*Standard deviation*
Effectance	0.71	6.41	0.95
Perceived Competence	0.84	5.20	0.95
Elicited Agent Knowledge	0.85	5.29	1.01
Contributing to Scientific Knowledge	0.83	6.74	0.53
Building Community	–	6.56	0.80
Sociality	–	6.14	1.04

In addition to completing the three questionnaires, each participant kept a weekly log about their sampling experience. Nearly all participants (93%) reported that they named their AMODs. The average score for the logs in the main study was $M = 0.60$, $SD = 0.89$. While the mean was lower than the control group in the pilot study (1.54), it is still higher than we had for the control group in the pilot study (0.15). Also, across the 164 logs, the uses of anthropomorphic language in the main study followed a similar pattern to the pilot study. Using a name was the most frequent anthropomorphic language, being within 34.10% of entries, followed by mentions of lifelikeness within 14.00% of the entries. Pronouns were used in 7.90% of entries, with the least frequent variables being displaying intention (3.70% of entries) and displaying emotions (2.40% of entries) on behalf of the samplers. Both the average score and pattern of anthropomorphic language use in the logs suggests that the anthropomorphism priming worked well enough for this main study.

5 · Findings

To test H1, Spearman's rank correlations were computed to assess the relationship between Sociality and the Desire to Build Community. We tested this relationship across times, as well as at the pre-test, midpoint, and post-test time periods, because there could be a potential effect of time on the relationship between variables. The average scores for sociality were relatively high with slight variations over time, averaging around 6 points on the 7-point Likert scale (Table 4). The average scores for desire to build community were similarly high, though more stable across times (Table 4). There was a positive, statistically significant correlation between the two variables at all times $r(28) = 0.46$, $p < 0.01$ (Table 5).

To test H2, Spearman's rank correlation was computed to assess the relationship between Effectance and Perceived Competence. As these scales were only computed at the midpoint

3. The atmospheric data collected for this paper were gathered as part of a larger study [Wendt et al., 2023].

Table 4. Means (M) and standard deviations (SD) for sociality and desire to build community across times, at the pre-test (T1), midpoint (T2), and post-test (T3).

	Sociality		*Desire to build community*	
	M	SD	M	SD
Pre-test (T1)	6.58	0.72	6.61	0.81
Midpoint (T2)	5.90	1.05	6.55	0.78
Post-test (T3)	5.89	1.05	6.52	0.85
Across times	6.14	1.04	6.56	0.80

Table 5. Spearman correlation between sociality and desire to build community across times, at the pre-test (T1), midpoint (T2), and post-test (T3).

	Spearman	*One-tailed significance*
Sociality * Building Community	0.46**	0.00
Sociality T1 * Building Community T1	0.48**	0.00
Sociality T2 * Building Community T2	0.46**	0.00
Sociality T3 * Building Community T3	0.48**	0.00

** Correlation is statistically significant at $p < 0.01$.

Table 6. Means (M) and standard deviations (SD) for effectance and perceived competence across times and at the midpoint (T2) and post-test (T3).

	Effectance		*Perceived Competence*	
	M	SD	M	SD
Midpoint (T2)	6.38	1.12	5.06	0.93
Post-test (T3)	6.63	0.91	5.35	0.97
Across times	6.41	0.95	5.20	0.95

Table 7. Spearman correlation between effectance and perceived competence across times and at the midpoint (T2) and post-test (T3).

	Spearman	*One-tailed Significance*
Effectance * Perceived Competence	0.26*	0.03
Effectance T2 * Perceived Competence T2	0.32*	0.04
Effectance T3 * Perceived Competence T3	0.13	0.27

* Correlation is statistically significant at $p < 0.05$.

and post-test, Spearman correlations were only run then. The average scores for effectance were close to the high point of the Likert scale (7-point), with some variation between times (Table 6). The average scores for perceived competence were around 5-points on the 7-point scale, with some variation between times (Table 6). There was a positive, statistically significant correlation between the variables across all times, $r(28) = 0.26$, $p < 0.05$, and at the midpoint (T2), $r(28) = 0.32$, $p < 0.05$. There were positive trends, though statistically nonsignificant correlations at the post-test (T3) (Table 7).

