Proceedings of the 56th Hawaii International Conference on System Sciences | 2023

# Extending the Affective Technology Acceptance Model to Human-Robot Interactions: A Multi-Method Perspective

Sarah A. Jessup
Consortium of Universities
Wright-Patterson, AFB, OH
sarah.jessup.ctr@us.af.mil

Sasha M. Willis
General Dynamics Information Technology, Dayton, OH
willis.149@wright.edu

Gene M. Alarcon
Air Force Research Laboratory
Wright-Patterson AFB, OH
gene.alarcon.1@us.af.mil

## Abstract

*The current study sought to extend the Affective Technology Acceptance (ATA) model to human-robot interactions. We tested the direct relationship between affect and technology acceptance of a security robot. Affect was measured using a multi-method approach, which included a self-report survey, as well as sentiment analysis, and response length of written responses. Results revealed that participants who experienced positive affect were more likely to accept technology. However, the significance and direction of the relationship between negative affect and technology acceptance was measurement dependent. Additionally, positive and negative sentiment words accounted for unique variance in technology acceptance, after controlling for self-reported affect. This study demonstrates that affect is an important contributing factor in human-robot interaction research, and using a multi-method approach allows for a richer, more complete understanding of how human feelings influence robot acceptance.*

**Keywords:** human-robot interaction, technology acceptance, affect, qualitative analysis, Affective Technology Acceptance model.

## 1. Introduction

Autonomous robots are "intelligent machines capable of performing tasks in the world by themselves, without explicit human control" (Bekey, 2005, p. 1), and are a form of embodied artificial intelligence (Pfeifer & Iida, 2004). Autonomous robots have demonstrated their usefulness in industries such as food service (Shacklett, 2020), military (Voth, 2004), and education (Belpaeme et al., 2018). As autonomous robots become more engrained in society and the workplace, their acceptance by the human user becomes critical to realizing the benefits these robots can provide. User attitudes towards autonomous robots are critical in high-risk workplace domains, often characterized by ambiguity and uncertainty. Multiple factors influence robot acceptance, and these factors may change depending on context (e.g., Sanders et al., 2019).

Affect is one notable factor that has been empirically shown to influence technology acceptance (Hoong et al., 2017; Lee & Lim, 2016), and indirectly influence behavioral intentions to work with a social robot (Piçarra, & Giger, 2018). The Affective Technology Acceptance (ATA) model (Hoong et al., 2017) posits that positive affect positively influences technology acceptance, whereas negative affect negatively influences technology acceptance, and factors related to user evaluations (i.e., perceived usefulness, ease of use) moderate these relationships. To our knowledge, the ATA model has yet to be applied to evaluate human-robot interaction (HRI).

The assessment of factors related to HRI can take many forms, though psychologists typically rely on self-report scales (e.g., Likert-type response scales) for evaluation (Tian et al., 2021). Although self-report scales are a valuable tool, these measures have several disadvantages, which we describe below. By utilizing a multi-method approach, combining qualitative and quantitative data (i.e., through triangulation; Todd et al., 2004), researchers are able to extract an abundance of information from respondent data and uncover a more accurate, comprehensive picture of HRI. Importantly, this approach allows researchers to uncover factors relevant to end-user acceptance (or reluctance) of autonomous robots.

The aim of this paper is to extend the ATA model to HRI. We investigate the relationship between affect and technology acceptance of a security robot. User affect was assessed using a multi-method approach (i.e., self-report survey, response length, and sentiment analysis) to explore the complexity of different measurements and gain a deeper understanding of factors related to technology acceptance.

URI: https://hdl.handle.net/10125/102690
978-0-9981331-6-4

## 2. Related work

### 2.1. Affect and technology acceptance

Evaluations of robots consist not only of the cognitive assessments of their potential advantages (e.g., beliefs about a robot's performance such as accuracy, consistency, and predictability), but also include a significant affective component of how a user feels about these interactions (Lu et al., 2019). Affect refers to different feeling states such as emotions and moods (Niven, 2013) that can vary in valence (negative to positive) and level of arousal (low to high) (Russell, 1980). Some examples of negative affect (NA) include feelings of nervousness, anger, and fear; whereas positive affect (PA) can encompass feelings of enthusiasm, excitement, and alertness (Watson et al., 1988). Affect can direct one's attention, aid in decision making, and influence behaviors (Cacioppo & Berntson, 1999).

Recently, user affect has been found to influence technology acceptance (Hoong et al., 2017; Lee & Lim, 2016). Research has shown that the more positive someone's mood is, the more likely they are to react positively to new technology (Djamasbi et al., 2010, cited in Karimi & Liu, 2020). Based on the Theory of Reasoned Action (Ajzen & Fishbein, 1980), the Technology Acceptance Model (TAM; Davis, 1986) has been used to investigate user evaluations of information systems (Surendran, 2012). This model posits that aspects of user assessments, such as perceived ease of use and usefulness influence one's acceptance of technology (Davis, 1989). The Affective Technology Acceptance (ATA) model (Hoong et al., 2017), which is a variation of the TAM, hypothesized a direct link between affect (PA and NA) and behavioral intentions (also referred to as intention to use technology). This relationship has been empirically supported (Hoong et al., 2017; Lee & Lim, 2016). In these former two studies, affect was measured using a shortened version of the positive and negative affect schedule (PANAS; Watson et al., 1988), and participants were asked to think about how they felt in past situations when interacting with knowledge-sharing technology (e.g., wikis, blogs, discussion forums, social media). Other research has found that PA and NA predict technology acceptance of a mobile phone (Perlutz, 2004).

