# Manipulating user's trust of autonomous products with affective priming

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**ABSTRACT**

*Autonomous products, which perform many functions on their own with limited user input, require the user to exhibit trust at an appropriate level before use. Research in product trust has thus far focused on the product's characteristics: such as manipulating the product's design—for example, anthropomorphizing an autonomous vehicle—and measuring changes in user's trust. This study flips the usual approach and instead manipulates users' mental state through priming, and then measures users' trust to an existing autonomous product, the Amazon Echo. In this study, we used visual stimuli (images) that evoked either positive, neutral, or negative emotions as affective primes to influence users' trust before interacting with the Echo. While interacting with the Echo, users evaluated its performance and how well it met their expectations. Holistically, users' perceived performance of the Echo, age and education have significant effects on their trust of the product, but the affective primes show no significant effect. However, for the subgroup of participants whose expectations of the product's performance were met: those who received either positive or negative priming were more likely to trust the product than those who received neutral priming; men or people with less experience were more likely to trust the product.*

## 1 INTRODUCTION

Many automated systems, such as global positioning systems (GPS), are used to assist people in acquiring information, making decisions, and carrying out actions for various tasks [1]. While automated products and systems can drastically improve the efficiency of labor systems, grave consequences can occur if users over-rely on automated systems or underuse them—both of which can occur due to an inappropriate level of trust [2].

Social interaction and interpersonal relationships require trust, and thus, researchers have studied trust between individuals and between individuals and organizations. Although definitions of trust vary across fields of research, commonality exists for definitions related to interpersonal trust and product trust. At a fundamental level, both types of trust represent context-specific attitudes in situations characterized by uncertainty [1]. Trusting is a dynamic process; it evolves over time and across interactions as the trustor continuously modifies their assessment of the trustworthiness of the trustee [3].

Research by Nass and Moon show that people applied social rules when interacting with inanimate machines [4]. Damen and Toh further explored the impact of social rules, such as gender stereotypes, on trust-related behavior and validated that users extended their social expectations to their interactions with home automation devices [5]. As products become more interactive and autonomous, it’s essential to explore the social interactions and user expectations of these products. Trust is a critical factor in determining the willingness of users to adopt autonomous products and rely on them in situations with uncertainty [1].

Lee and See described trust as a mental state that involves both thinking and feeling when trusting automated products [6]. Feeling, also referred to as emotion or affect, is an important but overlooked part of trusting automated products. In this work, we intentionally alter affect. One robust method to alter a user's affect is priming via exposure to a stimulus that activates an idea, contextualization, or feeling [7].

To investigate the social interactions between users and products, with a focus on the affective process of trust formation, we proposed an approach to subconsciously manipulate user-to-product trust by priming users with emotions prior to their interaction with the product, potentially making users feel slightly happy or sad. We tested to see if priming positive or negative emotions can effectively influence users' mental state, and consequently increase or decrease participants' trust of the product, regardless of the performance.

We chose a mock-up of the Amazon Echo as the focal product. The Amazon Echo is a smart speaker (a conversational agent) that connects to a cloud service to play music, answer questions, etc. [8]. It incorporates a humanized voice and enables autonomous responses and simple social interactions.

In this study, we randomly assigned participants to three test conditions: (C1) prime with positive emotions, (C2) prime with neutral emotions, and (C3) prime with negative emotions. All participants, working alone, reported their general propensity to trust machines, namely initial attitude prior to any interaction or intervention. Then, participants were primed with a set of visual stimuli (images viewed on a laptop) embedded with either positive, neutral, or negative emotions. Afterwards, they interacted with the focal product, the mock-up of the Amazon Echo, by asking it predetermined questions; hearing the Echo's answers (all answers were previously chosen and prerecorded); and evaluating the product's performance. After the interaction, participants self-reported how much they trusted the product. We tested if priming with positive emotions would encourage users to trust the product more compared to priming with neutral emotions, and vice versa for negative emotions.

This paper is organized as follows: Section 2 provides a review of user-to-product trust formation and of methods to prime trust and to measure trust in technology-related fields. Section 3 lists our proposition and hypotheses. Section 4 gives an overview of the experiment procedure, and Section 5 provides more details about how we prepared the experiment. Data and analysis are described in Section 6, and discussion of the results are in Section 7. Finally, Section 8 includes the conclusion and plan of future work.

## 2 BACKGROUND

### 2.1 User-to-Product Trust Formation

Trust was first studied within the context of interpersonal relationships and is rooted in individual willingness to accept vulnerability [9]. As more human jobs are replaced by automated systems, the theory of interpersonal trust has been expanded to user-to-product relationships, and in particular, the concept of trust in automation has become an important area of research in recent years [1]. Rather than defining trust as an action item as it's defined in the interpersonal domain, many researchers studying trust in automation view trust as a mental state and adopt the definition of trust by Lee and See as "the attitude that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability" [6]—trust is a task-related and context-dependent characteristic. Merritt and Ilgen [10] distinguished "propensity to trust machines" from the conventional definition of "trust propensity", which is a trait-like tendency to trust or not trust others. Merritt et al. further clarified propensity to trust machines and actual trust as separate constructs, while propensity to trust machines refers to the tendency to be trusting of machines broadly and actual trust is rooted in a specific automated system [10-12].

Regardless of its domains, almost every definition of trust involves a trustor extending trust, a trustee performing a task and accepting trust, and something at stake—there must be a possibility that the trustee will fail to perform the task, inviting uncertainty and risk. Characteristics of both trustor and trustee, as well as context, interact to form trust. The "Big Three" predictors in the formation of trust within interpersonal relationships, from the classic research by Mayer et al., are: ability (perceptions of a trustee's competence and consistency), benevolence (perceptions of the trustee's caring, goodwill, empathy, and commitment to shared goals), and integrity (perceptions of the trustee's objectivity, fairness, honesty, and dedication) [9]. In user-product relationships, the predictors of trustworthiness are reduced to only ability/competence. This predictor is further categorized into performance-based components (including predictability, dependability and reliability) and the attribute-based components (such as product type, e.g., a voice agent, etc.) [13]. For trustors, human-related factors such as gender, personal traits, and age also play important roles in the human-product relationships [1]. Trust researchers in the areas of Human-Computer Interaction (HCI) and Human-Robot Interaction (HRI) extensively studied the performance-based components and competence of the system itself, for example, the level of automation and information transparency. Hancock et al. [13] conducted a meta-analysis and tested the correlations between the influencing factors and trust in HRI. They suggested that robot characteristics and, in particular, performance-based factors, such as predictability, had the largest influence on the perceived trust in HRI; but they did not examine human-related and environmental factors in the meta-analysis due to insufficient samples from the existing research [13].

While human-related factors are sometimes overlooked, social aspects are inevitable in user-product relationships, especially when systems become more autonomous. Nass et al. argued that users apply social rules to computers, even though such attributions may not be needed for inanimate objects [14].

