MCI Older Adults' User Experience with Introverted and Extraverted Humanoid Robot Personalities

ANONYMOUS AUTHOR(S)*

This study aimed to investigate the impact of different personalities in humanoid robots for cognitive training scenarios with older adults with mild cognitive impairment (MCI). In particular, we have designed an application with two opposite personalities based on the Extraversion dimension of the Big Five Factors model. A user test with 16 Italian-speaking participants diagnosed with MCI aged 68+ was performed. The analysis of the data collected suggests that the robot's personality can have an effect on the engagement of such users and also found that participants can discriminate between the two personalities. Overall, the study highlights the importance of designing human-robot interactions considering personality-related aspects when considering MCI older adults.

CCS Concepts: • **Human-centered computing → User studies**.

Additional Key Words and Phrases: robot personality, HRI, user test, MCI older adults

ACM Reference Format:
Anonymous Author(s). 2018. MCI Older Adults' User Experience with Introverted and Extraverted Humanoid Robot Personalities . In *XXX'23*. ACM, New York, NY, USA, 17 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

With a senior population foreseen to more than double by 2050 worldwide [51], increasing demand for high-quality older adult support is likely to be expected in the coming years. Among the various disabilities typically associated with ageing, cognitive impairments affect a significant part of people aged 65 plus. In particular, Mild Cognitive Impairment (MCI) is an intermediate stage between the cognitive decline associated with normal ageing and more severe forms of dementia. Seniors with MCI often show memory loss or forgetfulness and may have issues with other cognitive functions such as language, attention and visual-spatial abilities. Thus, MCI affects, in particular, the completion of complex tasks usually performed in normal health conditions, such as cooking, managing the home, and shopping. MCI does not interfere notably with daily life activities but can increase the risk of progression to dementia, particularly of the Alzheimer's type. In general, MCI has an incidence of 8–58 per 1000 per year, and older adults risk developing dementia of 11–33% over two years [17]. Mild cognitive impairment affects 10–25% of people over 70 years [31]. Currently, cognitive training for seniors with MCI is administered by professional caregivers who often use paper-based material. In this context, socially assistive robots (SARs) can be a solution to cope with the problems of the tediousness of cognitive training and engage the user more during tasks. This kind of technology in this field can potentially promote seniors' cognitive, physical, and emotional well-being and reduce the healthcare system's workload. A socially assistive robot is a system that employs different interaction strategies such as non-verbal communication, speech, facial expressions, communicative gestures, and sensors to assist human users through social interaction [15]. There has been increasing interest in using SARs in social contexts, such as improving the quality of life and engagement for older adults and people with cognitive disabilities. In literature, some SARs have been used for engaging with older adults with cognitive impairments during cognitive training [38] [5] [4] [27]. Other studies [15] [16] aim to identify additional characteristics to implement social interactions, such as expressing emotions, communicating with high-level dialogues, using natural cues, and performing distinctive personalities. However, little work has considered how to represent personalities in humanoid robots. Personality can be defined as an individual's "characteristic pattern of behaviour in the broad sense including thoughts, feelings, and motivation" [3]. Several schools of thought regarding human personality exist. One of the most popular prospective is trait-based. The traits are viewed as the primary mechanism by which personality manifests. A trait in personality can be defined as "a component or distinguishing characteristic of an individual's stable personality across time, and external situations" [11]. Personality traits can indicate an individual's attitudes and behaviour and have been identified as an essential facilitator of human-robot interaction.[41]. Although there are several traits models, the most used is the Big Five Factor model [41] [42] [13]. The factors underlying each model dimension do not change over time or situations and influence people's behaviour [43]. The Big Five personality traits include extroversion, agreeableness, conscientiousness, neuroticism, and openness to experience [28] [18]. In particular, extroversion is the degree to which an individual is sociable, outgoing, assertive and talkative. The opposite of extroversion is introversion, the degree to which a person is shy, quiet and reserved. We have focused our study on this dimension.