To test H3, Spearman's rank correlation was computed to assess the relationship between elicited agent knowledge and contributing to scientific knowledge. The average scores for

Table 8. Means (M) and standard deviations (SD) for elicited agent knowledge and contributing to scientific knowledge across times, at the pre-test (T1), midpoint (T2), and post-test (T3).

	Elicited agent knowledge		*Contributing to Scientific Knowledge*	
	M	SD	M	SD
Pre-test (T1)	4.70	1.07	6.81	0.46
Midpoint (T2)	5.40	0.84	6.64	0.62
Post-test (T3)	5.86	0.73	6.78	0.52
Across times	5.29	1.01	6.74	0.53

Table 9. Spearman correlation between elicited agent knowledge and for contributing to scientific knowledge across times, at the pre-test (T1), midpoint (T2), and post-test (T3).

	Spearman	*One-tailed Significance*
Elicited Agent Knowledge * Contributing to Scientific Knowledge	0.16	0.08
Elicited Agent Knowledge T1 * Contributing to Scientific Knowledge T1	0.15	0.22
Elicited Agent Knowledge T2 * Contributing to Scientific Knowledge T2	0.28	0.08
Elicited Agent Knowledge T3 * Contributing to Scientific Knowledge T3	0.39*	0.02

* Correlation is statistically significant at $p < 0.05$.

elicited agent knowledge were closer to the midpoint of the 7-point Likert scale, with some variations between times (Table 8). The average scores for contributing to scientific knowledge were at the upper bounds of the 7-point Likert scale and relatively similar between times (Table 8). There was a positive trend, though statistically nonsignificant, between the two variables across all times, at the pre-test (T1), and at the midpoint (T2). There was a statistically significant, positive correlation at the post-test (T3), $r(28) = 0.39$, $p < 0.05$ (Table 9).

6 ▪ Discussion

Maintaining volunteer participation for projects that take longer than a day is a known challenge that researchers have faced with citizen science [e.g., Levontin et al., 2022; Frensley et al., 2017]. Incorporating anthropomorphism into citizen science projects with technology may boost participation rates. Our study provides partial experimental support for the proposed relationships between the SEEK model of anthropomorphism determinants (sociality, effectance, and elicited agent knowledge [Epley et al., 2007]) and motivations to participate in citizen science projects, including desire to build community, perceived competence, and the desire to contribute to scientific knowledge [e.g., Raddick et al., 2013; Curtis, 2018; Tiago et al., 2017; Phillips et al., 2017]. Sociality and building community were significantly correlated at each measurement point in the main study. Effectance and perceived competence were significantly correlated at the midpoint and across the entire time of the study. The correlation between elicited agent knowledge and contributing to scientific knowledge was only supported at the post-test. Potential reasons that the statistical support was not seen across each variable at all times of the study could include how some of the variables were measured. The items used came from the literature [e.g., Phillips et al., 2017], but did vary in the number of items across variables. For example, two variables were measured with only a single item. Additionally, our sample was composed of participants that had high technological competency, as they were university students from scientific disciplines. Their knowledge of air quality samplers, feelings towards technology, and desire to contribute to science may have been different than other citizen scientists. Even so, the partial support found in the conceptual model connecting anthropomorphism and motivation is promising.

We integrated anthropomorphism primes into the scientific instruments (e.g., AMOD sampler) and communication materials of our citizen science project, like Frayer [2010]. This was relatively easy, as adding name tags (and anthropomorphic language to describe the design of our equipment such as the "wake-up" sequence) was simple to incorporate when planning the study as well as to reinforce throughout the project by the research team. Especially as technology can be more difficult to anthropomorphize than a living being like an animal [Darling, 2015], this study provides an innovative strategy for increasing motivation to participate in citizen science projects. Additionally, this study included a pilot test that showed the anthropomorphism approach worked. While the scores for anthropomorphic language were not the strongest in the logs, we did see a difference between the control and the experimental groups. This effect, though small, was still seen in the quasi-experimental design of the main study.

