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Preference Learning for Personalization in Human-Robot Interaction?

Adaptive Robots are Perceived as More Competent and Trustworthy than Adaptable Robots

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Abstract Learning and matching a user's preference is an essential aspect of achieving a productive collaboration in long-term Human-Robot Interaction. However, there are different techniques on how to match the behavior of a robot to a user's preference. The robot can be *adaptable* so that a user can change the robot's behavior to ones need, or the robot can be *adaptive* and autonomously tries to match its behavior towards a user's preference. Both types might lead to the same preference matching results. However, the Level of Automation (LoA) of the robot is different between both methods. Either the user controls the interaction, or the robot is in control. In this paper, we present a study on the effects of these different LoA of a Socially Assistive Robot (SAR) on a user's evaluation of the system in an exercising scenario. We conducted a between-subject design study (*adaptable* robot vs. *adaptive* robot) with 40 subjects. The results show that users evaluate the *adaptive* robots as more competent, warm and report a higher alliance. Moreover, this increased alliance is significantly mediated by the perceived competence of the system. This result provides empirical evidence for the relation between the LoA of a system, the user's perceived competence of the system and the perceived alliance with it.

Keywords

1 Introduction

Future scenarios of socials robots envision a personalizable system that is flexible and adapts itself to the user's preferences [20].Though, building customized systems for each user is seldom feasibilty. Anticipating every potential user type and pre-programing the system for their needs will be an obstacle to deploy robots in household settings that engage the users beyond the exploration phase. Ths, robots will eventually need to have capabilities to adjust to different users profiels (*e.g.*, match a user's personality [1]). Adapting to different users and enhancing the interaction is already successfully implemented in web-based applications (e.g., recommender systems on Amazon, Google, eBay). However, adaptation remains a challenging issue for social robots that is not attached to a user database which could enable techniques like collaborative filtering. Therefore, social robots will face a cold start problem, which requires the system to gather initial user data. Hence, deploying an *adaptive* system comes with some difficulties:

First, querying the user for information in real time Human-Robot Interaction (HRI)might be more costintensive than in web-based applications. Cakmak, Chao, and Thomaz [6] showed that a constant stream of questions in a Learning by Demonstration (LdB) task annoys users.

Second, robots making autonomous personalization decisions could result in diametral effects for the user's HRIexperience satisfaction. Having the robot in control of the interaction personalization could lead to a disuses of the technology. This is plausible either when the systems learns a wrong user profile or when the user preferes to be in control of the interaction [5]. Thus, it is essential to consider whether it also sufficient to just provide an interface for the human to adjust the system's behavior instead of having the robot adapt by itself. This different types of possible personalization strategies would influence the autonomy of the system, which in turn might affect the interaction experience in different ways.

Based on Epley, Waytz, and Cacioppo's theory of anthropomorphization, an autonomous *adaptive* system could create an unexpected experience for the user [10]. This unexpected experience could increase a user's perceived anthropomorphization of the robot. Furthermore, this higher degree could enhance the credibility of the system and might influence the trust in it. In contrast, a system that is controlled and adjusted by the user should increase the match between the robot's behavior and the user's expectation and therefore reduce anthropomorphic effects. The investigation of these two aspects is the core of this work. We try to find an answer to the question:

Research Question What effects have different types of a robot's personlization methods on the user's perceived acceptance, trust in the alliance and motivation to interact with the system?

To investigate the effects of different preference matching behaviors of the system this work presents a study that compares the impact of having an *adaptive* robot or an *adaptable* robot as an exercising partner for physical activities. Previous work on robots for exercising and coaching have investigated the motivational effects of using such coaching systems [12, 45, 16]. However, most of the previous studies used only one type of exercises (*e.g.*, arm or plank exercises). Thus, the users could not choose between different exercises. In this work, we present a system that offers a range of exercises to the users and raise the question of what is a suitable preference matching framework to provide a personalized interaction for the user. Therefore, in the *adaptive* condition, the robot proposes different activities for the user and tries to learn an exercising category preference of the user based on preference feedback. In the *adaptable* condition, the robot is directly controlled by the user, and the user can always decide what kind of exercises they want to do together with the robot.

1.1 Objectives and Contribution

To summarize, this paper has two major objectives. The first objective is to test a preference learning (*i.e.*, k-armed Dueling Bandit Learning) approach suitable for online interaction that is novel for the HRIcommunity and test the feasibility in a realistic use case study in comparison to a user-controlled adjustment method. The second objective is to investigate how the different type of personalization methods influence the user's evaluation of the system. We show that k-armed Dueling Bandit Problem is a suitable approach for online preference learning in HRI. Moreover, we provide evidence that the alliance to an adaptive robotic exercising partner is perceived as more trustworthy and that this is mediated by the perceived higher competence of the system.

1.2 Organization

The difference between *adaptive* and *adaptable* robots will be explained in section 2 along with the concepts of automation and relationship, which might be important variables when looking at the adaptivity of a system. section 3 introduces the system design and 4 explains the study design to test the effects of a robot's different personalization mechanisms. 5 presents the results of the study, which are discussed in **??**. Finally, 8 gives a conclusion of this work.

2 Adaptation, Automation and Alliance

This section gives a brief introduction into the concepts of adaptation, automation and alliance. Discussing these topics is a challenging task because they are used differently across disciplines (*e.g.*, philosophy, psychology, economics, biology). Therefore, the following explanations can not be exhaustive and will focus mainly on a computer science and psychology perspective.

2.1 Adaptation: adaptivity versus adaptability

In computer science adaptation referes to the informative-based process of adjusting the behavior of an interactive system to meet the need of individual users [43]. Even though computer software or robots are running through many software design cycles, it is hard to anticipate the requirements for every possible user. The goal of the *adaptive* process is to minimize the discrepancy between the user needs and system behavior after the deployment. This *adaptive* process can either be automatically initiated by the system, in this case, the system is *adaptive* (*e.g.*, the system chooses exercises for the users by itself), or users can adjust the system by themselves, in this case the system is *adaptable* (*e.g.*, the users can choose the exercises by themselves). Adaptation can be based on different user profiles (*e.g.*, age, gender, personality), various times (*e.g.*, morning/evening, days of the week, summer/winter) or other user characteristics (*e.g.*, mood, expertise over time).