Various studies [50] [47] found that a SAR with personalities can facilitate the interaction, as happens in human-human interaction during cognitive training by a human therapist. Characterising the robot's behaviour using personalities can also build long-term relationships between the SARs and the users in cognitive therapy scenarios. Personalities may create social and emotional interaction with the user to increase acceptability and engagement in the user. Increasing acceptability and engagement may increase the possibility of reaching the training goal in less time and with better results [47]. Emerging SARs may open up new possibilities in more effectively engaging MCI older adults during repetitive cognitive training [27]. For these reasons, we decided to investigate whether robots performing personalities can engage MCI users. In this work, we report and discuss how robot personalities have been designed, implemented, and tested on a serious game for cognitive training with 16 older adults diagnosed with MCI participating in a cognitive training programme.

2 RELATED WORK

Some studies have investigated obtaining robot personalities using various cues to test their systems with a wide age range of users. Most studies tested the robot personalities with children or young adults.

Min Lee et al. [24] evaluated Sony AIBO's introverted and extraverted personalities in a between-subject experiment with 48 participants (ages 19-34). As a result, they found that participants could accurately recognise the robot's personality based on its verbal and non-verbal behaviours. The main limitation was the limited interaction with the robot due to the restricted set of words that the robot recognised.

Tapus et al.[47] conducted a study with 19 participants, young adults between 18 and 30 years old, and investigated the role of the robot's personality in a therapy process for the rehabilitation of post-stroke users. The study used an Active-Media Pioneer 2-DX mobile robot to assist, encourage, and socially interact with the patients engaged in rehabilitation exercises. They manipulate the interaction distance and proxemics, speed and amount of movement, and verbal and para-verbal communication (such as volume and speech rate). This experiment aimed to test the adaptability of the robot's behaviour to the user's personality-based therapy style preference. The study investigated the preference for personality matching in the assistive domain and the effectiveness of robot behaviour adaptation to user personality and performance. The main limitations were the limited interaction with the robot due to the restricted set of words that the robot recognised and that the system was designed for post-stroke users but tested with young adults. Celiktutan et al. [6] used a Nao robot in which they manipulated the behaviour to obtain extrovert and introvert behaviour. They manipulated verbal cues, such as feedback, pitch voice and speech rate, while for non-verbal manipulation, they modulated the robot hand gesture and posture shifts. The test was performed with 18 users, PhD and post-doc students, and a significant correlation was observed between the participants' extraversion traits and the subjects' perceived enjoyment of the extroverted robot. However, the interaction was controlled using a Wizard-of-Oz setup. Another work [52] explored the user experience of older adults when interacting with humanoid robots that have either introverted or extraverted personalities but did not consider MCI users as in the study presented in this paper.

Previous studies show that various parameters can manifest extraverted and introverted personalities in robots. Additionally, most studies have used the Wizard of Oz approach to simulate autonomous robot behaviour while relying on hidden humans to control it remotely. In our study, we have implemented a software architecture that automatically modulates robot personality parameters without external manual human control. In most studies, interaction with the robot was limited to a narrow set of sentences or possible interactions. In the presented case, the robot is implemented in a way that does not force the user to remember specific commands to perform the task or to keep the application going. The application was developed to guide the user throughout the session and aims to exhibit the robot's behaviour with two personalities. Furthermore, we combined verbal and nonverbal modalities to represent the robot's personality. According to the personality, the robot exhibits vocal features such as feedback, speech rate, pitch rate, volume, dialogue style, and pauses, considering the state of the serious cognitive game and a nonverbal behaviour modulating different parameters. In addition, studies with robot personalities and MCI users have not yet been investigated. This user typology is very important because there are many MCI people, and the disease may degenerate into some form of dementia. This approach can be useful in cognitive training to avoid the dropout risk. For these reasons, we want to investigate the effects of different personalities in a humanoid robot for cognitive training scenarios with MCI older adults. These lead to our research questions:

- RQ1 Robot personality can influence the user experience of MCI older adults?
  In current times, a crucial aspect is how to capture and retain the attention of individuals during short and prolonged healthcare interactions with social robots. Investigating the user experience, specifically engagement, may aid in developing more natural and captivating interactions during cognitive training scenarios [49]. A robot's personality can improve engagement and, in general, user experience, making the interaction more intuitive and effortless.
- RQ2. Is there any relationship between participants' personalities and their preferences for a specific robot personality?
  Previous studies [12] [30] [32] have investigated how to align or mismatch the robots' personalities with the users and determine which variables may impact this relationship. Nevertheless, there is currently no evidence linking older adults' personalities with their experience of the representation of robot personalities. This study wants to investigate whether there is any connection between user personality and the user perception of robot personality representation in interactive sessions.
- RQ3. Were the users able to detect differences between introvert and extrovert robot behaviour, according to how they perceived some aspects associated with their interaction with the robot?
  Several theories suggest that various cues can indicate extraversion and introversion. Specific, verbal and non-verbal cues have been found to be the most significant in portraying personality traits [24] [47]. Hence, in this

study, we examined whether combining verbal and non-verbal cues of a Pepper robot would result in appropriate representations of robot personalities that MCI older adults would consider suitable during a cognitive training scenario.

