Exploring Robot Personality Traits and Their Influence on User Affect and Experience

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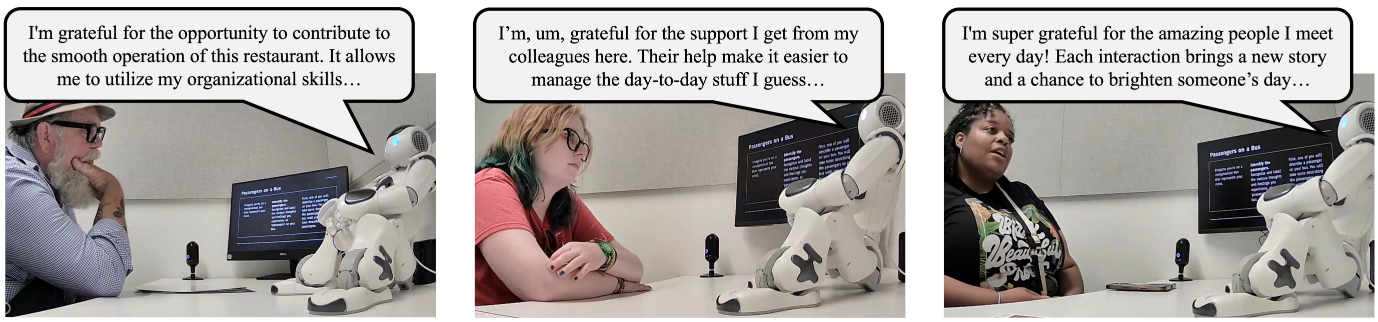

a) Baseline Robot Personality **b) High Neuroticism Robot Personality** **c) High Extraversion Robot Personality**

Fig. 1: We explored the influence of three distinct robot personalities on user engagement and interaction outcomes in a human-robot interaction designed to improve participants' overall well-being. The three robot personalities we explored were: (a) a Baseline Robot Personality, (b) a High Neuroticism Robot Personality, and (c) a High Extraversion Robot Personality.

***Abstract*—As human-robot interactions become more social, a robot's personality plays an increasingly vital role in shaping user experience and its overall effectiveness. In this study, we examine the impact of three distinct robot personalities on user experiences during well-being exercises: a Baseline Personality that aligns with user expectations, a High Extraversion Personality, and a High Neuroticism Personality. These personalities were manifested through the robot's dialogue, which were generated using a large language model (LLM) guided by key behavioral characteristics from the Big 5 personality traits. In a between-subjects user study (N = 66), where each participant interacted with one distinct robot personality, we found that both the High Extraversion and High Neuroticism Robot Personalities significantly enhanced participants' emotional states (arousal, control, and valence). The High Extraversion Robot Personality was also rated as the most enjoyable to interact with. Additionally, evidence suggested that participants' personality traits moderated the effectiveness of specific robot personalities in eliciting positive outcomes from well-being exercises. Our findings highlight the potential benefits of designing robot personalities that deviate from users' expectations, thereby enriching human-robot interactions.**

***Index Terms*—human-robot interaction; robot personality**

I. Introduction

An increasing number of human-robot interactions are becoming highly social in nature, spanning applications such as robot tutors [1], companionship robots [2], [3], entertainment robots [4], [5], home assistant robots [6], [7], and mental health robot coaches [8], [9]. These social robots are often perceived as having personalities, with distinct character traits, backstories, and other human-like attributes [10], [11]. The personality of a robot can significantly influence user engagement and satisfaction across diverse user groups [12]. Understanding the impact of robot personality on user experience is crucial for fostering long-term acceptance of robots in our inherently social communities [13].

Some robot personalities in human-robot interactions are meticulously crafted with the intention of achieving specific goals. For instance, the robot *Pepper* is programmed with a friendly, approachable personality for customer service roles [14], while Amazon's Astro is designed to be endearing and pet-like [7]. Similarly, Disney robots are infused with distinct characters, personalities, and backstories to enhance user engagement [15], [16]. Other robots, however, have personalities that arise without intentional design, often embodying social characteristics and fitting stereotypes of what people think of as "robot-like" [17]. For instance, most users expect robots to never disobey commands [18] and complete tasks to perfection [17].

Regardless of whether a robot's personality is intentionally designed or emergent, it profoundly impacts how people perceive and interact with robots. Using a broad conceptualization of "personality" defined by characteristics such as a robot's sociability [19] or friendliness [20], some prior work in the field of human-robot interaction (HRI) has found that factors such as robots having human-like faces [19] and users assembling the robot themselves [20] improve people's perceptions of a robot's overall personality. Notably, other work in HRI has extensively investigated user experiences with robots that vary specifically in extraversion [10], [21]–[23], one of the traits from the Big 5 personality model [24]. Some studies have found that higher extraversion in robots results in better interaction outcomes [21], while others have shown that participants respond more favorably to robots whose extraversion either matches [23] or complements [10] their own personality.

Extraversion is just one dimension of the Big 5 personality model, and little research has explored how other traits, such as neuroticism, influence human-robot interactions. Previous studies have used rule-based [21], handcrafted [25], or crowd-sourced [26] methods to create personality-consistent dialogue, which are not easily scalable. To address this gap, we examine how different Big 5 traits affect interactions by designing three robot personalities using a large language model (LLM): (1) a Baseline Personality aligning with typical user expectations, (2) a High Extraversion Personality, and (3) a High Neuroticism Personality.

