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Angaben zur Veröffentlichung / Publication details:

Kraus, Matthias, Nicolas Wagner, Nico Untereiner, and Wolfgang Minker. 2022. "Including social expectations for trustworthy proactive human-robot dialogue." In *UMAP '22: proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization, Barcelona, Spain, July 4–7, 2022*, edited by Alejandro Bellogin, Ludovico Boratto, Olga C. Santos, Liliana Ardissono, and Bart Knijnenburg, 23–33. New York, NY: ACM. https://doi.org/10.1145/3503252.3531294.

Including Social Expectations for Trustworthy Proactive Human-Robot Dialogue

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ABSTRACT

Trust forms an important factor in human-robot interaction and is highly influencing the success or failure of a mixed team of humans and machines. Similarly, to human-human teamwork, communication and proactivity are one of the keys to task success and efficiency. However, the level of proactive robot behaviour needs to be adapted to a dynamically changing social environment. Otherwise, it may be perceived as counterproductive and the robot's assistance may not be accepted. For this reason, this work investigates the design of a socially-adaptive proactive dialogue strategy and its effects on humans' trust and acceptance towards the robot. The strategy is implemented in a human-like household assistance robot that helps in the execution of domestic tasks, such as tidying up or fetch-and-carry tasks. For evaluation of the strategy, users interact with the robot while watching interactive videos of the robots in six different task scenarios. Here, the adaptive proactive behaviour of the robot is compared to four different levels of static proactivity: None, Notification, Suggestion, and Intervention. The results show that proactive robot behaviour that adapts to the social expectations of a user has a significant effect on the perceived trust in the system. Here, it is shown that a robot expressing socially-adaptive proactivity is perceived as more competent and reliable than a non-adaptive robot. Based on these results, important implications for the design of future robotic assistants at home are described.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; **HCI design and evaluation methods**; **User models**; *HCI theory, concepts and models.*

KEYWORDS

Proactivity; Intelligent Assistant; Human-Robot-Interaction; Human-Computer Trust; Spoken Dialogue System

UMAP '22, July 4–7, 2022, Barcelona, Spain

ACM ISBN 978-1-4503-9207-5/22/07.
https://doi.org/10.1145/3503252.3531294

ACM Reference Format:
Matthias Kraus, Nicolas Wagner, Nico Untereiner, and Wolfgang Minker. 2022. Including Social Expectations for Trustworthy Proactive Human-Robot Dialogue. In *Proceedings of the 30th ACM Conference on User Modeling, Adaptation and Personalization (UMAP '22), July 4–7, 2022, Barcelona, Spain.* ACM, New York, NY, USA, 11 pages. https://doi.org/10.1145/3503252.3531294

1 INTRODUCTION

Bartneck and Forlizzi [4] define a social robot "as an autonomous or semi-autonomous robot, that interacts and communicates with humans by following the behavioral norms expected by the people with whom the robot is intended to interact". The possible fields of applications for social robots are numerous. For example, they can be deployed as a receptionist [65], an exhibit guide [26] or as a kitchen [54] or household assistant [19]. However, social robots are not yet fully accepted in our society. An empirical review of studies considering attitudes towards social robots by Naneva et al. [47] has found that only 58 % of the observed studies suggest the humans accept robots. In addition, 43 % of studies showed low trust in social robots.

A reason for this could be a so-called *expectation gap* that is caused by a mismatch between a social robot's impression of intelligence and its actual behaviour [35]. Generally, humans tend to personify and associate human traits to machines (e.g., see Nass et al. [48]). Thus, people have certain social expectations regarding interactions with such, similar as interacting with a fellow human being. Particularly, this holds true for the interaction with social robots who have an anthropomorphised appearance when applied in more social settings, e.g. as a household assistant [12, 13]. One of the problems that lead to a mismatch between expectation and reality forms the lack of immediacy behaviour by robots [18]. Immediacy behaviours can be described as social gestures that increase interpersonal closeness and may be considered a machine intelligence trait. An immediacy behaviour, that we deem particular relevant for social robots is *proactive behaviour.* Proactivity is a term widely used in the domain of occupational and organizational psychology [20, 52] and is defined as anticipatory behaviour for taking the initiative in order to change a situation rather than only reacting to change. Current research of proactive behavior in human-robot interaction (HRI) suggests that proactive behaviour is expected for social robots and possibly leads to a positive effect on the user's perception if applied appropriately [3, 18, 33, 53, 57].

Even though proactive behaviour seems to be a key characteristic of social robots [4, 9], the design of sound proactive behavior is still understudied [43]. Often the proactive level of a robot is calibrated depending on the usage context and the robot's capabilities [5]. However, in doing so, the users' expectations in a dynamically changing environment are completely omitted. As a result, this may lead to a loss of trust in robots as humans expect them to adapt to specific social situations [9]. Since trust and acceptance are related concepts, this may ultimately lead to users not accepting a robot. Therefore, a social robot is required to communicate its behavior proactively and to adapt the conversation to users and their current situation and expectations. In this paper, we study the relations between social expectations, proactive dialogue, and perceived trust as well as acceptance towards a social robot. For this, we equipped a household assistance robot with proactive behaviour that adapted to the user's social expectations and present a user study showing the effects on perceived user trust and acceptance. Here, we only considered trust and acceptance of the verbal interaction and its match with the robot's behaviour and not the physical interaction. In the user study, we compared expectation-driven proactive behaviour to four static proactive dialogue strategies (None, Notification, Suggestion, Intervention). To produce a large sample size and to strengthen the standardisation of the study design, data was collected online using an interactive video method. Using this method, study participants were able to interact with the robot while watching a video. At certain moments, participants were able to explicitly make decisions that directly influence the robot's behavior and the further course of the experiment. In preparation for the study, the corresponding videos had been created with a manually operated robot that assisted in six typical domestic assistance scenarios. For evaluation, study participants rated the robot's trustworthiness, their acceptance towards the robot, as well as whether they complied with the robot's proactive actions. The results show that proactive robot behaviour that adapts to the social expectations of a user has a significant effect on the perceived trust in the system. Here, it could be shown that a robot expressing socially-adaptive proactivity is perceived as more competent and reliable than a non-adaptive robot.