Previous work in HRIinvestigated the implementation of *adaptive* processes to match a user's personality,

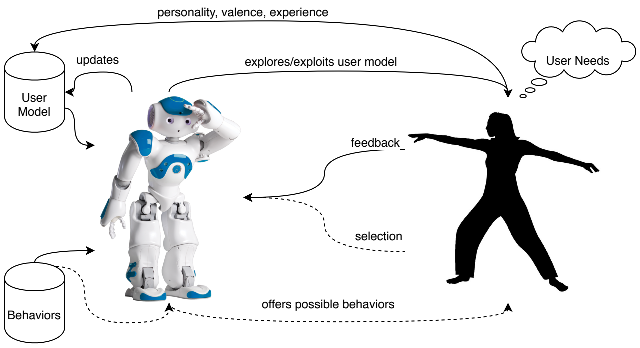

Fig. 1: The adaptable system (dashed lines) comes with a set of behaviors it can offer to the user. The user selects her/his preferred behavior and the system performs the action. The adaptive system (solid lines) explores which behavior is preferred by the user by querying prefernce feedback. The system updates it's user model and can exploit the obtained information over time. Alternatively, the system can also make stereotypical predictions based on the user personality, as well as the valence or exerperience of the user.

generate empathic behavior, adapt therapy sessions, interaction distance, linguistic style or puzzle skills. [47, 26, 48, 31, 39, 27, 18]. The results of these works show show an improvement in task performance based on personalized lessons or user personality matching [47, 27, 18]. Additionally, providing adaptive empathic impact also improved user engagement [26]. Other works present evidence for the feasability of certain adaptation algorithms (*e.g.*, [31]). Overall, there is evidence adaptive personalization is a crucial capability for robots. Though, there are still many open issues that future works need to target. For example, what are the best objectives for the robot to adapt to? How can the system adapt when the objective are not evident? Should the adaptation process be communicated and transparent and who should be in control of the adaptation process?

Although some have compared *adaptive* robots with experimental baseline control conditions (*e.g.*, [26, 27]), to the best of our knowledge, no investigation looked at the effects of robot-initiated personalization versus user-initiated personalization. It is reasonable to argue that the users could control and adjust the robot behavior to their preferences. Leyzberg et al. [27], for example, investigated the effects of a robot that gives personalized lessons to the user. These tutorials are selected by the robot's decisions. However, also the user could have requested for a specific lesson.

Both strategies might match a user's preference and increase the interaction satisfaction, but the underlying difference in decision making is fundamental. One can interpret the different strategies as either more transparent or as more competent. Generally, the question of whether to build an *adaptive* or *adaptable* system raises the concern of who is in control and how does it affect the interaction experience. The issue of who is in control is, in general, associated with the LoA of the system.

2.2 Level of Automation

An autonomous agent acts based on the information it receives from its sensors, knows in which state it is and makes a decision accordingly which is associated with an agent's action [see 41, ch. 1]. LoA of a system changes an agent's capability to act and react based on information on its own without any other external control instances. Thus, the LoA of an agent is altered by the task and environment of the agent and whether a human can interfere with an agent's control loop.

It becomes essential were robots are carrying out delicate tasks (*e.g.*, lethal autonomous weapons). There are various frameworks that can be used to identifiy the LoA of a system (*e.g.*,[46, 9]). However, most recently, [2] have proposed a taxonomy to classify the level of robot autonomy for HRI.

Regardless of the exact different LoA, systems can be categorized as human-in-the-loop systems where the human has to approve a control decision by the autonomous agents, human-on-the-loop where the human is informed about decision but the agent would carry out a decision if the human operator is not interfering or human-off-the-loop, where a human cannot interfere with the agent's decisions[1].

The relevance to consider different LoA are apparent in sensible domains such as military operations or medical applications (*e.g.*, surgery or medicine dispenser), but (yet) less apparent in socially assistive domains (*e.g.*, rehabilitation or teaching). Nevertheless, also social situations will require to understand whether a social robot should act autonomously, semi-self controlled or is in full human control. For the interaction experience it will be crucial to understand the effects of different LoA. In the course of this work, we are interested in the effects of whether a robot exercising companion is in control to choose the exercises or the users can decide which exercises they want to do. The question of whether the LoA is appropriate and which effects it will have on the interaction will be related to the rela-

[1] Earliest examples of hands-off-the-loop agents are land and naval mines.

tionship and trust between the users and the Socially Assistive Robot (SAR) [2].

2.3 Alliance

The impact of trust in alliance between a user and a robot has recently been investigated in use cases in which a robot shows a faulty behavior, gives explanations for actions, or varies the degree of expressivity and vulnerability [42, 40, 49, 29] Besides these aspects, it is significantly related to whether humans trust a robot's capabilities if the systems has, for example, a high LoA and makes autonomous decisions. [13].

Trust is defined in Human-Computer Interaction (HCI) as "the extent to which a user is confident in and willing to act by, the recommendations, actions, and decisions of an artificially intelligent decision aid" [30, p. 25]. As Madsen et al. [28] state, this definition "encompasses both the user's confidence in the system and their willingness to act on the system's decision and advice" [28, p. 1]. Thus, it already incorporates a notion of user trust regarding the willingness to take a system's recommendations into account.

To understand how trust influences HRI, Hancock et al. [17] reviewed different applications where confidence is an essential factor when robots and humans are working together in a team. They state that it is a crucial aspect of industry, space or warfare applications. Additionally, trust will also be essential to understanding social tasks due to the rise of SAR for rehabilitative, therapeutic or educational tasks [22, 12]. Hancock et al. found several factors influencing trust in HRI, which are related to the human, the robot, and the environment. However, the robot related factors were the most important ones in their meta-review. They found that essential factors influencing the associated trust are the human's perception of the system's behavior, adaptability, competence, and performance [17]. Considering how different types of personalization change the LoA and how this might alter the perceived trust, we question how the manipulation of the LoA (for example how the system adapts or can be adapted) influences the associated competence and the perceived confidence in the system.