The ATA model (Hoong et al., 2017) also theorizes PA and NA influence perceptions related to usefulness and ease of use, and further posits that attitudes toward use mediate the relationship between behavioral intentions and perceptions of both usefulness and ease of use (Hoong et al., 2017). Previous research has focused on both the direct and indirect effects of affect and technology acceptance utilizing self-reports. We instead focus on the direct relationship between affect and behavioral intentions of robot use, which we refer to as technology acceptance. Though the TAM (Davis, 1986) has previously been applied to human-robot interactions (HRI), to our knowledge, the ATA model has not been applied to HRI.

Based on the research cited above, we propose the following hypotheses:

*Hypothesis 1 (H1)*: *H1a*) Self-reported positive affect will be positively correlated with technology acceptance, and *H1b*) self-reported negative affect will be negatively correlated with technology acceptance.

*Hypothesis 2 (H2)*: Self-reported positive and negative affect will predict technology acceptance, controlling for condition.

### 2.2. Multi-method approaches to HRI

When conducting experimental studies, researchers can use a variety of tools and methods, such as self-report surveys, behavioral measures, interviews, and writing prompts to ascertain latent factors related to HRI. Each approach to data collection has its own advantages and disadvantages, and the limitations of one method can be overcome by the strengths of another. The trade-offs of using surveys and open-ended writing prompts are discussed below.

Survey response data remains undeniably useful for many research domains, including the study of HRI. Standardized questionnaires often undergo considerable assessments (e.g., tests of reliability and validity) that improve the credibility of the results obtained from these measures (Chan, 2010). Their quick, cost-efficient administration allows for large amounts of data to be collected from a sizable pool of respondents. Indeed, state affect is often measured by self-report surveys (Loiacono & Djamasbi, 2010). Additionally, survey items are able to measure explicit attitudes by plainly stating the referent in the instructions or in the items (Wiese et al., 2017). As with any research method, self-reports have limitations. First, self-report surveys provide a relatively superficial assessment of the underlying constructs being measured because participants are rarely able to provide an explanation as to why they responded a certain way to a particular item (Paulhus & Vazire, 2007). Second, self-report surveys can suffer from response bias, such as response styles (Rorer, 1965), which can obfuscate the underlying construct being assessed. Third, insufficient effort responding (i.e., a lack of motivation and/or attention when responding to a survey) can be problematic for self-report surveys as it can artificially inflate or deflate correlations between constructs (Huang et al., 2012).

Qualitative data is useful for researchers who wish to explore and understand participants' attitudes, beliefs, and feelings on a deeper level (Almalki, 2016). Using open-ended questions provides participants with an opportunity to express their opinions and provides researchers with rich qualitative data that can be used to explain results of quantitative data, guide future research, and uncover themes related to HRI that have not yet been studied empirically. However, questions may have multiple meanings (or interpretations), and may lack clarity on what type of response the researcher is expecting. For example, with the writing prompt "Would you feel comfortable interacting with this robot in the future?", participants may wonder, "In what context?", or "How much autonomy will the robot have?" when contemplating how they will construct their response. Furthermore, it can be laborious to respond thoughtfully to open-ended questions, which can contribute to insufficient effort responding (e.g., one-word responses). Finally, written responses can be difficult for researchers to analyze due to the time and labor intensity involved in coding the data.

By acknowledging the aforementioned benefits of surveys and writing prompts, the current research capitalizes on both these data sources for gaining insight into the human user's affective assessments of investigational HRI experiences. Because the ATA model (Hoong et al., 2017) has yet to be applied to HRI research, we aim to demonstrate the usefulness of analyzing user affectivity from both qualitative and quantitative data to provide a comprehensive picture of how affect influences technology acceptance.

### 2.3. Affective qualitative data and technology acceptance

Collecting and analyzing qualitative data is advantageous, as the data can be explored in a variety of ways. Response length can be used as an indirect measure of psychological constructs. Response length has been related to trust, distrust, and suspicion, with suspicious and distrustful experiences eliciting longer responses than trustful experiences (Jessup et al., 2020). A negative event can narrow and focus one's attention, leading to better memory recall (Spachtholz et al., 2014). Remembering more details about a negative experience may lead to writing more information about the experience. Indeed, researchers have found that negative experiences (Barnard et al., 2020) and dissatisfaction (Hoon et al., 2013) elicit longer written responses compared to positive experiences and satisfaction. In addition to response length, sentiment analysis be used to garner affective information from written responses.

Sentiment analysis is defined as "the task of finding the opinions of authors about specific entities" (Feldman, 2013, p. 82), and can reveal the writer's affective state (Hovy, 2015). Sentiment analysis can be performed either manually by human raters or by a computer program (e.g., LWIC, WordNet). These programs frequently use dictionaries or lexicons to classify text as positive or negative (Taboada et al., 2011). Results from sentiment analysis allow researchers to view positive and negative words respondents use when writing. Research that has examined the relationship between online review comments and product sales reveal that sentiment in reviews predicts user behaviors, such as product sales (Li et al., 2020).

