Balancing User Control and Perceived Robot Social Agency through the Design of End-User Robot Programming Interfaces

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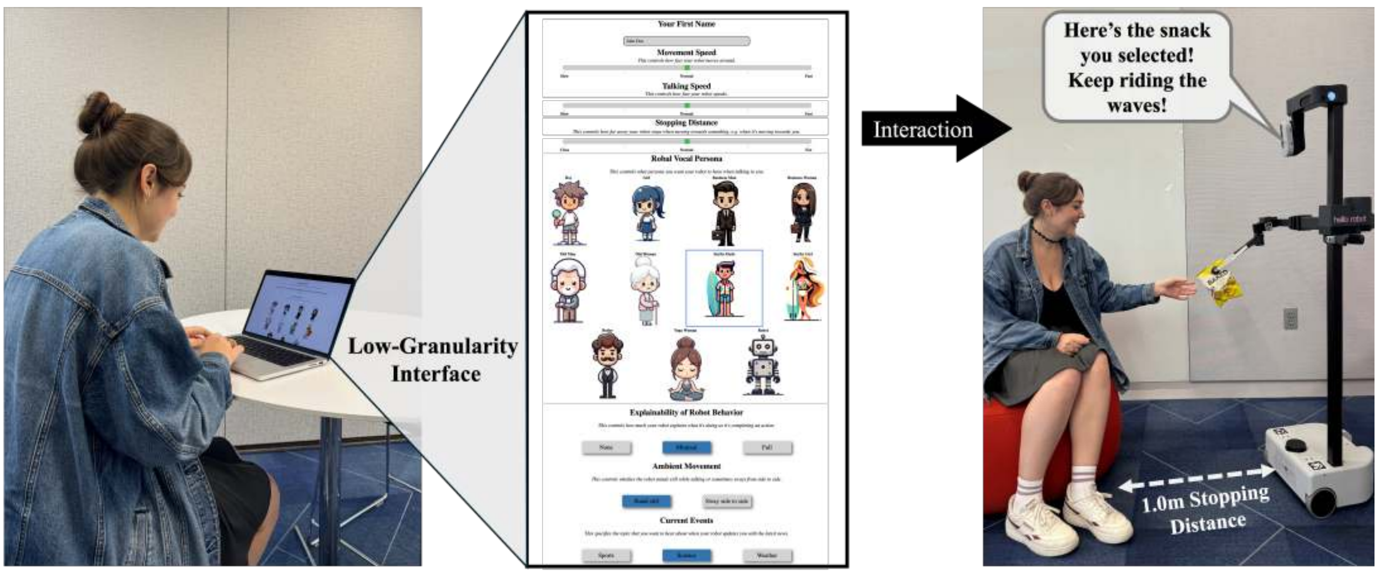

Fig. 1: Left: User personalizing the robot's behavior through the Low-Granularity Interface, with the "surfer dude" persona and a "normal" stopping distance selected. Right: Robot executing the interaction scenario, reflecting the user's customizations.

***Abstract*—Perceived social agency–the perception of a robot as an autonomous and intelligent social other–is important for fostering meaningful and engaging human-robot interactions. While end-user programming (EUP) enables users to customize robot behavior, enhancing usability and acceptance, it can also potentially undermine the robot's perceived social agency. This study explores the trade-offs between user control over robot behavior and preserving the robot's perceived social agency, and how these factors jointly impact user experience. We conducted a between-subjects study (N = 57) where participants customized the robot's behavior using either a High-Granularity Interface with detailed block-based programming, a Low-Granularity Interface with broader input-form customizations, or no EUP at all. Results show that while both EUP interfaces improved alignment with user preferences, the Low-Granularity Interface better preserved the robot's perceived social agency and led to a more engaging interaction. These findings highlight the need to balance user control with perceived social agency, suggesting that moderate customization without excessive granularity may enhance the overall satisfaction and acceptance of robot products.**

***Index Terms*—end-user programming; personalization; HRI**

I. Introduction

With the proliferation of large language models (LLMs), robot products with social and conversational capabilities are becoming increasingly common. The vision of human users forming social bonds with their robot products is increasingly realized in various contexts, such as providing companionship for older adults [1]–[3], supporting adolescent education [4], [5], and even facilitating social interactions between people [6], [7]. While not every user may see their robot products as social–especially those designed for specific utilitarian functions (e.g., robot vacuums)–prior work has shown that many users do view even utility-focused robots in a social manner, akin to a pet or even a family member [8], [9]. It is not difficult to envision a future where social interactions between humans and robots are commonplace both in public and at home.

Given this context, it is increasingly important to consider a robot's *perceived social agency*, a term we use to describe people's perceptions of a robot as a "social other," including perceptions of the robot's autonomy, agency, intelligence, social intelligence, and social presence. Perceived social agency is important to the success of robots in everyday settings [10]–[12]. Research in the field of Human-Robot Interaction (HRI) has highlighted that users are more likely to accept and engage with robots that they perceive as socially intelligent and possessing a social presence beyond utilitarian functionalities [13]–[15]. Perceived agency, autonomy and intelligence are crucial for robots to be seen not just as tools, but as a social other in daily activities [15], [16], often leading to more enjoyable human-robot interactions [17], [18].

