User Perception of Teachable Robots: A Comparative Study of Teaching Strategies, Task Complexity and User Characteristics

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Published version

TARAKLI, Imene and DI NUOVO, Alessandro (2023). User Perception of Teachable Robots: A Comparative Study of Teaching Strategies, Task Complexity and User Characteristics. In: AL ALI, Abdulaziz, CABIBIHAN, John-John, MESKIN, Nader, ROSSI, Silivia, JIANG, Wanyue, HE, Hongsheng and GE, Shuzhi Sam, (eds.) Social Robotics. 15th International Conference, ICSR 2023, Doha, Qatar, December 3–7, 2023, Proceedings, Part II. Lecture Notes in Computer Science (14454). Singapore, Springer Nature Singapore, 357-370.

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User perception of Teachable Robots: A comparative study of Teaching Strategies, Task Complexity and User Characteristics.

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Abstract. This study explores the influence of teaching methods, task complexity, and user characteristics on perceptions of teachable robots. Analysis of responses from 138 participants reveals that both Teaching with Evaluative Feedback and Teaching through Preferences were perceived as equally user-friendly and easier to use compared to the non-interactive condition. Additionally, Teaching with Evaluative Feedback enhanced robot responsiveness, while Teaching with Preferences yielded results similar to the passive Download condition, suggesting that the degree of interactivity and human guidance in the former may not substantially impact user perceptions. Personality traits, particularly extraversion and intellect, shape teaching method preferences. Task complexity influenced the perceived anthropomorphism, control, and responsiveness of the robot. Notably, the classification task led to higher anthropomorphism, control, and responsiveness scores. Our findings emphasise the importance of task design and the need of tailoring teaching methods to the user's personality to optimise human-robot interactions, particularly in educational contexts. Project website: https://sites.google.com/view/teachable-robots.

Keywords: Users perception · Robot Teaching · Education.

1 Introduction

Education has shown an increasing interest in the use of social robots to support children's learning [14]. Studies revealed that social robots stimulate a wider array of valuable social behaviours in children, prompt engagement with the physical world through their embodiments, and promote a personalised and tailored learning environment to the individual's student needs [3] [4].

The pedagogical potential of social robots allows them to assume active roles in classrooms, including tutor, peer, or learner roles (see [20] for a detailed taxonomy). A prominent trend of portraying the robot as a novice learner has been noted in the recent literature [14]. In this setting, the robot, acting as a less knowledgeable peer, receives guidance from students to enhance its performance. This concept is based on the learning-by-teaching paradigm, a well-acknowledged psychological approach in which learners instruct a third party, leading to a deeper understanding on their part.

Research reveals that engaging with a novice robot improves children's learning outcomes by establishing a non-judgmental context, boosting student confidence, and fostering meta-cognitive skills [13]. However, for a robot to effectively play the role of a novice learner, it must comprehend student instructions, explanations, and feedback, necessitating it to emulate child-like learning capabilities.

Interactive Reinforcement Learning (RL) emerges as a promising approach to endow robots with cognitive capabilities. Within this framework, non-technical human instructors guide the robot's learning process by providing feedback. Different forms of feedback can be employed to teach the robot including demonstration, instruction, and evaluative feedback [19]. While most methods assume an optimal and rational teacher [5], a presumption often unsuited for children, evaluative feedback offers a sturdy alternative. In this method, users guides the robots by providing information about the quality of its actions. This type of feedback can not only accommodate human errors [9] but also cultivates active learning, pushing the robot towards trial-and-error which requires from the human teacher a deeper comprehension of the task. Moreover, a more recent trend in interactive RL is preference-based learning [6] [16] [11]. Here, the teacher provides information about the relative preferences of different actions of the robot, guiding the learning process with comparisons rather than explicit evaluations.

While Interactive RL systems have demonstrated considerable success in instructing robots across a range of tasks, prior studies have predominantly focused on optimising the robot's learning algorithm, often overlooking the user's perspective on these teaching methods. However, understanding the user's perspective is essential for designing robotic systems that better align with the user's expectations, and fostering engaging, intuitive, and satisfying interaction with social robots. This aspect holds particular significance in education, where the quality of interaction directly influences the effectiveness of the learning process.