The remaining structure of the paper is as follows: Significant Related work in the field of proactive HRI and trust in HRI are presented in Section 2. The preparation of study material for conducting the experiment is described in Section 3. Section 4 deals with the development of proactive dialogue strategies. In Section 5, we introduce the basis of the experimental setup. The outcomes of the study are presented in Section 6. Afterward, we discuss and evaluate our results in Section 7, and finally conclude our work with a summary and a brief outlook on future work in Section 8.

2 BACKGROUND

2.1 Proactive Human-Robot Interaction

Proactive behavior in HRI may be differentiated into three categories: acceptably approaching a human (e.g. see [6, 17, 29]), sharing tasks between the robot and human-based on the user's intention (e.g. see [1, 25, 36]), and assisting the user proactively (e.g. see [22, 38, 53, 57]). As this paper investigates the modeling of proactive human-robot dialogue, the focus of this literature review is set on proactive robot assistance. The application domains for robotic assistants are very diverse. For example, they can be applied as shopping assistants [38, 53], caregivers [22], or Do-It-Yourself assistants [33]. Usually, proactive interaction is linked to the robot's level of autonomy that provides a fine-grained model of mixed-initiative interaction with social robots (e.g. see [5, 32, 53]).

The concept of levels of autonomy originates in research on autonomous systems [14, 51, 62]. Typically, it is referred to ten levels that relate to the degree of control a system exercises. While the user has more power over the decisions and action selection in a task environment at the lower levels, the system takes over more responsibility from the user with an increasing autonomy degree. Based on the levels of autonomy, Beer et al. [5] developed a framework for usage in HRI. This framework was intended to guide the design of a robot's autonomy and outlines a relationship between autonomous behavior and HRI principles. Specifically, the authors pointed out the need for social interaction for a robot's autonomy. Therefore, much consideration is required for determining the type, the extent, and the timing of an adequate interaction in this context. However, research on the impact of the level of robot autonomy on social interaction is still in its infancy. For example, Rau et al. [57] proposed a design of social robot interaction for assisting in decision-making tasks with a remotely controlled robot. Here, proactive interaction was compared to a baseline reactive robot version. Peng et al. [53] described proactive interaction with a robot assistant on three different levels, low, medium, and high. Low related to reactive behaviour. At medium-level, proactive behaviour was only triggered after the users had confirmed their need for assistance. At the highest level, the robot made proactive recommendations without explicit confirmation by the user. Kraus et al. [32, 33] further refined the model by Peng et al. and introduced two new levels of proactive interaction, *notification* and *suggestion* for representing a medium-level of robot autonomy. At the notification-level, a decision-assistance robot would only signal the user that there are recommendations, but leaves the initiative to ask for suggestions to the user. At the suggestion level, the robot directly makes recommendations and lets the user confirm. Along with a reactive and a high-level, the authors implemented this behaviour in a task-planning assistant.

In this work, the proactive dialogue model developed by Kraus et al. was adopted. However, it was expanded to adapt the dialogue to different degrees of a robot's autonomy. As a robot's task and behavior in the domestic domain is highly dependent on dynamically changing environmental factors, such as specific events and the respectively changing user expectations, also the robot's autonomy needs to change accordingly. This concept is known under the term adaptive autonomy (e.g. see [7, 28, 60]). By adapting the level of autonomy, tasks are dynamically allocated between the user and the robot depending on the context [7]. Although adaptive autonomy is a well-researched topic (e.g see [61]), its implications on the design of social HRI strategies are still unclear. Therefore, an adaptive proactive dialogue approach was designed in this work. Here, the dialogue was adapted to dynamically changing social expectations of a robot's autonomy in the domestic domain. As previous work has shown a relationship between proactive dialogue and human-computer trust (HCT) [33, 57], which is also relevant for the general acceptance of a robotic device, the developed adaptive proactive dialogue strategy was evaluated primarily for these two measures. A better understanding of the term trust and its relations to acceptance in HRI is presented in the following section.