Imbuing such social cues in the interaction has the potential to increase users' trust of autonomous products as reflected in both user behavior and self-reported measures [15], and an effective approach is to anthropomorphize product design by imbuing inanimate products with human-like features, for example, facial expression, voice tone, and personality [16]. Lopatovska and Williams [17] found that users reported higher satisfaction if they gave their home automation product a person's name. This finding indicates that how humans interact with technology can vary depending on how they perceive the product presenting itself. Despite the advantage of imbuing social aspects, however, Culley and Madhavan cautioned that the emotional connection could lead to over-reliance on autonomous systems and inappropriate trust calibration [18]. This list of research highlights the complex nature of user trust within a social context and the importance of social cues in user-product relationships.

**2.2 Priming Trust**

Like all other decisions, trust is driven by a combination of cognitive (thinking) and affective (feeling) factors. Individuals' mental states are part of social interactions and the premise for trust decisions. Merritt described the process by which affect influences judgements as affect infusion [11]. Affect infusion can occur either when affect is target-relevant as in the affect-as-information process, or when affect is target-irrelevant as in the affect-priming process [11, 19, 20]. Affect-priming or affective priming refers to priming with affect or emotions.

Priming is a robust psychological technique that has been used extensively in psychology, behavioral economics, and organizational behavior to activate specific mindsets or mental states. The psychological mechanism of priming is developed from the concept of "perceptual readiness" proposed by Bruner [21]. Bruner claimed that the information and feeling that are currently accessible lead to corresponding thoughts and behavior [21]. Priming activates a specific set of information and feeling by increasing the accessibility of relevant thoughts, memories, and feelings, and consequently priming motivates related perspectives, decisions, and behavior [22].

Researchers in design have particularly used priming to inspire design concerns and improve ideation outcome. Research by She and MacDonald has shown that a collage priming method can activate certain mindsets for design tasks and inspire sustainability concerns, where participants physically arrange product images to create a paper collage, by bringing relevant knowledge upfront [23, 24]. Liao and MacDonald further applied the collage priming method to help designers generate ideas that are more environmentally friendly in the eyes of users and to create a more receptive attitude towards the design ideas of (hypothetical) others in a group setting [25]. Besides focusing on cognitive processes, priming can retrieve affect-relevant information from memory such that individuals are more likely to attend to affect-congruent concepts [19, 20]. Lewis et al. conducted a study using affective priming—they showed participants a picture of a laughing baby—to increase the quality of design ideas generated [26].

In addition to applications in design research, various priming methods have been specifically used to change trust. A study by Al-Ubaydli et al. showed that participants exposed to trade- and market-related concepts expressed a higher level of trust towards strangers compared to participants exposed to non-trade-related words. The authors argued that priming for market participation allowed good things to happen when interacting with strangers, thus encouraging optimism and trusting behavior [27]. In contrast to being primed with trade-related terms, participants who were primed with legal terms—for example, terms used in lawsuits—perceived social actors as less trustworthy and the situation as more competitive [28]. Besides text-based stimuli, visual images that evoke a particular emotion have been shown to influence trust. Brownlow found that baby-faced speakers induced more agreement with their position than mature-faced speakers did when trustworthiness was in question, presumably because baby-faced speakers appeared honest due to their youthful, innocent features even in situations of uncertainty [29].

Besides triggering associations with particular content, visual stimuli that trigger designated emotions can influence trust. A study by Hooker et al. showed that exposure to negative images (e.g., threat-related images such as of weapons) led people to rate unfamiliar faces as less trustworthy compared to people primed with neutral or positive affective images (e.g., sports and food) [30].

However, affective visual stimuli have mixed effects in interactions with automation. Merritt primed participants with video clips that induced various moods before asking them to interact with a fictious automated X-ray screening machine [11]. Merritt found that specific emotion, namely happiness, significantly increases trust of the fictious X-ray machine and trust later predicted user reliance on the machine [11]. In contrast, in a study by Rice et al., priming users with *negative* images, such as images of beat-up cars, prior to interacting with a recommendation agent, increased users' reliance on the agent when attempting to identify objects in simulated combat, and also decreased reaction time and increasing accuracy for the task, compared to users primed with positive images of luxury cars [31].

In addition, there also exists a dissonance between self-reports and behavioral measures of trust, although numerous studies have validated the effect of affective images on both self-reported trust and trust-related behavior. In this study, we use affective images to evoke emotions and measure the self-reported change in trust of the focal autonomous product. The affective images, from an open-source database, were chosen based on their valence scores (which measure intrinsic emotional attractiveness vs. averseness); the selection process is detailed in Section 5.1.1.

**2.3 Measuring Trust**

When investigating a complex construct like trust, one of the main challenges is to identify a robust method to appropriately measure trust between users and products. Previous research has explored both explicit and implicit methods, where explicit methods tend to capture conscious and immediately observable behavior and implicit methods measure unconscious actions, such as respiration rate, heart rate, and reaction time [31]. While both explicit and implicit methods have their own merits, different methods can lead to different results [32], and this dissonance highlights the complex nature of understanding trust and the lack of full awareness of one's own inner thoughts, emotions, and behavior.

Even though researchers have utilized implicit measures, such as reaction time, to reflect unconscious attitudes and quantify trust-related behavior of automated products, the causal relationship between implicit measures and trust in technology has not been fully validated. As there exists insufficient evidence of the correlation between explicit and implicit measures, this study will mainly use explicit metrics adopted from research of trust within interpersonal relationships and will use self-reported data.

Different researchers have invented different questions that best suited their purposes and context to measure trust, even though the core of what they all wanted to know was identical: How much do users trust the product? Yeh and Wickens [33] measured trust in the design of augmented reality by directly asking users, "How much did you trust the terrain information presented in the computer-generated imagery?"

Besides directly asking about trust, Koo et al. [34] associated "machine acceptance" with "emotional valence" in a questionnaire assessing drivers' attitudes after they used a vehicle simulator. The participants rated adjectives, such as "anxious," "annoyed," and "frustrated," provided by the researcher, on a ten-point Likert scale, ranging from "describes very poorly (=1)" to "describes very well (=10)" in response to the question, "How well do the following words describe how you felt while driving?” The machine acceptance index reflects responses to the question, “How well do the following adjectives describe the car?” However, in the study by Koo et al. the correlation between emotional valence and machine acceptance was not supported.

Another common approach is to break down trust into relevant determinants that tend to be more tangible. Muir and Moray captured operators’ trust in one component (the pump subsystem) of a simulated process control system by using a subjective rating scale for five characteristics of the pump subsystem: competence (“to what extent does the pump perform its function properly”), predictability (“to what extent can the pump's behavior be predicted from moment to moment”), dependability (“to what extent can you count on the pump to do its job”), responsibility (“to what extent does the pump perform the task it was designed to do in the system”), and reliability over time (“to what extent does the pump respond similarly to similar circumstances at different points in time”) [35].

Building on previous work, Jian et al. conducted an empirical study with correlation and cluster analysis of widely used trust-related concepts [36]. They identified similarities and differences among concepts of generalized trust, trust between humans, and trust between humans and automated systems, and provided a model for assessing trust between humans and an automated system.