There were some limitations to this study that are important to address. First, this study had a small sample size ($n = 30$), which could explain why we saw only partial support. There may be a potential ceiling effect in this sample for the Likert scales used; while there were varied response items, an increased sample size could help mitigate this effect. Future studies could address this limitation by replicating the anthropomorphism primes with larger experimental and control groups or multiple project periods per year. Additionally, due to constraints imposed on the study design by the COVID-19 pandemic, participant interactions were entirely virtual. A citizen science project that had more direct communication and interaction between the project's scientists and the anthropomorphism primed instruments could have had a larger effect on the participants. For example, scores on sociality and building community could have been affected if participants had weekly in-person interactions with the research team, rather than with just interacting with their sampler on their own and via email. If a project like this one were to be run again on a larger scale, we would suggest having participants interact with the scientists on a regular basis to help boost sociality. We also recommend including and testing additional items for building community and sociality to have more robust measures. Additionally, participants' effectance scores could have been higher in this study because participants had to interact with their samplers almost entirely on their own due to the remote status of the project. A different citizen science project where participation was done more in groups with other participants and researchers could have had participants use the samplers with less independence.

This work adds to the examples of studies where social science and participant outcomes are intentional foci of citizen science projects [e.g., Pateman et al., 2021; Robinson et al., 2021; Wright et al., 2015]. Incorporating anthropomorphism has a positive relationship with motivation to participate, which is a highly desired attribute of citizen science [Curtis, 2018; Frensley et al., 2017; Raddick et al., 2010; Tiago et al., 2017]. Future studies should test the proposed model between anthropomorphism and motivation to participate further, potentially creating more predictive models to explain other desired aspects of citizen science, like engagement or volunteer retention over time. This study pushes the field of citizen science towards understanding more about the human dimensions of participatory research through the novel approach of anthropomorphism.

7 ▪ Conclusion

Using a quasi-experimental design, our study shows promising, partial support for the proposed model connecting motivation to participate and anthropomorphism, which was experimentally framed in a technological citizen science project. As both the literature that informs this study and the experimental results show, incorporating anthropomorphism into the materials and instruments of a citizen science project should be tried by other project managers to encourage participant motivation. It is important to understand what motivates people to interact with new technologies, especially as we develop new instruments to measure our world. Citizen science provides a participatory context to study how people connect with technology. A better understanding of this can benefit both salaried and volunteer participants.

Acknowledgments

This research was supported by NASA grant 80NSSC18M0120. Data are available from the corresponding author upon reasonable request.

References

Alender, B. (2016). Understanding volunteer motivations to participate in citizen science projects: a deeper look at water quality monitoring. *JCOM*, *15*(03), A04. https://doi.org/10.22323/2.15030204

Bartneck, C., Belpaeme, T., Eyssel, F., Kanda, T., Keijsers, M., & Šabanović, S. (2020). What is human-robot interaction? In *Human-robot interaction: an introduction* (pp. 6–17). Cambridge University Press. https://doi.org/10.1017/9781108676649.002

Bartz, J. A., Tchalova, K., & Fenerci, C. (2016). Reminders of social connection can attenuate anthropomorphism: a replication and extension of Epley, Akalis, Waytz, and Cacioppo (2008). *Psychological Science*, *27*(12), 1644–1650. https://doi.org/10.1177/0956797616668510

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science*, *49*(4), 632–658. https://doi.org/10.1007/s11747-020-00762-y

Campos, R., Monteiro, J., & Carvalho, C. (2021). Engaged Citizen Social Science or the public participation in social science research. *JCOM*, *20*(06), A06. https://doi.org/10.22323/2.20060206

Cappa, F., Laut, J., Porfiri, M., & Giustiniano, L. (2018). Bring them aboard: rewarding participation in technology-mediated citizen science projects. *Computers in Human Behavior*, *89*, 246–257. https://doi.org/10.1016/j.chb.2018.08.017

Christoforakos, L., & Diefenbach, S. (2023). Fulfilling social needs through anthropomorphic technology? A reflection on existing research and empirical insights of an interview study. *Zeitschrift für Arbeitswissenschaft*, *77*(1), 78–91. https://doi.org/10.1007/s41449-022-00339-1

Connell, P. M. (2013). The role of baseline physical similarity to humans in consumer responses to anthropomorphic animal images. *Psychology & Marketing*, *30*(6), 461–468. https://doi.org/10.1002/mar.20619

Csikszentmihalyi, M. (1990). *Flow: the psychology of optimal experience*. Harper & Row.