Our study investigates how these personalities impact user experiences during well-being-focused interactions, addressing three research questions:

- **RQ1:** Does a robot personality that deviates from user expectations enhance the interaction experience?
- **RQ2:** Do some robot personality traits (e.g., neuroticism, extraversion) improve the user experience of all users, regardless of the user's personality?
- **RQ3:** Do a user's own personality traits influence how robot personality traits affect their experience?

Through this investigation, we aim to deepen the understanding of how robot personalities shape interactions and how user personalities mediate the robot's effectiveness, particularly in the context of mental health and well-being. This work highlights the potential benefits and challenges of designing robot personalities tailored to user characteristics, contributing to the development of more engaging and supportive social robots.

II. Background

We review prior work on the Big 5 personality traits and work exploring robot personality.

A. Big 5 Personality Traits

The Five-Factor Model (FFM), or the "Big 5" personality traits, is one of the most influential models in personality psychology. Initially introduced by Fiske in 1949 [27] and later expanded by researchers such as Goldberg [28], Costa and McCrae [29], and Soto [30], the FFM categorizes personality into five core traits: Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Neuroticism—summarized by the acronym "OCEAN." These traits are typically measured through questionnaires based on Likert scales, and the model has become a cornerstone of personality psychology [24]. Empirical support for the FFM emerged from psychological trait measures and adjective-based scales, or lexicons, developed by researchers such as Allport and Odbert [31], Galton [32], and Cattell [33].

Research shows that the FFM is applicable across diverse settings, including professional, educational, and recreational [34]. For instance, Agreeableness, Conscientiousness, and Openness have been found to correlate significantly with academic performance [35] while job statisfaction has been linked to Neuroticism, Extraversion, Conscientiousness, and to a lesser extent, Agreeableness [36]. Given the empirical support, we use the FFM to both design robot personalities and assess participant personalities in our study.

To measure Big 5 traits, we utilized the 20-item Mini International Personality Item Pool (Mini-IPIP), known for its brevity and accuracy in in-person settings [37], [38]. Notably, the IPIP assesses "Intellect/Imagination" instead of "Openness to Experience," [29]. While related, "Intellect/Imagination" focuses on intellectual curiosity, whereas "Openness" emphasizes the interest in the arts [39].

B. Robot Personalities

Many prior studies in HRI have evaluated users' perceptions of a robot "personality" [19], [20], [25], [40], defining the robot's personality using general social characteristics (e.g., sociable, friendliness) instead of a strictly factor based personality model (i.e., Big 5 personality traits). For instance, Broadbent et al. [19] found that robots with human-like faces were perceived as having better personalities based on measurements of the robot's perceived sociability. Groom et al. [20] showed that users preferred the personality of robots they assembled themselves and non-humanoid car robots over humanoid ones, using modified Wiggin's personality measures such as friendliness, integrity, and malice. Furthermore, Lohse et al. [25] utilized a self-developed set of descriptive adjectives (e.g., friendly, obedient, boring) to show that extraverted robot behavior was associated with traits like intelligence, friendliness, and diversity when participants evaluated videos of robots.

A significant portion of research has also drawn upon the Five Factor Model (i.e., Big 5 personality traits) to design and evaluate robot behavior [6], [10], [23], [26], [41]–[43]. Most of these studies focused heavily on one of the five traits: extraversion. For example, Lee et al. [10] discovered that extraverted participants enjoyed interacting with introverted AIBO robots, while introverted participants preferred extraverted AIBO robots. Tapus et al. [23] demonstrated that matching a robot's extraversion to that of the user's improved task performance and satisfaction. Additionally, Tay et al. [22] found that high extraversion paired with a healthcare worker role led to greater user acceptance, whereas introversion paired with a security guard role also enhanced acceptance, aligning with cultural stereotypes. Meerbeek et al. [21] crafted dialogue representing more extraverted versus introverted personalities and found that participants preferred an extraverted personality with low user control in the context of a TV assistant robot, while keeping neuroticism and intellect/imagination constant in their robot design.

Our work builds upon this body of research by making novel direct comparisons of multiple Big 5 personality traits, including neuroticism and extraversion, and evaluating their impact within the context of well-being interventions. Furthermore, unlike most prior studies that relied on rule-based [21], handcrafted [25], or crowd-sourced [26] dialogue systems to convey robot personality, we developed a method using LLMs to generate dialogue consistent with various personality types and traits, thereby providing a scalable and flexible approach for future HRI research.

III. Study 1: Establishing a Baseline Robot Personality

In this first study, we aimed to determine the personality traits that people expect a robot to have. From this "baseline" robot personality, we designed and tested deviations in Study 2 (Section V).

A. Methods

Participants watched a brief video featuring a Softbank Robotics NAO robot, which introduced itself as a restaurant greeter. After viewing the video, participants completed a questionnaire evaluating the robot's Big 5 personality traits. This study was approved by the University of Chicago's Institutional Review Board (Protocol IRB24-0145).

1) Robot Video: Robot characteristics such as morphology [44] (e.g., humanoid vs. non-humanoid), capabilities [45] (e.g., ability to use natural language), and context [46] (e.g., restaurant greeter) significantly affect how people perceive a robot's personality. To ensure consistency, we used the same NAO robot–a common platform in HRI research [47]–[51]–in both Study 1 and Study 2. In both studies, the robot was presented as a restaurant greeter.

