Understanding and Quantifying Human Factors in Programming from Demonstration: A User Study Proposal

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Programming by demonstration (PbD) is a promising method for robots to learn from direct, non-expert human interaction. This approach enables the interactive transfer of human skills to the robot. As the non-expert user is at the center of PbD, the efficacy of the learned skill is largely dependent on the demonstrations provided. Although PbD methods have been extensively developed and validated in the field of robotics, there has been inadequate confirmation of their effectiveness from the perspective of human teachability. To address this gap, we propose to experimentally investigate the impact of communicating robot learning process on the efficacy of the transferred skills. This paper outlines the preliminary steps in designing experiments to identify human-related performance shaping factors in PbD. The purpose of this article is to establish the foundation for an experimental study that focuses on the human component in PbD algorithms and provides new insights into human factors in PbD design.

Keywords: Programming By Demonstration, Robotics, Human Factors, Human Robot Interaction

1. Introduction

Looking back over the past decade, it is evident that intelligent robotic systems have the potential to improve ergonomics on factory floors by assisting humans in the production process. However, as the industry moves towards mass customization, the myriad of skills a robot is expected to hone will be impractical to pre-program through traditional methods. To this end, Programming by demonstration (PbD), where an operator can teach complex robot tasks through demonstration, has garnered considerable attention. PbD is based on the idea that similar to humans who learn by observing their environment, robots can also learn by demonstrations as shown in Fig. 1. PbD is aimed to make cyber-physical systems more accessible to non-experts as it does not require programming expertise.

In the field of PbD, researchers primarily focus on ensuring efficient demonstration acquisition and generalized execution of skills. While technological advances have significantly improved robotic performance, however, the robot's learned behavior becomes a black box, making it difficult for non-expert demonstrators to discern how and what it has learned during the teaching process. In this context, researchers propose developing a more sophisticated model to handle ambiguous

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demonstrations Sena et al. (2019); Sakr et al. (2022); however, an alternative solution is to take advantage of the natural adaptability of the human demonstrator to improve the performance of the system.

Since the efficacy of the learned policy depends on the quality of interactions and data provided by humans Sakr et al. (2022), it is important to assess how communicating the robot's learning to nonexpert teachers can impact their behavior specifically in terms of their ability to teach and handle the workload. Therefore, to determine the impact of communicating the robot's learning to non-expert demonstrators, we propose an empirical study that facilitates the formal assessment of human performance based on robot learning knowledge, considering state-of-the-art methods. The study adopted a multifaceted approach, with the high-level goal of quantifying teaching efficacy across varying levels of knowledge regarding the robot's mental model and assessing the demonstrator's workload, all within the framework of PbD.

PbD provides several communication modalities for transmitting training data from humans to the robot, including kinesthetic teaching, haptics, speech, and augmented reality Müller et al. (2021). This study uses a kinesthetic interface for robot teaching, where a human teacher demonstrates the task by physically guiding the robot manipulator. The use of kinesthetic teaching in PbD offers several advantages, including the elimination of correspondence problems due to direct guidance, and demonstrations are limited to the kinematic limit of the robot. Also, there is no need for extra instrumentation beyond the robot's sensors and actuators Mahler and Goldberg (2017).

The article is organized into the following sections: the background and related work of PbD and human factors are presented in Section II; Section III discusses the study design, including apparatus and experimental setup. Section IV provides the potential plan for the data analysis. Finally, Section V concludes the proposal with future implications.

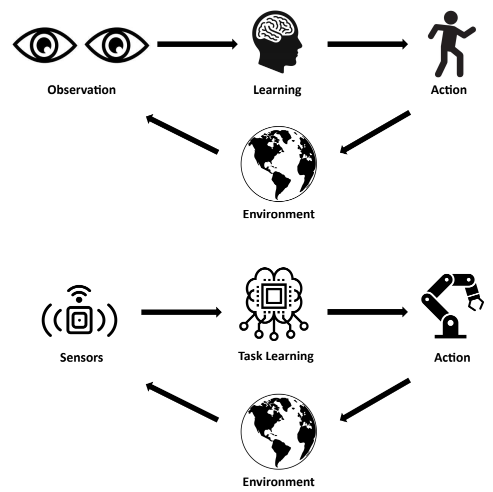

Fig. 1.: Human and robot task learning cycle.