Based on the reviewed literature, we propose the following hypotheses:

*Hypothesis 3 (H3)*: *H3a*) Response length will be negatively correlated with technology acceptance, *H3b*) number of positive sentiment words will be positively correlated with technology acceptance, and *H3c*) number of negative sentiment words will be negatively correlated with technology acceptance.

*Hypothesis 4 (H4)*: *H4a*) Response length, *H4b*) number of positive sentiment words, and *H4c*) number of negative sentiment words will predict technology acceptance above and beyond condition and self-reported positive and negative affect.

## 3. Current study

Based on research cited in the previous sections, we sought to extend the ATA model (Hoong et al., 2017) to an HRI context and investigate the relationship between affect and technology acceptance. Using a multi-method approach, we explored participants' self-report ratings, length of responses, and number of positive and negative sentiment words as measures of affect. We hypothesized that participants' affective state would influence their acceptance of technology, regardless of experimental condition, and that affective written response data would account for unique variance in technology acceptance beyond self-reported affect.

## 4. Method

### 4.1. Participants

A post-hoc power analysis was conducted using power simulations within the R environment. A simulation study was run with 10,000 iterations for logistic regression, which included six predictors and one binary outcome. Results indicated a sample size of 453 participants was needed. A total of 500 participants were recruited online from Amazon Mechanical Turk (MTurk), which allowed for an extra 10% for attrition and careless responding. Requirements to participate were to be 18 years of age or older, located within the United States, and proficient in the English language. The study took approximately 30 minutes to complete, and participants were compensated with $3.00 USD. The data were cleaned for participants who attempted to complete the task more than once, who did not finish, and for insufficient effort responses using indices outlined in Gibson et al. (2021), which left 272 participants' data for analyses. The final sample of participants were 62% male and ranged from 20-70 years of age (*M* = 37.16, *SD* = 10.34). The study was overseen and approved by the Air Force Research Laboratory institutional review board.

### 4.2. Task and stimuli

After consenting to participation and filling out demographic information, participants were asked to rate how they were feeling in the moment by filling out a self-reported affect questionnaire (see Materials), which was then followed by the video portion of the study. The task and stimuli used in the current research were requested for reuse and permission was granted by the corresponding author of Gallimore et al. (2019). Participants viewed two videos of a BAXTOR robot positioned at a security checkpoint, with the authority to allow or prevent access to a restricted area based on identification badges from two male actors (see Figure 1). The robot was equipped with a variant of a laser dazzler, which is a non-lethal weapon used in military operations near restricted areas to deter unauthorized personnel (Lyons et al., 2021). Participants were provided with information about the robot's ability to detect threats and an individual's authorization level via multiple sensors (e.g., proximity sensor, motion-tracking camera, radio frequency identification). Participants then viewed the first of the two videos.

In both videos, a man approaches the security robot and the robot says, "Hello. You have entered a restricted area. Only authorized personnel will be


**Figure 1. Screenshot of the security robot presented in videos.**

allowed to proceed. Please proceed to the facility checkpoint and present a valid facility ID. Otherwise, please exit immediately." The robot informs the man that an ID check is required, and the man holds up his ID card for the robot to scan. In the first video, after the scan is complete, the robot grants the man access to the restricted area. After viewing the first video, participants were provided with an explanation stating that the robot allowed an authorized person access to the secure area, which was a correct acceptance.

In the second video, when the man held up his badge, the robot informed him that access was denied and asked him to report to the security office for assistance. The man then got closer to the robot, at which time the robot raised its arms and said, "Stop. Withdraw from this area or force will be used against you." The man did not listen and attempted to scan his badge again. Then the robot said, "Force authorized," and emitted a loud siren and directed bright strobe lights towards the man. The man then retreated toward the direction he entered.

The information presented to participants following the second video differed between two randomly assigned conditions: false alarm (FA) or correct rejection (CR). In the FA condition, participants received the following information: "In the scenario you just viewed, the robot failed to allow an authorized person access to the secure area. This was a false alarm. The robot should have let the person through the checkpoint." In the CR condition, participants were shown the following information: "In the scenario you just viewed, the robot prevented an unauthorized person access to the secure area. This was a correct rejection. The robot should not have let the person through the checkpoint." Following the robot videos, participants were asked if the robot they witnessed in the video should be used for security purposes and to explain their choice in the provided text box (see Materials). Participants were then thanked for their time, debriefed, and compensated through MTurk.

Data from the technology acceptance question and condition were part of a larger study, analyzed as part of a different research question (Gibson et al., 2022). As such, no hypothesis was made concerning these data. However, we have included these variables so we can control for condition in our hierarchical binomial logistic regression analysis, which is beyond the scope of Gibson et al. (2022).

