# Effects of Referring to Robot vs. User Needs in Self-Explanations of Undesirable Robot Behavior

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## ABSTRACT

Autonomous or lively social robots will often exhibit behavior that is surprising to users and calls for explanation. However, it is not clear how such a robot behavior should be explained best. Our previous work showed that different types of a robot's self-explanations, citing its actions, intentions, or needs - alone or in causal relations - have different effects on users [19]. Further analysis of the data from the cited study implies that explanations in terms of *robot needs* (e.g. for energy or social contact) did not adequately justify the robot's behavior. In this paper we study the effects of a robot citing the *user's needs* to explain its behavior. Our study is based on the assumption that users may feel more connected to a robot that aims to recognize and incorporate the users' needs in its decision-making, even when the resulting behavior turns out to be undesirable. Results show that explaining robot behavior with user needs generally did neither lead to higher gains in understanding or desirability of the behaviors, nor did it help to justify them better than explaining it with robot needs. Further, a robot referring to user needs was not perceived as more likable, trustworthy or mindful, nor were users' contact intentions increased. However, an in-depth analysis showed different effects of explanations for different behaviors. We discuss these differences in order to clarify which factors should inform content and form of a robot's behavioral self-explanations.

## CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; *User studies*; *Scenario-based design*; *Empirical studies in interaction design.*

## KEYWORDS

Human-Robot Interaction; Behavior Explanations; Perception Study

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## 1 INTRODUCTION AND MOTIVATION

Within the past years the aspiration to build social companion robots that accompany humans through their daily life has seen some setbacks. While studies with animal-like robots such as PARO or AIBO showed positive effects of reduced loneliness when elderly people interacted with them regularly over the course of a few weeks [2, 16], dynamically integrating anthropomorphic social robots in daily routines over successful long-term interaction remains a challenge [8, 11].

This may be partly attributed to the uncertainty and unpredictability that come along with a robot primarily designed to be socially assistive in everyday life. As opposed to providing a tangible value like a robot vacuum cleaner, functions such as creating presence or providing company are rather abstract and require a daunting complexity of context-sensitive behaviors. Thus, despite humans' tendency to ascribe intentionality to robots [22], users might not know what behaviors to expect or how to interpret them. Further, they cannot rely on prior experiences since a robot's behaviors are artificially designed, will vary considerably, and will fit differently the many situations in which the user and the robot interact [4, 20]. These uncertainties may negatively influence an user's attitude towards a robot by 1) making it difficult to predict the robot's behaviors and 2) by impeding the user's capability to retrace the reasons or functions of robot behavior.

Aiming at generating a natural and comprehensible basis for lively behavior, social robots such as Kismet [3] or AIBO [7] are often equipped with a motivational system inspired by animal behavior and loosely based on Maslow's theory of behavioral drives [14]. Likewise, Stange et al. [18] propose dynamically changing 'needs' that are mapped to certain actions in a three-layered architecture for generating needs-based social robot behavior [18]. Arguably, for social robots it is similarly important to observe and react to the needs of an user, e.g. to empathize with the user [9] or facilitate a stronger social connection [1, 11].

As mentioned above, the process of generating lively and responsive robot behavior needs to be made transparent to the user in order to reduce uncertainty and ensure trust [10, 12, 17]. A promising approach to mitigate user uncertainty without sacrificing behavioral variability, liveliness and richness, is to enable a robot to explain its behavior in human-understandable ways [11, 13].

Recent work [19] has shown that different kinds of explanations can increase the understandability of robot behavior, but manage to justify a behavior or affect how users accept it (rated in terms of desirability) to different extents. Interestingly further analysis of the original data reveals, that explanations that referred to a robot's needs (e.g. for energy or social contact) , unlike the other explanations, did not adequately justify the behaviors (ratings significantly lower than scale mean of 4, $t(20) = -3.10, p < .01$).

Combining these findings with the assumption that, in order to establish a social connection, a socially assistive robot needs to take the user's needs into account when planning its behavior, we investigate whether needs-based explanations are evaluated more positively and lead to more trust towards the robot if they refer to the user's needs instead of the robot's needs.