3 ROBOT PERSONALITY DESIGN

Personality is a central construct in understanding human behaviour and influences the quality of interactions between individuals [9]. Some studies [45][47][50] have addressed the characteristics of personalities and have observed a close relationship between personalities and the modes of interaction between humans and robots [45] [26]. Therefore, they suggest that adding personality can improve and make interactions more consistent and heighten user engagement and user experience [6]. Moreover, several studies [24] [47] [50] found that a robot with different personalities can simplify the interaction, as happens in human-human interaction during cognitive training by a human therapist. This is particularly useful when the users are older adults, for example, for performing cognitive training exercises. Indeed, emerging humanoid robots may open up new possibilities in more effectively engaging MCI older adults during repetitive cognitive training [27]. Consequently, personalities can be influential in engaging the user during therapy and facilitating enhanced robot interaction [24]. Thus, it may be critical to take advantage of richer communication with robots, one that does not rely only on verbal communication [37] [44] [29] but also considers nonverbal communication. Incorporating the two types of communication may be helpful to maximise the expressiveness of behaviours in humanoid robots and facilitate human-robot interaction for cognitive training. For such reasons, we designed the possibility of exhibiting two opposite personalities in a social robot. This study focuses on the Extraversion dimension of the Big Five Factors model for several reasons. Firstly, numerous studies have demonstrated that Extraversion is the most easily noticeable trait among the Big Five Factors [10, 21, 25, 32]. Secondly, it has been proven critical in human-robot interactions, with Isbister and Nass [20] finding that extroversion-introversion is a significant dimension in non-verbal cue research. Thirdly, this trait affects users' quality of life and satisfaction during interactions [22, 23]. Fourthly, verbal and non-verbal parameters for expressing extraversion and introversion have been defined in the literature and can be efficiently controlled in robots [20, 24, 48]. Lastly, the personality of a robot can offer users better affordance, which makes it easy and intuitive for them to understand the robot's behaviour [19, 24, 34]. Extroversion and introversion personality traits can be shown through multiple cues, such as physical appearance, vocal parameters, comportment, occupation, economic status, language, and gestures. In particular, verbal and nonverbal cues, including voice, language, pitch, speech rate, gestures, and body movement, are considered the most reliable and significant indicators of personality by several researchers Pittam [39] [40] [30].

3.1 Verbal Cues

Various studies have identified different cues for extraverted personality, such as speaking louder, faster, and with a higher pitch [20, 46], using less extensive vocabulary, talking more about oneself, having broader and faster body movements, and performing more idle movements [12, 24]. Conversely, introverts tend to be more socially anxious, speak slowly, take longer to answer, and have narrower and slower body movements [7, 14]. Previous research indicates that verbal and nonverbal cues effectively manifest extraversion in synthesised speech [32] and social robot behaviour [24].

Nass and Moon [33] focus on the extraversion-introversion dimension in linguistics and investigate how personality can be expressed through the speaking style. They suggest that extroverted individuals speak with wider frequency than introverted ones [2, 46]. Moreover, voices are perceived as more extraverted when spoken at a high volume, faster, and high-pitched [32, 33]. The opposite characterisation of these cues is used for introverted robot voices, with a lower pitch, slower speech rate, and lower volume [7, 39, 45].

In addition to vocal parameters, robot feedback is associated with the representation and judgment of extraversion and introversion [2, 14, 37, 39]. The extraverted robot provides more encouraging feedback, while the introverted one is more neutral and hesitant. For example, after asking a question, the extraverted robot reacts with enthusiastic feedback, while the introverted one reacts with hesitant feedback after a few seconds [7, 39, 45].