## 4.3. Materials

**4.3.1. Self-reported affect**. A shortened 7-item version of the positive and negative affect schedule (PANAS; Watson et al., 1988) measured participants' self-reported positive affect (PA) and negative affect (NA). Researchers have utilized various shortened versions of the PANAS in previous automation and robot studies (e.g., Jessup et al., 2020; Perlutz, 2004; Stokes et al., 2010). Jessup and colleagues suggested selecting PANAS items that are relevant to task-specific contexts. For example, some tasks may not elicit certain emotions (e.g., distressed, proud). As such, the authors selected items they believed were most appropriate for this context (PA items: interested, alert, attentive; NA items: upset, scared, irritable, nervous). Participants were asked to rate how they were feeling in the moment on a 5-point response scale (1 = *very slightly or not at all* to 5 = *extremely*). Both scales had adequate reliabilities (see Table 1).

**4.3.2. Technology acceptance**. In order to assess participants' acceptance of the security robot from the videos, participants were asked, "Do you think this robot should be used for security purposes?" and could answer "Yes" or "No" via a radio button. For ease of interpretation, "Yes" will be referred to as "Use" and "No" will be referred to as "Don't Use" for the remainder of the paper.

**4.3.3. Open-ended responses.** Participants were asked to "Please explain" their use choice and were provided with a text box to type out their response. The open-end responses were analyzed to gather information regarding response length and number of sentiment words. Response length was calculated as the number of words each participant wrote in their written responses. Sentiment analysis identified words related to affect as either positive or negative sentiment. Prior to sentiment analysis, data were cleaned for spelling, but not grammar. Stop words (i.e., a, the, and, etc.) were removed utilizing the *tidytext* package (Silge & Robinson, 2016), and data were analyzed utilizing the *bing* sentiment lexicon (Hu & Liu, 2004) in the *textdata* package (Hvitfeldt, 2020) in R (version 4.1.0). After removing stop words, there were 741 words left for sentiment analysis.

# 5. Results

## 5.1. Technology acceptance – H1 and H3

To assess the relationship between measures, correlation tests were conducted for condition, self-reported PA, self-reported NA, response length, positive sentiment words, and negative sentiment words, collapsed across conditions. Correlations, means, and standard deviations are presented in Table 1. Interestingly, self-reported PA was not significantly correlated with positive sentiment words. Additionally, self-reported NA had a significant negative correlation with negative sentiment words. Results of the correlation analyses also revealed that self-reported PA was positively correlated with technology acceptance. H1a was supported. Self-reported NA was not significantly correlated with technology acceptance. H1b was not supported. Similarly, response length was not significantly related to technology acceptance. H3a was not supported. However, positive sentiment words were positively correlated with technology acceptance, and negative sentiment words were negatively correlated with technology acceptance. H3b and H3c were supported.

## 5.2. Technology acceptance – H2 and H4

We performed a hierarchical binomial logistic regression in SPSS (version 25) to test Hypotheses 2 and 4. We used the Nagelkerke (1991) pseudo $R^2$ value to test the extent the predictors explained variance in the technology acceptance outcome. The first step of the hierarchical binomial logistic regression that regressed condition on technology acceptance was significant, $\chi^2(1) = 38.19$, $p < .001$, which served as a manipulation check. Participants in the CR condition had 4.77 times higher odds to accept the technology than those in the FA condition. Condition accounted for 17.5% of the variance in technology acceptance (see Table 2 for full model). The second step included self-reported PA and NA, and this model was statistically significant, $\chi^2(2) = 10.04$, $p = .007$. The addition of self-reported PA and NA to the prediction of technology acceptance accounted for an additional 4.2% of variance. Increasing self-reported PA was associated with an increased likelihood of technology acceptance, but self-reported NA only marginally predicted technology acceptance (and in the opposite

**Table 1. Descriptive statistics and correlations among the study variables.**

| | *M* | *SD* | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|---|---|
| 1. Condition | | | - | | | | | |
| 2. PA (self-report) | 3.88 | 0.78 | .09 | (.72) | | | | |
| 3. NA (self-report) | 1.52 | 0.84 | -.04 | .00 | (.90) | | | |
| 4. Response length | 22.48 | 17.52 | .00 | $-.14^{*}$ | $-.17^{**}$ | - | | |
| 5. Positive sentiment words | 1.09 | 1.06 | .11 | -.06 | -.03 | $.45^{**}$ | - | |
| 6. Negative sentiment words | 1.10 | 1.27 | $-.14^{*}$ | $-.16^{**}$ | $-.12^{*}$ | $.61^{**}$ | $.14^{*}$ | - |
| 7. Technology acceptance | 0.53 | 0.50 | $.37^{***}$ | $.17^{**}$ | .10 | -.17 | $.13^{*}$ | $-.38^{**}$ |

*Note*. Cronbach's alphas are reported in parentheses on the diagonal for the PANAS. Condition was coded: False alarm = 0, Correct rejection = 1. Technology acceptance was coded: Don't use = 0, Use = 1. PA = Positive affect. NA = Negative affect. $^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$.

direction we expected). H2 was partially supported. Written response data (response length, positive sentiment words, negative sentiment words) were added to step three of the model, and this final model was significant, $\chi^2(3) = 41.20$, $p < .001$. The addition of the written response data accounted for an additional 15.7% of the variance in technology acceptance. Positive and negative sentiment words accounted for a significant amount of additional variance in technology acceptance, over and above that of condition, self-reported PA, and self-reported NA. H4b and H4c were supported. However, response length did not predict technology acceptance (see Table 2). H4a was not supported.