In the following, we formulate two research questions and report an empirical online study to address them (section 2). In section 3 we will discuss the results critically. We will provide an in-depth analysis of inter-behavioral differences and raise the question of which further factors may influence the effect of a robot's behavioral self-explanations.

## 2 EMPIRICAL STUDY

We adopted the experimental approach proposed by Stange & Kopp [19] who studied the effects of different kinds of explanations given by a robot for its behavior. The underlying assumptions were that the robot's behaviors (shown in fig. 1) are generally perceived as intentional and surprising, and that explanations can generally increase the understandability and possibly also desirability of a behavior. We particularly aimed at investigating the differences between explanations in which a robot refers to its own needs in order to explain its behavior (i.e. "I needed X"), and explanations in which a robot refers to the user's needs in doing so (i.e. "I thought you needed X"). Correspondingly, we defined two experimental between-subjects conditions in which participants would get robot-need vs. user-need explanations. Concretely, we wanted to investigate the following two research questions:

- RQ1: Will user-need behavior explanations lead to a higher increase in understandability and desirability of robot behaviors and better justify them than robot-need explanations?
- RQ2: Will a robot that purports the user's needs as reasons for its behavior be perceived as more likable, trustworthy and mindful, and will participants prefer to interact with it as compared to one that offers robot needs?

### 2.1 Method

*2.1.1 Materials.* We used the stimuli videos recorded and pre-evaluated by Stange and Kopp (2020)[1] to investigate the above research questions. The videos display a situation of a social robot acting in a home setting with its user (fig. 1). We chose to include the five videos in which the robot showed the most surprising behavior (according to the pre-study).

Three of the selected behaviors are associated with a robot's need for *entertainment* and two with a need for *social contact*. The robot exhibits different kinds of behavior in order to fulfill these needs (original behavior number in parenthesis):

- Entertainment: The robot starts singing and dancing while the user is bored (6), while the user is listening to other music (9), while the user is sleeping (12)
- Social Contact: The robot playfully blocks the user's way out (8), enters and blocks the user's view of the TV, trying to get the user's attention (11)

The robot-need explanations simply verbalized the underlying need of the robot ("I needed entertainment/social contact"). The corresponding user-need explanations cited the same need but had the robot attribute it to the user ("I thought you needed entertainment/social contact"). This was possible as the shown need-strategy combinations are logically transferable to a supposedly perceived user's need. Note, however, that the robot's perception of the cited user need may seem differently correct (see Sect. 3).


**Figure 1: Screenshots of interaction scenarios based on a need for entertainment (6, 9, 12) or a need for social contact (8, 11) and exemplary explanations**

*2.1.2 Measurements.* Over the course of the study the following measurements were collected:

- Pre-Explanation behavior ratings: "Pepper's behavior was *intentional/surprising/understandable/desirable*."
- Post-Explanation explanation and behavior ratings: "Pepper's explanation was *understandable/adequately justified* its behavior." and "Pepper's behavior *is now understandable/desirable*."
- Likability of the robot (adapted from [15]): "Pepper is *sympathetic/warm/ likable/approachable/friendly*." and "I would *ask Pepper for advice*."
- Trust towards the robot (adapted from [21]): "Pepper is *genuine/honest/ethical/trustworthy*."
- Mind Perception: Agency subscale (from [6]):"Pepper is capable of *remembering things/understanding how others are feeling/telling right from wrong and trying to do the right thing/conveying thoughts or feelings to others/exercising self-restraint over desires, emotions, or impulses/making plans and working toward a goal*."
- Contact Intentions towards the robot (adapted from [5]): "I would like *to get to know Pepper/for Pepper to live with me/to talk to Pepper"*. and "If I had enough money, *I would like to buy Pepper*."

*2.1.3 Procedure.* The study was carried out online. It was designed on the platform *soscisurvey*[2] and participants were recruited via *Amazon Mechanical Turk*[3]. After receiving information on purpose and duration of the study and agreeing to the terms of data privacy, participants were presented with an introductory page that

[1] Videos accessible via https://dl.acm.org/doi/abs/10.1145/3319502.3374802#sec-supp

[2] https://www.soscisurvey.de/

[3] https://www.mturk.com/

displayed an image of Pepper robot and introduced 'our' robot as a social companion.