In summary, the extraverted robot speaks louder, faster, and with a higher pitch, uses shorter and more encouraging sentences, and employs more positive words. In contrast, the introverted robot speaks more quietly, is slower, uses longer pauses and various utterances of hesitation, and has a more neutral tone. The extraverted robot's behaviour is happier and more active, while the introverted one is more reserved and calm.

3.2 Non-verbal Cues

In this study, we aimed to model extravert and introvert conditions by modulating non-verbal parameters, such as gestures, posture, and body movement. These elements are essential for representing extraversion and introversion. Previous research [1, 24, 40] has demonstrated the significance of non-verbal cues in personality representation. Isbister and Nass [20] previously modulated the extravert behaviour of virtual agents by adjusting their gestures. We followed a similar approach and designed the extravert robot to perform more expansive gestures with broader movements towards the listener. In contrast, the introverted robot performs movements close to its body with less wide gestures. Nonverbal cues such as gestures, posture, and body movement are crucial elements for representing extraversion and introversion [1, 24, 40]. The non-verbal parameters chosen to design the two personalities are gestures, speed, and motor movements. In this category, some robot body movements can be obtained by modulating different robot joints and actuators, such as the head, left and right arms, and hips. Motor movements are concerned with manipulating the "mobile" trajectories the robot can make, where the orientation and the direction of the robot's motor movement are manipulated to approach or move away from the user. In the extraversion condition, the robot's gestures are more expansive, with broad gestures to simulate openness towards the user [20]. The gestures generated in this condition usually involve the elbows and hands moving away from the body using larger angles. In addition, the robot's movements are more dynamic than those of the introverted one and are faster and broader. Conversely, for the introvert condition, the robot's gestures tend to be more limited and contained in such a way as to appear reserved toward the user. The gestures generated in this condition usually involve the arms positioned close to the body, determining smaller angles. Another gesture implemented in this condition involves the robot's head, which lowers and avoids the user's gaze to convey shyness [20]. In addition, the animations created are slightly less dynamic than those created for the extraverted. The robot in the extravert condition performs movements faster, leading to higher gesture rates and dynamics, and follows more articulated trajectories of lateral, forward, diagonal, and slightly backward displacements [20]. In contrast, the robot's (gesture and motor) movements in the introvert condition are slightly slower and restricted regarding angles. The introvert robot performs movements slightly slower and makes less articulated trajectories composed mainly of lateral, forward, and more accentuated backward displacements [20]. The introvert robot uses more inward-directed movements, while the extravert robot uses outward-directed movements because they convey a message of openness to the user. In contrast, inward-directed movements tend to convey a message of closure and shyness [20].

3.3 Implementation

3.3.1 Apparatus. Pepper is a 1.2m-tall wheeled humanoid robot with 17 joints for expressive body language and three omnidirectional wheels to move around. Pepper has multi-modal interfaces for interaction: touchscreen, speech, tactile head, hands, bumper, LEDs and 20 degrees of freedom for motion in the whole body. The robot is supplied with an LG CNS screen of 10.1 inches with a resolution of 1280x800 for supporting touch interaction. In addition, Softbank robotics provides a library called QiSDK and an android studio plugin called Pepper SDK, and libraries to generate and modulate gestures and the robot joint's movements and the development of interactive vocal dialogues [36].

3.3.2 Personality Parameters . To control verbal parameters, we have used the Speech Synthesis Markup Language (SSML), whose tags allow programmers to customise the pitch variation, the volume of the robot, the speech rate, and the duration of the pauses during speech. A combination of SSML tags and feedback is used to modulate the verbal cues of each personality. We created different phrases, sentences, and exclamations for each personality to further support verbal cues. The robot has been programmed with a distinct set of feedback to create a more natural and social interaction. In this manner, the answers and sentences reproduced by the robot should vary according to the personality. Various exclamations using a more straightforward and enthusiastic dialogue style (such as" Hey, what is the second ingredient?") are used for the extravert condition. Also, in this condition, the robot refers directly to the user using primarily personal pronouns and present tenses. Instead, for the introvert, a set of hesitant interjections such as (" Ehm, could you please tell me the first ingredient?" and "Might I ask if you..") and a dialogue style that manifests hesitation is used. In this condition, the robot refers indirectly to the user using a more formal language. For manipulating nonverbal cues, we used the Animation Editor provided by QiSDK. In particular, the animations modulating different robot joints and actuators (the head, left and right arms, and hips) have been produced. A further modulation for non-verbal cues concerns the robot's movements. The Trajectory Editor was used for this, allowing the designer to define a robot trajectory, modulating speed, orientation, and duration and combining multiple paths. Figure 1 shows how the robot exhibits extraverted personality traits when users provide a correct answer.