This work aims to investigate users' perspectives on interactive teaching methods involving robots. Our primary focus centres on two distinct methodologies: teaching with evaluative feedback and teaching through preferences. Firstly, we conduct a comparative analysis of these teaching methods to investigate the impact of these methods on the users' perception of robots. Secondly, we assess whether the nature of the task impacts the user's perception of the teaching method. Lastly, we examine the potential influence of users' personality traits on their preference for specific teaching approaches. By exploring these aspects, this research aims to understand the relationship between the teaching method and the users' perceptions of the robot, thus contributing to a deeper understanding of how robots can be effectively incorporated into educational settings.

2 Related Work

Prior work in Human-Robot Interaction (HRI) extensively investigated how human would interact with teachable robot [22] [17] [12]. These studies have primarily focus on understanding users' intention and training strategies when providing evaluative feedback to robots. The insights from these works have contributed to the refinement of the learning algorithm that are better aligned with the user. While these findings are essential for effective HRI, earlier research focused more on improving the robot performance through algorithmic design, often overlooking the investigation of users perception of the robot.

In a recent study [18], researchers investigated the influence of diverse teaching methods, including interactive Reinforcement Learning (RL), on users' perceptions of a care robot. Their findings highlighted a correlation between the level of anthropomorphism attributed to the robot and the extent of involvement in the teaching. Moreover, they observed that the perceived success of the robot had a greater impact on user trust and usability compared to the teaching method employed. While this study offers an initial insight, our research aims to extend these observations to different contexts, such as educational settings, by assessing the perceived intelligence and control over the robot. We will assess factors like perceived intelligence and control over the robot, as well as measure the perceived usability of the teaching method itself, rather than solely focusing on the robot's usability as previously done.

To our knowledge, no prior research has explored preference-based learning within the context of HRI. Our study stands a pioneering effort, investigating the application of preference-based learning in HRI for the first time.

3 Methodology

To investigate the user's perspective on various teaching methods involving robot, we conduct an online between-subject study. Participants are randomly assigned to view one video showcasing a specific teaching method among three conditions: teaching with evaluative feedback, teaching with preferences, and a control group devoid of teaching intervention. They also engaged in a specific training task chosen from navigation, control, and classification tasks. This study has been granted ethical approval by the Ethics Committee of Sheffield Hallam University (Application ID: ER56422859, July 12th, 2023).

3.1 Teaching conditions

We conduct a comparative analysis of three teaching scenarios involving distinct teaching methods: Interactive RL from Evaluative Feedback, Preference-based RL, and a Download condition where the robot learns without a human intervention. The latter condition was inspired by the work of Moorman et al. [18] and represents the control group of the study as no interaction with the robot is invovled. Figure 1 depicts the three teaching scenarios.

Download: In this condition, no teaching from the user is involved. This condition serves as a control in the study because it represents a baseline scenario where no active teaching intervention from the user is present. Participants are solely passive observers, watching a video where a robot retrieves and executes a pre-existing robotic program that corresponds to the training task.

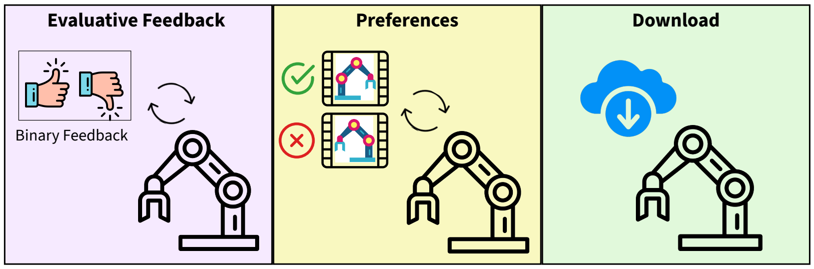


Fig. 1: Overview of the teaching condition. From left to right: Teaching with Evaluative Feedback, teaching with Preferences and Download condition.