Curtis, V. (2015). Motivation to participate in an online citizen science game: a study of Foldit. *Science Communication*, *37*(6), 723–746. https://doi.org/10.1177/1075547015609322

Curtis, V. (2018). Patterns of participation and motivation in Folding@home: the contribution of hardware enthusiasts and overclockers. *Citizen Science: Theory and Practice*, *3*(1), 5. https://doi.org/10.5334/cstp.109

Darling, K. (2015). 'Who's Johnny?' Anthropomorphic framing in human-robot interaction, integration, and policy. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2588669

de Kleijn, R., van Es, L., Kachergis, G., & Hommel, B. (2019). Anthropomorphization of artificial agents leads to fair and strategic, but not altruistic behavior. *International Journal of Human-Computer Studies*, *122*, 168–173. https://doi.org/10.1016/j.ijhcs.2018.09.008

Deci, E. L., & Ryan, R. M. (1985). *Intrinsic motivation and self-determination in human behavior*. Plenum Press. https://doi.org/10.1007/978-1-4899-2271-7

DiSalvo, C. F., Gemperle, F., Forlizzi, J., & Kiesler, S. (2002). All robots are not created equal: the design and perception of humanoid robot heads. *DIS '02: Proceedings of the 4th Conference on Designing Interactive Systems: processes, practices, methods, and techniques*, 321–326. https://doi.org/10.1145/778712.778756

Dorion, K. (2011). A learner's tactic: how secondary students' anthropomorphic language may support learning of abstract science concepts. *The Electronic Journal for Research in Science & Mathematics Education*, *15*. https://ejrsme.icrsme.com/article/view/8552

Epley, N., Akalis, S., Waytz, A., & Cacioppo, J. T. (2008). Creating social connection through inferential reproduction: loneliness and perceived agency in gadgets, gods, and greyhounds. *Psychological Science*, *19*(2), 114–120. https://doi.org/10.1111/j.1467-9280.2008.02056.x

Epley, N., Waytz, A., Akalis, S., & Cacioppo, J. T. (2008). When we need a human: motivational determinants of anthropomorphism. *Social Cognition*, *26*(2), 143–155. https://doi.org/10.1521/soco.2008.26.2.143

Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: a three-factor theory of anthropomorphism. *Psychological Review*, *114*(4), 864–886. https://doi.org/10.1037/0033-295x.114.4.864

Eveleigh, A., Jennett, C., Blandford, A., Brohan, P., & Cox, A. L. (2014). Designing for dabblers and deterring drop-outs in citizen science. *CHI '14: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 2985–2994. https://doi.org/10.1145/2556288.2557262

Eyssel, F., Kuchenbrandt, D., & Bobinger, S. (2011). Effects of anticipated human-robot interaction and predictability of robot behavior on perceptions of anthropomorphism. *HRI '11: Proceedings of the 6th International Conference on Human-Robot Interaction*, 61–68. https://doi.org/10.1145/1957656.1957673

Fink, J., Mubin, O., Kaplan, F., & Dillenbourg, P. (2012). Anthropomorphic language in online forums about Roomba, AIBO and the iPad. *2012 IEEE Workshop on Advanced Robotics and its Social Impacts (ARSO)*, 54–59. https://doi.org/10.1109/ARSO.2012.6213399

Ford, B., Pierce, J. R., Wendt, E., Long, M., Jathar, S., Mehaffy, J., Tryner, J., Quinn, C., van Zyl, L., L'Orange, C., Miller-Lionberg, D., & Volckens, J. (2019). A low-cost monitor for measurement of fine particulate matter and aerosol optical depth — Part 2: Citizen-science pilot campaign in northern Colorado. *Atmospheric Measurement Techniques*, *12*(12), 6385–6399. https://doi.org/10.5194/amt-12-6385-2019

Frayer, M. (2010). *Giving the toaster eyes: applied anthropomorphism and its influences on user-object relations with everyday objects* [Master's Thesis]. Lund University. https://www.lunduniversity.lu.se/lup/publication/1604671

Frensley, T., Crall, A., Stern, M., Jordan, R., Gray, S., Prysby, M., Newman, G., Hmelo-Silver, C., Mellor, D., & Huang, J. (2017). Bridging the benefits of online and community supported citizen science: a case study on motivation and retention with conservation-oriented volunteers. *Citizen Science: Theory and Practice*, *2*(1), 4. https://doi.org/10.5334/cstp.84