## 5.3. Post-hoc analyses

Upon viewing the results of the correlation and hierarchical binomial regression analyses, we were curious about the amount of variance overlap between the self-report affect scales and the sentiment analyses. To determine the unique variance of each measure, we re-ran the hierarchical binomial regressions with the written response data in Step 2 and self-reported affect in Step 3. The first step, which regressed condition on technology acceptance was the same as the previous analyses. The second step included written response data (response length, positive sentiment words, and negative sentiment words), and was statistically significant, $\chi^2(3) = 46.50$, $p < .001$. The addition of written response data to the prediction of technology acceptance in Step 2 (rather than Step 3) accounted for an additional 18.2% of variance in technology acceptance. Both positive ($b = 0.46$, $p = .006$) and negative ($b = -0.73$, $p < .001$) sentiment words significantly predicted technology acceptance, but response length did not. Self-reported PA and NA were added to step three of the model, but the step was not statistically significant, $\chi^2(2) = 4.70$, $p = .094$. The addition of self-reported affect accounted for an additional 1.7% of the variance in technology acceptance.

**Table 2. Hierarchical binomial logistic regression predicting likelihood of technology acceptance.**

| Variable | *b* | *SE* | Wald | *df* | Odds Ratio | $R^2$ | $\Delta R^2$ |
|---|---|---|---|---|---|---|---|
| Step 1 | | | | | | $.175^{***}$ | .175 |
| Constant | -0.61 | 0.18 | $11.73^{**}$ | 1 | 0.54 | | |
| Condition | 1.56 | 0.26 | $35.35^{***}$ | 1 | 4.77 | | |
| Step 2 | | | | | | $.217^{***}$ | .042 |
| Constant | -2.73 | 0.75 | $13.19^{***}$ | 1 | 0.07 | | |
| Condition | 1.59 | 0.27 | $34.57^{***}$ | 1 | 4.88 | | |
| PA (self-report) | 0.42 | 0.18 | $5.73^{*}$ | 1 | 1.52 | | |
| NA (self-report) | 0.32 | 0.17 | $3.81^{\dagger}$ | 1 | 1.38 | | |
| Step 3 | | | | | | $.374^{***}$ | .157 |
| Constant | -1.81 | 0.87 | $4.32^{*}$ | 1 | 0.16 | | |
| Condition | 1.52 | 0.29 | $26.73^{***}$ | 1 | 4.58 | | |
| PA (self-report) | 0.35 | 0.19 | $3.39^{\dagger}$ | 1 | 1.41 | | |
| NA (self-report) | 0.20 | 0.18 | 1.30 | 1 | 1.23 | | |
| Response length | -0.01 | 0.01 | 0.33 | 1 | 0.99 | | |
| Positive sentiment words | 0.46 | 0.17 | $7.56^{**}$ | 1 | 1.58 | | |
| Negative sentiment words | -0.71 | 0.17 | $18.44^{***}$ | 1 | 0.49 | | |

*Note*. PA = Positive affect. NA = Negative affect. Nagelkerke's pseudo $R^2$ was used. $^{***}p < .001$. $^{**}p < .01$. $^{*}p < .05$. $^{\dagger}p < .10$.

**5.3.1. Thematic analysis.** In addition to examining the relationship between sentiment words and technology acceptance, we sought to explore the words participants were using and the context in which they were being used through thematic analysis. Table 3 provides a list of sentiment words that were used at least three times.

**Table 3. Sentiment words used three or more times across conditions.**

| Positive | | Negative | |
|---|---|---|---|
| accurate(ly) | perfect | alarm | mistake(s) |
| better | proper(ly) | bad | oversight |
| capable | reliable | dangerous | problem |
| correct(ly) | right | error(s) | restricted |
| effective | safe | failed | risk |
| enough | secure | faulty | unreliable |
| fine | trust(ed) | harm | wrong |
| good | useful | hurt | |
| great | well | issue | |
| important | work | kill | |
| like | | | |

One limitation of the sentiment analysis used in the current study is that the sentiment is based on individual words and not the proceeding or following words. For example, trust is a word that was coded as a positive sentiment word but there were instances when participants wrote "I do not trust" or "should not be trusted," which changes the sentiment from positive to negative. In order to understand the rationale participants provided in relation to technology acceptance, all written responses were assessed for the presence of statements containing participants' attitudes and feelings by six independent coders. We have provided a few examples for both conditions:

CR Condition, participants selected "Don't Use"

"*I feel like it's too dangerous to have a machine alone making these kinds of decisions. There should be a human there too*."

"*If it makes even one small mistake it could seriously harm or possibly even kill someone. It seems to be correct in its judgments, and if it didn't have the ability to harm people, I would be willing to use it without a doubt*."

CR Condition, participants selected "Use"

"*It is more accurate than humans, in many ways. It poses less of a risk of being harmed than a living being, as it is a robot. It is competent in accomplishing whatever it must do in that post*."

"*From what I saw, i.e. those two interactions, the robot took the correct measures, so it seems like it's been correctly programmed and is able to do the job. But I'm still worried that if anything went wrong and if the robot made a mistake, it could use force against an innocent person. Robots or other automated systems like that should not be able to deploy force*."