Interactive RL from human evaluative feedback: In this condition, users teach the robot by proving feedback about the quality and correctness of its actions. Through trial and error, the robot progressively improves its performance by refining its strategies based on the evaluations provided by the human instructor. The design of this condition draws inspiration from the TAMER framework [15], where the teacher consistently provided evaluate feedback to the robot. To illustrate this to the participants we present paired videos: one showcasing the robot's trial-and-error learning and the other illustrating a teacher using a gaming controller to provide evaluative feedback. The teacher, the experimenter in this case, pushes a red-labelled joystick to provide negative feedback, and a green-labelled joystick to provide positive feedback to the robot. The human teacher within the video is presented as rational, consistently providing accurate feedback to guide the robot to optimal performance outcomes.

Preference-based Reinforcement Learning: In this scenario, users instruct the robot by providing ranked preferences over pairs of executed trajectories. The robot employs these preferences to enhance its performance through a classic Reinforcement Learning (RL) algorithm. The prevalent approach in the literature consists of initially training the robot in a simulation. Here, human preferences are collected by comparing side-by-side video clips of the robot's trajectories. Once the learning is completed in the simulated environment, it is then transferred to real-world robots. An alternative, through less common, consists of directly training the robot in real-life scenarios by offering preferences for sequential trajectories executed by the robots. In a prior study, we compared both strategies and found no statistically significant difference in user perception between them. Consequently, we have chosen to proceed with the widely adopted strategy of instructing the robot through simulation-derived videos. Specifically, the design of this condition is inspired by the work of Christiano et al. [6], wherein side-by-side trajectory snippets possess varying start and end states. To illustrate this teaching condition to the participants, we present them with a video featuring an experimenter in the role of a teacher. The teacher employs a web interface to convey her preferences for the robot's trajectories. Within the web interface, each page displays two video clips of the robot's trajectories side by side. The teacher is provided with three choices: expressing a preference for video 1, expressing a preference for video 2, or opting to skip if no preferences are held. Similar to the previous teaching scenario, the teacher is rational and provides accurate preferences to guide the robot toward optimal performance.

3.2 Task Domain

The robot's teaching is conducted across three distinct tasks: navigation, control, and classification. All tasks are performed using the Vector robot and are illustrated in figure 2.

- **Navigation Task:** In this task, the objective is to instruct the robot to navigate through a maze and reach a predetermined position while avoiding colliding with obstacles.
- **Control Task:**In this task, the robot must approach a cube, lift it, and accurately place it in a specific location. Although this task shares similarities with the navigation task, it introduces more complexity by expanding the range of actions to manipulate the cube.
- **Classification Task:** The goal of this task is teaching the robot how to categorise object in two distinct groups. object into two categories. To simply the teaching process, we consider three actions: classifying an object into category A, category B, or opting not to classify it.

By considering a variety of tasks, our goal is to broaden the study's applicability to ensure our aim is to ensure that the finding can be readily extrapolated to various pedagogical applications.

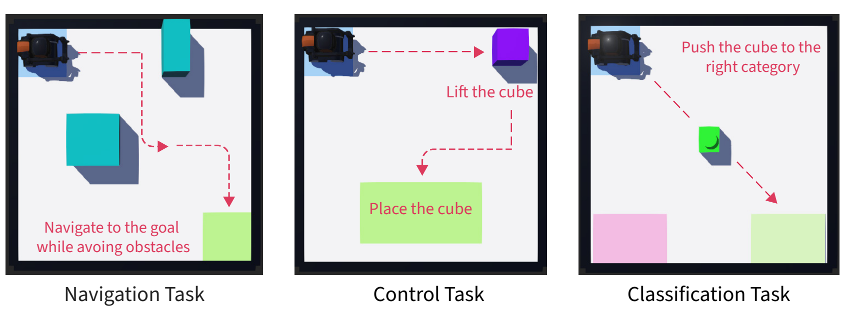


Fig. 2: Experimental tasks: Participants observe the teaching process of a robot within one of three types of tasks: navigation, control and classification.

3.3 Research Questions

The study focuses on two research questions:

- **RQ1.** How does different interactive teaching method influence users' perceptions of the robot?
- **RQ2.** To what extent does the user's characteristics influence their preference for a specific teaching method?
- **RQ3.** How does the nature of the task influence the user perceptions of the robot?

3.4 Participants

We determined the recommended sample size N of participants by conducting an a priori analysis on G*Power (version 3.1) for a MANOVA (α = .05, power = .95, number of groups = 9). By considering a small effect ($f^2(V) = 0.0625$), the analysis suggested a sample size of N = 144.