In addition to the emerging importance of perceived social agency in robot products, the importance of tailoring the behavior of robot products to individual user preferences cannot be overstated. Adherence to user preferences is not only a matter of functional efficiency but also plays a significant role in fostering user acceptance and long-term engagement with robots [19]–[23]. Being able to personalize a robot's behavior enhances a user's satisfaction by making interactions more intuitive and aligned with their individual needs, which is particularly important in domains such as healthcare, education, and personal assistance [19], [24], [25].

One potential solution to ensure that robots behave according to user preferences is enabling end-user programming (EUP) [26], [27]. However, this customization could come with trade-offs in the robot's perceived social agency. Robot product designers and story writers invest considerable time and effort into crafting behaviors that make up the robot's character and personality [28]. For example, Amazon's Astro robot is designed to be endearing and pet-like [29], while robots developed by companies like Disney [30], [31] are imbued with specific characters, personalities, and backstories. Allowing end-users to alter the robot's behavior could disrupt these carefully designed attributes, potentially diminishing the robot's social agency and, consequently, its appeal and effectiveness [16].

Therefore, the challenge in designing EUP interfaces for such robots involves balancing the need for user preference adherence with the preservation of robot social agency. Granular control through detailed interfaces can enhance adherence by offering flexibility and precision [32], but may lead to the robot being seen as overly "pre-programmed," reducing its social agency. Conversely, eliminating customization could enhance social agency but risk misalignment with user preferences. Achieving enjoyable interactions likely depends on striking a balance: aligning the robot's behavior with user preferences while maintaining its perceived social agency.

This work examines the trade-offs in EUP interface granularity, focusing on how customization levels impact adherence to user preferences, perceptions of social agency, and overall user experience. We conducted a between-subjects study comparing three approaches: a High-Granularity Interface with block-based programming, a Low-Granularity Interface with broader input-form customizations, and a No End-User Programming condition where customization was unavailable. By evaluating user interactions with a home assistant robot, we aim to identify the approach that best balances user control and social agency for a satisfying and effective experience.

II. Background

A. End-User Robot Programming

End-User Programming (EUP) allows individuals without specialized programming skills to customize and control robot behaviors based on their specific needs [26], [33]. Personalizing robot actions enhances user engagement and satisfaction [34]–[37] and improves perceptions of robot effectiveness and helpfulness [25], [38], [39]. Various EUP methods have been developed to facilitate robot customization, including Robot Learning from Demonstration (LfD), which enables robots to learn skills without explicit programming by users and can be integrated into more complex behaviors [40]–[44]. Augmented Reality (AR) and Mixed Reality (MR) interfaces support gestures and direct interaction, reducing context switching [45]–[48], while speech and natural language are often combined with other modalities for EUP [45], [49]–[51]. Tangible programming, involving the manipulation of physical objects, is often designed for children [52]–[56].

Visual programming has become a prevalent EUP method due to its intuitive and accessible nature [26], [57], [58]. These interfaces allow users to create robot programs by manipulating graphical elements such as blocks [34], [58]–[61], icons [52], [55], flow diagrams [25], and behavior trees [36], [37], [62]. Block-based systems like Blockly [61], [63] and Scratch [58] are particularly popular for their intuitive and user-friendly drag-and-drop design, enabling users to build complex robot behaviors through simple actions [59] and are often as accurate as more complex, code-based alternatives [34]. Beyond block-based programming, visual interfaces also incorporate graphical UI components such as buttons, input-forms, menus, and sliders [35], [38], [64], [65] to gather user inputs. In this work, we compare user perceptions of a robot when customized using a highly detailed block-based EUP interface versus a low-granularity interface with simpler UI elements like sliders and buttons, as no prior work to our knowledge has systematically compared these EUP paradigms.

B. Perceived Social Agency in Human-Robot Interaction

We use the term "perceived social agency" to the perception that a robot can perform social actions–behaviors that affirm or threaten the "face" of another, as conceptualized by politeness theory [10], [66]. This perception, particularly at the user's level of abstraction (LoA), encompasses qualities like interactivity, autonomy, and adaptability [10], [67], [68], which make robots appear socially intelligent and capable of dynamic engagement. Interactivity enables bidirectional communication, autonomy suggests independent decision-making, and adaptability mirrors human-like responsiveness, all contributing to the perception of a robot as a social other [67]. Users are more likely to engage with robots they perceive as

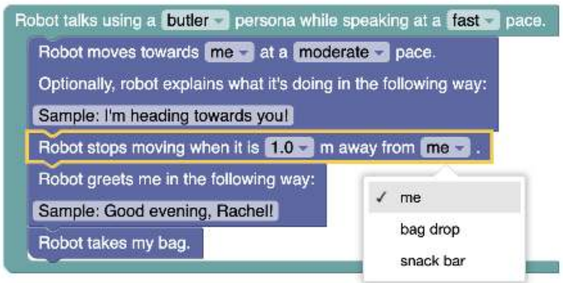

Fig. 2: Users of the High-Granularity Interface build their programs by dragging and dropping robot behavior blocks and selecting customization's of the robot's behavior via drop-downs and text-entry boxes.

socially agentic, which enhances trust, enjoyment, and long-term interaction [13], [15], [17]. For example, Snackbot [69] illustrates how social agency can foster deeper engagement through personalized, context-aware interactions, with socially responsive robots often perceived as more empathetic and human-like [70]. Despite the importance of perceived social agency to user engagement, no work to our knowledge has examined how perceived social agency can be balanced with preference adherence on overall user experience.