Rau, Li, and Liu [37] investigated the influence of a social robot's LoA on the user's trust in the Human-Robot Alliance (HRA) based on the robot's decision making. They manipulated the robot's LoA by either giving the human the possibility to make a team decision and the robot could suggest a different decision (low autonomy) or the robot makes the team decision and the human can either reject or accept this decision (high autonomy). They hypothesized that a highly autonomous robot would increase the associated trust. Their results show the influence of an autonomous robot on human's decision making, but in contrast to the hypothesis, people rated that they trust the low autonomous robot more.

Other works investigated how perceived anthropomorphization influenced perceived trust in autonomous vehicles [50]. Waytz et al. [50] found that the degree of anthropomorphization is associated with higher confidence in its competence. This indicates that the perceived level of skill might also influence the related trust. However, there is, to the best of our knowledge, no other works that investigated the influence of a social robot's LoA, based on its decision making capabilities, on the perceived trust in the HRA and competence besides the work of Rau, Li, and Liu [37].

2.4 Hypotheses

Based on the reviewed literature, we found that there is a substantial lack in understanding the effects of adaptive social robots for future HRI scenarios. We found that it is still uncertain which is the best way to personalize the robot's behavior (*i.e.*, should it be in control of the user or the robot). Additionally, it remains also unclear how the different LoA changes the user trust in the HRA and the perceived competence of the system in a social scneario and how these variables are related to each other. To find emperical evidence that can help answer these questions, we derived four hypothesis from previous works.

Due to the robot's initiative and control of the interaction people will be likely to associate the robot with higher competence [17]. Since users do not have to control the robot on their own, the robot creates the impression of proactively deciding on its own, which create unexpected experiences for the user. Based on the theory of Epley, Waytz, and Cacioppo [10], we hypothesize that:

Hypothesis 1 *Users perceive an adaptive robot as more competent than an adaptable robot.*

We hypothesize that this different level of perceived competence is associated with the perceived trust or relationship with the agent.

Even though research from Rau, Li, and Liu [37] did not show any significant effects on perceived trust in HRA depending on the LoA, we still hypothesize that the LoA will affect the associated trust. It is likely that the previous research did not find an effect on the trust because the robot was only a marginal partner that was not important for the task. Instead in our work, the robot is not just a member of the team but also an instructor and exercising partner. Therefore, the trust in alliance will be an essential feature for the relationship between the user and the robot.

Hypothesis 2 *The relationship to an adaptive robot is rated better than to an adaptable robot.*

Since we hypothesize that the participants in the conditions will perceive both the competence and trust differently, it is plausible to argue that the perceived competence and trust will be somehow correlated. Based on the review on trust in HRI, one can argue that users will more likely trust a system that is perceived by the users as competent [17]. Thus, we hypothesize that:

Hypothesis 3 *The associated trust in HRA between the conditions is significantly mediated by the perceived competence of the system.*

Additionally, low trust is often associated with the misuse or disuse of an autonomous robot [2]. Previous works hypothesized that if the people do not trust a robot, they stop using it. This trust in the competence of an interaction partner to achieve the desired goal is also highly critical between a client and a therapist [19]. Perceived higher competence increases the trust in the relationship to achieve a common goal. Thus, if people do not feel the competence in the relationship to achieve a common goal, they do not trust the therapist and are more likely to stop the therapy or intervention.

Thus, we draw our final hypothesis for this work:

Hypothesis 4 *An adaptive robot increases the participant's motivation to engage in a second interaction compared to an adaptable robot.*

To investigate these hypothesis, we present in the following a system and study design that incoporates two different adaptation strategies in a exercising scenario.

3 System Design

Figure 2 shows a highlevel view of the system and interaction flow. The system consists of different components that communicate in a distributed system. The composiiont includes a database of different exercises for Nao, a session controler monitoring the exercises of the user and executing the robot's behavior, a simple computer vision system using a 3D depth sensor to analyse the skeleton of the user, a position controller for the robot as well as a preference learning algorithm. The system and decision components are implemented using the framework presented in [44].

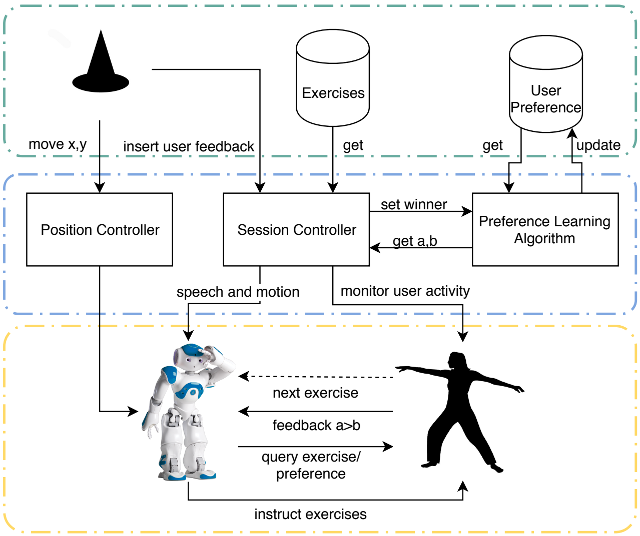

Fig. 2: System and interaction overview for the *adaptive* robot condition.

3.1 Ecercise Database

As previously found, exercising preference is individual for each person [38]. Thus, for the aim of this study, we developed a system that provides a variety of different exercises. We have chosen 25 exercises in total from 5 different categories: strength, stretch, cardio, Taichi, and meditation. This set of exercises tackles one of the open issues in SARs for exercising tasks. Previous work often looked at a single type of exercises like arm movements [11, 12, 16]. The approach of using a spectrum of different exercises might show that people can perform various exercises together with a robot.