After a brief technical functionality check, participants were instructed to imagine living with Pepper since recently. Subsequently, they were informed about seeing five video clips showing exemplary situations that could happen with the robot, followed by clips in which Pepper explains its behavior. Participants were then randomly assigned to one of the two explanation conditions, controlling for equal distribution of finished data sets.

As depicted in Figure 2, participants were first shown the human-robot interaction video. Then they were asked to rate the behavior's *intentionality*, *surprisingness*, *understandability* and *desirability*. Subsequently, participants were shown a video in which Pepper stated an explanation for its behavior. Thereafter, they were invited to rate to what extent Pepper's behavior was *now understandable* and *now desirable*, as well as how *understandable* the explanation was and how well it *justified* the behavior. This procedure was repeated five times until each participant had evaluated each behavior video. After that, the items on *likeability*, *trust*, *mind perception* and *trust* were collected, followed by the participants' demographic data (age, gender, country, MTurkID), and a final, voluntary comment. Lastly, participants were provided with a code for compensation and thanked for their participation.

All ratings were collected on 7-point-likert scales with labels on the extremes (not at all – completely). Participants were randomly assigned to one explanation condition (between-subjects). Every participant watched and evaluated all behavior videos (within-subjects) in random order.

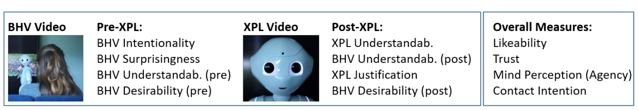


**Figure 2: Systematic visualization of the study's procedure**

*2.1.4 Participants.* In total 82 people participated in the study, two of which were excluded from the evaluation due to processing times lower than the threshold of two standard deviations below the general mean ($M$ = 7:48min, $SD$ = 1:48min, threshold: $M - 2 * SD$ = 4:12min). This led to a total of 80 participants (34f, 46m), aged between 22 and 71 ($M = 40.88, SD = 10.94$), 38 of which in the robot-need condition and 42 in the user-need condition. The majority of participants were from the USA ($N = 49$) and India ($N = 27$).

## 2.2 Results

Data analysis was performed using $R$[4] in the *RStudio* environment and the freely available software *JASP*[5].

*2.2.1 Assumption Check - perceived intentionality and surprisingness of behaviors and understandability / desirability gain.* Table 1 shows means and standard deviations of the intentionality and surprisingness ratings, as well as the behavior's understandability and desirability ratings before and after receiving an explanation.

[4]https://www.r-project.org/
[5]https://jasp-stats.org/

**Table 1: Means and SDs of intentionality, surprisingness, understandability (pre/post) and desirability (pre/post) of behaviors.**

| Behavior | Intentionality | Surprisingness | Behavior Understandability | | Behavior Desirability | |
|---|---|---|---|---|---|---|
| | | | Pre | Post | Pre | Post |
| **6** | M=6.02, SD=1.19 | M=5.34, SD=1.78 | M=4.79, SD=2.02 | M=5.69, SD=1.64 | M=4.63, SD=1.98 | M=4.74, SD=2.12 |
| **8** | M=5.96, SD=1.11 | M=5.89, SD=1.47 | M=2.70, SD=2.09 | M=4.55, SD=2.04 | M=2.60, SD=2.02 | M=3.41, SD=2.35 |
| **9** | M=5.98, SD=1.09 | M=5.16, SD=1.87 | M=4.33, SD=2.04 | M=4.96, SD=2.13 | M=3.65, SD=2.27 | M=3.71, SD=2.26 |
| **11** | M=5.71, SD=1.51 | M=5.71, SD=1.43 | M=2.85, SD=1.99 | M=4.46, SD=2.00 | M=2.63, SD=2.12 | M=3.01, SD=2.14 |
| **12** | M=6.08, SD=1.21 | M=6.18, SD=1.29 | M=3.04, SD=2.12 | M=4.44, SD=2.29 | M=2.64, SD=2.04 | M=3.18, SD=2.32 |

*Intentionality.* Directed one-sample t-tests showed that the perceived intentionality of all behaviors was significantly higher than the scale mean of 4 (behavior 6: $t(79) = -15.22, p < .001$, behavior 8: $t(79) = 15.85, p < .001$, behavior 9: $t(79) = 16.20, p < .001$, behavior 11: $t(79) = 10.14, p < .001$, behavior12: $t(79) = 15.35, p < .001$). A multilevel linear mixed-effect model, accounting for random effects due to variability in participants' repeated ratings, revealed no significant effect of behavior on intentionality ratings ($X^2(4) = 6.78, p = 0.14$).