The video was 15 seconds long and featured the NAO robot using the "Shimmer" voice from OpenAI's Text-To-Speech (TTS) Whisper-1 API. This voice was chosen for its gender-neutral tone and lack of inherent personality traits. In the video, the robot introduces itself as follows:

"Hi there, my name is NAO. I am a humanoid robot that works at restaurants, particularly in greeting guests as they walk through the door. I let people know the current wait time and I help with booking reservations as well."

2) Protocol: Participants were recruited through the Prolific platform, with eligibility criteria including a minimum 95% approval rating, fluency in English, and residence in the United States. After providing informed consent, participants watched the 15-second robot video and then completed the 20-item Mini-IPIP questionnaire [37] to assess their perceptions of the robot's Big 5 personality traits.

3) Participants: A total of 50 participants took part in the study. Their ages ranged from 18 to 67 years ($M = 35.42$, $SD = 11.97$). The gender breakdown was 26 female, 22 male, and 2 non-binary. In terms of ethnicity, 33 participants identified as White, 10 as Asian/Pacific Islander, 9 as Black, 2 as Hispanic/Latino, and 1 as Native American. Participants who identified with multiple ethnicities were counted in each relevant category.

TABLE I: Perceptions of the Robot's Big 5 Personality Traits in Study 1 (Range: [0, 1])

Trait	**Mean (SD)**	**Level**	**Visualization**
Conscientiousness (C)	0.761 (0.190)	High	
Extraversion (E)	0.425 (0.179)	Moderate	
Agreeableness (A)	0.358 (0.248)	Moderate	
Intellect/Imagination (I)	0.316 (0.244)	Low	
Neuroticism (N)	0.230 (0.181)	Low	

B. Results

Table I displays the average ratings for each personality trait of the robot. Participants perceived the robot as having high Conscientiousness (C) with a normalized score of 0.761 ($SD = 0.190$), moderate levels of Extraversion (E) at 0.425 ($SD = 0.179$) and Agreeableness (A) at 0.358 ($SD = 0.248$), and relatively low scores for Intellect/Imagination (I) at 0.316 ($SD = 0.244$) and Neuroticism (N) at 0.230 ($SD = 0.181$). These findings establish a baseline personality profile for our robot. We categorized the Big 5 traits into three uniformly sized buckets—Low (0.0–0.33), Moderate (0.34–0.66), and High (0.67–1.0).

IV. Generating Personality-based Robot Dialogues using LLMs

Having established a baseline robot personality, we next wanted to test the baseline robot personality and several deviations from that baseline personality in a user study. Since the robot primarily expresses its personality through verbal dialogue, we developed a method to craft robot dialogue consistent with the Big 5 personality traits selected for each personality.

Our approach leverages two critical aspects to create a consistent overall character and personality:

1) **Backstory**: A narrative that provides context and depth to the character and the world it inhabits.
2) **Personality Traits**: Specific attributes the character should exhibit, guiding their behavior and interactions, often aligned with the Big 5 personality traits.

To generate personality-consistent dialogue, we first used an LLM to create a robot backstory based on the desired traits, defined by categorical descriptors (low, moderate, high) and related characteristics. This backstory was then used to guide the LLM in generating consistent dialogue. We employed OpenAI's GPT-4o (temperature = 0) without character-specific fine-tuning. To ensure consistency, we minimized reliance on the model's general inference capabilities. Testing revealed that vague prompts produced indistinct, inconsistent dialogue, complicating differentiation between intended personalities.

A. Generation of Robot Backstories

In order to generate robot backstories consistent with specific Big 5 personality traits for our study, we provided the

LLM with a *Big 5 Personality Traits Characteristics Table*– a researched compilation of specific behaviors and attributes commonly associated with individuals who score high on each trait. Some examples of table items include: "Responsible to others" [52] for Conscientiousness, "Likes to start conversations with strangers" [53] for Extraversion, and "Processes negative information about themselves" [54] (see supplemental documents for full list). This table served as a foundational guide for the model, ensuring that the generated backstories intricately reflected these personality details, resulting in coherent and distinct robot personalities.

In addition to the characteristics table, we prompted the model with the following components:

- **Objective**: *"Write a 3-paragraph coherent backstory that touches on all of the Big 5 personality traits without explicitly mentioning them. Show, don't tell."*
- **Context**: *"NAO is a humanoid robot in Chicago that works at restaurants, particularly in greeting guests as they walk through the door. It lets people know the current wait time, current availabilities, and books reservations as well."*
- **Personality Settings**: *"High Conscientiousness, Moderate Agreeableness, Moderate Extraversion, Low Intellect/Imagination, and Low Neuroticism."*

The full backstories we generated using the prompts above can be found in the supplemental documents.

1) Generation of Robot Dialogue: The LLM-generated backstories were paired with a one-line note on speaking style, based on prior research documenting how individuals with high levels of Big 5 traits typically communicate. For example, the note for highlighting extraversion is "You speak warmly, assertively, and are talkative" [55] and the note for highlighting neuroticism is "You speak less formally and struggle to speak fluently" [56], [57]. (The full speaking style notes for every Big 5 trait is available in the supplemental documents).