1 presents the list of the chosen exercises. They have been selected based on a variety of criteria: a) the possibility to animate and execute them on Nao (*i.e.*, Nao cannot jump.), b) the difficulty that users can perform them (*i.e.*, exercises should not be too challenging for the participants), c) the exercises should challenge the full embodiment of the robot (*i.e.*, laying down, balancing, standing).

Moreover, we limited the set of exercise to five categories and five exercises per category due to two considerations. First, we chose five categories to make sure that the user is presented at least with once with every combination of exercising categories[2]. Second, we chose five exercises per category so that the user's eventually try out some other categories after they start repeating.

[2] *i.e.*, $\binom{5}{2} = 10$. Adding another category would result in $\binom{}{2} = 15$ possible comparisons

All of them have been animated on Nao using Choregraphe [34, 15]. Figure 3 shows an example of a user exercising together with the robot.

Fig. 3: Robot and user performing the Taiji drill *Parting kick* together.

3.2 Preference Learning Framework

This section will briefly introduce preference learning as a formal problem from the perspective of the Multi-Armed Bandit problem.

Preference learning is a subfield of machine learning that aims to learn predictive models from previously observed information (*i.e.*, preference information) [14]. In supervised learning, a data set of labeled items with preference information is used to predict preferences for new items or all the other items from a data set. In general, the task for preference learning is concerned with the problem of learning to rank.

There are many different approaches to preference learning. It can be solved using supervised learning, unsupervised learning and also reinforcement learning. Since there exists no particular data set we could use for supervised or unsupervised learning, it is challenging to build a model that can predict preferences from previously observed information. Therefore, we are focusing on how the system can learn an initial preference relation for a given itemset without any prior information (*i.e.*, the cold start problem). Thus, we are trying to solve the preference learning problem using online methods for the Multi-Armed Bandit problem or more precisely Dueling Bandit algorithms [54].

The dueling bandit problem consists of $K(K \geq 2)$ arms, where at each time step $t > 0$ a pair of arms $(\alpha_t^{(1)}, \alpha_t^{(2)})$ is drawn and presented to a user. A noisy comparison result w_t is obtained, where $w_t = 1$ if a user prefers $\alpha_t^{(1)}$ to $\alpha_t^{(2)}$, and $w_t = 2$ otherwise. The distribution of the outcomes is presented by a preference matrix $P = [p_{ij}]_{KxK}$, where p_{ij} is the probability that a user prefers arm i over arm j (*e.g.*,$p_{ij} = P\{i \succ j\}, i, j = 1, 2, .., K$).).

The goal of the preference learning task is, given a set of different actions (*e.g.*, different sport categories), to find the user's preference order for these categories by providing the user two α_i and α_j and update the user preferences based on the selection of the preference between $\alpha_i \succ \alpha_j$ or $\alpha_i \prec \alpha_j$.

Thus, the challenge is to find the user's preference by running an algorithm that balances the exploration (gaining new information) and the exploitation (utilizing the obtained information). In this work, we are using the Double Thompson Sampling (DTS) algorithm presented in [53]. Since there are several implementations to solve the dueling bandit problem we need to answer the question of why we have chosen this specific kind of algorithm.

Two reasons mainly drive this decision, the state of the art algorithms at the time of this study were DTS, RMED and its successor ECW-RMED [25, 24]. Both perform reasonably well regarding their asymptotic behavior. However, at this point, we are not interested in the long-term run of these algorithms but in the initial phase. If one takes a look at the first steps of these algorithms, one can see a significant difference between them that likely influence the HRIexperience. RMED and ECW-RMED both have an initial phase where all possible pairs are repeatedly drawn for some time [25, 24, Algorithm 1]. From an algorithmic perspective this is reasonable, but looking at it from the viewpoint of the interaction, this would lead to systematic comparisons that could result in boredom and even annoyance when the interaction partner is seemingly interrogating the user for her/his preferences. Thus, we assume that the DTS algorithm is more useful for HRI(especially for the initial contact between the trainee and the robot coach), because it does not rely on a systematic comparison of all possible pairs.

3.3 Session Manager: System and Interaction Flow

The system waits for a user to be present in the room. Depending on the distance, it asks the participant to come closer. The system introeduces itself to the user, explains its behavior and asks whether the user wants to start the exercising program. Afterward, in the *adaptive* condition, the algorithm selects two exercises from the database, and Nao instructs the user to do the exercises. Following, it asks the participant which kind of exercises she or he prefers (preference feedback).

Table 1: Used exercises for the presented study.

Strength	Stretch	Cardio	Meditation	Taiji Drills
Push up	Neck	Jumping Jacks	The boat	Golden rooster
Squats	Triceps	Front Lunge	9 breathes	Rainbow
Crunches	Hip	Side Lunge	relaxation	Punch
Superman	Quadriceps	Boxing	Inner light	Parting kick
Bridge	Side	Mnt. Climbers	Piece sign	Lifting water

At the beginning, we used the internal speech recognition of Nao. However, prototype experiments showed that the speech recognition capabilities are below an acceptable recognition rate, therefore we manually inserted the user's feedback using a Wizard of Oz (WoZ) style. Additionally, when Nao performs the exercises, it moves away from the initial position. We have implemented a simple marker based localization strategy. However, the robot needed too long to localize in the room and move to the correct position. Since it is a significant disturbance for the HRIexperience, we also have implemented a WoZ position controller to move the robot to the correct position manually after each exercise.

The primary interaction flow for the *adaptive* conditions is as follows: Based on the current user's preference database the algorithm selects two exercises, then the session manager runs these exercises sequentially. During the exercises, the session manager receives user skeleton information and monitors whether the user is doing the exercises. This exercising information was used to synchronize the exercising speed of the user and the robot. Afterward, the robot asks the user which of the exercises she or he prefers. The wizard listens to the user's feedback using an installed microphone in the experimental room and feeds the user's input back to the session manager. The robot acknowledges the decision by repeating the chosen exercise. The preference learning algorithm updates the user's preference database and selects the next exercises based on the current user preference.

4 Sudy Design

We conducted a study with a between-subject design (*adaptive* robot vs. *adaptable* robot) where participants were randomly assigned to one of two conditions.