Although the primary focus of this study is to comprehend user perceptions within an educational context, recruiting this number of school-age children as participants would have posed logistical challenges. Consequently, participants were recruited through Prolific, with an age criterion of 18 to 26 years. We hypothesize that by targeting individuals within this younger age range, the findings of this research will extend to a younger demographic, akin to children.

Initially, 145 participants were recruited online. Every participant received a compensation of £1.80 upon completing the study. After excluding individuals who did not fully complete the questionnaire, failed the attention check, and exhibited outliers (>3 standard deviations) for more than one variable of interest, the final sample size consisted of 138 participants ($M_{age} = 22.87$, $SD_{age} = 1.78$, 80 men, 56 women, 1 non-binary).

3.5 Measures

In the following, we outline the metrics used to assess the user's perspective of teaching methods during the study. For metrics assessed using Likert scales, a 5-point scale (1 = Strongly Disagree to 5 = Strongly Agree) was utilised, unless indicated otherwise.

- **Demographics:** We collect the participants age, gender and education level.
- **Personality:** We measure five personality traits (Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness) by using the Mini-IPIP, 20-item Likert scale [8].
- **Robotic Prior Experience:** We assess the participants' prior experience with robot through the robotics experience scale, 5-item Likert scale [18].
- **Perceived Control:** we measure the perceived control of participants over the robot by adapting a 3-item Likert scale from Delgosha et al. [7].
- **Responsiveness:** we measure the responsiveness of the robot by adapting the the Godspeed's animacy scale into a 2-item Likert scale [1].

- **Likability, Anthropomorphism and Intelligence**: To assess the likability, anthropomorphism and intelligence, we adapted Godspeed's Likability, Anthropomorphism and Intelligence, to 5-item Likert scale. [1].
- **Usability and Acceptance:** To assess the usefulness, ease of use, and intent to use of the teaching method, we utilise an 8-item Likert scale adapted from the Technology Acceptance Model (TAM) [2].
- **Perceived success:** We measure the participants' perceived success of the robot by collecting a binary metric.

3.6 Procedure

The study was conducted online through Qualtrics. The survey begun with an informed consent page, followed by questions about demographics, personality traits, and their prior experience with robots.

Afterwards, participants were assigned to one of three teaching conditions (Teaching with evaluative feedback, Teaching with Preferences, and Download condition). Within the teaching condition, participants were further randomly assigned to observe the teaching of a robot in a specific task out of three (navigation, control, and classification). This design yielded a between-subject study structure comprising a total of nine distinct groups.

The rest of the study was organised as follows:

- **Introductory phase:** Participant are first familiarised with their assigned teaching condition, during which we provide explanations about the teaching process involving the robot.
- **Training phase:** Next, participants watch a video of the experimenter instructing a robot to execute a task. The teaching method and task's nature are tailored to each participant based on their assigned conditions. At the end of the training, participants observe the identical final performance of the robot within the assigned task. By maintaining the final performance constant across teaching conditions, we aim to mitigate the risk of performance confounding.
- **Testing phase:** After visioning the training video, participants proceed to watch a sequence of four videos, in which the robot's performance is assessed across diverse environments of the same nature as the assigned task. Similar to [18], we consider different trajectories in the testing trials, encompassing two successful, one ambiguous and one failure. In the ambiguous trajectory, the robot actions may not optimal but ultimately lead to success. By demonstrating a success rate of 75%, as was suggested in prior works [24] [18], we aim to replicate real-life scenarios, where failures are more likely to occur. It's worth noting that the testing videos remain consistent for the assigned task, regardless of the teaching condition.

Following this, the participants proceed to complete the survey, where they provide their rankings for their perception of the robot, its task completion success, the effectiveness of the teaching method. To ensure the participant engagement, we introduce an attention check between the testing phase and the questionnaire during the online study.

All videos involving the experimenter training and testing the robot are demonstrated via a Wizard-of-Oz approach. This choice is made to maintain the failure and agent's performance consistent between the conditions [18]. The links to all videos can be found on the project website.