FA Condition, participants selected "Don't Use"

"*I think until the technology is perfected it can't be trusted on its own. I think it can be used for some tasks but nothing where the decisions made could be life or death*."

"*Not allowing access to someone who is actually authorized is one thing, but I would be incredibly nervous if the opposite could happen and it would let someone through by mistake*."

FA Condition, participants selected "Use"

"*I think it can be used IF it is monitored in the sense that when it gives an alarm, a human should be notified and can bypass or see from the robot's perspective just in case it made a mistake. I'd rather have a robot that is TOO secure than one that is lenient on security*."

"*There should be a maybe option above as well. I can see some good that could come from having the robots in the security field. However, it's easy to imagine a lot of bad that could be made from having the robots too*."

Although these examples are only a few responses from the study, it is clear that negative feelings such as fear, uncertainty, and concern were expressed, even when participants did not see the robot err. However, most participants seemed to suggest that if a human were in the loop, the robot demonstrated perfect accuracy, and/or the robot was unable to inflict harm on humans, then they would be more willing to accept the security robot in a real-world context.

## 6. Discussion

The current study explored the role of user affect in technology acceptance. We replicated previous findings (Hoong et al., 2017; Lee & Lim, 2016), such that users experiencing positive affect (PA) are more likely to accept technology and users experiencing negative affect (NA) are less likely to accept technology, extending this research to robotics. Additionally, we found the multi-method approach to the measurement of affect particularly important in the current study.

### 6.1. The ATA model

The ATA model theorizes user affect (both positive and negative) has both a direct and indirect relationship with behavioral intentions to use an information system (Hoong et al., 2017). Although the theory advocates affect has an indirect effect on the criterion through perceived ease of use and perceived usefulness, we focused on the direct effects of affect on technology acceptance in the current study. Additionally, whereas previous research has explored affect with technology, such as cell phones or websites (Hoong et al., 2017; Lee & Lim, 2016; Perlutz, 2004), we extended the literature to robotics, specifically in a security setting.

In the current study, the robot's performance (manipulated by CR and FA conditions) influenced technology acceptance. Participants were less likely to accept the robotic technology if the system had erred and more likely to accept it if it had not erred. Additionally, we found that affect does influence technology acceptance directly, demonstrating usefulness of the ATA model in HRI, but this relationship was measurement dependent. We found that PA and NA, as measured by self-report scales were both positively related to technology acceptance in our correlation and regression analyses, although NA did not reach statistical significance. This is in contrast to our hypothesis, which stated self-reported PA would be positively related to technology acceptance, but that NA would be negatively related to technology acceptance. Our sentiment analyses illustrated not only significant findings in the directions we would expect, but also lent insight into the relationship between affect and technology acceptance. However, affect and condition accounted for 37.4% of the variance in technology acceptance of a robot in a security setting. Although this variance is significant, there is still a large amount of variance unaccounted for by our variables. There may be other mediators between affect and technology acceptance that influence technology acceptance, namely situational factors.

The potential for harm, either accidental or purposeful, appeared to weigh heavily on the participants as noted by the thematic analyses. The potential for harm may be related to perceived usefulness, in that they are both functions of the context of interaction with the robot. However, the potential for harm is focused on the consequences of using the system in a given environment. For example, the lights, sounds, and arm movements made by the robot were performed in a security context to avert possible intruders from a secure area, which participants in the current study were wary of given the ability to harm a human, even when the system acted appropriately. However, if the system were utilized in a different context, such as a fire alarm robot, there may be differences in how the robot is perceived as alarm sounds and flashing lights are typical of industrial alarms.

### 6.2. Measurement of affect

We found that the measurement of affect and its relationship to technology acceptance was important in the current study. Results from the correlation analyses indicate sentiment analysis more accurately captured the user affective experience. Positive and negative affect (analyzed by sentiment analysis) were both significant and in the expected direction hypothesized for their relationship with technology acceptance. In contrast, self-reported NA was not significantly correlated with technology acceptance, although PA was significantly positively correlated with technology acceptance as hypothesized. Another interesting finding was that self-reported NA and negative sentiment words were significantly negatively correlated. One reason we believe this occurred was because there appeared to be a floor effect with self-reported NA ($M$ = 1.52). The majority of participants may have been experiencing low negative affect prior to viewing the scenarios, but the expression of negative affect in the form of using negative sentiment words may have been more prevalent after viewing the scenarios.

Regression analyses revealed the sentiment analyses of positive and negative affect accounted for all the significant variance in technology acceptance related to affect. Our initial hypothesis was that sentiment analysis would add additional variance after controlling for the PANAS, which was supported. Once we re-ran the regressions in the opposite order, it became clear the sentiment analyses accounted for all of the significant variance. Sentiment analyses may be able to more accurately assess the complexity of affect in relation to a robot. Indeed, the thematic analyses revealed that negative feelings such as fear, anxiety, and uncertainty were expressed even when the robot did not err. Participants were hesitant to have a robot possibly harm an individual, even if the person was not authorized to enter a secure area. This complexity would be difficult to uncover from a self-report scale, unless researchers directly addressed these issues in scale items. Second, the PANAS responses were collected prior to viewing robot interactions. The scenarios may have evoked an increase in participants' affective state.