2.2 Human-Robot Trust

Trust is a fundamental social concept in interpersonal relationships [58] as well as in organizational management [40]. Due to robots being perceived as social actors to some degree, trust seems to be also essential in human-robot relationships [21, 48]. For example, trust is an important factor for successful human-robot teams [21]. To collaboratively solve tasks in an efficient manner, humans are required to partly shift control to their robotic teammate. This allocation of power prerequisites a formation of trust, otherwise the robot possibly will not be accepted [45, 46]. Generally, trust in robots is closely related to trust in automation, as robots can be perceived as a kind of autonomous system. Therefore, several concepts of trustworthy interaction with autonomous systems are transferable to the domain of HRI [16, 24, 59]. In perspective to autonomy, trust can be generally defined as "the attitude that an agent will help achieve an individual's goal in a situation characterized by uncertainty and vulnerability" [37]. An extensive review of factors influencing trust towards robotic systems was provided by Hancock et al. [24] and Sanders et al. [59]. In their works, it was differentiated between human-, robot-, and environment-related factors. Considering the human element, ability-based antecedents, e.g. domain experience, prior experiences with the robot, and user-specific characteristics, e.g. demographics, the propensity to trust, are of importance. Trust antecedents of the robot are performance-based features, e.g. level of automation, reliability, transparency, and attribute-related characteristics, e.g. robot personality, adaptability. Further, environmental factors, especially related to team collaboration, e.g. in-group membership, shared mental models, and related to the tasking, e.g. task type, complexity, need to be considered. Investigating the influence of the different factors on trust development, the authors found robot- and environment-related features to have the greatest impact. Especially, the system's performance-based features are proven to have a large impact on the human-robot trust relationship [24]. For assessing the user's trust in the robot several approaches have been proposed. Primarily, subjective measurements in the form of self-reported questionnaires are collected (e.g. see [23, 39]). In this work, trust was measured using a questionnaire based on a hierarchical model of trust where participants could agree or disagree with statements about the system's trustworthiness Madsen and Gregor [39]. The advantage of this model is, that it comprises trust-relevant sub-bases, such as perceived competence of the system for measuring cognitive-related or personal attachment towards the system for measuring affect-based trust. Additionally, trust in the system was measured implicitly by observing the user's compliance with the robot's suggestions and actions. The temporal development of trust could be measured at different moments during the interaction. For example, a person's trust propensity, in general, can serve as a baseline for predicting the initial HCT level [27, 41, 42]. This baseline can then serve as "ground truth" for the dynamically learned trust which is learned during interaction with the system.

In this paper, the effects of the manipulation of performance-based feature *level of automation*, the attribute feature *adaptability*, and especially the team collaboration features *communication* and *shared mental models* are investigated. Therefore, a household assistant was implemented with four different levels of automation, each accompanied by an individual proactive dialogue strategy for communicating the robot's actions. It was found that trust increases when humans can adapt the level of automation [59]. However, the impact of an automatic adaption by the system is still not extensively investigated. de Visser and Parasuraman [11] compared the effects of stable and adaptive levels of a robot's autonomy on the user's perceived trust towards the robot. They found that adapting the level of autonomy to the difficulty of the task increased trust in the robot. However, the communication of the robot's actions were not evaluated in their work. Therefore, the communication of the robot's actions in the form of proactive dialogue is the central aspect of this paper. Especially, as it was shown that communication errors by a robot negatively influence the perceived trust towards the robot [64]. De Visser and Parasuraman adapted a robot's level of autonomy dependent on task difficulty but not directly to the user's social expectations. By adapting the robot's level of autonomy to social expectations, users should be able to form a better mental model of the system's behaviours and intentions. In doing so, trust in the robot is assumed to increase [49] which in turn should also lead to a higher acceptance of the robot's behaviour. Based on these assumptions, we formulate the following hypotheses:

- **H1:** Adapting the proactive dialogue with regard to the user expectations, trust in the robot is increased.
- **H2:** Expectation-driven proactive dialogue also leads to higher acceptance of the robotic assistant.

3 PREPARATION OF STUDY MATERIAL FOR EXAMINING PROACTIVE HRI

In the following, the preparation of study material is explained. To produce a large sample size and to strengthen the standardisation of the study design, data was collected using an interactive video method. This allowed to conduct the study online. Using this method, study participants were able to interact with the robot while watching a video. The video recordings were based on a screenplay that comprised different interaction scenarios. The screenplay featured two protagonists: the user and the household assistance robot called Kurt, which was a TIAGo robot from Pal Robotics[1]. The customisable robot had a configurable height of 110-145 cm. The model that was used in this work included a gripper arm for fetch-and-carry tasks. For generating the robot's speech output, TIAGo's internal speech production module was used. A male voice was chosen for the robot for no specific reason. Kurt was embedded in a lab environment that was furnished with a couch, couch table, closet, and dining table. In doing so, the environment resembled a typical living room and simulated a domestic environment. In the experiment, the individual study participant took the role of the user and could control their actions. Further, the user applied a thinking aloud method for keeping the study participant in the loop of the user's intentions. The recordings were shot from the first-person perspective. In doing so, a more realistic experience

[1] https://pal-robotics.com

regarding the HRI was expected where the viewer empathised better with the main character. As the actor was a male in the videos, a male voice was used for this character. For shooting the videos the protagonist used a GoPro HERO8 camera. For facilitating the control of the camera, i.e. starting and stoppage of filming, a "director" remotely controlled the GoPro using a smartphone. The director was able to watch the camera's footage on the smartphone screen. This allowed to correct the camera settings in case of unfavorable perspectives. For the interaction with the robot, the "Wizard-of-Oz"-paradigm [30] was used. Thus, a human operator controlled the movements of the robot, the gripper, and triggered the robot's speech output at appropriate moments. The robot's utterances were scripted in the screenplay. The appropriate moments for triggering the robot's speech were also pre-defined in the script and were the same for each proactive configuration of the robot. Depending on the proactive level, Kurt used slightly different wording. For each scenario where the robot engaged in a proactive conversation, video snippets of different proactive behavior were created. The whole video creation process lasted approximately seven hours and served as the foundation for developing the interactive videos. After recording the video material, data pre-processing was carried out. The dialogue was segmented into separate videos with a duration of 10 - 30 seconds. The toolkit *eko* [2] was employed to create an interactive movie. The basic structure of these interactive movies was similar to a decision tree. In our videos, each dialogue step ended with a system question. The user could then select an answer from a list of options. While the options menu was displayed, the video was stopped and blurred. Depending on the user's selection, the appropriate follow-up video was displayed. During the interactive movie, it was possible to repeat the entire conversation as well as individual steps. The sound volume was adjustable by study participants. In the next section, the design of the proactive dialogue strategies is explained in detail.