Moreover, in the training phase videos, the teaching with evaluative feedback condition entailed giving feedback to an actual robot, whereas the preference-based condition involved expressing preferences over simulated trajectories of the robot, following the established practice in the literature. All simulations of the study were designed and executed on Webots [23].

4 Results

Prior to conducting the analysis, we evaluated the internal consistency of the survey items using Cronbach's alpha test. Results are reported in the project website. Moving forward, we performed Multivariate Analysis of Variance (MANOVA) considering various dependent variables based on the experimental conditions, accompanied by post-hoc follow-up analyses.

To ensure the validity of parametric tests (such as univariate ANOVA and t-tests), we first checked if the assumptions of normality and homoscedasticity were met using the Shapiro-Wilk test and Levene's test, respectively. In cases where the data did not meet these assumptions or was of an ordinal nature, non-parametric tests were employed. However, MANOVA was an exception to this approach, for which we employ the Pillai-Bartlett trace test, known for its robustness in the presence of assumption violations [10].

We calculated the effect size, d, using Cohen's d coefficient and considered statistical significance at the level of $p < 0.05$. Through the analysis, we made a conscientious effort to align with the recommended best practices detailed in the guidelines by Schrum et al. [21].

4.1 Impact of the teaching method on the user's perception

To assess the potential impact of the teaching method on users' perceptions of the robot, we aggregated data from all tasks and conducted a MANOVA, where teaching methods were treated as independent variables. By employing Pillai's trace as the measure, we identified a significant influence of the teaching method on perceived anthropomorphism, responsiveness, control, and ease of use ($V = 0.11, F(8, 266) = 1.99, p = 0.048$). Figure 3a depicts the significant differences between the teaching conditions.

- **Responsiveness:** A Kruskal Wallis (KW) test revealed a significant effect of the teaching method on perceived responsiveness ($H(2) = 6.46, p = 0.040$). A subsequent Wilcoxon rank sum test with Bonferroni correction indicated that instructing the robot with Evaluative Feedback ($M = 8.14, SD =$

1.33) led to significantly higher perceived responsiveness compared to the Download condition ($M = 7.33, SD = 1.58$), $W = 2.45, p = 0.014, d = 0.56$. However, the perceived responsiveness of the robot while being taught through providing Preferences ($M = 7.69, SD = 1.67$) did not significantly differ from the teaching methods involving Evaluative Feedback and the Download condition.

– **Ease of use:** A significant main effect of the teaching method on the perceived ease of use of the method was identified through a KW test ($H(2) = 6.37, p = 0.041$). Although not meeting the Bonferroni correction threshold, a comparison between teaching conditions showed that the download condition ($M = 7.33, SD = 1.58$) was somewhat perceived as less user-friendly compared to both teaching with evaluative feedback ($M = 8.15, SD = 1.33$), $W = -2.15, p = 0.03, d = -0.42$, and teaching with preferences ($M = 7.69, SD = 1.67$), $W = -2.13, p = 0.03, d = -0.44$. No significant different in perceived ease of use was found between Teaching with Evaluative Feedback and Teaching with Preferences.

However, our analysis did not reveal any significant main effects of the teaching condition on the perceived anthropomorphism, control, intelligence, likability, perceived usefulness, or intent to use the teaching methods.

4.2 Relationships between User Characteristics and Perceptions of Robot and Teaching Methods

We examined whether the users' personality and background variables were associated with their perceptions of the robot and the teaching method. To ensure the validity of our analysis, we ensured that relevant qualitative measures were evenly distributed across all training conditions, thereby ruling out potential correlations due to sampling biases.

– **Extraversion:** Extraverts demonstrated a more positive perception of the robot in the Teaching with Evaluative Feedback condition. Indeed, in this condition, extraversion traits exhibited a significant positive correlation with the perceived responsiveness ($r = 0.42, p = 0.003$), perceived intelligence ($r = 0.46, p = 0.001$) and likability of the robot ($r = .36, p = 0.015$). Moreover, a Wilcoxon rank-sum test on Extraversion with perceived success as an independent variable indicated that participants who perceived the robot as successful exhibited higher extraversion traits ($M = 11.33, SD = 3.65$) compared to those who perceived the robot as having failed ($M = 9.69, SD = 4$), $W = 2.226$ $p = 0.02$, $d = 0.44$.
– **Intellect:** Intellect traits were highly correlated with the ease of use of the Teaching with preferences ($r = 0.42, p = 0.002$), and likability of the robot ($r = 0.35, p = 0.015$) in the Teaching with Evaluative Feedback condition. Similarly, intellect traits were significantly related to the perceived responsiveness of the robot in the Teaching with Evaluative Feedback ($r = 0.36, p = 0.013$).