4 SCENARIO

In this paragraph, we describe one scenario used to design an application for cognitive training with MCI older adults exploiting the robot personalities.
Luisa is an 85-year-old teacher. Since she was diagnosed with MCI, she regularly attends cognitive training in a cognitive centre near her house. Recently, a clinic added one-to-one cognitive training with a humanoid robot to her program. On Monday mornings, as usual, she goes to the clinic, Monday being the day dedicated to training with the robot. When she arrives at the clinic, psychologists welcome her and take her to the training room. After the introductory phase, she is shown some information about the cooking game: its rules and how she can interact with the robot using only her voice. The session with the robot begins: first, the psychologist selects the robot personality best suited for her. At this point, the robot introduces itself, asks Luisa's name, and the cooking task begins. Then, the robot introduces the cooking game and sequentially shows the ingredients and the weight of each ingredient in the first level:
Extrovert version

- After sequentially displaying the ingredients with their respective images in the table, Pepper vocally asks about them with high pitch, volume, and slightly faster speed, "What is the first ingredient?". At the same time, it brings its right arm to its left side and holds out the palm of its left hand to the user, moving its left arm slightly up and down. At the same time, the robot moves toward the user.

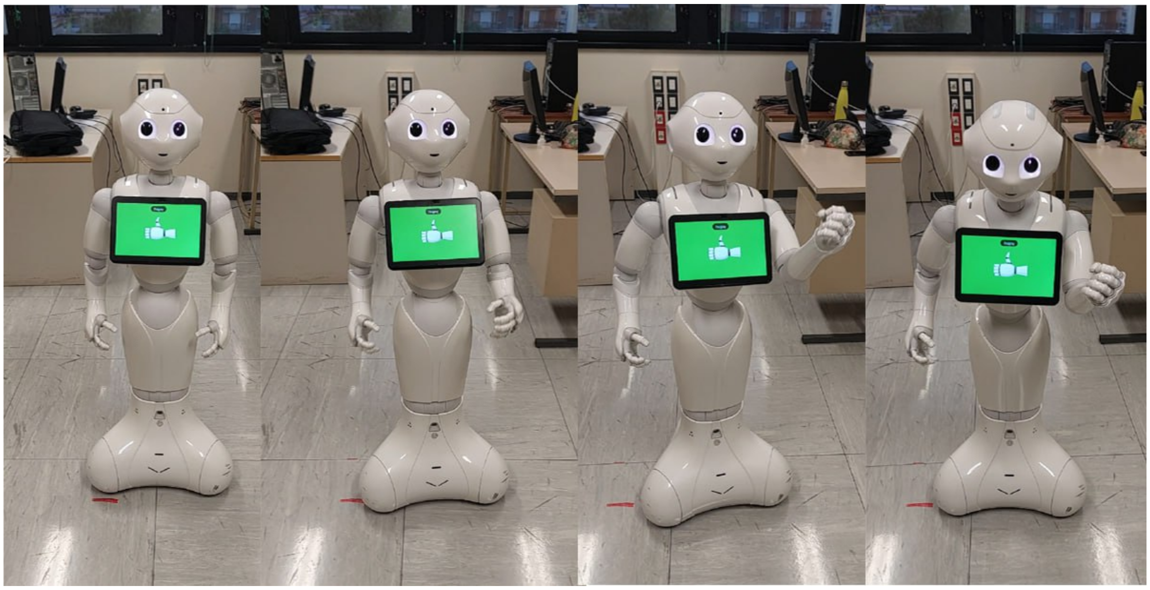


Fig. 1. Example of animation the extroverted robot performs after the user has given a correct answer. First, the robot swings its arms back and forth while performing a left and right shift. Then it reaches its initial position and mimes a victory sign with its right arm.