## 7. Limitations and future research

The current study is not without limitations. First, self-reported affect was measured prior to viewing the stimuli (i.e., robot videos), which diverges from previous research supporting the ATA model.

Researchers have previously induced affect by asking individuals to reflect on prior technological experiences and then measured affect via a self-report (Hoong et al., 2017; Lee & Lim, 2016). Although (in the current study), affect was analyzed following the interaction through qualitative methods, future research should also measure self-reported affect after experience with a robot. Second, following the suggestion from previous researchers to use only items from the PANAS that are relevant to the task at hand (Jessup et al., 2020), the authors used a shortened 7-item version. Even though both PA and NA demonstrated acceptable reliabilities, future research should extend the present work by assessing validated shortened (Perlutz, 2004) and full PANAS measures (Watson & Tellegen, 1985) in this and similar experimental tasks to replicate our findings. Third, the results of the power analysis revealed that 453 participants were needed. After data cleaning procedures, the sample size for analysis was 272. As such, we may have been underpowered for our logistic regression analyses. Future research should replicate findings with a larger sample size.

## 8. Conclusion

The current study extended the ATA model to the HRI literature. We found positive and negative affect were both directly related to technology acceptance, however its relationship depended on the way the constructs were assessed. We found the relationship of affect and technology acceptance was more complex than theorized in the literature. Specifically, we found the potential for harm, desire for human oversight, and accurate performance were important aspects expressed in the affective written responses from participants. Future research will want to explore this aspect of the affect and technology acceptance relationship, and possibly update the theoretical model depending on how it is related to other constructs.

**Acknowledgement.** DISTRIBUTION STATEMENT A. Approved for public release: AFRL-2021-1889. Any opinions, findings, and conclusions or recommendations expressed in this article are those of the authors and do not necessarily reflect the views of the U.S. Air Force.

## 9. References

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Prentice Hall.

Almalki, S. (2016). Integrating quantitative and qualitative data in mixed methods research—challenges and benefits. *Journal of Education and Learning, 5*(3), 288–296.

Barnard, M. P., Pampel, S., Burnett, G., Allen, H. A., & Chapman, P. (2020). How do drivers recall positive and negative driving events? A quantitative approach to analysing driving diaries. *Transportation Research Part F: Traffic Psychology and Behaviour*, *69*, 28–37.

Bekey, G. (2005). *Autonomous robots: From biological inspiration to implementation and control*. MIT Press.

Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., & Tanaka, F. (2018). Social robots for education: A review. *Science Robotics*, *3*(21), 1–9.

Cacioppo, J. T., & Berntson, G. G. (1999). The affect system: Architecture and operating characteristics. *Current Directions in Psychological Science, 8*(5), 133–137.

Chan, D. (2010). So why ask me? Are self-report data really that bad? In C. E. Lance & R. J. Vandenberg (Eds.), *Statistical and methodological myths and urban legends* (pp. 329–356). Routledge.

Davis, F. D. (1986). Technology acceptance model for empirically testing new end-user information systems theory and results [Unpublished doctoral dissertation]. MIT.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340.

Feldman, R. (2013). Techniques and applications for sentiment analysis: The main applications and challenges of one of the hottest research areas in computer science. *Communications of the ACM*, *56*(4), 82–89.

Gallimore, D., Lyons, J. B., Vo, T., Mahoney, S., & Wynne, K. T. (2019). Trusting robocop: Gender-based effects on trust of an autonomous robot. *Frontiers in Psychology*, *10*, Article 482.

Gibson, A., Alarcon, G., Lee, M., & Hamdan, I. A. (2021). Could you please pay attention? Comparing in-person and MTurk responses on a computer code review task. *Proceedings of the 53rd Hawaii International Conference on System Sciences*, 5099–5108.

Gibson, A. M., Capiola, A., Alarcon, G. M., Lee, M. A., Jessup, S. A., & Hamdan, I. aldin. (2022). Construction and validation of an updated perfect automation schema (uPAS) scale. *Theoretical Issues in Ergonomics Science*, Advance online publication.

Hoon, L., Vasa, R., Schneider, J. G., & Grundy, J. (2013). *An analysis of the mobile app review landscape: Trends and implications* [Unpublished manuscript]. Swinburne University of Technology.

Hoong, A. L. S., Thi, L. S., & Lin, M-H. (2017). Affective technology acceptance model: Extending technology acceptance model with positive and negative affect. In A. Kobir, C. Yuliang, M. Mohiuddin, & N. Halilem (Eds.), *Knowledge management strategies and applications* (pp. 147–165). InTech.

Hovy, E. H. (2015). What are sentiment, affect, and emotion? Applying the methodology of Michael Zock to sentiment analysis. In N. Gala, R. Rapp, G. Bel-Enguix (Eds.). *Language production, cognition, and the lexicon. text, speech and language technology* (Vol. 48, pp. 13–24). Springer.

Hu, M., & Liu, B. (2004). Mining and summarizing customer reviews. *Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 168–177.

Huang, J. L., Curran, P. G., Keeney, J., Poposki, E. M., & DeShon, R. P. (2012). Detecting and deterring insufficient effort responding to surveys. *Journal of Business and Psychology*, *27*(1), 99–114.