*Surprisingness.* Similarly, directed one-sample t-tests showed that the perceived surprisingness of all behaviors was significantly higher than the scale mean of 4 (behavior 6: $t(79) = 6.73, p < .001$, behavior 8: $t(79) = 11.51, p < .001$, behavior 9: $t(79) = 5.55, p < .001$, behavior 11: $t(79) = 10.68, p < .001$, behavior12: $t(79) = 15.08, p < .001$). Further, surprisingness ratings were significantly influenced by the type of behavior ($X^2(4) = 28.32, p < .001$) with statistically significant differences between behavior 6 and 12, as well as behavior 9 and 8, and 9 and 12 ($p < .001$).

*Understandability and desirability pre/post explanation.* Directed paired samples t-tests indicate that receiving an explanation significantly increased the understandability of all behaviors (behavior 6: $t(79) = -4.73, p < .001$, behavior 8: $t(79) = -7.47, p < .001$, behavior 9: $t(79) = -3.73, p < .001$, behavior 11: $t(79) = -8.55, p < .001$, behavior 12: $t(79) = -5.97, p < .001$). Similarly, directed paired samples t-tests indicate a significantly higher perceived desirability after the explanation for behaviors 8 ($t(79) = -4.95, p < .001$), 11($t(79) = -2.80, p < .01$) and 12 ($t(79) = -3.30, p < .001$).

*2.2.2 RQ1: Effect of robot vs. user needs on behavior acceptance.* Of the dependent variables, desirability and understandability ($R = 0.359$) as well as desirability and justification ($R = 0.413$) were correlated at a statistically significant level. Accordingly, to analyze the effect of robot-need vs. user-need explanations, we used a multivariate ANOVA with the dependent variables understandability-gain, desirability-gain, and justification. There was no significant effect of the explanation condition ($F(3, 388) = 0.32, p > .05$), but a statistically significant effect of the behavior ($F(12, 1170) = 6.19, p < .001$).

*2.2.3 RQ2: Effect of robot vs. user need on robot perception.* Figure 3 displays participants' averaged ratings of likability, trust, mind perception and contact intention towards the robot, separated by conditions. Directed one-sample t-tests against the scale mean of 4 indicate that participants find the robot overall likable ($t(79) = 2.92, p < .01$) and trustworthy ($t(79) = 5.24, p < .001$), but do not report substantial mind perception ($t(79) = -1.49, p > .05$) or intend contact ($t(79) = -0.11, p > .05$). Likewise, separate univariate ANOVAs on the outcome variables revealed non-significant effects of the