4.1 Conditions

adaptive The robot in the adaptivity condition used the algorithm described in [53]. During the introduction phase, the system explains to the user that it will do different exercises together with the user and will ask for preference feedback relating to the different exercises. At each time step, the system selects two exercises based and executed them consecutively with the user. Afterward, the system queries the user for a preference statement. This behavior repeated for 14 exercises (or seven iterations). After the 14 exercises, the system asks whether the user wants to continue exercising for two more exercises or quit the experiment. After the two additional exercises, the robot finishes the interaction. It states the user's learned preferences and thanks for the participation. We limited the additional exercises to two exercises, due to battery concerns and overheating of joints.

adaptable The robot in the adaptability condition did not use any preference learning algorithm and did not select the next exercises autonomously. In the introduction phase, the system explains that it offers different exercises they can do together. The robot verbally listed the possible exercising categories in a randomized order and the user could choose the exercise category she or he wants to experience. Thus, the user was in control of the exercise session and could choose the exercise category she or he prefers. Also in this condition, the human and robot did 14 exercises together, and the robot asked whether the user wants to do two additional exercises.

4.2 Participants

Participants ($N = 40$; average age $M = 26.02$, $SD = 5.48$, 13 female and 7 male in the adaptivity condition; 12 female and 8 male in the adaptability condition) were mostly university students that were acquired by information on the campus and social media. The majority of the participants were naive robot user and had no background in computer engineering or programming.

4.3 Procedure

Participants arrived at the lab individually. First, they had to sign a consent form. Then, the experimenter led the participants to a room where they can change their clothes. Later, they were told to enter the lab and follow the instructions of the system. Until this point, the participants did not know that they will be interacting with a robotic system. We neglected this prior information to not bias the participants or raise false beliefs. Then the participants entered the lab without the experimenter. The interaction happened for approximately 40 minutes, and the experimenter monitored the experiment from a control room. After the interaction finished, participants had to answer a questionnaire and had a voluntary post-study interview. Finally, they were debriefed and received 8 Euros for their participation. The ethical committee of our university approved the procedure.

4.4 Measurements

In this study, we are investigating whether different personalization methods change a user's subjective perception of the robot, the alliance to it and motivation to interact with the system. The following measures were used in this study to find evidence for our presented hypotheses. We used Cronbach's α as a measure for the internal consistency of the scales [8].

Negative Attitudes Towards Robots Attitudes towards robots were measured using the Negative Attitudes towards Robots Scale (NARS, *e.g.*, $\alpha = 0.8$) on a five-point Likert scale [33]. Negative attitudes towards robots could be a confounding factor explaining results obtained on the perception of the robot.

Physical Activity Enjoyment Participants rated their physical training enjoyment using the Physical Activity Enjoyment Scale (PAES, $\alpha = 0.91$) [21]. The average overall item responses calculate the overall enjoyment score.

System Usability System's usability was measured by the System Usability Scale (SUS, $\alpha = 0.84$) with ten items on a 5-point Likert [4].

Team Perception We measured the user's perceived team perception using scales from [32]. These scales measure the general team perception ($\alpha = 0.38$), the openness to suggestions from the team member ($\alpha = 0.94$) and the perceived cooperation ($\alpha = 0.39$). All scales were on a 5 point-based Likert-scale.

Perception of the Partner Participants were asked to rate the perception of the robot on the Robotic Social Attribute Scale (RoSAS). This scale includes the perceived warmth ($\alpha = 0.85$), competence ($\alpha = 0.77$) and discomfort ($\alpha = 0.76$) on a 9 point-based Likert-scale [7].

Motivation To have an additional measure to see whether people are interested in exercising a second time with the robot, we let the participants opt-in for voluntarily exercising with the robot again without monetary compensation. Participants were asked at the end of the questionnaire to enter their email address if they want to exercise again in the following week.

Trust in Alliance Finally, we used the Working Alliance Inventory (WAI), $\alpha = 0.91$, as a measure commonly used in helping alliances to assess trust and belief in a common goal of helping that a therapist, clinician or coach has for another [19]. This measure has recently been used in HCI and HRIstudies for assessing the alliance and trust between the human and a SAR [3, 23].

5 Quantitative Results

Data were analyzed using the statistical computing language R [36]. We tested the data for normality assumptions and used Welch's two-sample t-test if the data meet the criteria and Wilcoxon rank sum test respectively [51, 52]. To increase reproducible science, we will publish, on acceptance of this paper, the data and scripts for the analysis on Github.

Manipulation Check The data was checked for differences in the participant's previous experience with technology, their average weekly exercising activity, personality, physical activity enjoyment (PAES) and the attitudes towards robots. Previous experience ($W = 146.5$, $p = 0.15$), exercising activity ($W = 237$, $p = .45$), PAES ($W = 164$, $p = .34$, $r =$ -.96), as well as NARS ($t(37.7) = 1.78$, $p = 0.08$) were not significantly different between the conditions.

The general hypothesis unrelated measurements show that participants did not evaluate the usability of the systems significantly different, $t(35.56) = 0.95$, $p = .35$, $d = .30$. There was also no significant different evaluation regarding the openness to folow the system's suggestions, $W = 204$, $p = .92$, $r =$ -.10. Participants did not feel significantly more discomfort difference between the conditions, ($W = 210$, $p = .80$, $r =$ -.26.