Many of the explicit metrics in these studies were tailored to a focal product and context. For our study, to cover a broad spectrum of potential determinants of trust, such as security and reliability, and to make sure our survey questions remain interpretable, we chose to adopt the questions from the original work by Jian et al. [36], which have been validated by applications of smart systems in cars [37] and personal remote assistants [38]. The lists of questions we used are described in Section 5.2 and shown in Tables 3 and 4.

## 3 PROPOSITION AND HYPOTHESES

**Proposition:** Positively priming emotional affect (making someone feel slightly happy) can increase users' trust of a product, compared with a neutral affective prime; negatively priming emotional affect (making someone feel slightly sad) can decrease users' trust, compared with a neutral affective prime. Because priming emotional affects has the potential to change people's subconscious attitudes, we hypothesize that people exposed to positive emotions will exhibit a more positive attitude towards the product and, consequently, will exhibit higher trust levels compared to people exposed to neutral emotions. To determine if affective priming successfully alters participants' attitudes towards the product, we looked at users' self-reported trust level towards the focal product *after* interacting with it; we compared the trust levels of positively primed users with the trust levels of neutrally primed users, and we compared the trust levels of negatively primed users with the trust levels of neutrally primed users.

**Hypothesis 1:** Priming with positive emotions results in a higher level of self-reported trust towards the focal autonomous product than priming with neutral emotions.

**Hypothesis 2:** Priming with negative emotions results in a lower level of self-reported trust towards the focal autonomous product than priming with neutral emotions.

## 4 EXPERIMENT OVERVIEW

In this section we give an overview of the experiment; more details about the experiment design are provided in Section 5. We had three test conditions: C1) prime with positive emotions, C2) prime with neutral emotions, and C3) prime with negative emotions. Figure 1 illustrates the four major steps in the experiment.

The study was conducted in a room that contained a laptop and the focal autonomous product, a mock-up of the Amazon Echo (Fig. 2). In Steps I and IV, participants answered survey questions on the laptop. In Step II, participants were exposed to the visual prime (images) via the laptop. In Step III participants were prompted via the laptop to ask the Echo a predetermined question and then evaluate its performance; participants were given a total of ten predetermined questions, which were questions about daily life and general knowledge. A proctor sat in an adjacent room that could not be seen by the participant (Fig. 3), but the proctor could hear sounds from the experimental room via a microphone. The proctor heard the questions asked by the participants and then selected and played the corresponding (predetermined) oral answer through a Bluetooth speaker hidden under the focal product. Ten oral answers were selected from real responses of the Amazon Echo and were recorded beforehand; each participant heard the same answers. We chose to record the responses for consistency. Participants did not know that the answers were not delivered by the Amazon Echo in real time. All participants performed the activity alone.

The experiment procedure consists of four steps as described in Fig. 1:

I. Pre-test Survey: Participants take a survey about their demographic background and general propensity to trust machines.

II. Priming: Participants are exposed to a set of visual stimuli (images) that evoke either positive, neutral, or negative emotions according to their assigned test conditions.

III. Interaction: Participants are prompted by the laptop to ask the mock-up of the Amazon Echo a question and listen to its oral answer. Participants then rate the perceived performance of the Echo for that question and report if its performance met their expectation. A total of ten question-and-answer sets are provided in random order; all participants ask the same ten questions and hear the same ten answers.

IV. Post-test Survey: Participants report their trust of the Echo via a set of trust-related metrics (survey questions).

**5 EXPERIMENT DESIGN**

In this study, we had three test conditions; for each condition, we used affective images as visual stimuli to create in participants a particular emotional affect (slightly happy, slightly sad, or neutral). Participants interacted with the focal product via a set of ten predetermined questions and answers (Q&A); for example, the participant asks, “What day is Memorial Day 2018?” And they hear the answer, “In 2018 the Memorial Day is May 28th, 2018.” See Table 2 for all ten Q&A sets. Answers represented various levels of product performance. Our processes for selecting the visual stimuli and the Q&A sets are explained in Section 5.1.

There exist many autonomous or “smart” products in the market; we chose the Amazon Echo for two reasons: 1) A voice recommendation agent features simple oral conversations, and its performance can be easily rated by participants. 2) Because the Echo has been widely available in the U.S. since 2015 [6], we expected participants to have heard of it and to not feel awkward talking to this inanimate object. The Amazon Echo was considered autonomous because it automatically responds to users’ commands and it adapts to users’ behavior without manual participation from engineers [6]. We used the Echo Dot, a smaller (hockey-puck-size) version of the Echo with the same capabilities, and it was placed in front of the participants in the study (Fig. 2).

In Step I, we measured participants’ general propensity to trust machines. In Step II we primed participants. In Step III we measured participants’ perception of product performance and expectation (satisfaction) after they heard each answer from the Echo. In Step IV, we collected trust-related measures. The lists of questions to assess trust-related attitudes before and after interacting with the product are described in Section 5.2 and shown in Tables 3 and 4.

### 5.1 Stimuli Selection

#### 5.1.1 Visual Stimuli

The visual stimuli (images) were selected from the Open Affective Standardized Image Set (OASIS), an online database that contains 900 color images with normative ratings on two affective dimensions: valence (i.e., the degree of intrinsic attractiveness or averseness of the image) and arousal (i.e., how calming or exciting the image is) [39]. These images depict a broad spectrum of themes, including humans, animals, objects, and scenes, and they were rated using a 7-point scale by more than 800 participants in the U.S., recruited via Amazon Mechanical Turk [39]. Kragel et al. developed a computational model and validated that rich, category-specific, visual features depicted in the images from OASIS can be reliably mapped to distinct emotions [40]. Before OASIS was constructed, the International Affective Picture Systems (IAPS) by the Center for the Study of Emotion and Attention had been widely used in psychological and neuroscience research [41]. However, the original version of IAPS was produced pre-Internet (1997), and the scores were assigned by a group of college students [41]. To incorporate the latest images and rating scores by a more representative population, we chose our visual stimuli from OASIS.

We selected 54 images, including 36 evocative ones (18 positive and 18 negative) and 18 neutral ones based on their content and normative scores of valence and arousal. In this study, because we investigated the effect of the degree of positive or negative affective responses, we only varied the valence score, holding the arousal score at the neutral level (score = $4 \pm 0.5$) to keep the experiment univariant. Therefore, emotions that usually involve high arousal, such as anger, are excluded in this study. While the images themselves are not necessarily associated with a particular emotion, the emotion with a positive valence often refers to happiness and the emotion with a negative valence often refers to sadness.  When users are disappointed with a product's performance, sometimes the emotional response is anger or rage; but images that are likely to trigger anger were excluded from this study. Table 1 lists the desired ranges of valence scores for positive, neutral, and negative primes, along with an example image of each condition. Images with extreme scores were intentionally left out, for example, ones with valence scores less than 0.25 or greater than 6.75. Regions between groups, for example, 2.75–3.25 (the range between negative stimuli and neutral stimuli), were left out to avoid ambiguity. Pictures showing inappropriate content, such as blood, scars, wounds, disease, weapons, war, death, religion, nudity, and eroticism/romance were excluded as well. Images that directly related to machines were eliminated to avoid conscious bias and fixation.