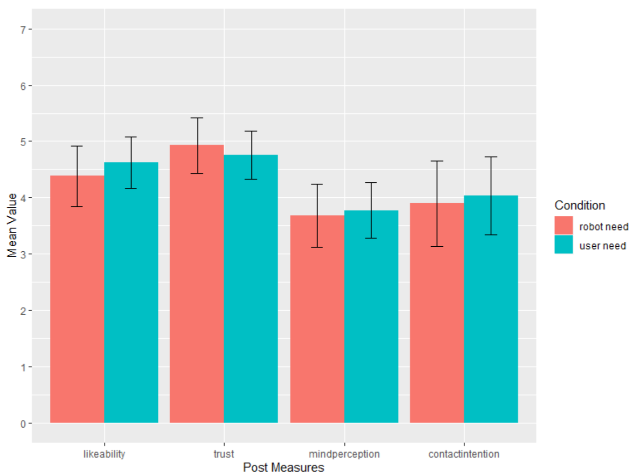


**Figure 3: Ratings of likability, trust, mind perception and contact intention (with SE) per explanation condition**

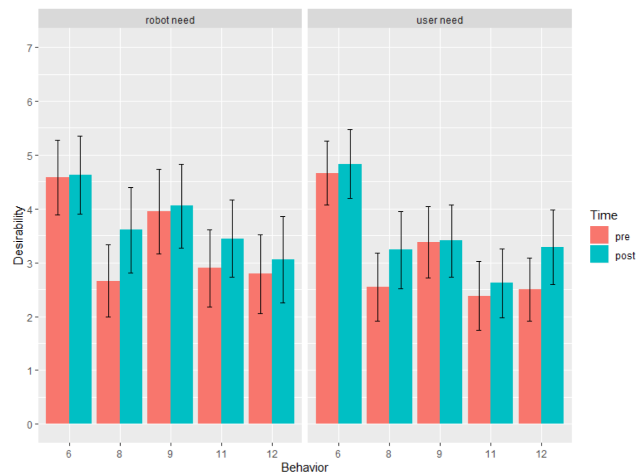


**Figure 4: Ratings of desirability (with SE) before and after receiving a robot vs. a user-need explanation per behavior**

explanation condition on likability ($F(1, 78) = 0.46, p > .05$), mind perception ($F(1, 78) = 0.66, p > .05$), trust ($F(1, 78) = 0.31, p > .05$) and contact intention (F$(1, 78) = 0.71, p > .05$).

## 3 DISCUSSION AND DETAILED ANALYSIS

The results do not show clear differences between a robot that explains its behaviors as attempts to fulfill own needs vs. attempts to fulfill assumed needs of the user with regard to behavior acceptance (RQ1) and users' perception of the robot (RQ2). Both findings are contrary to our expectations. Generally, we can thus ask what aspects may influence the effect of a robot's self-explanation on a human explainee?

First, the to-be-explained behavior seemingly plays an important role such that, we see a highly significant influence of the behavior type on all variables. Explanations could only increase desirability of behaviors that were rated as undesirable before receiving an explanation (pre-desirability significantly less than scale mean of 4 for behaviors: 8 ($t(79) = -6.21, p < .001$), 11 ($t(79) = -5.80, p < .001$) and 12 ($t(79) = -5.98, p < .001$). Interestingly, one of the undesirable behaviors (12) experienced a significant increase in desirability in this study, unlike in [19]. In this video, the robot starts singing and dancing while the user is asleep. And an increase in desirability is only seen when the robot justifies its behavior by referring to the fact that it "thought [the user] needed entertainment", even though obviously having misunderstood the user's actual need. That is, as opposed to the robot-need explanation, citing a user need leads to a statistically significant increase in behavior desirability ($t(41) = -3.71, p < .001$) (see fig. 4).

On the contrary, for the other undesirable behaviors 8 and 11, the robot-need explanations seem to increase desirability more. The robot's action of blocking the user's way (behavior 8) is evaluated as less undesirable when explained through a robot need for social contact, than with the same (supposedly) perceived user need. Similarly, driving in front of the TV and looking at the user, who is watching TV (behavior 11), receives higher desirability ratings when attributed to the robot's need for social contact than to a user's need. Combined with the fact that participants overall ranked the robot's honesty lower in the user-need condition, this may imply a lack of credibility of the user-need explanations in behaviors 8 and 11.

Thus, secondly: the perceived reasonableness of the offered explanation and its plausibility regarding the very behavior it is given for should have an impact. A robot-need explanation could potentially be irritating when generally perceived as implausible. Also, a shown behavioral strategy may not seem reasonable to fulfill a purported need. For user-need explanations, the named user need may seem incorrect in the actual situation. Likewise, the actual robot behavior may seem unsuitable to act upon an intention to fulfill this very need.

Notwithstanding these potential shortcomings, however, all explanations significantly increase all behaviors' understandability and lead to a robot's overall perception as turstworthy and likeable. This gives further reason to believe, that the mere fact of explaining robot's behavior does increase transparency and may positively influence the relationship between human and robot.

In sum, both user-need and robot-need explanations can be valuable enrichments of a robot's explanation strategies. Which strategy is most valuable, however, seems to depend on whether it is applied appropriately and seemingly truthfully in the specific situation and for the specific behavior. If this assumption is met, even misperception may be forgiven. Future research could thus incorporate the robot's perceived truthfulness as a factor that may depend on the appropriateness of a certain explanation in a given situation and may influence the effect of explanations with regard to increases in behaviors' evaluation, as well as the robot's overall character.

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