III. System Design

In this section, we present two distinct end-user programming (EUP) interfaces developed to control the behavior of the Stretch Research Edition 1 robot, with varying levels of granularity. Participants used the interfaces to customize how they wanted their robot assistant to interact with them upon returning home from work.

A. High-Granularity EUP Interface

The High-Granularity EUP Interface (see Figure 2) leverages the widely used block-based Blockly programming environment [63] due to its robustness and prevalence in current robot products [34], [58]–[61]. This interface allows for precise control of robot actions through programmable blocks.

In our implementation, each robot action during the interaction (e.g., stopping at a specific distance) corresponds to a single block, enabling participants to configure the robot's behavior at the task level (e.g., "Robot takes my bag") without needing to combine multiple lower-level commands like lower, extend, or retract the arm. This approach was intended to reduce participant fatigue and the time needed to program.

The High-Granularity Interface included a variety of blocks to enable users to customize each feature for each individual action within the interaction sequence, allowing it to be much more expressive in tailoring the robot's behavior to the user's exact preferences (see Figure 2 for examples). The primary types of blocks available to users were:

- **Mobile Base Movement Blocks:** Specify the robot's destination (e.g., user or snack bar), movement speed, and how far it should stop from a target. Users could also customize the robot's verbal explanations of its own actions during execution.
- **Conversation Blocks:** Customize social interactions by defining scenarios (e.g., "Robot greets me in the following way:") and input exact phrases or messages for the robot to deliver, tailoring the interaction to their preferences.
- **Task Blocks:** Represent specific tasks (e.g., "Robot takes my bag") with limited customization, except for the news update block, where users could choose genres and topics.
- **Outer Bracket For Vocal Customization:** Adjust the robot's voice and speech pace, with changes applied across all applicable blocks within the bracket.

Users submitted their customizations via a button at the bottom of the interface. A sample of the full interface is available in the supplemental documents.

B. Low-Granularity EUP Interface

The Low-Granularity Interface serves as a middle ground between no customization and the detailed controls offered by the High-Granularity Interface. It simplifies the customization process using sliders, buttons, and selectors for broad, macro-level adjustments (see Figure 1) while still allowing the users to customize the same set of features as that of the High-Granularity EUP Interface. Customizable features include:

- **Movement Speed:** Adjusts the robot's movement speed using a 5-point slider.
- **Talking Speed:** Controls how fast the robot speaks using a 5-point slider.
- **Stopping Distance:** Sets the distance at which the robot stops when approaching a target via a 5-point slider.
- **Robot Persona:** Selects one of 11 preset vocal personas (e.g., surfer dude, butler, robot) using clickable icons with text labels.
- **Explainability of Robot Behavior:** Chooses from None, Minimal, or Full explanations of robot actions via buttons.
- **Ambient Movement:** Decides whether the robot stays still or sways while talking, selectable via buttons.
- **Current Events:** Selects the news topic (e.g., sports) the robot will discuss, chosen via buttons.

This interface offers broad adjustments that apply across the entire interaction sequence, emphasizing ease of use over detailed customization.

C. Back End Implementation

We designed our backend to be mostly autonomous, where a human operator was only involved to signal the robot when to move on to the next task and adjust the mobile base when needed to help the robot achieve its objective. Once initiated, the robot performed tasks autonomously, using ARUCO tags and YOLO-based object detection for navigation, while the Intel RealSense camera's depth sensor managed stopping distances. Speech transcription and vocal interactions were powered by Whisper-1 and GPT-4, which transcribed participant utterances and generated context-aware responses