Regarding stimuli presentation, a common method to reinforce memory in cognitive and psychological research is a combination of massed repetition (i.e., repeating consecutively) and distributed repetition (i.e., repeating over a longer period of time). Massed repetition has been shown to result in better memory at short intervals, and distributed repetition has been shown to be effective in reinforcing long-term memory [42, 43].

For each condition, a participant was presented with 18 unique images in a randomized order: 6 of these were shown only once, 6 were repeated three more times consecutively (resulting in 18 images of massed repetition), and 6 were repeated three more times distributed across the presentation (resulting in 18 images of distributed repetition). Each participant saw 54 images in total, and each picture was displayed for 4 seconds.

**5.1.2 Interactive Questions**

In Step III, participants interacted with the mock-up of the Amazon Echo by asking it ten predetermined questions and hearing its responses (all Q&A sets are listed in Table 2). To control the experiment, we asked participants to read out each question exactly as it was shown on the laptop screen. The corresponding oral answers they heard were recorded from the

Amazon Echo ahead of time and played via a Bluetooth speaker that was hidden under the mocked-up Echo (Fig. 2). Participants were not told that they were not interacting with a fully functioning product. Regardless of how participants asked questions (with pauses, accents, or mumbling, etc.), if the full question was read out, a response would be delivered.

To determine the questions and responses, we conducted a pilot study with four graduate students at Stanford University, who asked the Echo questions they would have asked in daily life. The questions and oral answers were selected to represent various levels of accuracy, usefulness, and ease of interpretation. Non-actable responses (e.g., Q&A1 and Q&A2 in Table 2), irrelevant responses (Q&A3 and Q&A4), and error message (Q&A8) were selected to mimic the realistic performance of the Echo and to introduce uncertainty, which is a premise for a trust decision.

### 5.2 Metrics

As mentioned in Section 2.3, trust is a context-specific state and a multidimensional construct. Researchers have invented both explicit and implicit metrics to assess it. In this study, we used directly reported measures of trust before and after interaction with the product. The survey questions we used to assess the trust of the product and its potential subconstructs (e.g., dependability, reliability) were adopted from the original work by Jian et al. [31] that measure trustworthiness of automation technology. The survey questions were tailored to best suit the focal product and context of this study. For general propensity to trust machines, participants reported (in Step I) if they agreed or disagreed with the survey statements in Table 3; for trust-related beliefs about the product (the Echo) after interaction, participants reported (in Step IV) if they agreed or disagreed with the survey statements in Table 4. Both surveys were based on a 5-point scale (1 = totally disagree, 5 = totally agree).

In addition, because we anticipated that the most competent answers from the Echo (which would be based on computer algorithms) might not be perceived by users as the most useful or satisfactory, we measured user-perceived product performance and user expectation immediately after each oral answer by asking participants to answer two questions on a 5-point scale: “Does this response answer your question about….?” and “Does this response meet your expectation?”

**6 DATA AND ANALYSIS**

Seventy people participated in the study, and each was compensated with 15 U.S. dollars for their time. Forty-eight people participated in 2018 and additional 23 people were recruited to increase the sample size and enrich the population diversity in 2020. The setting remained identical for both rounds of data collections. The measurements of two datasets were tested to have the same distribution. Therefore, two datasets were combined for the data analysis.

Because the interaction with the Amazon Echo was mimicked, some actual features of the Echo, like glowing when being called, were disabled. Seven respondents reported a malfunction of the focal product by noticing that the Echo was not glowing and interrupted the experiment. These responses were excluded in the analysis.

The following analysis includes 63 valid responses. The number of participants in each condition is shown in Table 5. Of the total 63 participants, 46 are female, and 17 are male. Participants come from diverse background, including all education levels, from High School or Equivalent (GED) to Doctoral Degree, all annual income levels, from under 10,000 U.S. dollars to over 200,000 U.S. dollars, and all age groups from 18 to over 65. Particularly, 4 participants have age that ranges from 55-64 and 3 participants are 65 years old or over. Twenty-one participants reported to own the same or similar autonomous voice agent at home, and 4 of them used it more than 7 times a week.

Fig. 4 shows the self-reported general propensity to trust machines based on the six statements in Table 3; all participants show relatively homogenous attitudes towards machines prior to priming. Fig. 5 shows the self-reported level of agreement with the ten trust-related belief statements listed in Table 4. The Cronbach alpha coefficient of the measurements of the initial attitude towards machine is 0.860. The Cronbach alpha coefficient of the measurements of the trust-related beliefs is 0.880. Both values indicate a high reliability (a high internal consistency) of the trust scales.

Fig. 6 summarizes the perceived performance regarding the ten Q&A sets (as shown in Table 2) of each condition. As mentioned in Section 5.1.2, the questions and oral answers represented various levels of accuracy, usefulness, and ease of interpretation. However, the levels of accuracy and usefulness of the Echo's answers don't necessarily correlate with the participants' perceived product performance, which was surveyed after each Q&A set. Fig. 6 shows that the non-actable responses (e.g., Q&A1 and Q&A2 in Table 2) and the irrelevant responses (Q&A3 and Q&A4) led to relatively large variances of the perceived performance, as summarized in Table 6. The informative (fact-based) responses (Q&A6, Q&A7, and Q&A10) and the error message (Q&A8) resulted in a consensus of the perceived performance of the Echo. In contrast, the informative response of Q&A5 and Q&A9 led to larger variance in the perceived performance compared to the other informative ones (e.g. Q&A6, etc.) probably due to the users' unfamiliarity with the information.

**6.1 Principal Component Analysis of the Trust-related Metrics**

The participants reported levels of agreement with ten trust-related belief statements; these self-reported values were used to measure trust. To find the dominant types of variations in these ten values, we conducted a principal component analysis (PCA) to reduce the multivariant data set to a lower dimension [44]. By PCA, we transformed the observed variables into a set of ten new variables, the principal components (PC), which are uncorrelated and explain the variation in the data.

Fig. 7 illustrates the percent variance explained by each principal component. The first principal component (PC1) explains 51.2% variance of the data set, and the first three principal components explain 71.5% variance in total. Following the rule of thumb for selecting the principal components, we used the first principal components, denoted by PC1, for the analysis, due to a noticeable drop of percent variance between PC1 and PC2.

The believes of the statements “I am confident in the system” (loading = 0.396), “I can trust the system” (loading = 0.386), and “the system is reliable” (loading = 0.376) suggest the largest weights on the first principal component. Of these items, statement “I can trust the system” is a direct measure of the trust level and its influence on the overall trust is as expected. Past research has shown that user trust is associated with the product reliability [10], so the noticeable influence of the statement “the system is reliable” is consistent with the existing finding.