Hvitfeldt, E. (2020). *textdata: Download and Load Various Text Datasets. R package version 0.4.1*. https://rdrr.io/cran/textdata/

Jessup, S. A., Alarcon, G. M., Capiola, A., & Ryan, T. J. (2020). Multi-method approach measuring trust, distrust, and suspicion in information technology. *Lecture Notes in Computer Science, 12210*, 412–426.

Jessup, S., Gibson, A., Capiola, A., Alarcon, G., & Borders, M. (2020). Investigating the effect of trust manipulations on affect over time in human-human versus human-robot interactions. *Proceedings of the 53rd Hawaii International Conference on System Sciences*, 553–562.

Karimi, S., & Liu, Y. L. (2020). The differential impact of "mood" on consumers' decisions, a case of mobile payment adoption. *Computers in Human Behavior*, *102*, 132–143.

Lee, A., & Lim, T.-M. (2016). Behavioral intention to use knowledge sharing tools: Positive and negative affect on affective technology acceptance model. *Proceedings of the Knowledge Management International Conference*, 191–196.

Li, K., Chen, Y., & Zhang, L. (2020). Exploring the influence of online reviews and motivating factors on sales: A meta-analytic study and the moderating role of product category. *Journal of Retailing and Consumer Services*, *55*, Article 102107.

Loiacono, E., & Djamasbi, S. (2010). Moods and their relevance to systems usage models within organizations: An extended framework. *AIS Transactions on Human-Computer Interaction*, *2*(2), 55–72.

Lu, L., Cai, R., & Gursoy, D. (2019). Developing and validating a service robot integration willingness scale. *International Journal of Hospitality Management*, *80*, 36–51.

Lyons, J. B., Vo, T., Wynne, K. T., Mahoney, S., Nam, C. S., & Gallimore, D. (2021). Trusting autonomous security robots: The role of reliability and stated social intent. *Human Factors*, *63*(4), 603–618.

Nagelkerke, N. J. (1991). A note on a general definition of the coefficient of determination. *Biometrika, 78*(3), 691–692.

Niven, K. (2013) Affect. In M. D. Gellman & J. R. Turner (Eds.), *Encyclopedia of behavioral medicine* (pp. 49–50). Springer.

Paulhus, D. L., & Vazire, S. (2007). The self-report method. In R. W. Robins, R. C. Fraley, & R. F. Krueger (Eds.), *Handbook of research methods in personality psychology* (pp. 224–239). The Guilford Press.

Perlusz, S. (2004). Emotions and technology acceptance: Development and validation of a Technology Affect Scale. *IEEE International Engineering Management Conference*, *2*, 845–847.

Pfeifer, R., & Iida, F. (2004). Embodied artificial intelligence: Trends and challenges. *Lecture Notes in Computer Science*, *3139*, 1–26.

Piçarra, N., & Giger, J.-C. (2018). Predicting intention to work with social robots at anticipation stage: Assessing the role of behavioral desire and anticipated emotions. *Computers in Human Behavior*, *86*, 129–146.

Rorer, L. G. (1965). The great response-style myth. *Psychological Bulletin*, *63*(3), 129–156.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology*, *39*, 1161–1178.

Sanders, T., Kaplan, A., Koch, R., Schwartz, M., & Hancock, P. A. (2019). The relationship between trust and use choice in human-robot interaction. *Human Factors*, *61*(4), 614–626.

Shacklett, M. (2020). How robots are reinventing food service. TechRepublic. https://www.techrepublic.com/article/how-robots-are-reinventing-food-service/

Silge, J., & Robinson, D. (2016). tidytext: Text mining and analysis using tidy data principles in R. *Journal of Open Source Software*, *1*(3), 37.

Spachtholz, P., Kuhbandner, C., & Pekrun, R. (2014). Negative affect improves the quality of memories: Trading capacity for precision in sensory and working memory. *Journal of Experimental Psychology: General*, *143*(4), 1450–1456.

Stokes, C. K., Lyons, J. B., Littlejohn, K., Natarian, J., Case, E., & Speranza, N. (2010). Accounting for the human in cyberspace: Effects of mood on trust in automation. *International Symposium on Collaborative Technologies and Systems*, 180–187.

Surendran, P. (2012). Technology acceptance model: A survey of literature. *International Journal of Business and Social Research*, *2*(4), 175–178.

Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-based methods for sentiment analysis. *Computational Linguistics*, *37*(2), 267–307.

Tian, L., Robinson, N., Carreno-Medrano, P., Chan, W. P., Sakr, M., Wu, T. L., Abdi, E., Croft, E., & Kulić, D. (2021). *Designing and conducting human-robot interaction studies: Proposed guidelines and an interactive specification approach*. Monash University.

Todd, Z., Nerlich, B., & McKeown, S. (2004). Introduction. In Z. Todd, B. Nerlich, S. McKeown, & D. D. Clarke (Eds.), *Mixing methods in psychology: The integration of qualitative and quantitative practice* (pp. 2–15). Psychology Press.

Voth, D. (2004). A new generation of military robots. *IEEE Intelligent Systems*, *19*(4), 2–3.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063–1070.

Wiese, E., Metta, G., & Wykowska, A. (2017). Robots as intentional agents: Using neuroscientific methods to make robots appear more social. *Frontiers in Psychology*, *8*, Article 1663.