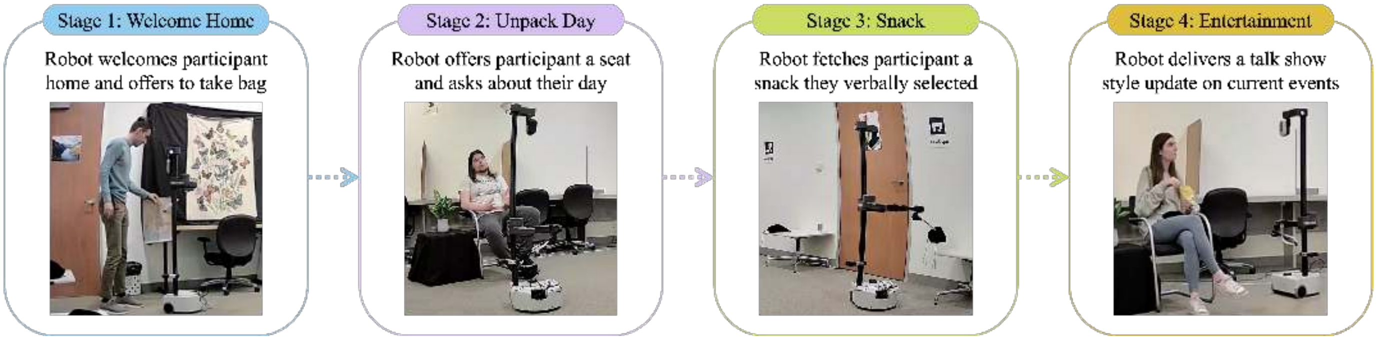

Fig. 3: Participants were asked to imagine that they are returning home from work. This is how the interaction with the robot assistant, Stretch, unfolded. The interaction can be roughly broken down into four stages.

tailored to user-selected vocal profiles. To maintain consistency in the interaction flow, GPT-4 responses were tightly constrained with context-specific prompts, character guidelines (see supplemental documents for our GPT-4 prompts), and a temperature setting of 0 to minimize response variability. In the Low-Granularity Interface and No EUP conditions, GPT-4 was used to rephrase scripted dialogues to fit the robot's selected robot persona (e.g., "Your potato chips are here, enjoy the gentle crunch and a moment of peace and tranquility" for a "yoga woman" persona) while grounding responses in the ongoing conversation context. In the High-Granularity Interface condition, GPT-4-generated scripts were limited to news updates, with the rest of the interaction strictly defined by user specifications.

IV. Methods

We conducted a between-subjects study where participants were randomly placed into one of three experimental conditions differentiated by how they programmed the Stretch robot: (1) the **High-Granularity Interface Condition** (see Section III-A), (2) the **Low-Granularity Interface Condition** (see Section III-B), or (3) the **No EUP Condition**. This study was approved by the University of Chicago's Institutional Review Board (Protocol IRB23-1720).

A. Hypotheses

Personalization through end-user programming (EUP) can enhance the alignment of robot behavior with individual user preferences [23], [26], [27], which fosters user acceptance and satisfaction [19]–[22]. The complexity and granularity of control in EUP interfaces often increase in proportion to the level of expression and customization they support [71], [72]. Therefore, we hypothesized:

- **H_1 (Preference Adherence)** – End-user programming will result in robot behavior that more closely **adheres to user preferences**, with the High-Granularity (HG) Interface providing the most alignment compared to the Low-Granularity (LG) Interface. We predict that users' preference adherence will follow **HG** $>$ **LG** $>$ **No EUP**.

However, the level of control afforded by EUP can alter the perceived autonomy and social capabilities of the robot, shifting the Level of Abstraction (LoA) from the user's perspective to something closer to a developer's viewpoint [10], [68]. This shift may compromise the robot's perceived social agency—a key aspect for robots to be viewed as social entities rather than mere tools, enhancing enjoyment and interaction quality in daily activities [15]–[18]—by making its behavior appear as less of a social other and more of a controllable tool. As such, we hypothesized that:

- **H_2 (Perceived Social Agency)** – Increasing the EUP interface's granularity of control will decrease users' perception of the robot's social agency. We predict that the robot's perceived social agency will follow **No EUP** $>$ **LG** $>$ **HG**.

Ultimately, the balance between customization granularity and social agency preservation plays a substantial role in shaping the overall user experience. While high customization can improve the robot's adherence to user preferences, it may also lead to a less engaging and enjoyable interaction if the robot is perceived less as a social other. Conversely, too little customization might maintain social agency but fail to meet individual user needs, suggesting that a balanced approach could yield the best overall experience:

- **H_3 (Overall UX)** – The Low-Granularity Interface will offer the best overall user experience compared to the High-Granularity Interface and No End-User Programming conditions: **LG** $>$ **No EUP** and **LG** $>$ **HG**.

B. Human Robot Interaction Scenario

We designed a realistic "returning home from work" scenario to simulate relatable daily interactions that could benefit from personalized robot behaviors. The scenario consists of four stages (see Figure 3):

- **Stage 1: Welcome Home** – The robot greets the participant upon their entry into the "living room", offers to take their bag, and directs them to sit while it puts the bag away.
- **Stage 2: Unpack Day** – The robot initiates a brief conversation, asking about the participant's day and sharing an anecdote about its own.

- **Stage 3: Snack** – The robot offers a choice between Rice Krispies and Potato Chips, retrieves the selected snack, and delivers it.
- **Stage 4: Entertainment** – The robot provides a 1-2 minute update on current events, with topics chosen based on participant preferences (or pre-determined in the No EUP condition).

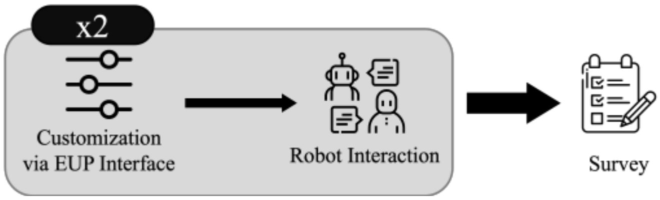

Fig. 4: After the first customization and interaction, participants returned to the EUP interface for a second time to update their customizations before going through the interaction again. Participants finished with a post-experiment survey.