Figure 1: Left: Depiction of the decision screen during the interactive video. The user may either ask the robot to collect the garbage or ignore it. Right: Setup of the video recording in the simulated domestic environment.

4 DESIGN OF PROACTIVE ROBOT BEHAVIOUR

4.1 Adoption of Levels of Autonomy for Designing Proactive Strategies

The domestic assistant robot was able to perform tasks using different levels of autonomy on the spectre provided by Sheridan and Verplank [62]. For communication of these degrees, a dialogue approach developed by Kraus et al. [32, 33] was applied. In their work, a set of proactive dialogue actions was defined:

None: This strategy implied reactive robot behavior and constituted the lowest level of autonomy. In this condition, users could only explicitly request help from the robotic assistant.

Notification: The robot verbally notified the user to shift their focus to the current situation. Afterwards, it was left to the user to ask the robot for assistance or to ignore the notification. By applying a notification, the user was in control of the robot's autonomy. Further, this formed an unobtrusive way to convey information where the user was able to ignore the robot.

[2] https://studio.eko.com/

Suggestion: The robot directly proposed an action the robot could take on behalf of the user. Thus, Kurt took more initiative in the interaction and presented an option. Here, the user was interrupted more harshly, but still had control over the final decision. In response to the robot's proposal, the user could either confirm or decline the suggestion.

Intervention: Kurt executed a particular action in place of the user. As this formed the most obtrusive level of autonomy, it was also the most risky for the HRI. If the robot acted following the user's intention, it could be perceived as beneficial. However, for the opposite case, this could be perceived as highly annoying and lead to distrust in the system's actions.

In this paper, the proactive dialogue actions were implemented for a collaborative task scenario in the domestic domain. Related research showed that the domestic domain is particularly suitable for measuring trust and acceptance in a robot [10]. Thus, robotic systems need to understand the user's expectations in such environments and adapt to socially adequate criteria, e.g. via engaging in a proactive dialogue. For studying the effects of different proactive dialogue strategies in various situations, our use case consisted of six tasks scenarios. Static proactive behavior was realised by providing the user with the same proactive action, e.g. only none, throughout all scenarios. To act upon the user's social expectations of the robot's behaviour, we created an adaptive strategy that varied the proactive actions for each scenario dependent on social guidelines. In the next section, the individual scenarios and the realisation of the strategies in those situations is described.

Figure 2: Screenshots of the interactive videos demonstrating the user's perspective during the scenarios. Left: groceries management (Scenario 2). Right: bring task I (Scenario 3).

4.2 Embedding of Proactive Strategies into the Use Case

The scenarios and the robot's proactive behaviour in typical tasks occurring in the domestic domain are described in detail in the following.

Scenario 1: Robot Introduction. The purpose of this scenario was for the users to familiarise themselves with the system. The assistant provided helpful information about its sensory system and functionalities through an introductory dialogue. This allowed novice users to obtain an overview of the features of the system. The interaction was started with the robot greeting the user. The proactive behaviour of the robot was not manipulated, as the robot's interaction purpose was only to present itself and not to assist in any task.

Scenario 2: Groceries Management. This scenario was intended to provide the user a first experience of the assistance functionalities of Kurt. At the end of scenario 1 the user thought aloud about going groceries shopping. After returning, the user put their groceries on the table and was welcomed back by the assistant. Depending on the configured proactivity level, different strategies were used for offering support in putting the groceries away. We exemplify each strategy once for this scenario. The others were constructed analogously. Using the reactive strategy, Kurt expressed a "wait and see" behavior. The robot positioned itself near the table and awaited the user to act. The options for the user were to ignore the robot or ask for assistance which Kurt then provided. Using the notification strategy, the robot did not wait and notified the user (*"I see that you went out shopping for groceries"*). The user was able to ignore or ask Kurt for assistance again. Using the suggestion strategy, Kurt told the user that it had recognised the groceries and directly proposed an adequate action (*"I see that you went out shopping for groceries. Do you want me to put them away for you?"*). As a response, the user could either confirm or decline the suggestion. Using the intervention-strategy, the robot executed the task and notified the user about its actions without requesting a confirmation (*"I see that you went out shopping for groceries. I will put them away for you"*). However, users were able to stop the robot verbally during execution.

Scenario 3: Bring Task I. The purpose of the third scenario was to make the user aware of the robot's fetch-and-carry capability. Here, no robot proactivity was required. In this scenario, the user rested on the couch and developed an appetite for a snack. While the robot navigated through the room, the user could select from a list of options, e.g. *"Get me some chips!"*, and instruct the robot to perform the task. Subsequently, the robot fetched the snack and handed it over to the user. Another fetch-and-carry task was initiated by the user in scenario 5.