Along with the backstory and speaking style note, we used the following prompt to guide the model: *"Respond to all further queries as if you are NAO. Respond with around four sentences. You must generate a response that fits your backstory. Make sure to stay true to the personality in the backstory. Use colloquial language."*

V. Study 2: Exploring the Benefits of Different Robot Personalities

To explore the impact of distinct robot personalities on human-robot interactions, we conducted an in-person, between-subjects study where a robot accompanies a participant through three exercises designed to improve overall well-being. This study was approved by the University of Chicago's Institutional Review Board (Protocol IRB24-0145).

A. Experimental Conditions

We designed three robot personality conditions to explore their impact on user interactions. The **Baseline Robot Personality** was created based on results from Study 1, reflecting the traits participants typically expect from the NAO robot. Given the extensive research on extraversion in HRI [10], [23], [43], we included a **High Extraversion Robot Personality** to examine its influence on well-being exercises, adjusting only the personality setting to "High Extraversion" and used the extraversion speaking note for LLM dialogue generation. Additionally, in contexts where emotional resilience and coping support are essential, increasing the neuroticism trait of a robot may provide insights into adapting robot interactions to better engage users who might respond better to a robot that has a personality more similar or relatable to their own, especially for those who may not be highly extraverted or those high in neuroticism [8]. Therefore, we developed a **High Neuroticism Robot Personality** using the "High Neuroticism" setting and speaker note. This setup allowed us to investigate the differential effectiveness of well-being interventions based on varying robot personality traits.

B. Exercises to Improve Overall Well-Being

We designed an interaction between a robot and a human participant, where the robot, acting as a peer, accompanied the participant through three well-being exercises. Throughout the exercises that were facilitated by the computer screen in the room, the robot maintained its backstory element as a restaurant greeter, consistent with Study 1. We chose this as the interaction setting since it is a highly social human-robot interaction, where the robot would have many opportunities to self-disclose and display its distinct personalities. We structured our study around three exercises commonly used by mental health professionals to enhance well-being [58]: the Three Good Things Exercise [59], the Passengers on the Bus Metaphor [60], and the Three Signature Character Strengths Exercise [59], [61]. Study instructions provided to participants can be referenced in the supplemental documents.

C. Protocol

Participants began by reviewing a consent form and completing a pre-experiment survey. A research assistant then led them into the interaction room with the NAO robot and a computer screen. The research assistant explained that the participant would complete three well-being exercises with the robot, with instructions displayed on the screen. After the robot introduced itself and the research assistant left the room, the instructions for the first exercise (Three Good Things) appeared on the screen, and the robot prompted the participant to begin. The robot embodied the role of an exercise partner, following the instructions on the computer screen, taking turns with the participant and acknowledging their responses. GPT-4o generated the robot's dialogue, with a human operator approving every generated statement to ensure accuracy and catch any potentially inappropriate responses. In our study, the human operator intervened no more than once for every 100 generated responses. After completing all exercises, the research assistant guided the participant to a post-interaction survey. Participants were then debriefed and compensated for 30 minutes of their time with 600 points (equivalent to \$6 USD) redeemable for museum prizes.

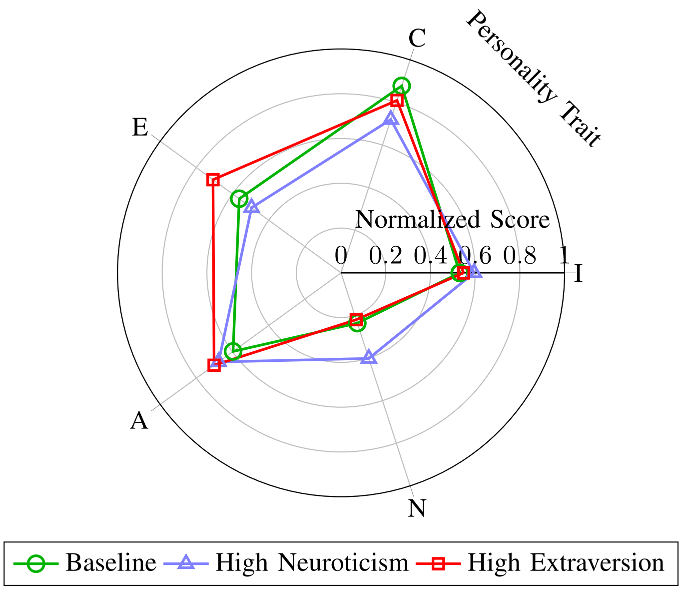

Fig. 2: Radar Plot of Mean Mini-IPIP Scores for Robot Personality Traits Across Conditions

D. Measures

We assessed participants' interaction experience using pre-experiment and post-experiment questionnaires and by analyzing their interaction transcripts (see supplemental documents for exact questionnaire items).

1) Big 5 Personality Traits: To capture both the participant's Big 5 personality traits and those of the robot, participants completed the 20-item Mini-IPIP questionnaire [37] about themselves before the experiment and the same questionnaire in the post-experiment survey about the robot.

2) Emotional State: We used a modified version of the Self-Assessment Manikins (SAM) [8], [9], [62] to capture changes in participant Arousal, Control, and Valence before and after the interaction with the robot. Arousal refers to the intensity of emotional activation, Control measures the degree to which participants felt in control during the interaction, and Valence represents the positivity or negativity of the emotional experience. This measure was administered both before and after participants interacted with the robot.

3) Readiness Ruler: Participants were asked to complete the readiness ruler [9], [63] to measure their (1) willingness and (2) confidence to make behavioral changes to improve their mental well-being. This measure was administered both before and after participants interacted with the robot.