C. Protocol

Participants began by reviewing a consent form and were introduced to their assigned EUP interface with an accompanying instruction manual. In the High-Granularity condition, they followed step-by-step instructions to program the robot for tasks aligned with the four stages of the interaction scenario (Section IV-B), customizing the robot's behavior to fit their ideal home assistant interaction. Low-Granularity participants received an interface manual and a brief overview of the upcoming interaction, while No EUP participants used a simple interface to enter their name. To minimize the impact of any single robot vocal persona in the No EUP condition, we rotated through 11 personas evenly across participants.

After programming, participants interacted with the robot in a staged living room setting for about 10 minutes, then returned to the interface to make any desired adjustments, now that they had seen how their customizations translated into tangible expressions in the robot's behavior. Participants in the No EUP condition submitted their name again, using the same simple interface. All participants then interacted with the robot for a second time (see Figure 4). We had participants complete the task twice to simulate real-world usage, where users program the robot, interact with it, and then make adjustments based on their experience. This allowed participants to refine their settings and observe how their changes impacted the robot's behavior in a second interaction. Programming times varied: participants in the High-Granularity condition took an average of 17.55 minutes ($SD = 4.62$) initially and 5.76 minutes ($SD = 3.30$) for adjustments, while those using the Low-Granularity Interface took under 2 minutes for both initial programming and adjustments. The study concluded with a post-experiment survey, taking approximately one hour. Participants were compensated $20 USD.

D. Measures

Participants completed a post-experiment survey to assess various aspects of their interaction with the robot (See supplemental documents for exact questionnaire items).

1) Adherence to User Preferences: Adherence to user preferences was evaluated using items such as how well the robot's behavior aligned with participants' expectations and the ease of modifying its actions. Responses were on a 7-point Likert scale from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*), with a high internal consistency (Cronbach's $\alpha = 0.80$).

2) Perceived Social Agency: Perceived social agency was measured through the following constructs:

- **Autonomy:** Assessed using the concept of non-deterministic autonomy, defined by Kim et al. [73] as the degree to which a robot's behavior is not specified prior to run-time, via a 7-point Likert scale from 1 (*Strongly Disagree*) to 7 (*Strongly Agree*).
- **Perceived Agency:** Measured using the 13-item Perception of Agency scale by Trafton et al. [74].
- **Social Presence:** Evaluated using the 17-item Social Presence scale by Chen et al. [75].
- **Social Intelligence:** Assessed using the Perceived Social Intelligence Scales (short form) by Barchard et al. [76].
- **Perceived Intelligence:** Measured via the Godspeed Perceived Intelligence subscale [77].

3) Overall User Experience: Overall user experience encompassed enjoyment, satisfaction with the interface, the desire to have the system at home, and engagement level, rated on a 7-point Likert scale. Responses were aggregated into an overall user experience score (Cronbach's $\alpha = 0.90$).

4) Open-ended Questions: Participants were asked open-ended questions such as, "How confident do you feel in making changes using the computer interface" and "Describe your interaction with the robot." We conducted qualitative analysis with two independent coders on the responses related to confidence (coded into "Yes, confident," "No, not confident," or "Mixed, including non-answers."), achieving high inter-coder reliability (Cohen's $\kappa = 0.86$).

E. Participants

A total of 75 participants were recruited to participate in the study, each randomly assigned to an experimental condition. We excluded 18 from our analysis due to participant non-compliance or substantial hardware/software failures (e.g., robot running out of battery during the interaction, failing to complete a successful grasp). Of the 57 participants included in our analysis, 20 were in the High-Granularity Interface condition, 18 in the Low-Granularity Interface condition, and 19 in the No EUP condition. Participants' age ranged from 18 to 50 ($M = 23.77$, $SD = 6.33$). 30 participants identified as women, 26 as men, and 1 as non-binary. Among the participants, 19 identified as White, 11 as South Asian, 11 as East Asian, 9 as Hispanic, 7 as Black, 7 as South East Asian, 2 as Middle Eastern, and 2 as Other. Those who identified with multiple ethnicities were double counted. No significant differences in demographic variables were present across the experimental conditions. A post-hoc power analysis showed that 57 participants across 3 conditions would allow us to detect effect sizes of $\eta_p^2 = 0.15$ with a power of 0.80.

V. Results

To assess the impact of different end-user programming interfaces on user experience, we conducted analysis of variance (ANOVA) tests, controlling for covariates including participant age, gender, and familiarity with programming. Effect sizes are reported using partial eta squared (η_p^2). Post-hoc pairwise comparisons were performed using Tukey's Honest Significant Differences (HSD) tests. For the analysis of qualitatively coded free-response labels, we utilized Chi-Square (χ^2) tests of independence and applied Bonferroni corrections for post-hoc pairwise comparisons.