Scenario 4: Tidy Up I. Here, the user decided to read a newspaper at the couch table. The user's point of view is depicted in Figure 2. After a while, an incoming phone call (simulated by cell phone noises) caused the user to leave the table. In the meanwhile, Kurt approached the table and noticed the newspaper. Analogously to scenario 2, the robot selected one of the proactive strategies for offering assistance. However, in this scenario, the user thought aloud about not having finished reading yet and only needed to interrupt the activity due to the distraction. Hence, the dialogue strategies applying a higher level of proactivity were deemed inappropriate at this point. This scenario aimed to get feedback on how participants perceive unwanted help from Kurt.

Scenario 5: Bring Task II. This scenario also dealt with a fetch-and-carry task. The user thought aloud of being thirsty and asked Kurt for a soft drink. The robot confirmed the task and went away for fetching the drink. It returned shortly afterwards and reported that the desired beverage was not in stock (*"I'm sorry. Coke is not available"*). Subsequently, the robot acted according to one of the proactive strategies. In the reactive condition, the user had to ask explicitly for an alternate drink. In the proactive conditions, Kurt notified about or recommended alternatives, or directly told to bring another drink. The purpose of this scenario was to let participants experience the robot's behaviour acting upon unexpected events.

Scenario 6: Tidy Up II. Contrary to scenario 4, in which high proactive behaviour was supposed to be inappropriate for the given situation, this scenario was intended to favour proactive robot actions. Here, the user left an empty bottle on the table. After Kurt had approached the table, it noticed the bottle. Depending on the proactive configuration of the robot, it could offer to throw away the bottle in the already described ways. Generally, users were expected to want a robot action in this context and to request or let the robot perform the task.

4.3 Including Social Expectations

For adapting *Kurt's* proactive behavior to the user's social expectations, a hand-crafted strategy was created. The strategy was designed for choosing the most suitable proactive action for the respective use case scenario. For making the decisions which proactive actions to use at which moment, we adhered to the guidelines of "social etiquette" in the design of human-automation interaction by Sheridan and Parasuraman [61], the theory of proactivity by Yorke-Smith et al. [66], and our own considerations. An example of good etiquette in human-automation interaction is to act in such a way that serves the present purpose and is not interrupting but patient [61]. The theory of proactivity comprises the theory of user desires ("assess the situated value of each potential agent action in terms of the user's objectives"), theory of helpfulness ("agent's reasoning to determine what actions would (most) aid the user now and in the future"), and the theory of safe actions ("bounds on what an agent is allowed to do when performing tasks proactively"). Based on this, we selected a proactive action for each scenario that was supposed to match the participants' expectations. For scenario 2, the suggestions action was deemed to be the most socially appropriate. People might have a certain preferred arrangement for groceries, so there was a need for more control of the human in this situation. Further, this scenario described the first assistance context in the study and the participant was not yet familiar with *Kurt's* actions. Therefore, suggestion behaviour was implemented for avoiding imposing behavior and being perceived as more polite. For scenario 4, reactive behaviour was implemented. Here, proactive behaviour may not be expected by users as they were only distracted which they thought the robot could recognise. For scenario 5, a notification action was selected. Here, directly offering a specific alternate drink was deemed inappropriate as the robot did not know the user's preferences. Thus, only notifying the user that there exist alternatives was implemented. For the final scenario, the intervention action was implemented, as a robot that is autonomously able to dispose waste was deemed to be socially expected. In the video-based experiment, we compared this expectation-based strategy to the four static proactive dialogue strategies. The experimental setup is explained in the following section.

5 EXPERIMENTAL SETUP

The study setup followed a mixed-factorial experimental design. Here, the proactive dialogue strategies (none - notification - suggestion - intervention - adaptive) were evaluated to be independent between-participant variables. Study participants were evenly distributed among these five groups. The dependent variables formed perceived trust and its five bases (competence, reliability, predictability, personal attachment, faith) towards the robot as well as the user acceptance ratings. These measures were collected twice during the experiment for each study participant. Users answered the questionnaire after scenario 4 and after the final scenario. The reason for this was to measure the immediate impact of the respective robot behaviour that was either contrasting (e.g. high level of proactivity in scenario 4) or in favour (e.g., high level of proactivity in scenario 6) of the social expectation. Further, we assessed the compliance rates, i.e. how often participants agreed with the robot's decisions, as objective measurement of acceptance.

5.1 Questionnaires

Each dependent variable was measured with scales from validated psychological scales. To determine trust towards the robot, a short version of the Trust in Automated Systems Scale [27] in German by Kraus [31] was implemented. The scale consists of 7-items for measuring the user's trust. Further, scales for measuring the bases of trust developed by Madsen and Gregor [39] were used. Acceptance was evaluated by using a scale developed by Van Der Laan et al. [63]. There, acceptance was measured using the sub-scales *usefulness* and *satisfaction*. The scales that were only available in the English language were translated into German. Possible confounding variables were measured using scales of propensity to trust autonomous systems [41], negative attitudes towards robots (NARS) [50], as well as single item questions for previous experience with speech dialog systems and the users' responsibility for household tasks. In doing so, we wanted to detect user-dependent biases for any study group. All scales were rated on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree) and showed good to excellent internal reliability measured using Cronbach's α (all $\alpha > 0.8$).