However, the systems was perceived as more warmth on subscale of the RoSAS scale, $t(36.23) =$ -2.47, p

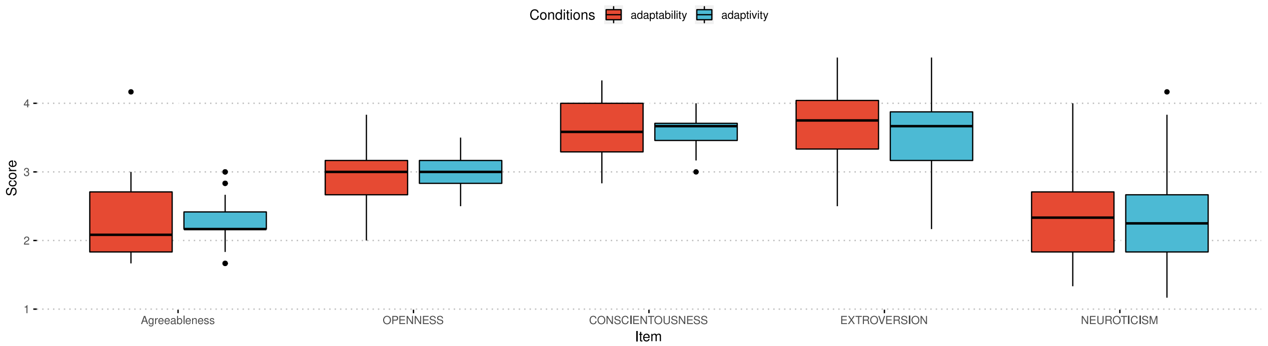

Fig. 4: Boxplot showing the user ratings for perceived cooperation, system usability, physical activity enjoyment, and working alliance.

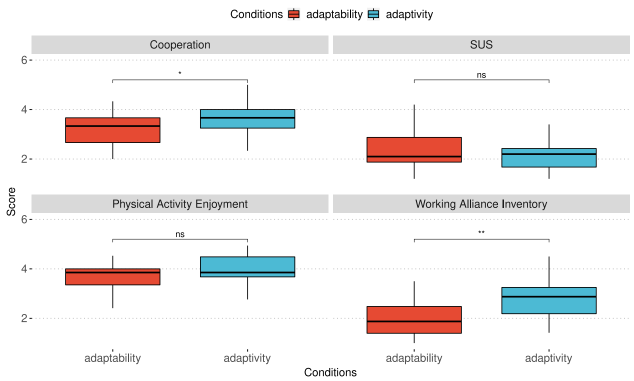

Fig. 5: Boxplot showing the user ratings for perceived cooperation, system usability, physical activity enjoyment, and working alliance.

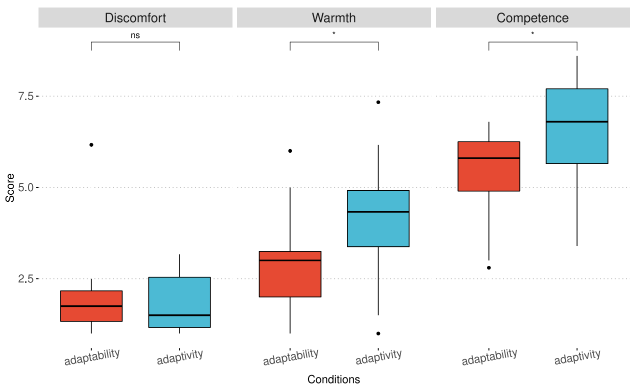

Fig. 6: Boxplot showing the user ratings for the RoSAS.

= .02, d = .78. The *adaptive* system is perceived as warmer (M = 4.08, SD = 1.62) than the *adaptable* system (M = 2.93, SD = 1.29).

Hypothesis 1 We hypothesized that the competence is perceived as higher in the adaptive condition compared to the adaptable condition. A Welch two-sample t-test confirms this hypothesis and shows a significant difference between the conditions, $t(34.55)$ = -2.49, p = .02, d = .79. The *adaptive* system is indeed perceived as more competent (M = 6.55, SD = 1.67) than the *adaptable* system (M = 5.4, SD = 1.2).

Hypothesis 2 We also hypothesized that the user's trust in the HRA is higher in the adaptive condition. The results of the WAI are depicted in Figure 5. A Welch two-sample t-test revealed significant difference between the conditions, $t(36.05)$ = -3.17, p = .003, d = 1.00. The *adaptive* system has been rated significantly higher on the alliance inventory (M = 2.8, SD = .93) than the *adaptable* system (M = 1.99, SD = .76).

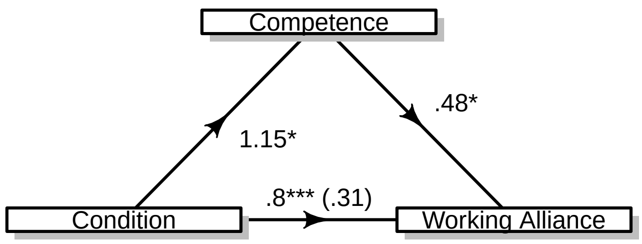

Fig. 7: Standardized regression coefficients for the alliance between conditions and user's alliance with the robot as mediated by the user's perceived competence of the robot. The standardized regression coefficient between the conditions and the WAI, controlling for perceived competence, is in parentheses.

Hypothesis 3 To assess whether the condition's effect on overall alliance was statistically mediated by perceived competence, we used non-parametric bootstrapping method based on the method from [35] and coded condition as adaptability = 0, adaptivity = 1. We tested assumptions for a mediation analyis using the `gvlma` package and used the `mediation` package to do the analysis. This analysis confirmed that perceived competence statistically mediated the alliance between *adaptive* condition and overall trust in the robot (ACME = .48, $p < .05$, 95% CI = .1 to .91; 10,000 resamples; see Figure 7) with no direct effect of autonomy of the system (ADE = .31, $p = .09$) and significant total effect ($p < .001$).

Hypothesis 4 The ratio for participant's wish to voluntarily repeat the interaction is depicted in Figure 9. Pearson's Chi-squared test showed that participants opted more often to exercise again with the *adaptive* condition ($\chi = 4.80$, $d.f. = 1$, $p = .03$). This effect is however not persistent when using Yates' continuity correction ($\chi = 3.33$, $d.f. = 1$, $p = .07$).

5.1 Preference Learning Results

The results for the learned exercising preferences by the system are depicted in Figure 8. The plot shows for each participant in the *adaptive* condition the user's own *ranked* preference set and the *learned* exercising preference from the system. Figure 9 shows the measured differences between the learned rankings and true rankings in a box plot. We highlight three different measurements that are used to compare item rankings. The position distance shows that the difference between the ranked position of the user's most prefered item in relation to the position where the learner has ranked it. The median for this ranking is 0, presenting evidence that for most users the system was able to identifiy the users most preferred exercise after a very short interaction time. This is a promising result, presenting evidence that these kind of learning algorithms indeed seem suitable to decrease the gap between user's preference and the system's behavior. It is important to notice here, that the system was not able to correctly rank the most preferred item. However, it never ranked the user's most preferred item on the last position. The only extreme example where the preference learning did not work out at al was for participant PB2.