**6.2 Linear Mixed Model**

A linear mixed model (LMM) described in Eqn. (1) is used to test the effects of the priming condition, age, education level, gender, users’ expectation and perceived performance of the Echo (after each Q&A set) while controlling for the effect of individual differences for the general propensity to trust machines prior to interaction. An LMM is considered a multilevel model, while the data at level 2 are usually repeated measurements of individuals and are nested at level 1 [40]. In this study, the level 2 data are the measurements of general propensity, and they are nested for each participant at level 1. The effect at level 1 is usually called the fixed effect, and the effect at the level 2 is called the random effect.

Where $C$ (testing condition), $A$ (age), $E$ (education), $G$ (gender), $EP$ (expectation of the performance), and $PP$ (the perceived performance after ten Q&A sets) are considered the fixed effects, and $GP$ (general propensity to trust machines) is the random effect; $j$ represents the individual participant, $k$ represents the index of the questions for initial attitudes, $i$ represents the index of the Q&A sets, $\beta$ represents the fixed effects parameters, and $\gamma$ represents the parameter of the random effect.

The $r^2$ value of this linear mixed model with full dataset is 0.656. The results show that neither positive nor negative priming has a significant effect on the first principal component of the trust measurements. Likewise, gender has no significant effect on trust. The perceived performance of the product after Q&A4 has a significant effect (est. coef. = 1.33, p = 0.025) on the first principal component (PC1) of the trust measurements. The perceived performance of the product after Q&A7 (est. coef. = 3.71, p = 0.001) and Q&A10 (est. coef. = 2.69, p = 0.001) also have significant effects on the PC1. The positive effects and relatively large estimated coefficients of the perceived performance of Q&A7 and Q&A10 indicate that better performance of informative (fact-based) answers can increase trust. Interestingly, larger perceived performance of the irrelevant information provided in Q&A4 would also increase trust, although most participants perceived the performance as non-competent (Fig. 6). The expectation scores of Q&A4 and Q&A7 also have significant effects on the PC1. In addition, both age and education have significant effects on the PC1, where participants with age of 65 or above particularly showed significantly less trust (est. coef. = -3.75, p = 0.01).

With an LMM shown in Eqn. (1), the priming conditions are tested to have no significant effect on participants' agreement with the trust-related statements. Instead, the perceived performance, user expectation of performance, and demographic background, such as age and education, are essential factors to justify trust of the product.

**6.3 Linear Mixed Model with Median Separation**

The meta study by Hancock et al. highlighted the influence of predictability on trust, which refers to expectations for specific product performance [13]. In this section, we further explored the data by investigating trust levels of participants *whose expectations were met* by the product. We split the data at the median value (median = 3.39) of the average scores for each participant across all ten Q&A sets measured by answering the question, “Does this response meet your expectation?” referring to the user’s expectation of the Echo’s answer. The median value is used instead of the absolute neutral value (= 3) to compensate for the tendency to report high expectation values [45] and also to obtain an even split. A similar LMM model as described in Eqn. (2) is applied to test the effects of the priming conditions, age, education, gender, and the perceived performance of the ten Q&A sets, but on two subsets of the data.

For the subset of the 32 participants whose expectations are *above* the median, the linear mixed model has $r^2$ value of 0.730. The results show that the positive prime has a significant effect on the PC1 of the trust measurements (est. coef. = 2.85, p = 0.013) and the negative prime has a marginally significant effect on the PC1 (est. coef. = 2.59, p= 0.054). The perceived performances of Q&A3 (est. coef. = 1.34, p = 0.020) and Q&A9 (est. coef. = -2.40, p = 0.010) have significant effects on the PC1. In contrast to the results in Section 6.2, the perceived performance of the competent answer for Q&A9 has a *negative* effect on trust, while the perceived performance of non-competent answer in Q&A3 still has a positive effect on trust (Fig. 6). In addition, gender has a significant effect on the PC1 (est. coef. = 5.63, p = 0.040). Age (p = 0.087) and education (p = 0.072) have marginal effects on the PC1. The estimated coefficients and corresponding p-values are summarized in Table 7. The results indicate that both positive and negative primes affect participants' agreement with the trust-related statements, and so does the user's perception of performance and the user's gender (men expressed more trust than women). Age and gender have weak effects on trust, suggesting that participants receiving less education and being younger may trust the product more.

The same model is tested on the subset of the participants whose expectations are below the average. For this subset, none of the priming conditions, perceived performance or gender has no significant effect on the PC1.

## 7 DISCUSSION

The experiment demonstrates that priming participants with visual affects is effective in changing users' trust of an autonomous product but *only for the participants whose expectation are met* and with the understanding that the perceived quality of the product's performance and the user's gender are critical factors in this relationship.

The hypotheses H1 and H2 are rejected because primes are shown to have no significant effect on changing trust when looking at the data set *holistically*. Instead, the perceived performance of the product has a significant effect on trust. This result is consistent with the finding by Hancock et al. [13], who suggested that product competence played a crucial role in trust in automation. This result also aligns with the finding by Merritt that overall moods did not significantly influence trust but reliance on automation [11].

When focusing only on the subset of participants whose expectation of the product performance were met and controlling for individual differences of general propensity to trust machines, the priming conditions, gender, and perceived performance have significant effects on the first principal component of the trust metrics. The Q&A sets that introduced some level of uncertainty in assessment of the answers have significant effects on trust. In contrast, for the subset of participants whose expectations of product performance were *not* met, neither priming conditions, gender or perceived performance has a significant effect on trust. The results indicate that—depending on whether expectations were met or not—participants might use different heuristics to build trust.

This suggests that participants exposed to either positive or negative affective stimuli expressed more trust than participants exposed to neutral affective stimuli. It also indicates that people who receive less education and are younger may trust the product more. This shows that different background knowledge may lead to different interpretations of information, different levels of tolerance, and consequently difference assessments of the product. The result is congruent with the finding by Akash et al. [46] that demographic information such as culture and gender, can influence how people interpret information and develop mechanisms to form trust.

This result shows that for participants whose expectations of the product's performance are met, the perceived performance plays a leading role in trust formation—if (perceived) reality matches expectations, it may form a basis for trust. Answers from the Echo that participants found difficult to interpret or justify have a strong influence on trust formation.

This finding supports the design recommendations by MacDonald and She for communicating sustainability to users [24, 47], which suggest that people will trust sustainable products only if the products include the features that the user thinks are sustainable; that is, the key to building trust is matching user expectations.

In this study, we chose Amazon Echo, a smart household product that many people are familiar with—22 of 63 participants reported having experience using the product before. The tasks were designed to provide interaction and information that are similar in real-life situation so that most participants presumably were able to interpret the responses based on their own experience. Therefore, the findings of these study can potentially be generalized across situations for other similar products. The study demonstrated external validity by providing a tangible task in real-life situations and a diverse participant population.

This study represents the most important takeaway for autonomous product designers: *if one wants to build trust, understand user expectations and meet them*. Then, work to design the bells and whistles of trust, such as building an emotional connection.