4) Overall User Experience: Overall user experience was measured using several items, including enjoyment, engagement level, desire to interact with the robot again, feelings of rapport, and the quality of the relationship with the robot. These items were rated on 7-point Likert scales, and responses were aggregated into an overall user experience score (Cronbach's $\alpha = 0.949$).

E. Participants

A total of 70 participants were recruited for our study. Of the 70, 4 were excluded from our analysis due to incomplete data collection or survey administration errors. Participants were randomly assigned to interact with one of 3 robot personality types: Baseline ($N = 22$), Highly Neurotic ($N = 23$), and Highly Extraverted ($N = 21$). Participants' age ranged from 18 to 79 ($M = 32.48$, $SD = 14.48$). 32 participants self-identified as female, 28 as male, and 6 as non-binary. Among the participants, 37 identified as White, 6 as South Asian, 5 as East Asian, 6 as Hispanic, 4 as Black, 3 as South East Asian, 4 as Middle Eastern, 2 as Other, and 1 declining to answer this question. Those who identified with multiple ethnicities were double counted in those ethnicities. No significant differences in demographic variables were present across the three experimental conditions. Based on the self-reported readiness ruler measures, there was no significant difference in baseline (pre-interaction) mental well-being across conditions.

VI. Results

To evaluate the impact of different robot personalities on user interactions, we conducted one-way Analysis of Covariance (ANCOVA) tests, controlling for covariates including participants' age, gender, neuroticism, and extraversion scores. Effect sizes were reported using partial eta squared (η_p^2). Post-hoc pairwise comparisons were performed using Tukey's Honest Significant Differences (HSD) tests. Additionally, Multiple Regression Analysis was conducted to examine whether different robot personalities (categorical) affect users differently based on participants' personalities (continuous). In this analysis, we reported regression coefficients (β), t-values, and adjusted p-values (p_{adj}), along with Cohen's f^2 for the effect size. For metrics with repeated measures, Mixed ANOVAs were implemented to evaluate within-subjects (e.g., pre-interaction versus post-interaction) and between-subjects effects (e.g., Robot Personality Condition). Post-hoc pairwise t-tests were conducted with Benjamini-Hochberg correction.

A. Manipulation Check: Perceived Robot Personalities

To ensure that participants perceived the robot personalities as intended, we examined participant perceptions of the robot's Big 5 personality traits. As illustrated in Figure 2, the Baseline Robot Personality was rated with the following means and standard deviations: Conscientiousness ($M = 0.88$, $SD = 0.17$), Extraversion ($M = 0.56$, $SD = 0.19$), Agreeableness ($M = 0.60$, $SD = 0.26$), Intellect/Imagination ($M = 0.53$, $SD = 0.24$), and Neuroticism ($M = 0.24$, $SD = 0.18$). The High Neuroticism Robot Personality was rated as follows: Conscientiousness ($M = 0.72$, $SD = 0.19$), Extraversion ($M = 0.50$, $SD = 0.18$), Agreeableness ($M = 0.68$, $SD = 0.15$), Intellect/Imagination ($M = 0.60$, $SD = 0.17$), and Neuroticism ($M = 0.40$, $SD = 0.17$). The High Extraversion Robot Personality had ratings of Conscientiousness ($M = 0.81$, $SD = 0.16$), Extraversion ($M = 0.71$, $SD = 0.20$), Agreeableness ($M = 0.70$, $SD = 0.26$), Intellect/Imagination

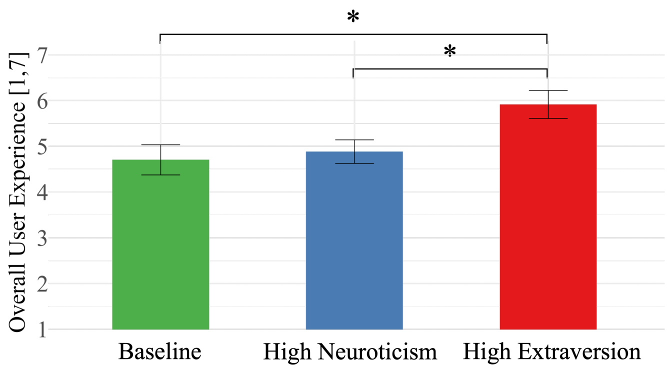

Fig. 3: Participants who interacted with the High Extraversion Robot Personality reported the best overall user experience. (*) denotes $p < 0.05$. Error bars show one standard error from the mean.

($M = 0.55$, $SD = 0.27$), and Neuroticism ($M = 0.22$, $SD = 0.13$).

Significant differences were found between the robot personalities in perceived Conscientiousness, Extraversion, and Neuroticism. For Extraversion, we found a significant difference between the conditions ($F = 8.14$, $p = 0.001$, $\eta_p^2 = 0.20$); the High Extraversion Robot Personality was rated as more extraverted than both the Baseline Robot Personality ($p = 0.037$) and the High Neuroticism Robot Personality ($p = 0.001$). Neuroticism also showed significant differences between the robot conditions ($F = 5.90$, $p = 0.005$, $\eta_p^2 = 0.15$), with the High Neuroticism Robot Personality perceived as more neurotic than both the Baseline ($p = 0.003$) and High Extraversion Robot Personalities ($p = 0.001$). These differences in robot neuroticism and extraversion align with our designs for the experimental conditions, serving as a successful manipulation check.