- When Luisa answers the question correctly, Pepper immediately says, "Excellent Luisa, it is the right one! Good job!" maintaining the vocal parameters identified for the extravert personality. At the same time, it raises both arms twice, nods its head markedly, and moves slightly first to the right and then to the left.
- Then the robot asks "How many grams of sugar are needed for the recipe?". Pepper opens both arms at 40 degrees outwards to encourage her and moves slightly toward the user.
- At her wrong answer, Pepper says with a loud voice and a positive intonation, "You made a mistake, but you can try again!". At the same time, it shakes its head twice and moves its arms up and down.
- Before the game ends, Pepper performs different gestures to simulate a victory animation. In the end, Pepper says goodbye to Luisa, saying, "Perfect job Luisa, it was fun to play with you! Hope to see you again next time!".

Introvert version

- Pepper says with neutral intonation and a low volume, "Ehm, could you please tell me the first ingredient?". After a few seconds, it slowly undulates its torso twice to the right and left while the arms slightly go behind its back.
- When Luisa answers correctly, Pepper says with a lower pitch and a slow speech rate, "Ehm...Good, that is right". Then, it pauses for two seconds and slowly nods its head two times, performing an inward trajectory that moves the robot slightly away from the user.
- Pepper says, "Ehm, could you please tell me how many grams of sugar are needed for, ehm, the recipe?" It gently opens its arm 20 degrees outwards.
- When Luisa answers incorrectly, Pepper says, "Wrong, try again." It lightly shakes its head one time and performs a more pronounced backward movement.
- In the end, Pepper moves one arm backwards and forwards, and it says goodbye to Luisa, saying "Good job... If you like, I hope to see you next time."

5 USER STUDY

An interview with a neuroscientist was performed on September 2022 to gather information about the proposed game task and the personalities implemented for the specific target of MCI older adults. Then, a user test with MCI older adults was conducted in a clinic in November 2022.

5.1 Interview with neuroscientist

The interview was performed to have an expert's feedback. The session took one hour to interact with both robot personalities and the interview. We performed a thematic analysis of the interview. The main aspects identified are memory and cognitive load in learning and recalling information, feedback on the recipe game interface and user experience, personality types and user experience. The first aspect focuses on the user's memory and mnemonic abilities, including the need for clear and concise information delivery to facilitate memorisation. The main issue the neuroscientist identified was the extravert robot's speech rate when it provided the recipe information, which was considered too high. The introvert speech rate was considered more appropriate. The second aspect regarded not repeating the same recipe twice in the game to avoid boredom and to provide a balanced and engaging experience for the user. Overall, the game was considered well organised, and the recipes were selected to avoid disadvantages for male users using non-Italian ingredients.

Furthermore, this type of game was already used in the clinic and stimulated interest from MCI users. Regarding how the two personalities implemented can increase engagement and interest, the expert suggested lowering the speech voice on the extravert robot and adding some pauses during the speech. Overall, the neuroscientist highlighted how this modality could efficiently increase engagement. The neuroscientist stated, "I could see this game with the robot personalities being used in the training we do in the clinic. It is consistent with one of those games we play, but it is a different mode, more engaging.". The suggestions provided by the neuroscientist were implemented before the user test with MCI older adults.

5.2 Context

The test was performed with a set of MCI users recruited from a local cognitive training programme. The project's primary goal is to prevent or slow cognitive decline in elderly individuals with mild cognitive impairment (MCI) by keeping their minds and bodies active. To identify patients at risk or with slight cognitive deficits, memory-disorders specialists evaluated them at the local university clinic using relevant neurological and clinical tests and information such as sociodemographic data, medical history, pharmacological drug use, and lifestyle habits.

The programme involves using games, social activities, physical activity, and a series of increasingly complex exercises, as well as face-to-face meetings, group stories, bike, and stretching exercises to stimulate the body and the brain. The programme consists of eight cycles, each divided into 18 activities that stimulate various cognitive functions, such as auditory and visual attention, visual-spatial memory, imagination, space-time and personal orientation, verbal memory, lexical skills, and affective memory. Participants attend two 60-minute sessions per day, three times a week.