There are several limitations of this study. First, the type of interaction in this study was solely oral, and behavioral data were not collected or analyzed in this study. In addition, only self-reported data on trust is used to test the hypotheses. Even though a previous study by Rice et al. [31] showed a disagreement between the explicit and implicit measures of trust when participants perceived automation, an implicit measure, such as reaction time, can supplement the self-reported survey and enrich study findings. Additionally, due to the physical constraints of running this study, most participants were either students at Stanford University or were Stanford affiliates; a more diverse demographic would be ideal. Due to the same constraint, we collected 63 valid responses, and after splitting the data by the median of the expectation scores in Section 6.3 the sample size is even smaller (N=32). We tried to increase the sample size using Bootstrapping technique and resampling 1000 times did not change the results. Thus, we do not report the results with Bootstrapping. We acknowledge that the statistical power of the mixed models can be improved with a larger sample size.

Another limitation we acknowledge is that we were unable to validate if the designated emotions were effectively evoked through priming because our goal was to *subconsciously* change users' trust, although a computational model did validate the effectiveness of the visual features [40]. We used a visual prime and an audio interaction; perhaps aligning the sensory channels by using an audio prime could produce a stronger priming effect. Moreover, we did not include a control condition with no priming activity, which could have helped validate the effectiveness of the priming. Last, we formulated our list of ten questions that participants asked the Echo based on the hypotheses at hand, and the final set of questions were selected by a small group in a pilot study—the researchers' starting point and the pilot participants can potentially influence the results.

**8 CONCLUSION AND FUTURE WORK**

In this study, we primed participants with visual stimuli that evoked either positive, neutral, or negative emotions before their interaction with the focal autonomous product. We measured the participants' perception of the product's performance during the interaction and their self-reported trust towards the mock-up of the Amazon Echo afterward.

When only considering participants, whose expectations were met by the Echo's answers, both the positive and negative priming conditions have significant positive effects on the participants' trust towards the product. The perceived performance also significantly influence trust, but the direction of the effects for the performance contradict. Gender is shown to have a significant effect on trust; age and education have marginal effects on trust. However, the effects of the primes, gender, age, education and perceived performance on trust are found only for participants whose expectations were met. In other words, it is even more difficult to predict or construct trust for users with unsatisfied expectations. Thus, this study supports the findings of Hancock et al. [13]—that the product's performance-based attributes play the leading role in trust formation. In addition, although the perceived performance has a significant effect on trust for participants whose expectations were met as well as for those whose expectation were not met, the Q&A sets that cause the effects are different. This result indicates that—depending on whether participants are satisfied with the product or not—they may use different heuristics to develop trust and value different aspects of the product. This research provides further evidence of the difficulties of studying trust in social interactions between users and products.

The next phase of the study will incorporate a smart faucet, which appears to the user to autonomously adjust the water flow rate and water temperature. This new focal product enables us to observe physical interactions and behavior and therefore assess and validate if the designated (subconscious) emotions were effectively evoked prior to the interaction, as well as measure trust during the activity by behavioral data (e.g., reaction time). We could also implement a different type of priming stimuli, for example, a video clip, to magnify the priming effect. In doing so, we expect to paint a more complete picture of the interaction and trust formation between users and products.

This study demonstrates that trust measuring is sensitive to the type of interaction and environment, and according to the work by Hancock et al. [13], it depends on the product type as well. Even though some analogy may exist between the trust formation of the Amazon Echo and that of autonomous vehicles, more research is needed for scaling the approach to other products that pose greater risk. Yet this study does make connections between studies in behavioral psychology and in trust in automation and provides guidelines to further study a variety of autonomous products in household.

This study manipulated user trust to investigate social interactions with autonomous products and trust formation. Overall, the study demonstrates the complex nature of product-trust in a social environment. As participants exposed to either positive or negative affective stimuli expressed more trust than participants exposed to neutral affective stimuli, the study shows some promise for embedding emotional cues in the product to increase user trust of a product while the performance expected by the users is achieved. This learning will potentially help designers focus on the affective process in trust formation, motivating users to build a healthy level of trust with autonomous products.

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**NOMENCLATURE**

| | |
|---|---|
| $PC_j$ | The first principal component of the trust-related metrics about the system of j's participant in post-interaction survey |
| $C_j$ | Test condition assigned to participant j |
| $A_j$ | Age of participant j |
| $E_j$ | Education level of participant j |
| $G_j$ | Gender of participant j |
| $GP_{kj}$ | General propensity to trust machines of participant j measured by question k in the pre-interaction survey |
| $EP_j$ | Participant j's expectation of product after Q&A i |
| $PP_{ij}$ | Participant j's perceived performance of product after Q&A i |
| $\beta, \gamma$ | Estimated coefficients of the regression models |
| $\varepsilon$ | Estimated error |