Surprisingly, we also observed a significant difference in Conscientiousness ($F = 4.99$, $p = 0.010$, $\eta_p^2 = 0.14$), with the Baseline Robot Personality rated as significantly more conscientious than the High Neuroticism Robot Personality ($p = 0.009$). Despite our original desire not to make any changes in the Conscientiousness trait in the experimental conditions, this phenomenon aligns with prior research indicating that neuroticism and conscientiousness tend to be negatively correlated [8], [64], [65]. No significant differences were found for Intellect/Imagination or Agreeableness across the three robot conditions.

B. Overall User Experience

Our one-way ANCOVA revealed that the robot's personality had a significant influence ($F = 5.868$, $p = 0.005$, $\eta_p^2 = 0.157$) on participants' overall user experience (see Figure 3. Participants interacting with the High Extraversion Robot Personality reported significantly higher overall user experience ($M = 5.91$, $SD = 1.40$) compared to those interacting with the High Neuroticism Robot Personality ($M = 4.88$, $SD = 1.24$, $p = 0.046$) and the Baseline Robot ($M = 4.70$, $SD = 1.55$, $p = 0.017$). There was no significant difference between the High Neuroticism Robot Personality and the Baseline Robot Personality conditions ($p = 0.903$). These findings indicate that the High Extraversion Robot Personality provided the best overall interaction experience.

C. Change in Affect after Well-Being Exercises

We conducted mixed ANOVAs to assess the impact of the robot condition (Baseline Robot, High Neuroticism Robot, High Extraversion Robot) and time (pre-interaction vs. post-interaction) on participants' *arousal*, *control*, and *valence* (see Figure 4. The robot condition was treated as a between-subjects factor, while time was treated as a within-subjects factor. To further investigate the significant interaction effect, we conducted paired-samples t-tests within each condition using False Discovery Rate (FDR) Benjamini-Hochberg (BH) correction to account for multiple comparisons.

1) Arousal: Our mixed ANOVA revealed a significant main effect of time ($F = 11.27$, $p = 0.001$, $\eta_p^2 = 0.152$) on participants' *arousal* levels, indicating that participants' arousal levels increased from before the interaction ($M_{\text{pre}} = 4.41$, $SD_{\text{pre}} = 1.16$) to after the interaction ($M_{\text{post}} = 5.05$, $SD_{\text{post}} = 1.29$). While we did not find a significant main effect of the robot's personality ($F = 0.73$, $p = 0.484$, $\eta_p^2 = 0.023$), we did find a significant interaction between time and the robot's personality ($F = 4.62$, $p = 0.013$, $\eta_p^2 = 0.128$), suggesting that the change in arousal over time differed across the robot personalities. Participants who interacted with both the robot with the High Extraversion Robot Personality ($M_{\text{pre}} = 4.24$, $SD_{\text{pre}} = 1.04$, $M_{\text{post}} = 5.57$, $SD_{\text{post}} = 0.93$, $t = -4.39$, $p_{\text{adj}} < 0.001$, $d = 1.35$) and the robot with the High Neuroticism Robot Personality ($M_{\text{pre}} = 4.22$, $SD_{\text{pre}} = 1.04$, $M_{\text{post}} = 4.91$, $SD_{\text{post}} = 1.16$, $t = -2.45$, $p_{\text{adj}} = 0.034$, $d = 0.63$) demonstrated significant increases in arousal over time. However, no significant change was observed in participants' arousal for those who interacted with the robot with the Baseline Robot Personality ($M_{\text{pre}} = 4.77$, $SD_{\text{pre}} = 1.34$, $M_{\text{post}} = 4.68$, $SD_{\text{post}} = 1.59$, $t = 0.23$, $p_{\text{adj}} = 0.817$, $d = 0.06$).

2) Control: There was a significant main effect of time on participants' perceptions of their sense of *Control* ($F = 7.43$, $p = 0.008$, $\eta_p^2 = 0.11$), with control levels increasing from pre-interaction ($M_{\text{pre}} = 5.03$, $SD_{\text{pre}} = 1.23$) to post-interaction ($M_{\text{post}} = 5.39$, $SD_{\text{post}} = 1.23$). Although the robot's personality had no significant main effect ($F = 0.08$, $p = 0.92$, $\eta_p^2 = 0.003$), there was a significant interaction between time and robot personality ($F = 9.90$, $p < 0.001$, $\eta_p^2 = 0.24$), indicating different changes in participants' sense of control across the conditions. Participants interacting with the High Neuroticism Robot Personality reported an increase in their sense of control from pre-interaction ($M_{\text{pre}} = 5.04$, $SD_{\text{pre}} = 1.20$) to post-interaction ($M_{\text{post}} = 5.52$, $SD_{\text{post}} = 1.04$, $t = -3.87$, $p_{\text{adj}} = 0.001467$, $d = 0.43$), as did those interacting with the High Extraversion Robot Personality ($M_{\text{pre}} = 4.67$, $SD_{\text{pre}} = 1.20$, $M_{\text{post}} = 5.71$, $SD_{\text{post}} = 0.85$,