2. Background and Related Work

Extensive studies have been carried out on robot learning Jaquier et al. (2020); Duque et al. (2019); Arduengo et al. (2023); Xiao et al. (2020), with special emphasis on policy development Kober and Peters (2008); Mahler and Goldberg (2017); Jang et al. (2022). To gain an understanding on the subject of robot learning, we suggest referring to Knox et al. (2013); Ravichandar et al. (2020). On the other hand, fewer studies have been found on human teaching to robots which focus on human performance. Vollmer and Schillingmann (2018) explored teacher's role in PbD. They addressed the strengths and drawbacks of each approach used to study human-teacher behavior in human-robot interaction, including behavioral analysis and physiological measurements. Sena et al. (2019) introduced a machine learning model to measure and analyze teaching behavior in human-robot interaction.

In Knox et al. (2013), the authors compare the efficacy of human teachers to alternative techniques for providing robots with examples and feedback in PbD. The study demonstrates that human teachers are more effective than alternative approaches, although the authors acknowledge the limits of using human teachers, such as the possibility of human error and ambiguous demonstrations. Therefore, assessing the human component for better understanding and applicability of PbD within the industry is a feasible solution. In addition, training human teachers to teach robots can also create effective demonstrations for the learners, which can assist in refining the robot learning model. In this regard, Cederborg et al. (2015) and Weiss et al. (2009) published their work focusing on the different aspects of training human teachers.

Researchers in the HRI domains have long focused on understanding human physical and cognitive dynamics as they relate to safety and performance in a collaborative setting Lorenzini et al. (2023). In scenarios where humans are assigned the role of teacher to a cyber-physical student, the added responsibility of the learner's performance places a greater burden on their shoulders. Teaching errors arise from unclear input and poor demonstrations, and other human-teacher dynamics can also influence robot policy development. Therefore, it is equally important to assess the dynamics mentioned above in addition to teaching efficacy based on the robot learning model. Providing a learning model to teachers can affect their behavior by changing how they approach teaching tasks.

Communicating Robot Learning to Humans in PbD. To improve communication with robots, it is essential to have a comprehensive understanding of their learning process. By communicating how robots interpret human input, demonstrators can adjust their approach and perform teaching tasks more effectively. While communicating human intention for improving robot performance has been widely acknowledged Wang et al. (2018), the human side of the equation, especially in PbD, requires further attention. A recent study on the sharing of robot conventions through shared autonomy highlights the requirement to provide a robot learning model to humans for policy development Jonnavittula and Losey (2022). However, the study does not directly contribute in this regard. The authors of Kwon et al. (2018) and Ma et al. (2022) proposed communication methods that enable learners to inform teachers what they have learned or are yet to learn, but these studies do not address the impact of communication on the demonstrator's performance.

Measuring Human Teaching Role. In the field of human-robot interaction (HRI), several efforts Lorenzini et al. (2023) to model and assess human behavior in collaboration or interaction with robots. However, in teaching new skills through PbD, the emphasis is persistently placed on the robot's performance.

While numerous works have recognized the importance of the demonstrator or teacher in the learning process as an active contributor, yet the importance of human factors in PbD remains unexplored. In this context, Sena and Howard (2020) have highlighted the importance of the human role in the teaching process and proposed a framework to quantify human behavior; however, their framework is limited to a set of metrics to assess the effectiveness of teaching behavior and does not compare with existing human behavior metrics. Furthermore, the experiments must cover the broader dynamics of human behavior in the teaching process. To gain insight into the metrics and techniques used to evaluate human behavior with robots, we refer the reader to Vollmer and Schillingmann (2018). The authors comprehensively review the existing literature and methodologies to identify best practices for evaluating human behavior.

Given the advantages of including the demonstrator's role in PbD and communicating robot learning to humans for effective demonstration, it is imperative to evaluate the human dynamics within the framework and obtain a more detailed understanding of the human teaching and robot learning process.