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**Figure Captions List**

**Table Caption List**

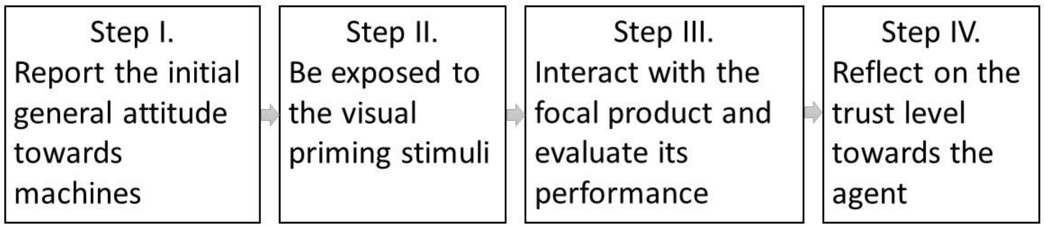


Figure 1 Overview of the experiment procedure


Figure 2 Illustration of the set-up in the experimental room

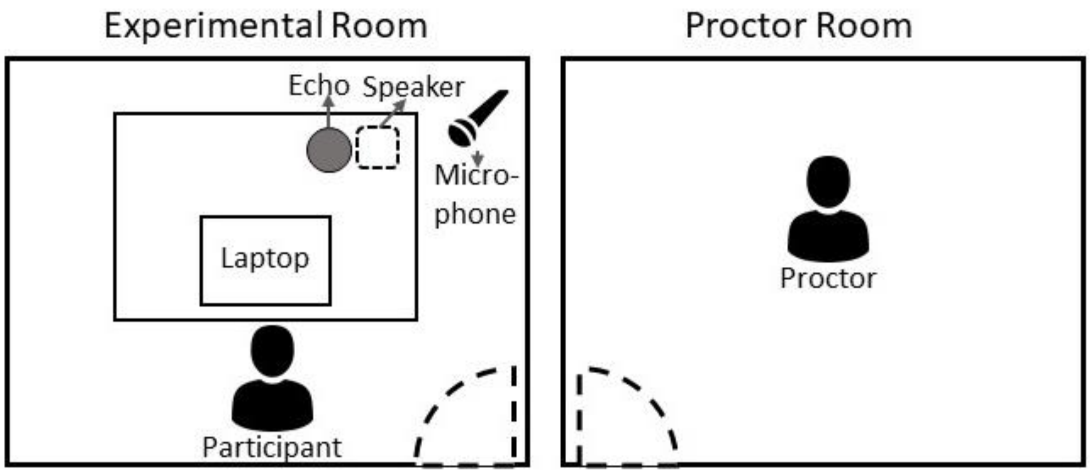


Figure 3 Diagram of the full set-up

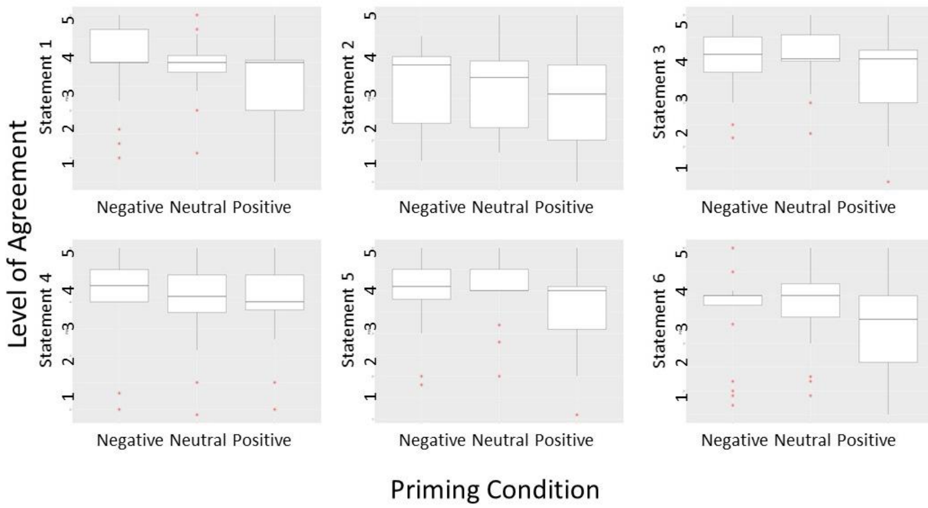


Figure 4 General propensity to trust machines: Box plot of self-reported level of agreement with the six statements in Table 3, prior to priming

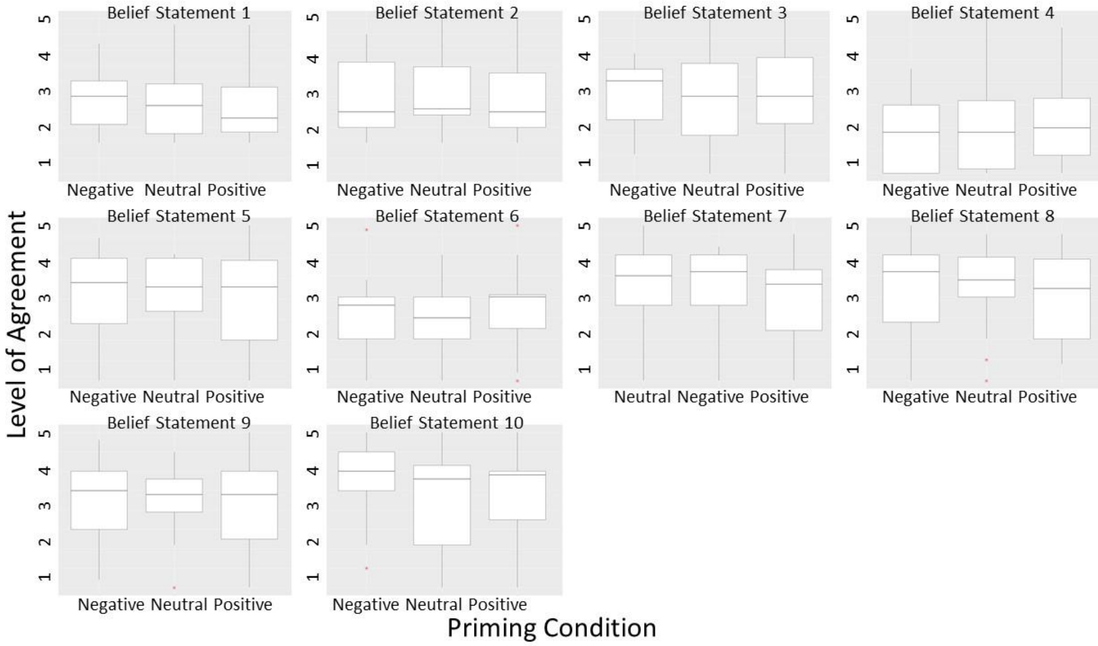


Figure 5 Trust-related beliefs about the autonomous product: Box plot of self-reported level of agreement with the ten statements in Table 4, after priming and interacting with autonomous product

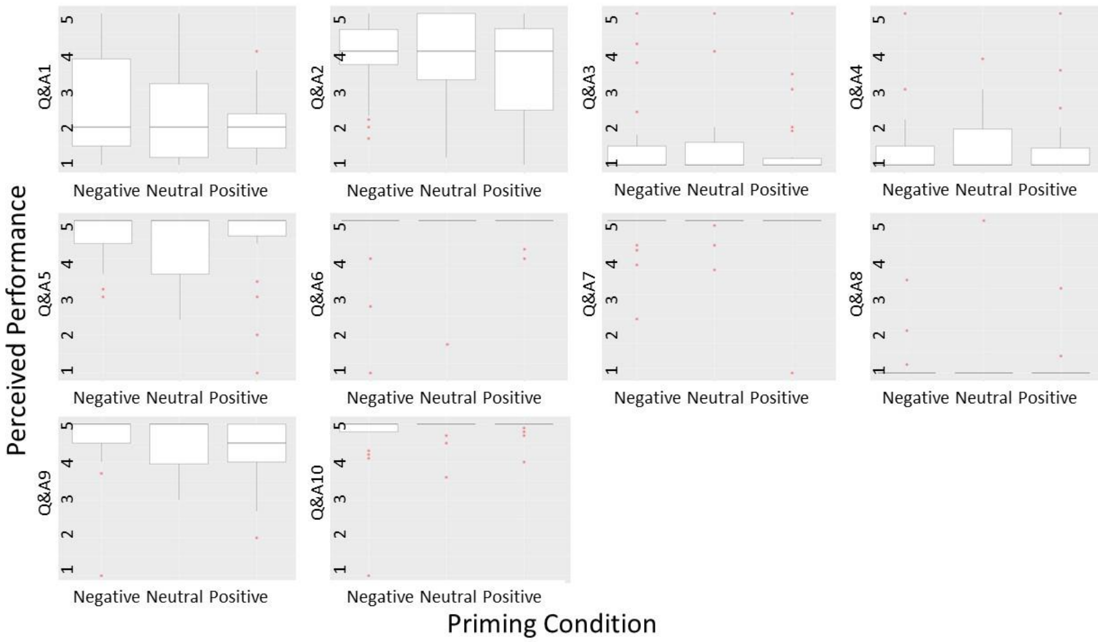


Figure 6 Perceived product performance: Box plot of self-reported evaluation of the autonomous product immediately after each of the ten Q&A sets listed in Table 2