Gardner, W. L., Pickett, C. L., Jefferis, V., & Knowles, M. (2005). On the outside looking in: loneliness and social monitoring. *Personality and Social Psychology Bulletin*, *31*(11), 1549–1560. https://doi.org/10.1177/0146167205277208

Gazzola, V., Rizzolatti, G., Wicker, B., & Keysers, C. (2007). The anthropomorphic brain: the mirror neuron system responds to human and robotic actions. *NeuroImage*, *35*(4), 1674–1684. https://doi.org/10.1016/j.neuroimage.2007.02.003

Higgins, E. T. (1996). Knowledge activation: accessibility, applicability, and salience. In E. T. Higgins & A. W. Kruglanski (Eds.), *Social psychology: handbook of basic principles* (pp. 133–168). The Guilford Press.

Humphreys, M. S., & Revelle, W. (1984). Personality, motivation, and performance: a theory of the relationship between individual differences and information processing. *Psychological Review*, *91*(2), 153–184. https://doi.org/10.1037/0033-295X.91.2.153

Jennett, C., & Cox, A. L. (2018). Digital citizen science and the motivations of volunteers. In K. L. Norman & J. Kirakowski (Eds.), *The Wiley handbook of human computer interaction* (pp. 831–841). Wiley. https://doi.org/10.1002/9781118976005.ch39

Krippendorff, K. (2019). *Content analysis: an introduction to its methodology* (4th ed.). SAGE Publications. https://doi.org/10.4135/9781071878781

Kullenberg, C., & Kasperowski, D. (2016). What is citizen science? — A scientometric meta-analysis. *PLoS ONE*, *11*(1), e0147152. https://doi.org/10.1371/journal.pone.0147152

Laut, J., Cappa, F., Nov, O., & Porfiri, M. (2017). Increasing citizen science contribution using a virtual peer. *Journal of the Association for Information Science and Technology*, *68*(3), 583–593. https://doi.org/10.1002/asi.23685

Levontin, L., Gilad, Z., Shuster, B., Chako, S., Land-Zandstra, A., Lavie-Alon, N., & Shwartz, A. (2022). Standardizing the assessment of citizen scientists' motivations: a motivational goal-based approach. *Citizen Science: Theory and Practice*, *7*(1), 25. https://doi.org/10.5334/cstp.459

MacInnis, D. J., & Folkes, V. S. (2017). Humanizing brands: when brands seem to be like me, part of me, and in a relationship with me. *Journal of Consumer Psychology*, *27*(3), 355–374. https://doi.org/10.1016/j.jcps.2016.12.003

Mankowski, T. A., Slater, S. J., & Slater, T. F. (2011). An interpretive study of meanings citizen scientists make when participating in Galaxy Zoo. *Contemporary Issues in Education Research (CIER)*, *4*(4), 25–42. https://eric.ed.gov/?id=EJ1072914

Palacin, V., Ferrario, M. A., Hsieh, G., Knutas, A., Wolff, A., & Porras, J. (2021). Human values and digital citizen science interactions. *International Journal of Human-Computer Studies*, *149*, 102605. https://doi.org/10.1016/j.ijhcs.2021.102605

Pateman, R., Dyke, A., & West, S. (2021). The diversity of participants in environmental citizen science. *Citizen Science: Theory and Practice*, *6*(1), 9. https://doi.org/10.5334/cstp.369

Phillips, T., Porticella, N., & Bonney, R. (2017). *Motivation to participate in citizen science scale* [Technical Brief Series]. Cornell Lab of Ornithology. Ithaca, NY, U.S.A.

Raddick, M. J., Bracey, G., Gay, P. L., Lintott, C. J., Cardamone, C., Murray, P., Schawinski, K., Szalay, A. S., & Vandenberg, J. (2013). Galaxy Zoo: motivations of citizen scientists. *Astronomy Education Review*, *12*(1). https://doi.org/10.3847/aer2011021

Raddick, M. J., Bracey, G., Gay, P. L., Lintott, C. J., Murray, P., Schawinski, K., Szalay, A. S., & Vandenberg, J. (2010). Galaxy Zoo: exploring the motivations of citizen science volunteers. *Astronomy Education Review*, *9*(1). https://doi.org/10.3847/AER2009036