3. The User Study

The study intends to adopt a mixed method strategy, combining quantitative and qualitative data collection techniques as shown in Fig. 2, for human behavior assessment within the PbD framework. The research design consists of a pre-test and post-test experimental design. Participants will carry out predefined tasks (discussed 3.2) on the experimental setup shown in Fig. 3, while being monitored for different performance-shaping factors.

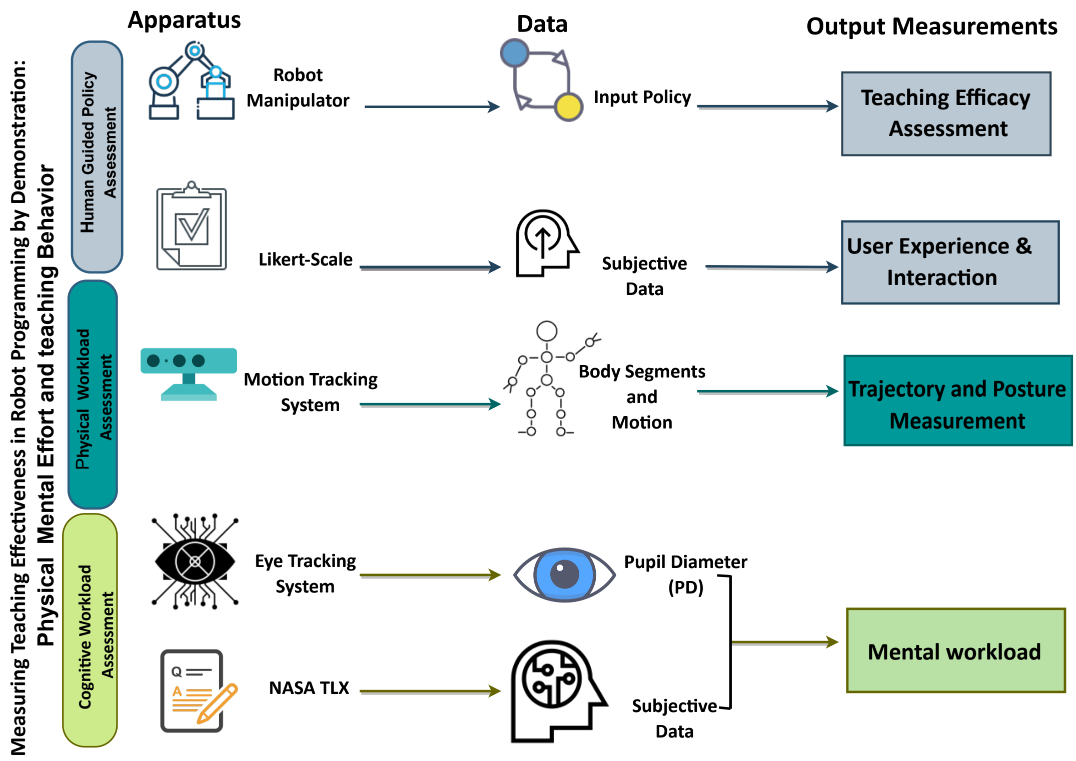

Fig. 2.: User Study Design

3.1. *Experimental Setup*

The experimental setup, as shown in Fig. 3 is based in Irish Manufacturing Research's pilot factory line and uses a UR10e manipulator with a gravity compensation controller and an RGB-D vision sensor with Aruco markers for object detection. The software implementation employs dynamic movement primitives Ude et al. (2014) combined with behavior trees Iovino et al. (2022). In addition, an intuitive human-machine interface (HMI) is designed to facilitate data collection, allowing participants to initiate and terminate the demonstration. Additionally,a vision sensor is used to capture human motion during the experiment. For cognitive data collection, a head-mounted eye tracker with a 100 Hz sampling rate is used to collect pupil diameter.

3.2. *Task Design and Implementation*

To evaluate the demonstrator's performance in accordance with the robot learning model, two distinct tasks are designed illustrated in Fig. 4. Both tasks require the spatio-temporal coordination of the object's placement in 3-D space. The participant is required to demonstrate each task by picking up the object from a random location, placing it to the target location in task A, and sliding the object onto the slider in Task B.