A. Interface Usage Summary

We first examined participants' customization selections using the Low-Granularity (LG) and High-Granularity (HG) interfaces (see supplemental documents for detailed reports). Participants in both conditions chose a wide range of customizations, highlighting the need for personalization to accommodate diverse preferences. Some examples include how all 11 robot vocal personas were selected at least once by LG users, and 9 out of 11 by HG users. Approximately 55% of participants in both conditions adjusted the robot's stopping distance from the default 1.0 meter, and while 16.67% of LG users kept the default movement speed of 0.3m/s, 64.17% of HG users retained it, with most changes favoring faster speeds.

Moreover, LG users were more likely to modify the robot's behavior between interactions compared to HG users. Specifically, 77.78% of LG users changed the robot vocal persona compared to 18.75% of HG users, and similar trends were observed for stopping distance (61.11% LG vs. 43.33% HG), movement speed (66.67% LG vs. 48.33% HG), and talking speed (66.67% LG vs. 33.75% HG). This increased willingness to customize in LG users may be due to the lower cognitive load of the interface, making it easier for participants to engage in personalization.

B. Adherence to User Preferences

Our analysis revealed significant differences across the experimental conditions ($F = 7.85$, $p = 0.002$, $\eta_p^2 = 0.20$) for how well the robot's behavior aligned with user preferences, shown in Figure 5a. Participants in the Low-Granularity Interface condition ($M = 5.39$, $SD = 1.25$, $p < 0.001$) and the High-Granularity Interface condition ($M = 4.80$, $SD = 1.31$, $p = 0.002$) reported that the robot more closely adhered to their preferences compared to those in the No EUP condition ($M = 3.19$, $SD = 1.52$). However, there was no significant difference between the High-Granularity and Low-Granularity Interface conditions ($p = 0.388$).

Additionally, we found through coded responses to an open-ended question that participants in the Low-Granularity Interface condition overwhelmingly felt confident in making

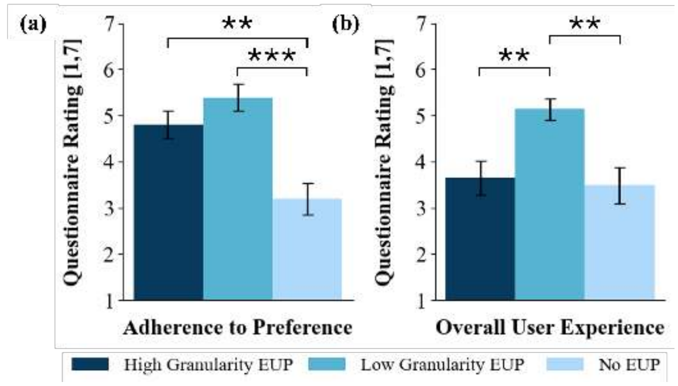

Fig. 5: (a) Participants that used either the High Granularity or Low Granularity EUP interface saw robot behavior that more closely aligned with their preferences. (b) Participants that used the Low-Granularity Interface enjoyed their interaction with the robot the most. (**), and (***) denote $p < 0.01$, and $p < 0.001$, respectively. Error bars show one standard error from the mean.

changes (88.89%), compared to those in the High-Granularity Interface (40%, $\chi^2 = 9.92$, $p = 0.007$) and No EUP (31.58%, $\chi^2 = 12.67$, $p = 0.002$) conditions. There was no significant difference between the High-Granularity Interface and No EUP conditions ($\chi^2 = 0.78$, $p = 0.6785$).

These findings partially support $\mathbf{H}_1$, indicating that enabling end-user programming generally leads to better adherence to user preferences compared to no programming, though the extra level of detailed control provided by the High-Granularity Interface did not yield significantly better adherence to user preferences than the Low-Granularity Interface.

C. Perceived Social Agency

The broader concept of perceived social agency was captured using the following five constructs: Autonomy, Perceived Agency, Social Presence, Social Intelligence, and Perceived Intelligence (see Figure 6).

1) Autonomy: When asked if they perceived the robot to be reacting to external stimuli with unscripted autonomous actions that were not pre-programmed, participants reported differences in perceived non-deterministic autonomy across the experimental conditions ($F = 3.05$, $\eta_p^2 = 0.16$, $p = 0.007$, see Figure 6a). Participants in the Low-Granularity Interface condition ($M = 4.33$, $SD = 1.41$) rated the robot as significantly more autonomous than those in the High-Granularity Interface condition ($M = 2.85$, $SD = 1.90$, $p = 0.024$). There was no significant difference in perceived autonomy between the Low-Granularity Interface condition and the No EUP condition ($M = 4.00$, $SD = 1.67$, $p = 0.819$), though participants in the No EUP conditions rated the robot as marginally more autonomous than those in the High Granularity Interface condition ($p = 0.092$).