Robinson, J. A., Kocman, D., Speyer, O., & Gerasopoulos, E. (2021). Meeting volunteer expectations — a review of volunteer motivations in citizen science and best practices for their retention through implementation of functional features in CS tools. *Journal of Environmental Planning and Management*, *64*(12), 2089–2113. https://doi.org/10.1080/09640568.2020.1853507

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, *55*(1), 68–78. https://doi.org/10.1037/0003-066x.55.1.68

Ryan, R. M., & Deci, E. L. (2017). *Self-determination theory: basic psychological needs in motivation, development, and wellness*. The Guilford Press. https://doi.org/10.1521/978.14625/28806

Sah, Y. J., & Peng, W. (2015). Effects of visual and linguistic anthropomorphic cues on social perception, self-awareness, and information disclosure in a health website. *Computers in Human Behavior*, *45*, 392–401. https://doi.org/10.1016/j.chb.2014.12.055

Sealey, A., & Oakley, L. (2013). Anthropomorphic grammar? Some linguistic patterns in the wildlife documentary series Life. *Text & Talk*, *33*(3), 399–420. https://doi.org/10.1515/text-2013-0017

Tiago, P., Gouveia, M. J., Capinha, C., Santos-Reis, M., & Pereira, H. M. (2017). The influence of motivational factors on the frequency of participation in citizen science activities. *Nature Conservation*, *18*, 61–78. https://doi.org/10.3897/natureconservation.18.13429

Waytz, A., Cacioppo, J., & Epley, N. (2010). Who sees human?: The stability and importance of individual differences in anthropomorphism. *Perspectives on Psychological Science*, *5*(3), 219–232. https://doi.org/10.1177/1745691610369336

Waytz, A., Epley, N., & Cacioppo, J. T. (2010). Social cognition unbound: insights into anthropomorphism and dehumanization. *Current Directions in Psychological Science*, *19*(1), 58–62. https://doi.org/10.1177/0963721409359302

Waytz, A., Morewedge, C. K., Epley, N., Monteleone, G., Gao, J.-H., & Cacioppo, J. T. (2010). Making sense by making sentient: effectance motivation increases anthropomorphism. *Journal of Personality and Social Psychology*, *99*(3), 410–435. https://doi.org/10.1037/a0020240

Wendt, E. A., Ford, B., Cheeseman, M., Rosen, Z., Pierce, J. R., Jathar, S. H., L'Orange, C., Quinn, C., Long, M., Mehaffy, J., Miller-Lionberg, D. D., Hagan, D. H., & Volckens, J. (2023). A national crowdsourced network of low-cost fine particulate matter and aerosol optical depth monitors: results from the 2021 wildfire season in the United States. *Environmental Science: Atmospheres*, *3*(10), 1563–1575. https://doi.org/10.1039/d3ea00086a

Wendt, E. A., Quinn, C., L'Orange, C., Miller-Lionberg, D. D., Ford, B., Pierce, J. R., Mehaffy, J., Cheeseman, M., Jathar, S. H., Hagan, D. H., Rosen, Z., Long, M., & Volckens, J. (2021). A low-cost monitor for simultaneous measurement of fine particulate matter and aerosol optical depth — Part 3: Automation and design improvements. *Atmospheric Measurement Techniques*, *14*(9), 6023–6038. https://doi.org/10.5194/amt-14-6023-2021

Wendt, E. A., Quinn, C. W., Miller-Lionberg, D. D., Tryner, J., L'Orange, C., Ford, B., Yalin, A. P., Pierce, J. R., Jathar, S., & Volckens, J. (2019). A low-cost monitor for simultaneous measurement of fine particulate matter and aerosol optical depth — Part 1: Specifications and testing. *Atmospheric Measurement Techniques*, *12*(10), 5431–5441. https://doi.org/10.5194/amt-12-5431-2019

White, R. W. (1959). Motivation reconsidered: the concept of competence. *Psychological Review*, *66*(5), 297–333. https://doi.org/10.1037/h0040934

Wiese, E., Metta, G., & Wykowska, A. (2017). Robots as intentional agents: using neuroscientific methods to make robots appear more social. *Frontiers in Psychology*, *8*, 1663. https://doi.org/10.3389/fpsyg.2017.01663

Wright, D. R., Underhill, L. G., Keene, M., & Knight, A. T. (2015). Understanding the motivations and satisfactions of volunteers to improve the effectiveness of citizen science programs. *Society & Natural Resources*, *28*(9), 1013–1029. https://doi.org/10.1080/08941920.2015.1054976