Task A: Object-Targeted Placement- Task A drives the robot manipulator to pick an object from its initial position (x_1, y_1, z_1) to a targeted position (x_2, y_2, z_2). To perform this task, the participant should control the gripper position (g) and orientation (qx, qy, qz, qw), as well as the end effector position (x_e, y_e, z_e) and the joint angles of the manipulator vector O.

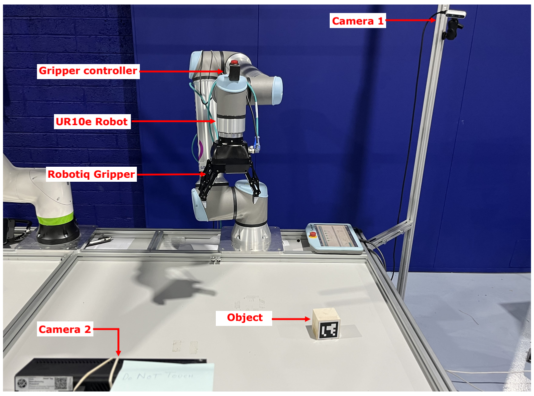

Fig. 3.: Experimental set-up of the proposed user-study. The setup consists of an UR10e robot equipped with Robotiq-3f gripper. Two cameras, to track the object in the workspace and to capture human motion respectively, are used. A customised button to control the gripper is used.

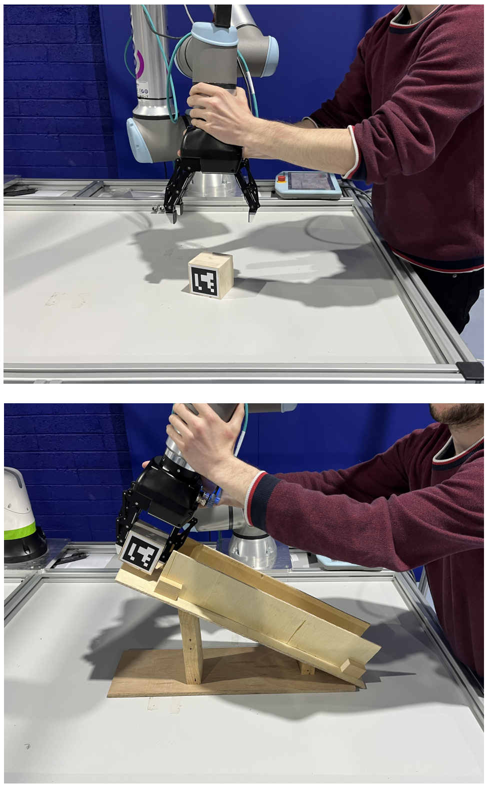

Fig. 4.: Task 1 (upper): The non-expert will have to pick and place an object from and to a designated pose. Task 2 (lower): The non-expert user have to pick an object and place it on the slide. The user has to deduce the end-pose to successfully slide the object.

Task B: Object Sliding - Similarly, task B requires the participant to move an object from a flat surface onto a slider and slide it using the robot manipulator. The initial position of the object and the gripper's position, orientation, and force definitions are identical to those of task A. However, the slider's position and orientation are described by a 3x3 rotation matrix R_s and a vector T_s.

3.3. *Course of the Experiment*

The experiments will be executed by following below procedures in different stages:

A) Preparatory Stage- Prior to starting the study, participants receive clear instructions in English and a consent form, as well as a preliminary survey to gauge their level of interaction with the robot. In addition, participants are informed of the data sources that will be recorded during the execution. To ensure a thorough understanding of the programming tasks, participants are given the opportunity to ask questions before execution. These measures aim to eliminate any sources of bias or confusion and acquire high-quality data that can be rigorously and precisely evaluated. We ensure that the experimental setup, like the basic device configurations, including the eye tracker and motion tracking system, complies with ISO 10218 and ISO/TS 15066.