– **Prior experience with robotics:** In the Download condition, we observed a strong correlation between prior expertise with robots with the perceived usefulness of the method ($r = 0.37$) as well as the perceived anthropomorphism of the robot ($r = 0.38$), (both $p = 0.013$).

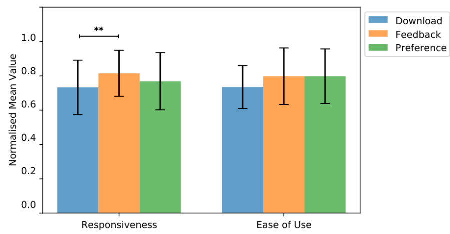
We did not identify any significant relationships between the gender, educational level and other personality traits of the users, and their perception of the robot and the teaching method.

4.3 Impact of the nature of the task on the user's perception

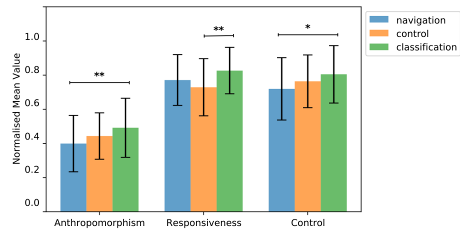
Finally, we investigated whether the nature of the training task influenced the perception of the robot, regardless of the teaching method employed. Combining data from all teaching conditions, we executed a MANOVA with the task's nature as the independent variable. By employing Pillai's trace as the measure, we identified a highly significant influence of the nature of task on perceived anthropomorphism, responsiveness, and control over the robot (V = 0.14, F(6, 268) = 3.41 , p = 0.003). Figure 3a illustrates the significant differences between the tasks.

– **Anthropomorphism:** A KW test revealed a significant difference in the perceived anthropomorphism of the robot within the different tasks (H(2) = 7.39, p = 0.025). After running a Wilcoxon rank-sum, we found that robots were significantly more anthropomorphised in the classification task (M=12.29, SD=4.32) than in the navigation task (M=9.98 ,SD=4.13), W= 2.6 , p=0.009, d=0.55 However, no significant difference emerged in comparison with the control task (M = 11.08, SD = 3.4).
– **Control:** After running a KW test, we identified a main effect of the nature of the task on the perceived control over the robot (H(2) = 6.15, p=0.046). A Wilcoxon rank-sum test revealed that a significantly higher control over the robot was perceived in the classification task (M=12.07, SD=2.52) than in the navigation task (M=10.8, SD=2.74), W=2.39, p=0.02, d=0.48. No difference with the control task was identified (M=11.46, SD=2.3).
– **Responsiveness:** A significant main effect of the nature of the task on the perceived responsiveness of the robot was identified through a KW test (H(2) = 8.41, p = 0.015). After performing a Wilcoxon rank-sum test, we identified that the perceived responsiveness of the robot was significantly higher in the classification task (M=8.27, SD=1.36) than in the control (M=7.29, SD=1.68), W=2.78, p=0.005, d= 0.63. No difference with the navigation task was identified (M=7.71, SD=1.49).

No significant difference was identified among the perceived intelligence and likability of the robot across the tasks.



(a)



(b)

Fig. 3: (a) Comparison of the responsiveness and ease of use between the teaching conditions. (b) Comparison of the anthropomorphism, control and responsiveness between the tasks.

5 Discussion

The results of the study indicate that a user's perception of a teachable robot can be influenced by various factors, including the chosen teaching method, the nature of the task, and the individual's inherent characteristics and background.