About the authors

Zoey Rosen
Dr. Rosen is a Postdoctoral Research Associate in the Institute for Public Policy Research and Analysis at the University of Oklahoma. She received her Ph.D. in Public Communication and Technology from Colorado State University. Her research examines risk communication during severe weather outbreaks, among other environmental topics such as air quality.

zoey.rosen@ou.edu @ZoeyRosen

Marilee Long
Dr. Long is a professor in and chair of the Department of Journalism and Media Communication; a member of CSU's Partnership for Air Quality, Climate, and Health; a professor in the Colorado School of Public Health; and a Fellow in the American Association for the Advancement of Science. Dr. Long's research interests are in health and science communication. In recent work, she has studied the use of citizen-science approaches to increase awareness, knowledge, and protective behaviors related to poor air quality caused by wildfire smoke and ozone.

marilee.long@colostate.edu

Bonne Ford
Dr. Ford is a Research Scientist in the National Park Service Group at CIRA at Colorado State University in Fort Collins, CO. She does data analysis and QA/QC for the IMPROVE Network. Her research is focused on air quality with interests in monitoring, modeling, and satellite analysis; along with citizen/community science, communication, and health impacts.

bonne.ford@colostate.edu

Eric A. Wendt
Dr. Wendt is a computer vision engineer and scientist at Trillium Engineering. Previously at CSU, he invented a low-cost monitor designed for deployment in crowdsourced networks of citizen-scientists to evaluate the transport of wildfire smoke in the continental United States and developed a cloud-screening algorithm for solar radiometry using all-sky images and deep transfer learning.

eawendtjr@gmail.com

Michael Cheeseman
Dr. Cheeseman is a Research Scientist at IMSG (NOAA NESDIS). He has conducted research on a broad array of topics including air pollution from anthropogenic and natural sources (especially wildfires), carbon cycle modeling, and environmental justice. He is interested in using citizen science measurements of PM2.5 and aerosol optical depth to improve satellite detection of air quality.

cheesemanmj@gmail.com

Casey Quinn
Dr. Quinn is a Senior Electric Vehicle Charging Infrastructure Reliability Engineer at Idaho National Laboratory, and previously was a Research Scientist in the Department of

Mechanical Engineering at CSU where he worked on energy related projects and developed low-cost sensors for assessing air and water quality. He is an experienced researcher and independent consultant with a demonstrated history of working on mechanical engineering, industrial hygiene, and public health focused projects.

quinn.casey@gmail.com

Christian L'Orange
Dr. Christian L'Orange is an Associate Professor in the Department of Mechanical Engineering at CSU. Dr. L'Orange's work focuses at the intersection of energy usage and the resulting climate and human health implications of that usage. His research focuses include household energy in the developing world, development of low-cost air quality sensors, and human health/climate implications of energy usage. He is a licensed Professional Engineer and a certified Project Manager.

christian.lorange@colostate.edu

John Volckens
Dr. Volckens is a professor of Mechanical Engineering and the Director of the Center for Energy Development and Health at Colorado State University (CSU). He holds affiliate appointments in Environmental Health, Biomedical Engineering, the Colorado School of Public Health, and the CSU Energy Institute. His research interests involve air quality, low-cost sensors, exposure science, and air pollution-related disease. He is a founding member of the CSU Partnership for Air Quality, Climate, and Health.

john.volckens@colostate.edu

Jeffrey R. Pierce
Dr. Pierce is a Professor in the Department of Atmospheric Science at Colorado State University. His research interests include Air pollution and health, Aerosol microphysics, aerosol-cloud interactions, cloud microphysics, aerosol climate effects, aerosol sources and sinks, near-source aerosol physics, new-particle formation and growth, aerosol and gas-phase chemistry, and aerosol remote sensing.

jeffrey.pierce@colostate.edu

How to cite

Rosen, Z., Long, M., Ford, B., Wendt, E. A., Cheeseman, M., Quinn, C., L'Orange, C., Volckens, J. and Pierce, J. R. (2024). 'Anthropomorphism and motivating participation in citizen science projects'. *JCOM* 23(08), A04. https://doi.org/10.22323/2.23080204.

ISSN 1824-2049. Published by SISSA Medialab. jcom.sissa.it