B) Study Execution Participants must perform designed tasks under defined criterion, to study how teachers perceive and comprehend robot learning process for the PbD method. The method is among subjects, where participants are divided to two groups, the one group receive on critical inputs for robotic learning perspective and the other group without training on critical inputs. Each group must perform programming tasks under defined conditions. The participants in group-I must perform programming tasks based on general instructions provided at the start of the experiment. After, participants in the other group will receive additional instructions about the mental model of the robot, including how it effectively learns and behaves in the future based on demonstrations.

The approach aims to evaluate how participants develop mental models of learning robots and to compare their performance.

C) Post-Task Assessment and Feedback

After executing the assigned tasks, the participants proceed to the post-task evaluation and feedback phase for subjective data collection. They are asked to undertake the NASA Task Load Index (TLX) questionnaire to assess their mental workload during task performance. Additionally, they are asked to use a 5-point Likert-scale to score their kinesthetic interaction with the robot. The information gathered from these evaluations seeks to provide useful insights into the participants' perceptions of the task's difficulty and the robot interaction's efficacy.

D) Debriefing Finally, the participants will be informed of the true objectives of the experiments and could have the opportunity to express their concerns.

3.4. *Goals and Research Questions*

This study aims to assess the efficacy of the PbD approach from a human perspective, by assessing the teacher's behavior with the robot's understanding of guided input. The following research questions will be investigated to achieve our objectives:

RQ 1: *Does teaching a human with basic training in critical inputs for robotic learning from a perspective of a cyber physical agent lead to faster and more accurate demonstrations by the human and better performance by the robotic arm?*

Generally, the standard PbD process involves two stages: The demonstration phase, where a human teacher demonstrates a specific task, and a policy-deriving stage, where the robot learner learns the policy from the demonstrated examples toward the intended task outcomesMa et al. (2022). In the aforementioned stages of PbD, the human demonstrator may not have full awareness of how the robot will interpret his input, which can negatively impact the performance of the teacher and the learner. This can result in incorrect policies learned. As mentioned above, the existing solution focuses on improving the performance of the learner by filtering the demonstration to remove misleading examples to improve the quality of the learned policy Sakr et al. (2022) Mahler and Goldberg (2017).

A user study is designed to address this research question by providing critical inputs for robotic learning from a cyber-physical agent perspective to the demonstrator and expecting experimental groups with robot learning knowledge to show increased teaching performance through demonstration data, including object positions, gripper's position and orientation, end effector's position, and joint angles of the manipulator.

RQ 2 *Can the workload experienced by the operator during an interactive task be significantly reduced by providing a shared operational picture for required inputs and feedback between a human teacher and a cyber physical agent?*

When humans are responsible for teaching a cyber-physical student, the added pressure of ensuring the student's performance can be overwhelming. Our hypothesis is that by communicating robot learning strategies and educating humans on how changes in a robot's "policy" parameters affect its behavior, we can help teachers build an accurate mental model of the learner, reducing the workload of the human demonstrator. Previous studies have shown that humans who have a more accurate mental model of a robot tend to perform better Ma et al. (2022), which is particularly important when humans are in the role of a demonstrator. Comparatively, little emphasis has been given to how well humans perform as a demonstrator, although the current research has evaluated different human factors and highlighted the significant role of humans in HRI domain.

To test this hypothesis, physical and cognitive data are collected from the user: whole-body motion capture kinematic data such as joint angles, limb position, and trajectories, and eye tracking with a pupilometer. Although the experimental setup and tasks used in both research questions are similar, this question requires the use of additional subjective and objective tools. Details on the experimental tools used to collect objective measures of human dynamics can be found in 3.1.

4. Conclusion and Future Implications

This ongoing work seeks to understand human behavior and performance within PbD through communication of robot learning. The experimental setup and research objectives proposed in this paper offer a solid foundation for designing experiments to evaluate human factors within a PbD framework.

Acknowledging the importance of understanding human roles in teaching robots, this study has significant implications for future research. Firstly, this research paves the path for designing experiments to investigate the impact of communicating critical inputs related to robots to teach them effectively. Second, it suggests the development of novel PbD approaches that consider human dynamics. Lastly, it demonstrates the possibility of enhancing robots' ability to learn from non-expert human demonstrators by incorporating critical inputs, resulting in more intuitive and effective human-robot collaboration.

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