Regarding the impact of teaching method on user perception of the robot (**RQ1**), the analysis revealed, with a medium effect size, that participants perceived the robot as more responsive in the Teaching with feedback condition compared to the Download condition. This suggest that the more interaction and human guidance is observed, the more responsive the agent is perceived. Additionally, Teaching with Feedback and with Preferences were perceived as equally user-friendly, and easier to use than the Download condition. This result is contrary to our prior assumptions, as the former methods requires more effort compared to the latter. However, Teaching with Feedback aligns more closely with natural human teaching methods, leading us to postulate that the perceived ease of use is positively influenced by the resemblance to familiar human interactions. However, contrary to [18], our study did not reveal any significant impact of the teaching method on the perceived anthropomorphism of the robot.

Moreover, we examined whether there was a relationship between the personality traits and background of the user with its perception of the robot (**RQ2**). The analysis identified a moderate correlation between extraversion traits and a favourable perception of Teaching with Feedback condition. Extraverts exhibited a significant correlation with the perceived responsiveness, intelligence and likability of the robot within this specific teaching condition. We hypothesize that Teaching with Evaluative Feedback fostered a more dynamic and engaging interaction as the teacher directly interacts with the robot, resonating well with the socially outgoing nature of extraverted individuals. Moreover, intellect traits exhibited a significant correlation with ease of use in the Teaching with Preferences condition and with likability and responsiveness in the Teaching with Evaluative Feedback condition. This implies that individuals possessing higher intellect traits are inclined to be more receptive towards innovative teaching methods that involve robots, diverging from the traditional Download condition. Lastly, we found a weak correlation between prior experience with robots and the perceived anthropomorphism and usefulness of the robot in the Download condition. This hints that individuals more familiar with robots tend to attribute higher human-like qualities to the robot when no direct interaction is involved. This familiarity also seemed to make them find the method more useful in the context of the study.

Lastly, we examined whether the nature of the training task could influence the user's perception of the robot (**RQ3**). The results showed that participants engaging in the classification task reported higher levels of perceived anthropomorphism, control, and responsiveness of the robot in contrast to those in other tasks. This result can be attributed to the classification task's higher level of demand and its incorporation of more social attributes, distinguishing it from the other tasks and necessitating a greater degree of engagement from the participants. We postulate that tasks that require greater engagement and complexity contribute to an increased sense of control and perceived responsiveness over the robot. Additionally, tasks that simulate a more intricate and human-like scenario tend to augment the perceived anthropomorphism of the robot in the eyes of the participants.

6 Limitation

While our study offers valuable insights, several limitations need to be acknowledged that may impact the interpretation and generalisation of the findings.

First, the metric assessing robot responsiveness displayed an internal consistency ($\alpha = 0.6$). While this score is generally perceived as passable, it does not exceed the acceptable range set in this study ($\alpha > 0.7$). Consequently, any results derived from this metric should be treated with caution.

Second, the study was conducted exclusively online. While this allowed a more diverse participant pool, future research could benefit from replication in a face-to-face setting where participants could engage in direct interactions with the robot. The contextual differences between online and in-person interactions could introduce variances in the observed outcomes.

Additionally, although we recruited participants within a young age range, our study primarily focused on adults. Consequently, the generalisability of our findings to children remains uncertain, and further investigation is needed to understand how age influences perceptions of teachable robots.

Lastly, the duration of training for the different teaching methods was not considered in our study. The time required to learn and execute a method could potentially impact participants' perceptions of the robot's performance. Future research could explore the relationship between training duration and user perceptions to gain a more comprehensive understanding of this aspect.

7 Conclusion

In this study, we investigated the impact of teaching methods, task nature, and user characteristics on users' perceptions of robot. Our findings provide valuable insights for including the robots in the education landscape. Teaching with Evaluative Feedback emerged as a preferred method, improving both responsiveness and ease of use compared to the non-interactive condition. Similarly, personality traits influenced teaching preferences, highlighting the need for personalised interactions. Moreover, the task's complexity influenced anthropomorphism, control, and responsiveness, highlighting the importance of task design.

Our study indicates the importance of considering intricate interplay of these factors in HRI, particularly within education. By aligning teaching methods with natural tendencies, personalising interactions based on personality traits, and crafting engaging tasks, we have the opportunity to create more enriching and enjoyable educational experiences with robots.

Acknowledgements : We thank Dimitri Lacroix for his statistical insights during the initial design of the study. This research was supported by European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 955778.

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