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6 Qualitative Results

To better understand how participants felt motivated by the robot and used the personalization mechanism, we conducted semi-structured post-study interviews. After participants finished the questionnaire, we asked them whether they would like to also answer some interview questions. Most of the participants gave, at least, some short responses. We asked the participants whether they felt motivated by the system and why they felt motivated by it. Additionally, we asked participants which strategy they used to select the exercises in the *adaptable* condition. In the *adaptive* condition, we asked participants on which criteria they made their preference selection. The following paragraphs briefly sketch the impressions from the interviews.

Exercising Motivation Six participants in the *adaptable* condition said that the system motivated them to exercise (e.g., *PA14*: Motivating, very nice during static workouts but not so good for cardio). In contrast, five participants stated that the system was not motivating or that they are intrinsically motivated and would not need it, but they would appreciate assistance when they are injured (e.g.,*PA12*:" I don't know. I am intrinsically motivated. For my daily live I would not use it, perhaps if I am injured as a rehabilitation tool.")

Eleven participants in the *adaptive* condition stated that the system would motivate them, while five said that they did not feel motivated by it. Table 2 presents some testimonies of the participants. Participants responded in various way, reflecting their internal heuristic to evaluate whether and why they felt motivated. The responses show that there are great differences in the important featur for each person. Participants felt either motivated by the appearance of the robot, the novelty of guiding them through new exercises, the fact that they do not feel evaluated by a robotic exercising partner, the companionship the robot can provide, as well as the possibility that the robot can quantify their training progress. Participants who stated that they did not feel motivated by the systems gave recommendations and use case suggestions for the system. The primary suggested use case for the system would be as a reminder system, as a partner for rehabilitative exercises or as a partner for people that just started exercising. As interactive suggestions, participants proposed that the robot should be faster and emulate emotions.

Exercise Selection Strategy We asked the participants in both conditions whether they used any strategy to select the next exercise and on which basis they chose their exercising preferences.

In the *adaptable* condition, 10 participants said that they tried to select everything once to see what the system has to offer (*PA8*: "No strategy, I tried to select everything once"). Seven participants selected the

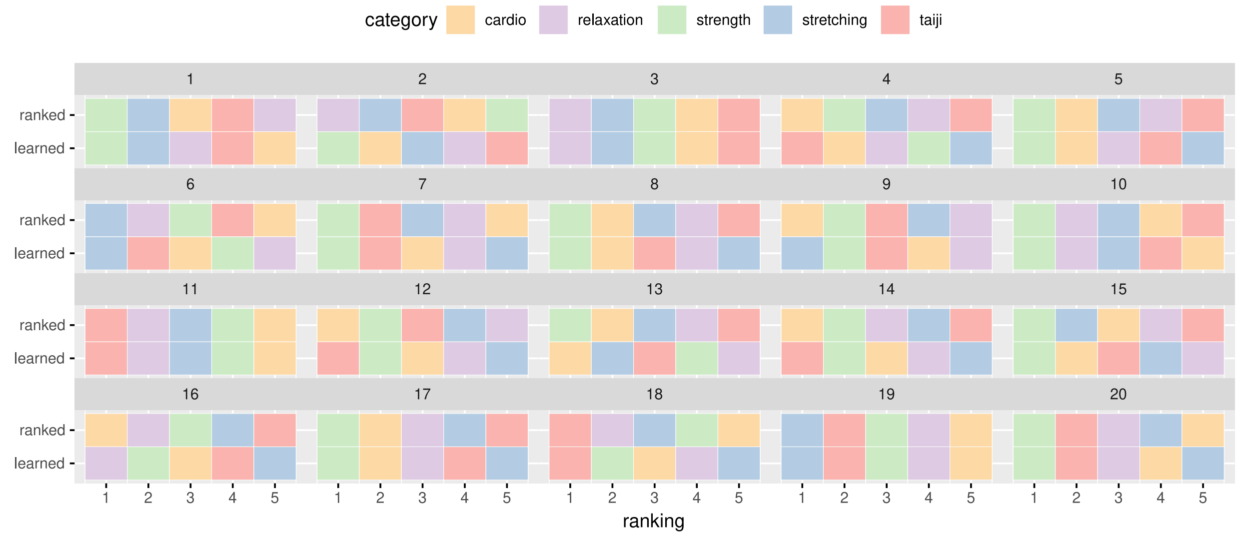

Fig. 8: Individually ranked and learned exercising preference for the different exercising categories .

Table 2: Used exercises for the presented study.

ID	Response	Reason
PB6	”I would motivate a lot of people. For me, I would have to **decide** on my own which exercises we’re doing.”	self-determination
PB7	”It motivated me to **try out** new things.”	novelty
PB9	“The robot was **sweet**, it was enjoyable”	appearance
PB10	“It’s nice when **somebody is around** who shows you the exercises and gives you structure. Especially, when you don’t have much time”	companionship
PB12	“It would motivate me when it is better developed. Currently, I just exercise with videos, it could replace exercising vides when it is more sophisticated. I would prefer it to a human partner or coach. The robot keeps a distance and **does not judge me**, it could feel more uncomfortable with a human partner”	judgement
PB13	“the **appearance** of the robot motivated me to follow its instructions and trust it. If a smartphone would ask me to do some exercises, I would just swipe them away, but a robot motivates me to try out new exercises.”	appearance, embodiment
PB16	“It was more fun, because I was **not alone**”	companionship
PB18	“ I would use it, because I think it’s cool. It would be a nice feature, if it could **track** my performance. I had bad experiences with fitness tracking devices, but a robot could be a companion for everything.”	quantifying
PB19	“Yes it helped me, because I am **not easily intrinsically** motivated”	extrinsical factor

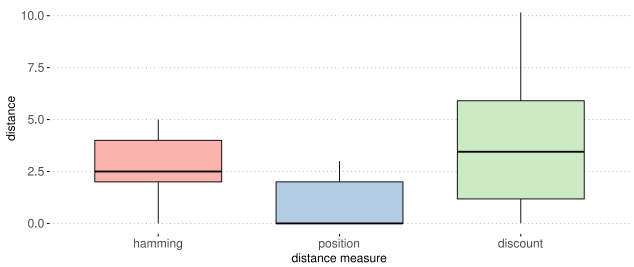

Fig. 9: Hamming, position and discounted distances between the learned and user ranked exercising preferences.

exercises based on their actual exercising preferences (*PA14*: ”I selected everything based on my preference. Therefore, I did not select cardio or relaxation exercises”).