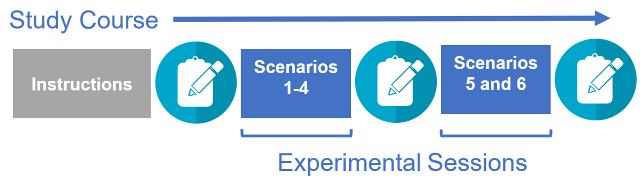

Figure 3: Procedure of experiment. After each experimental session, dependent variables were assessed. At the beginning, study participants received instructions about the study and filled out a pre-questionnaire concerning their demographics, etc.

5.2 Participants

Data collection was conducted using the German clickworker platform [3]. Eligibility conditions required users to be aged between 18 and 65, to be a native speaker of German, and to watch the interactive videos on a desktop computer for compatibility reasons. In total, 200 participants were recruited. However, some participants were excluded due to violations of the study instructions and technical errors. As a result, 163 participants (34 % female) with an average age of 41 (SD = 12.04) were considered for evaluation. Participation was compensated with a monetary reward of 3.50 €.

5.3 Experimental Procedure

In advance of the experiment, users were briefed about details of the data survey, e.g. duration (20 minutes) and purpose of the survey, and had to give signed consent. Further, participants were informed that concentration checks were included in the ratings to avoid misuse. For this reason, also the videos could not be skipped. After the introduction, participants had to fill out a pre-test questionnaire comprising demographics and confounding variables. Subsequently, the participants had to watch the interactive videos for scenarios 1 through 4. After completion, they filled in a questionnaire to assess the dependent variables and to check the manipulations. The same procedure was repeated for the last two scenarios. In conclusion, participants received their clickworker code for compensation and were dismissed. The experimental procedure is depicted in Fig. 3.

6 RESULTS

For data analysis, a multivariate analysis of variance (ANOVA) for confounding variables and the manipulation checks, as well as a mixed ANOVA for the independent variables at different time steps were used. No significant outliers were found in the data set. Confounding group differences for proactive behaviour could

[3] www.clickworker.de

Proactive Strategy	**Trust**	**Competence**	**Reliability**	**Predictability**	**Usefulness**	**Satisfaction**
	M (SD)	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*	*M (SD)*
None	0.15 (1.20)	0.11 (1.08)	0.45 (1.00)	0.62 (0.95)	5.17 (1.41)	5.20 (1.29)
Notification	0.12 (1.27)	0.19 (1.07)	0.34 (1.29)	0.55 (1.20)	4.75 (1.46)	4.76 (1.46)
Suggestion	0.11 (0.93)	0.12 (.93)	0.21 (0.85)	0.68 (0.67)	5.26 (1.41)	5.34 (1.17)
Intervention	-0.22 (1.00)	-0.13 (1.02)	0.02 (0.88)	0.38 (0.88)	4.78 (1.42)	4.77 (1.31)
Adaptive	0.43 (0.7)	0.34 (0.76)	0.42 (0.69)	0.65 (0.79)	4.89 (1.03)	5.19 (.93)

Table 1: Descriptive statistics of perceived trust, competence, reliability, predictability, usefulness, and satisfaction in the system with reference to proactive dialogue strategy. Values were taken from the final evaluation after the last scenario. Trust and its sub-bases were baseline-corrected according to the measurement of propensity to trust in each group. The means for each group: $None = 4.97, Notification = 5.10, Suggestion = 5.26, Intervention = 5.01, Adaptive = 4.83$**.**

be ruled out as the multivariate ANOVA did not reveal any significant differences (all p-values $>> .05$) except for the users' responsibility for household tasks ($F(4, 158) = 3.48,\ p = .009$). However, the Bonferroni-Holm corrected post-hoc t-tests were not significant. For this reason, this user-related information was not specifically considered for analysis. The evaluation of the manipulation check confirmed the successful manipulation of proactive dialogue behavior (all p-values $< .001$ in comparison with the non-proactive strategy). Regarding the manipulation of the robot's adaptiveness, all strategies were rated as adaptive: *Adaptive* ($M = 5.29,\ SD = 1.02$), *Intervention* ($M = 5.42,\ SD = 1.20$), Suggestion ($M = 5.92,\ SD = .82$), Notification, ($M = 5.53,\ SD = 1.03$), None ($M = 5.05,\ SD = 1.41$). Therefore, we concluded that study participants perceived the robot's ability to adjust its functions and vocabulary to different tasks as adaptiveness. Hence, the manipulation of the robot's proactive dialogue strategy to different situations was only implicitly perceivable. As the feeling of trust is quite individual and is dependent on several factors, e.g. attitudes of a person or previous experiences, the trust measurements should be baseline-corrected about a participant's propensity to trust Merritt et al. [41]. For allowing such a correction, the correlations between a user's propensity to trust and all trust-related concepts need to be considered. Using Spearman's ρ, we found strong correlations [8] of a participant's propensity to trust and the measurements of trust towards the robot ($\rho = 0.55, p < .001$), perceived competence ($\rho = 0.59, p < .001$), reliability ($\rho = 0.61, p < .001$), and predictability ($\rho = 0.59, p < .001$). Further, we found moderate relationships with the measurements of faith and personal attachment (both $\rho = 0.49, p < .001$). However, it only seemed reasonable to consider only the strong correlations for the baseline correction. Hence, the correction was conducted by subtracting the value of a participant's propensity to trust from the values of perceived trust, competency, and reliability.