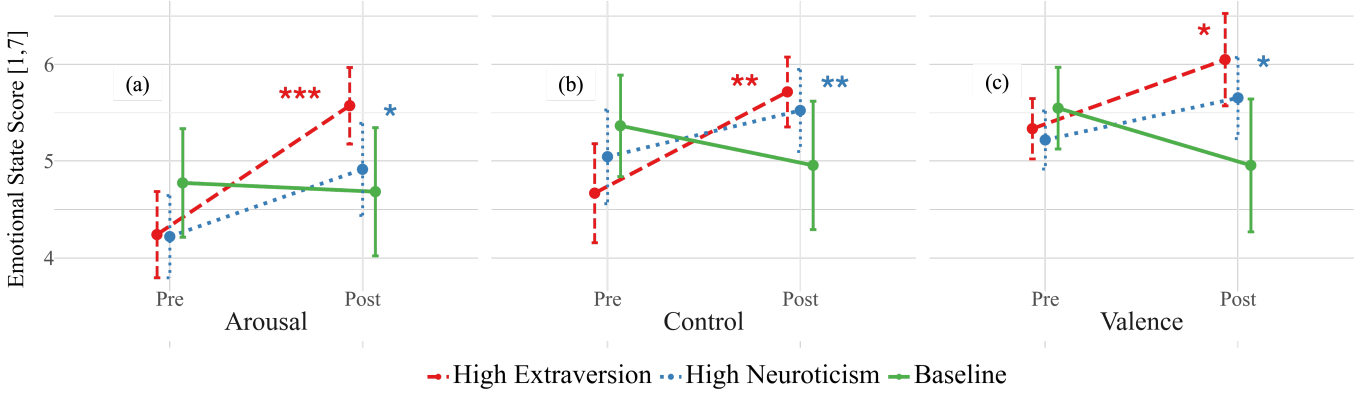

Fig. 4: Participants interacting with both the High Extraversion and High Neuroticism robot personalities demonstrated significant increases in (a) arousal, (b) control, and (c) valence. (*), (**), and (***) denote $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively. Error bars show one standard deviation from the mean.

$t = -3.86$, $p_{\text{adj}} = 0.001$, $d = 1.01$). While no statistically significant change was observed in the Baseline Robot Personality condition ($M_{\text{pre}} = 5.36$, $SD_{\text{pre}} = 1.26$, $M_{\text{post}} = 4.95$, $SD_{\text{post}} = 1.59$, $t = 1.48$, $p_{\text{adj}} = 0.154$, $d = 0.29$), participant's sense of control does seem to trend downwards after interacting with the Baseline Robot Personality.

3) Valence: We found a significant interaction between time and robot personality for *valence* ($M_{\text{pre}} = 5.36$, $SD_{\text{pre}} = 0.83$, $M_{\text{post}} = 5.55$, $SD_{\text{post}} = 1.35$, $F = 6.80$, $p = 0.002$, $\eta_p^2 = 0.18$), though the main effects of time ($F = 1.44$, $p = 0.234$, $\eta_p^2 = 0.02$) and robot personality ($F = 1.30$, $p = 0.279$, $\eta_p^2 = 0.04$) were not significant. Participants that interacted with the High Extraversion Robot Personality saw their valence increase significantly from pre- ($M_{\text{pre}} = 5.33$, $SD_{\text{pre}} = 0.73$) to post-interaction ($M_{\text{post}} = 6.05$, $SD_{\text{post}} = 1.12$, $t = -3.10$, $p_{\text{adj}} = 0.017$, $d = 0.76$). A similarly significant increase was observed in participants interacting with the High Neuroticism Robot Personality ($M_{\text{pre}} = 5.22$, $SD_{\text{pre}} = 0.74$, $M_{\text{post}} = 5.65$, $SD_{\text{post}} = 1.03$, $t = -2.47$, $p_{\text{adj}} = 0.032$, $d = 0.49$). However, the participants interacting with the Baseline Robot Personality seemed to experience a decrease in valence ($M_{\text{pre}} = 5.55$, $SD_{\text{pre}} = 1.01$, $M_{\text{post}} = 4.95$, $SD_{\text{post}} = 1.65$, $t = 1.68$, $p_{\text{adj}} = 0.108$, $d = 0.43$), although this change did not reach statistical significance.

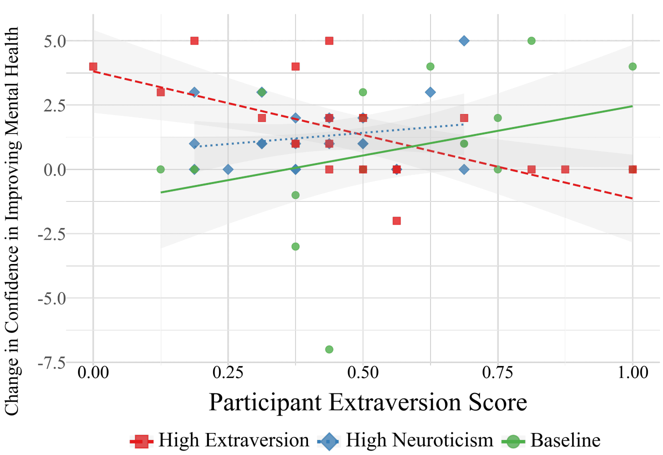

Fig. 5: Change in participants' confidence in improving mental health as a function of participant extraversion and robot personality.

D. *Influence of Participants' Personalities*

We explored how participants' personality traits influenced their interactions with the three robot personalities for each of our dependent variables. To account for multiple comparisons, we applied the False Discovery Rate correction using the Benjamini-Hochberg procedure (FDR-BH).