In the *adaptive* condition, ten participants selected the exercises based on their current enjoyment of the exercise (e.g., *PB9*: I thought about what was more fun for me and picked the exercise accordingly), and three selected the activities based on their actual exercising preference (e.g.,*PB18*: I chose the exercises based on my choice).

It is interesting to note that the interview responses show that the different types of personalization strategy lead to different approaches to select the exercises.

While in both conditions, there were participants that chose activities based on their actual preference, participants that did not use a favorite based selection approach used mainly two different kinds of selection criteria. Participants in the *adaptable* condition stated more often than they used their curiosity as selection criteria (e.g., "I wanted to see what the system has to offer"). In contrast, participants in the *adaptable* condition did not state that they used curiosity criteria. Instead, they used enjoyment as the salient criteria for stating their exercising preference.

This presents evidence that people use a different kind of qualitative criteria to maximize their interactive experience. In *adaptable* condition, participants concentrated more on the novelty as an evaluation criterion while in the other condition, participants used their enjoyment as an evaluation criterion. Though maximizing novelty can also be considered as an interaction enjoyment criterion, it is sufficiently different from the actual enjoyment evaluation. Maximizing novelty tries to optimize expected interaction experience in the future, while the other approach only evaluates the current interaction experience.

7 Discussion

This work investigated how a system's type of personalization mechanism based on different LoA alters the user's perception of it. It presented a study to investigate the effects of interacting with an *adaptable* or *adaptive* robot on the perceived alliance and trust with the system and the perceived competence of it depending on different personalization strategies. Thus, it closes a gap in the research literature on the effects of different personalization methods in HRI. The robot in our study was either indirectly controlled by a user's preference feedback or directly controlled by the user. In the case of the *adaptive* condition, we used a preference-learning method from dueling bandits. Thus, the presented study also presents a proof of concept that these kinds of preference learning algorithms might be suitable for preference learning in HRI.

We hypothesized that different LoA alters the perceived competence of the robot and alliance with it. The results present evidence that users perceive the robot as more competent, which is supported by a significant difference between the conditions on the RoSAS subscale. This evidence supports 1: An *adaptive* robot is perceived as more competent than an *adaptable* robot.

The results from the WAI regarding the perceived alliance with the robot also supports the 2: Participants had a stronger partnership with the *adaptive* robot. This result supports the hypothesis that [37] had, but could not find evidence to support it. Participants trusted the robot more if it was more autonomous then less autonomous. This result seems counter-intuitive. Why would the users trust the robot more, when they have less control over the robot. It might be that participants also could have felt overwhelmed by the exercising possibilities they had with the system. Thus, participants might have felt less burden to structure the interaction, because the *adaptive* system made the critical decision. Therefore, the mediation model supports 3 and provides further evidence of why the different conditions affected the perceived alliance. Different LoA influenced the perceived competence of the system which in turn increased the alliance to it.

Other researchers showed that anthropomorphism alters the trust in an autonomous vehicle [50]. Higher anthropomorphism leads to higher confidence in the car. However, these authors have not measured the perceived competence as an independent mediator. Thus it remains an open question whether the manipulation of the anthropomorphism alters the perceived competence in the system and therefore changes the associated alliance. In light of the theory of anthropomorphization, we assumed that an *adaptive* system could increase the perceived anthropomorphism of the system by showing unexpected behavior [10]. We found that users perceive the robot as more competent and warmth. Thus it indicates that the *adaptive* robot indeed increases the perceived anthropomorphism indirectly measured by the RoSAS [7]. However, further studies need to verify this by directly measuring the perceived anthropomorphism.

Finally, we could find partial evidence for 4. Participants in the *adaptive* condition opted more often to exercise a second time voluntarily. This result is probably due to the interest in a system that tries to personalize the interaction by itself. It might raise curiosity and participants are interested to see what other exercises the system can offer or whether the system can effectively learn the user preference. However, this result is only marginally significant after applying a continuity correction. To be sure whether this effect is genuinely substantial higher sample size is needed.

One limitation of the interpretation of the results above is the short interaction time during the study. Trust and alliance are build up over repeated interactions between two person. Therefore, the results on the effects of alliance need to be interpreted with caution. Additionally, the scale used in this experiment is primarily designed for measuring the trust and alliance in the client-therapist alliances. Therefore, the results might be different, if we have used a scale that is more focused on the trust in the technical competence of the system. Still, the trust in the relationship is an essential part for long-term HRIand especially for use cases where the human and robot partner are working towards a long-term goal like increasing physical activity.

Moreover, we have not quantitatively assessed the quality of the preference learning in this study. Future work will look at the user's real satisfaction with the learned preference by the system. To accomplish his goal, we need to conduct repeated long-term interactions.

8 Conclusion

This work presented a study on different techniques to adjust a SARs behavior towards a user's preference. The results of this study show that *adaptive* robots are perceived as more competent, warmth and trustworthy than *adaptable* robots. Further, it presents evidence that the perceived competence of the system significantly mediates the alliance with a system. This mediation effect can be an essential aspect for long-term interaction with robots and needs in-depth investigations in long-term studies. The question remains whether an *adaptive* system can continuously present new and personalized behaviors so that the system will remain interesting to interact with over time.

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