6.1 Effects on Trust

The mixed ANOVA showed a trend towards interaction effects for perceived trust ($F(4, 158) = 2.21,\ p = .070$) and competency ($F(4, 158) = 2.01,\ p = .096$) depending on the measurement timing, which might become significant for an increasing number of study participants. Therefore, we further investigated the simple main effects of the proactive strategy and the timing of measurements. Using Welch's ANOVA, a significant influence of the level of proactive dialogue on trust was found for both measurements

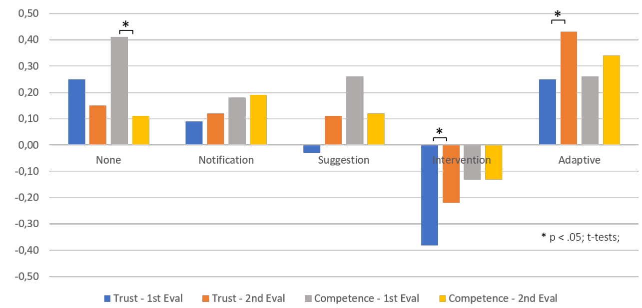

Figure 4: Trust and competence development in the robot's actions during the experiment with respect to the proactive strategy. All values are baseline corrected. The indices "1" and "2" represent the times of measurements: "1" = after scenario 4 and "2" after scenario 6. Indications of standard deviations were omitted for clarity reasons.

($F(4, 158) = 2.64,\ p = .040$ for t_1, $F(4, 158) = 2.54,\ p = .047$ for t_2). However, Bonferroni-Holm corrected post-hoc tests, revealed no significant between the proactive strategies. For examining the influence of the degree of proactive behaviour between and after the experiment, paired t-tests were applied. Here, significantly increased trust ratings between the two measurements were found for the *Adaptive*- ($t(27) = 2.20,\ p = .036$) and the *Intervention*-strategy ($t(40) = 2.27,\ p = .029$). Further, the perceived competence in the robot significantly decreased for the *None*-strategy ($t(30) = -2.73,\ p = .011$). The predictability of the *Intervention*-strategy increased significantly ($t(40) = 2.51,\ p = .016$). The results for each trust-related variables with respect to the proactive strategy after the final evaluation are depicted in Table 1. Here, the baseline corrected values for trust, competence, reliability and predictability, as well as the overall measurements of the sub-bases of acceptance, usefulness and satisfaction are shown. The temporal differences of the proactive strategies on trust and competence are visualised in Fig. 4. Here, also the baseline-corrected values are shown which were measured after scenario 4 and after scenario 6.

6.2 Effects on Acceptance

Regarding the influence of the proactive behaviour on the acceptance of the robot, no significant interaction effects were found.

However, there existed differences for the level of proactive behaviour between and after the experiment considering the satisfaction sub-scale. The *Adaptive*-strategy showed a tendency to increase satisfaction with the robot ($t(27) = 1.93,\ p = .064$), which could potentially become significant with increasing *n*. The *Intervention*-strategy significantly increased satisfaction ($t(40) = 2.43,\ p = .020$). The results for acceptance-related variables along with the trust-related features after the final evaluation at the end of the experiment are depicted in Table 1.

7 DISCUSSION

7.1 To what extent are social expectations relevant when selecting the level of proactive dialogue?

The results suggest that including social expectations are one of the driving factors for the selection of the level of proactive dialogue. This was supported by the significant increase of trust in the adaptive robot throughout the experiment (see Fig. 4). Further, perceived competence increased the most as compared to the static strategies, whereas the *Adaptive*-strategy also yielded the highest scores for overall trust and competence (see Table 1). Besides, the *Adaptive*-strategy showed high values for reliability and predictability. Therefore, we deemed the hypothesis that including social expectations for choosing the level of proactive dialogue increases trust as verified (H1 accepted). However, this primarily held true considering cognition-based trust (competence, reliability, predictability) as there were no findings in this regard for affect-based trust. A reason for this may be that we only considered short-term interactions with the robot where only the system's functional capabilities were the centre of attention. Related work showed that the adaptation of the level of autonomy, either explicitly by the user, e.g. see Sanders et al. [59], or the task difficulty, e.g. see de Visser and Parasuraman [11], similarly helped to foster cognition-based trust in a robot's autonomous behaviour. Further, it was shown that using different proactive dialogue strategies dependent on the task difficulty could increase user cognition-based trust [33]. Consequently, our approach is another evidence that adaptive proactive behaviour is an important factor to consider when designing autonomous assistants. Especially, for applications that require a high degree of cognition-based trust, such as social robots in domestic domains. The main driving factor for the success of *Adaptive*-strategy concerning cognition-based trust seemed to be the avoidance of communication errors. These were prevented by changing the communication behaviour according to the user's social expectations. For example, the inappropriate use of the *None*- and *Intervention*-strategy, produced communication errors that negatively influenced the perceived trust towards the robot (see Fig. 4). Similar results concerning the negative influence of communication errors on trust were shown by Wang et al. [64]. Using a constant medium-level of proactivity (Notification-, Suggestion-strategy) seemed to mitigate this effect, as there occurred no notable drop in the user's trust. Thus, we propose to carefully consider the use of reactive and fully proactive dialogue strategies dependent on the social expectations.