2) Perceived Agency: For the aggregated measure of perceived agency, participants reported significant differences

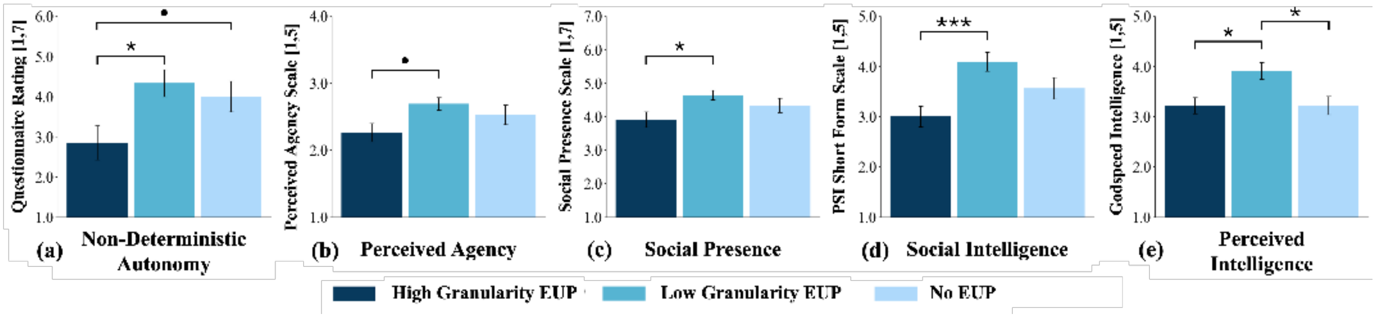

Fig. 6: Participants using the Low-Granularity Interface generally perceived the robot as having greater autonomy, agency, social presence, social intelligence, and perceived intelligence than those using the High-Granularity Interface. (.), (*), (**), and (***) denote $p < 0.1$, $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively. Error bars show one standard error from the mean.

across the experimental conditions ($F = 3.90$, $\eta_p^2 = 0.11$, $p = 0.030$, see Figure 6b). Participants in the Low-Granularity Interface condition ($M = 2.69$, $SD = 0.40$) tended to perceive the robot as having higher agency compared to those in the High-Granularity Interface condition ($M = 2.26$, $SD = 0.62$), although this difference did not reach statistical significance ($p = 0.060$). No significant differences in perceived agency were observed between the High-Granularity Interface and the No EUP condition ($M = 2.53$, $SD = 0.64$, $p = 0.313$) or between the Low-Granularity Interface and No EUP condition ($p = 0.661$).

3) Social Presence: Social presence scores varied significantly between conditions ($F = 5.37$, $\eta_p^2 = 0.13$, $p = 0.010$, see Figure 6c). Participants rated the robot as having greater social presence in the Low-Granularity Interface condition ($M = 4.64$, $SD = 0.61$) compared to the High-Granularity Interface ($M = 3.91$, $SD = 1.04$, $p = 0.037$). No significant differences were found between the Low-Granularity and No EUP conditions ($M = 4.33$, $SD = 0.93$, $p = 0.536$), nor between the High-Granularity Interface and No EUP conditions ($p = 0.310$).

4) Social Intelligence: Social intelligence ratings showed significant effects of interface type ($F = 5.67$, $\eta_p^2 = 0.12$, $p = 0.008$, see Figure 6d). Participants in the Low-Granularity Interface condition viewed the robot as being the most socially intelligent ($M = 4.09$, $SD = 0.81$), significantly more than participants in the High-Granularity Interface condition ($M = 3.00$, $SD = 0.91$, $p = 0.0012$). There were no significant differences between the Low-Granularity Interface and No EUP conditions ($M = 3.56$, $SD = 0.94$, $p = 0.179$), nor between the High-Granularity Interface and No EUP conditions ($p = 0.125$)

5) Perceived Intelligence: For participant perceptions of the robot's intelligence, participants reported significant differences across conditions ($F = 3.37$, $\eta_p^2 = 0.10$, $p = 0.047$, see Figure 6e). Participants in the Low-Granularity Interface condition ($M = 3.91$, $SD = 0.70$) rated the robot as significantly more intelligent than those in the High-Granularity Interface condition ($M = 3.22$, $SD = 0.72$, $p = 0.016$) and the No EUP condition ($M = 3.22$, $SD = 0.80$, $p = 0.018$). There was no significant difference between the High-Granularity Interface and No EUP conditions ($p = 1.00$).

Taken together, these findings suggest that participants in the Low-Granularity Interface condition generally perceive the robot as having greater social agency compared to participants in the High-Granularity Interface condition. Contrary to our hypothesis, participants did not think the robot in the No EUP condition had greater social agency than the robot robot in the Low-Granularity Interface condition despite not customizing any part of its behavior. Thus, $\mathbf{H}_2$ is partially supported.

D. Overall User Experience

We observed significant differences across conditions for the aggregated user experience metric ($F = 6.30$, $p = 0.005$, $\eta_p^2 = 0.14$), shown in Figure 5b. Participants in the Low-Granularity Interface condition reported significantly better overall user experience ($M = 5.14$, $SD = 0.99$) compared to those in the High-Granularity Interface condition ($M = 3.65$, $SD = 1.65$, $p = 0.009$) and the No EUP condition ($M = 3.49$, $SD = 1.68$, $p = 0.004$). No significant difference was found between the High-Granularity Interface and the No EUP conditions ($p = 0.937$). These findings support $\mathbf{H}_3$, indicating that the Low-Granularity Interface provided the most enjoyable user experience.