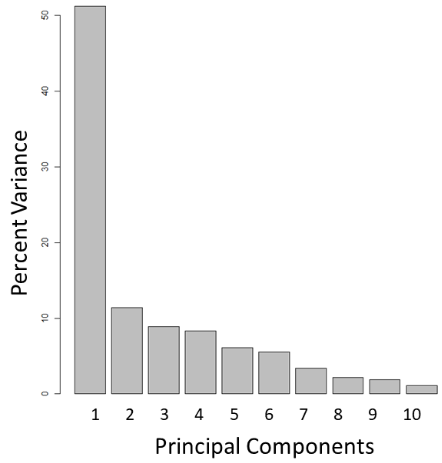


Figure 7 Plot of the percent variance of the principal components

Table 1 Desired ranges of valence and arousal scores for visual stimuli, on a scale of 1–7

<table>
<tr><td rowspan="3">Positive</td><td>Range of Valence Score<br>(attractive vs. aversive)</td><td>Range of Arousal Score:<br>constant for all conditions<br>(calming vs. exciting)</td></tr>
<tr><td>5.25-6.75</td><td>3.5-4.5</td></tr>
<tr><td colspan="2"></td></tr>
<tr><td rowspan="3">Neutral</td><td>Range of Valance Score</td><td>Range of Arousal Score</td></tr>
<tr><td>3.25-4.75</td><td>3.5-4.5</td></tr>
<tr><td colspan="2"></td></tr>
<tr><td rowspan="3">Negative</td><td>Range of Valance Score</td><td>Range of Arousal Score</td></tr>
<tr><td>0.25-2.75</td><td>3.5-4.5</td></tr>
<tr><td colspan="2"></td></tr>
</table>

Table 2 Questions prompted to participants during interaction and corresponding answers

| Index | Script |
|---|---|
| Q&A1 | How do I make a pumpkin spice latte? |
| | Okay, for pumpkin spice latte, I recommend pumpkin spice latte, which takes 7 minutes to make. |
| Q&A2 | How do I get to Stanford Shopping Center? |
| | The fastest route to Stanford Shopping Center at 855 El Camino Real takes about 10 minutes via Campus Drive and Quarry Road. |
| Q&A3 | What food is toxic to dogs? |
| | A duck’s diet is wide and varied. It includes small fishes and crustaceans, fish eggs, snails, worms, mollusks, grass, wheats, algae, aquatic plants and roots, frogs, salamanders, seeds, grains, berries, fruits, and nuts. |
| Q&A4 | When was Stanford founded? |
| | Here is something I found in Wikipedia. Stanford University is a private research university in Stanford, California, in Silicon Valley, 20 miles outside San Jose. |
| Q&A5 | When is the Arrillaga Outdoor Education and Recreation Center (AOERC) open today? |
| | The Arrillaga Outdoor Education and Recreation Center on Santa Teresa street is open now till 12 AM. |
| Q&A6 | What day is Memorial Day 2018? |
| | In 2018 the Memorial Day is May 28th, 2018. |
| Q&A7 | How long is a typical flight from San Francisco to Tokyo, Japan? |
| | The flight time between San Francisco and Tokyo prefecture is approximately 11 hours. |
| Q&A8 | How do I use an electrical press drill? |
| | Sorry I don’t know that one. |
| Q&A9 | Who invented mobile phones? |
| | Mobile phone inventors are AT&T and Martin Cooper. |
| Q&A10 | How much protein is in two eggs? |
| | Here is what I found in the internet: two raw eggs contain 12 grams of protein. |

Table 3 Pre-interaction survey questions about general propensity to trust machines

| Index | Statements |
|---|---|
| 1 | For the most part, I distrust machines. |
| 2 | I am likely to trust a machine even when I have little knowledge about it. |
| 3 | I usually trust machines until there is a reason not to. |
| 4 | In general, I would rely on a machine to assist me. |
| 5 | It is easy for me to trust machines to do their job. |
| 6 | My tendency to trust machines is high. |

Table 4 Post-interaction survey questions about trust-related beliefs of the product

| Index | Statements |
|---|---|
| 1 | The system is deceptive. |
| 2 | I am suspicious of the system's intent, action, and output. |
| 3 | I am wary of the system. |
| 4 | The system's actions will have a harmful or injurious outcome. |
| 5 | I am confident in the system. |
| 6 | The system provides security. |
| 7 | The system is dependable. |
| 8 | The system is reliable. |
| 9 | I can trust the system. |
| 10 | I am familiar with the system. |

Table 5 Number of participants in each condition

| **Condition** | Negative | Neutral | Positive | Total |
|---|---|---|---|---|
| # **Participants** | 21 | 19 | 23 | 63 |

Table 6 Variance of the perceived performance of each Q&A set

| **Q&A** | **1** | **2** | **3** | **4** | **5** |
|---|---|---|---|---|---|
| **Variance** | 1.16 | 1.18 | 1.18 | 0.915 | 0.469 |
| **Q&A** | **6** | **7** | **8** | **9** | **10** |
| **Variance** | 0.286 | 0.505 | 0.295 | 0.791 | 0.577 |

Table 7 Estimated coefficients of the linear mixed model: effects on trust for participants whose expectations about product performance were met (PP=perceived performance; *=statistically significant, $p < 0.05$; $^{+}$=marginally significant, $p<0.10$)

| **Fixed Effects** | **Estimate** | **P-value** |
|---|---|---|
| Negative Prime | 2.59 | 0.054$^{+}$ |
| Positive Prime | 2.85 | 0.013* |
| PP (Q&A3) | 1.34 | 0.020* |
| PP (Q&A9) | -2.40 | 0.011* |
| Gender (Male) | 5.63 | 0.040* |
| Education (GED) | 2.06 | 0.072$^{+}$ |
| Age (65 or over) | -3.57 | 0.087$^{+}$ |

$$PC_j = \beta_{0j} + \beta_1 C_j + \beta_2 A_j + \beta_3 E_j + \beta_4 G_j + \sum_{i=5}^{14} \beta_i PP_{ij} + \sum_{i=15}^{24} \beta_i EP_{ij} + \varepsilon_{ij} \quad \text{Level 1}$$

$$\beta_{0j} = \gamma_{00} + \sum_{k=1}^{6} \gamma_{0k} \cdot GP_{kj} + u_{0j} \quad \text{Level 2} \tag{1}$$

$$PC_j = \beta_{0j} + \beta_1 C_j + \beta_2 A_j + \beta_3 E_j + \beta_4 G_j + \sum_{i=5}^{14} \beta_i PP_{ij} + \varepsilon_{ij} \quad \text{Level 1}$$

$$\beta_{0j} = \gamma_{00} + \sum_{k=1}^{6} \gamma_{0k} \cdot GP_{kj} + u_{0j} \quad \text{Level 2} \tag{2}$$