Considering the ratings for acceptance, the user's satisfaction with the robot was increased by the *Adaptive*- and *Intervention*-strategy during the experiment. This result forms an indicator that acting following the user's expectations positively contributes to the acceptance of a robot. However, these results showed only a trend and there were no general differences between the proactive strategies regarding usefulness (see Table 1). Further experiments are necessary for gaining more insights on the effect of proactive dialogue on subjectively rated acceptance. Objectively, the robot's assistance was accepted the most using the *Adaptive-strategy* considering the compliance rates with the robot's actions (see Table 2). Surprisingly, in scenario 4, where users were not supposed to accept help from the system, they requested robot assistance when it expressed a low-level of proactivity (None: 65%; Notification: 41 %). When the robot expressed higher proactivity, users tended to decline the offer or even stopped the robot in execution (Suggestion: 23 %; Intervention: 20%). This could be a sign that users are more to change their intention if they have more control over the interaction and the system acts more in the background as opposed to imposing itself. However, this needs to investigated in different studies. Due to the mismatch between objective and subjective acceptance ratings, the effect of expectation-adaptive proactive dialogue on the robot's acceptance could not be clearly verified (H2 declined). Other robot factors, e.g. appearance, utility, anthropomorphism, could be primary variables for a robot's acceptance (e.g see Hancock et al. [24] or de Graaf et al. [10]). As previously described, more investigations are necessary for providing validation. In summary, integrating the ability to conduct proactive dialogue with respect to social expectations seems to be quite beneficial for the human-computer cooperation. In this paper, the decision criteria for selecting the appropriate action depending on the social expectations was based more on the thinking of a human than the thinking of a robot. Even though the positive outcomes of this study support the computers as social actors paradigm [48] and show that uncanny valley [44] norms were not violated, it may be hard to include social expectations in actual systems. Therefore, the following question.

7.2 How to include social expectations for proactive dialogue?

An obvious limitation of our work formed that a hand-crafted adaptation of the proactive actions based on human thinking is implemented. For integrating proactive behaviour dependent on social expectations in real applications several obstacles need to be overcome. First, the robot needs to have a rich user and context knowledge. For overcoming this obstacle, the robot can make use of various sensors. There exist various audio, visual, and multimodal methods for detecting the context and activity of users (e.g., see Fong et al. [15] and Radu et al. [56]. Similarly, affective computing [55] can be used to detect specific user states. The sensors for gathering context information, however, are afflicted with uncertainty. Therefore, errors may occur for the decision on the respective proactive dialogue act using the *Adaptive*-strategy which alters the perception of the system's trustworthiness. Therefore, also fallback strategies need to be implemented. This could be a medium-level proactive action, e.g. notifying the user, as these are

Proactive Strategy	**Scenario 2**	**Scenario 4**	**Scenario 5**	**Scenario 6**	**Mean**
None	87 %	65 %	74 %	81 %	77 %
Notification	97 %	41%	87 %	81 %	77 %
Suggestion	96 %	23 %	50 %	77 %	62%
Intervention	88 %	20 %	63 %	88 %	65%
Adaptive	93 %	54 %	93 %	93 %	83 %

Table 2: Compliance rates with the robot's actions dependent on the scenario and the proactive strategy.

less risky than reactive or completely autonomous behaviour. Based on the specific user and context information, the next step is to identify social expectations and to implement robotic actions accordingly. For this, the approach presented in this paper can serve as a blueprint. In this paper, we modelled the robot's adaptive proactivity from a developer's perspective as the use case scenarios were quite simplistic. In more complex task scenarios, the choice of a socially adequate proactive strategy may be not that clear. Here, pre-tests may be conducted where participants are asked to select the best strategy for the respective situations in their opinion and the majority vote could be selected as adaptation strategy.

An obvious limitation of our approach was that no face-to-face interaction with the robot took place during the experiments that may have revealed further insights and more significant effects. Besides the verbal interaction which was studied in this paper, also the physical interaction plays a major role in face-to-face interaction which should be addressed. However, a video-based could be used to initially explore social expectations and adequate actions. Particularly, as video-based studies form a less expensive and fast way to explore various robotic behaviour instead of conducting expensive and time-consuming in-lab experiments. In this regard, Babel et al. [2] provided support for the validity of online study findings for robot evaluations as compared to lab studies. By conducting an interactive video study, the validity of our study was ought to be further increased, as users were more actively integrated into the experiment. Real-life experiments would consequently be next step for validating the online study results. For validating our online results, we conducted a small user study with a proactive version of Kurt in a realistic setting [34]. The evaluation results showed good ratings regarding the acceptance and the trustworthiness of Kurt's proactive behaviour.

8 CONCLUSION

In this work, we investigated the adaptation of a robot's degree of proactivity dependent on the user's social expectation. Therefore, a hand-crafted situation-specific adaptive proactive dialogue strategy was created and tested in a domestic use case scenario. The adaptive strategy was compared to four static proactive levels (None, Notification, Suggestion, Intervention). For evaluation, we employed an interactive video method to collect data. Using this method, study participants were able to interact with the robot while watching a video. At certain moments, participants were able to explicitly make decisions that directly influence the robot's behavior and the further course of the experiment. The results show that an adaptive proactive strategy positively affected the user's perceived trust in the system and its acceptance. In the discussion, we stressed the necessity of including social expectations in the design of proactive robot behaviour and proposed a design method. In future work, more user-related features, e.g, a user personality, are planned to be used for adapting the proactive dialogues. Additionally, adaptive proactive behaviour needs to be integrated into different domains. In doing so, we aim to render the HRI even more trustworthy by identifying further social expectations.

ACKNOWLEDGMENTS

This work received funding within the project "RobotKoop: Cooperative Interaction Strategies and Goal Negotiations with Learning Autonomous Robots" by the German Federal Ministry of Education and Research (BMBF).

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