We observed a significant interaction between participants' extraversion and the High Extraversion Robot Personality on participants' perceived confidence in improving mental health ($\beta = -8.777$, $t = -3.703$, $p_{\text{adj}} < 0.001$, Cohen's $f^2 = 0.238$). As depicted in Figure 5, the change in participants' confidence after interacting with the robot varied by their own level of extraversion. In the High Extraversion Robot Personality condition, the change in confidence decreased towards zero as participant extraversion increased, indicating that less extraverted participants experienced a greater boost in confidence. In contrast, the High Neuroticism and Baseline conditions showed an upward trend, with confidence improvements increasing as participant extraversion scores rose.

VII. Discussion

In this paper, we investigated the impact of altering a robot's personality on user experience and the effectiveness of well-being exercises. In this section, we discuss the contribution of our robot-dialogue-generation method, how the robots' personalities results in different participant experiences, and how participants' own personalities may influence their experiences with the different robot personalities.

A. Impact of Robot Personality Traits on User Experience and Interaction Outcomes

Our study explored how different robot personalities influence user interactions and the effectiveness of delivering well-being exercises. Participants who interacted with the High Extraversion Robot Personality consistently reported immediate improvements in affective states–specifically in arousal, control, and valence–and rated the interaction as the most enjoyable. Notably, those who interacted with the High Neuroticism Robot Personality also experienced significant gains in arousal, control, and valence. These results suggest that deviating from the typical "Baseline" personality enhances user experience (addressing RQ1) and that specific personality traits, such as extraversion and neuroticism, add value to human-robot interactions (addressing RQ2).

The High Extraversion Robot Personality significantly enhanced positive affect in users and overall enjoyment during the interaction. Previous research has shown that extraverted individuals–characterized by being gregarious, active, and outgoing–tend to experience more positive emotions [66]–[68]. Participants perceived the Extraverted Robot similarly, describing it as "*engaging*" (P7, P10, P49, P68) and "*positive*" (P7, P40, P57). They also appreciated its "*social intelligence*" (P7, P25), "*emotional expressiveness*" (P7, P28), and felt it was "*human-like*" (P21, P59) and "*genuine and interested in hearing about others*" (P14, P36, P49). Echoing human-human interaction research, where positive emotions have been shown to create ripple effects [69], it is likely that interacting with the High Extraversion Robot enhanced participants' emotional states in a similar way, improving their interaction experience.

Interestingly, participants who interacted with the High Neuroticism Robot Personality also reported improvements in arousal, control, and valence. Many described this robot as "*human-like*" (P5, P17, P20, P31, P38, P41, P52, P61, P65, P69), whereas many noted the contrary for the Baseline Robot Personality. Participants highlighted the robot's anxious behavior and expressed surprise at its apparent understanding of complex emotions. One remarked, "*the robot seemed like a person who was trying to get by in the world*" (P52), while another commented, "*I think we both seem to make an effort to think about ourselves and do lots of inner contemplation*" (P31). This human-like portrayal may have led participants to take the exercises more seriously than with a stereotypical, emotionless robot [17], [70].

While most prior work in HRI on robot personality traits has focused on robot extraversion [10], [21]–[23], our findings highlight the unexplored potential of the neuroticism trait in social robots and its impact on user interactions. Incorporating traits that are seldom considered "robot-like"–as evidenced by our Study 1, where users expected robots to be low in neuroticism–can make robots appear more relatable and capable of understanding complex human emotions. This, in turn, enhances human-robot interactions by making the robot feel more human-like and encouraging users to engage more deeply with the well-being exercises.

B. Interaction Between Participant and Robot Personalities on Interaction Outcomes

The significant interaction between participant extraversion and the High Extraversion Robot Personality on participants' perceived confidence in improving mental health suggests that the robot's extraverted behavior affected participants differently depending on their own extraversion levels (addressing RQ3). Specifically, less extraverted participants experienced a greater increase in confidence after interacting with the High Extraversion Robot, while highly extraverted participants showed little to no change. This could be supported by complementary theory where robots that have complementary, as opposed to similar, personalities as the user tend to be more effective [10]. While our work demonstrated just one way in which a person's own personality can influence how they respond to a robot with a specific personality, more work with larger sample sizes is needed to capture more cases where a person's personality may interact with a robot's personality to produce different effects.

C. LLM-Based Method for Generating Robot Dialogue Consistent with Chosen Big 5 Personality Traits

We generated the robot's dialogue to showcase each of the three robot personalities (Baseline, High Neuroticism, High Extraversion) using a LLM. Our dialogue prompts were guided by a list of characteristics (e.g., pays attention to details for conscientiousness [71], worries about health for neuroticism [72]) and linguistic traits (e.g., speaks positively and warmly for agreeableness [73]) for each of the Big 5 personality traits based on prior research. Our results suggest that designing robots that embody personality traits beyond "extraversion" can also yield useful outcomes. Robots that display more nuanced personality traits like Neuroticism may have the potential to be perceived as more human-like or relatable, possibly enhancing its ability to support more diverse tasks – from encouraging participation in therapy to providing companionship for socially isolated individuals.

We specifically developed this robot dialogue generation method so that it could be easily replicated and utilized by the HRI community. While we expect LLMs to continually improve and change the output of the prompts we designed, we expect that the dialogue generated by future models to still hold true to the Big 5 personality traits, as our prompts are primarily guided by the characteristics and linguistic styles of the Big 5 personality traits. We encourage other HRI researchers to utilize these resources to more easily generate dialogue to convey any set of Big 5 personality traits they desire a robot to exhibit.

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