VI. Discussion

This study set out to explore the trade-offs between the level of control offered by EUP interfaces and the robot's perceived social agency, and how these factors impact overall user experience. By comparing a Low-Granularity EUP Interface that offered broad, macro-level customizations, a High-Granularity EUP Interface with detailed adjustments via block-based programming, and a No EUP condition where no customizations were possible, we explored how best to balance between customization and the preservation of social agency.

A. Adherence to User Preferences

Our findings confirmed that enabling EUP significantly improves the alignment of robot behavior with user preferences.

Both the Low-Granularity and High-Granularity Interfaces outperformed the No EUP condition in adhering to user preferences, supporting prior research on the value of personalization in fostering user satisfaction and engagement with robots [22], [24]. However, contrary to expectations, the High-Granularity Interface did not surpass the Low-Granularity Interface in preference adherence, despite providing more detailed controls. Qualitative data seem to suggest that this may be due to the complexity and time required for novice users, with participants stating, "*this was a lot of effort for a simple sequence*" (p66) and "*I trust my fellow humans...more than...scratch blocks they created*" (p23). This suggests that while customizations can empower users, there is a threshold where too much granularity can overwhelm rather than empower, detracting from the user experience.

In contrast, the Low-Granularity Interface achieved similar levels of adherence to user preference without the added complexity and time commitment. As one participant from the Low-Granularity Interface condition noted, "*if it is any more intense than the customization screen at the beginning of the study, I do not feel confident making changes*" (p8). This suggests that the Low-Granularity Interface aligns well with the level of customization complexity that novice users are comfortable managing. However, it is important to note that the study was conducted in a controlled setting with a one-hour timeframe. Given more time and opportunities for multiple iterations beyond the two allowed in our study, participants might have fine-tuned the robot's behavior more closely to their preferences using the High-Granularity Interface.

B. Perceptions of the Robot

Our findings revealed that participants in the Low-Granularity Interface condition perceived the robot as having greater social agency–measured by autonomy, agency, social presence, social intelligence, and perceived intelligence—compared to the High-Granularity Interface condition. At the same time, the Low-Granularity Interface improved the robot's behavior alignment with user preferences without requiring users to specify every detail of the robot's actions. As one participant noted, "*I would want to customize it to do the things I'd like it to do, but I also don't want to have a need of doing so beyond a certain point. I don't want to micromanage social interactions; I would rather program the robot to be polite and then have it auto-generate responses in a conversation*" (p42). This suggests that the macro-level customizations offered by the Low-Granularity Interface helped maintain the veil of social agency, keeping the robot's observable attributes within the average user's Level of Abstraction (LoA) [10], [67] without crossing into the "developer's LoA," which the High-Granularity Interface might have encouraged. By keeping users at a higher level of interaction, the Low-Granularity Interface may have preserved the robot's perceived social agency, preventing the user from being involved with the inner workings that could undermine these perceptions.

Interestingly, our hypothesis that the No EUP condition would result in the highest perceptions of social agency was not supported. A plausible explanation is that the robot's lack of variability in behavior between the first and second interactions led participants to view it as executing a fixed, preprogrammed sequence, possibly crafted by the robot designers. With no changes observed between the two interactions participants experienced, the robot appeared less adaptive, which likely diminished its perceived social agency. Comments from participants in the No EUP condition like, "*the robot is preprogrammed with info I have no interest in and will not stop on command*" (p68) illustrate this perception, suggesting that a lack of behavioral variation can make the robot feel less agentic [10], [67], [68]. In real-world settings, where user routines are not restricted by the study setup–such as users not being required to accept the snack–or the robot not be constrained to engage in specific interactions dictated by research protocols for consistency across participants, we anticipate that a similar home assistant robot without customization options would exhibit greater perceived social agency over time, as its actions would naturally adapt to more varied user interactions and contexts.

C. Overall User Experience and Wider Implications

Our findings indicate that the Low-Granularity Interface offered the most engaging and satisfying overall user experience compared to both the High-Granularity Interface and not having EUP at all. By balancing user customization with the preservation of the robot's social agency, the Low-Granularity Interface facilitated interactions that were not only better aligned with user preferences but also felt more socially interactive and meaningful [15], [16]. This balance contributed to a generally more enjoyable human-robot interaction experience [17], [18].

The broader implications of our study highlight the need for EUP interfaces that empower users while maintaining the robot's social qualities. Designers should aim to create programming interfaces that enable users to meaningfully shape robot behaviors in a way that is intuitive and manageable, avoiding overly granular controls that risk pushing users into a developer's level of abstraction–a perspective that may feel complex and disengaging for typical users. Our findings suggest a balanced approach to EUP interface design for robot products, where user control is carefully calibrated to preserve the robot's social agency. This approach could guide the development of more adaptable and user-friendly robots that appeal to a broad range of users. By emphasizing this balance, future robots may be better positioned to integrate into the social fabric of our homes and communities, enriching human experiences in nuanced and meaningful ways.

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