5.3 User test

Our participants were recruited by the local cognitive training project, and all were diagnosed with Mild Cognitive Impairment. All participants were invited to provide their informed written consent before the beginning of the study. The users were enrolled according to the following inclusion criteria: diagnosis of MCI, age over 65 years, and

Italian-speaking participants. For the test, the users interacted individually with the robot standing in front of the robot at a distance of about 60 cm. The experiment took an average of 50 minutes for each user to complete the test and the questionnaires. Additionally, for each participant, the interaction logs were saved. A moderator was present and took notes of user feedback, user behaviour and any significant event occurring during the test.

5.3.1 Participants. Sixteen (10 males) senior adults between 68 and 88 years old (M=77.93, SD=5.76) with a diagnosis of MCI were enrolled. Six had a high school degree, four had a university degree, five had a middle school diploma, and one had an elementary school diploma. All the users had no experience with robots and had never interacted with one before the test.

5.3.2 Test organization. It was a within-subjects test: all users were exposed to both conditions (interacting with an introvert/extravert robot). The within-subject design was chosen mainly because of the limited number of clinic training program participants. To avoid the limitations of the within-subjects study, the subjects' exposure conditions were counterbalanced: half users (randomly selected) first interacted with the introverted robot, then with the extraverted one, while the others did the opposite. The test was organised into five steps:
1) Introduction; 2) Mini-IPIP test; 3) 1st interaction with a robot personality + user's evaluation; 4) 2nd interaction with a robot personality + user's evaluation; 5) Semi-structured interview + final feedback.
In the beginning, the participants received a brief introduction to the study, its main goals and motivations; then, they signed a written informed consent indicating the purpose of the research, the procedure of the research study, duration, personal data processing information following the European Data Protection Regulation, the possibility to request the release of the data and how they are processed.

User Personality. We evaluate the user's personality using the Mini-IPIP questionnaire. The mini-IPIP shortened measures of the Big-five Domains [8] questionnaire was administered to understand the main traits of the personality of each user. The Mini-IPIP is composed of 20 items; each one is a phrase describing a behaviour (e.g., Do not talk a lot): the users indicate how accurately each phrase describes them using a 5-point scale (from 1= "Very inaccurate" to 5= "Very accurate"). The internal consistency of the mini-IPIP was assessed with Cronbach's alpha (α = .71). We considered the extraversion trait of the mini-IPIP: based on the associated scores, we divided the users into two groups: if the score was ≤ 3 they were classified as "extravert", otherwise as "introvert". 8 participants were considered "extravert", 8 "introverts".

Sessions with Robot personality. In this phase, there was an interaction with the robot showing a specific personality during a cooking game about preparing a recipe. After the users had to compile a questionnaire about sociodemographic data, information about previous experience/familiarity with robots, four statements regarding the user experience, and the User Engagement Scale - Short Form (UES- SF) questionnaire [35]. The UES-SF considers four dimensions of engagement: FA= Focused Attention (tendency to be absorbed and lose track of time), PU = Perceived Usability (Users' affective (e.g., frustration) and cognitive (e.g., effort) responses to the system), AE = Aesthetics (the attractiveness of the interface), RW = Reward (tendency to be rewarded during the interaction). The additional four statements aimed to gather user feedback on more specific aspects relevant to our study.
During the second session, the application proposed the same game involving a different recipe while the robot exhibited the opposite personality. After the second session, the same questions used in the first interaction were administered. However, those about demographic information were excluded, while a question asking the preferred robot personality

Table 1. UES values that were collected after the first and second interaction with the robot

First Interaction Scale	M(SD) Introvert Robot	M(SD) Extravert Robot
FA	4.62(0.48)	4.16(1.02)
PU	**4.75**(0.52)	**4.45**(0.91)
AE	4.45(0.81)	4.16(1.06)
RW	4.7(0.45)	4.33(0.84)
Overall Score	**4.63**	4.28
Second Interaction Scale	**M(SD) Introvert Robot**	**M(SD) Extravert Robot**
FA	4.37(0.75)	4.25(0.77)
PU	**4.58**(0.7)	**4.45**(0.91)
AE	4.5(0.57)	4.5(0.86)
RW	4.37(0.75)	4.25(1.16)
Overall Score	**4.45**	4.36

was added. In the semi-structured interview, we asked some questions regarding user personality, whether users had perceived differences between the two types of robot behaviour, particularly in gestural or vocal interaction, and the likeability of the two types of robot behaviour and whether they would improve anything in the robot.

6 RESULTS

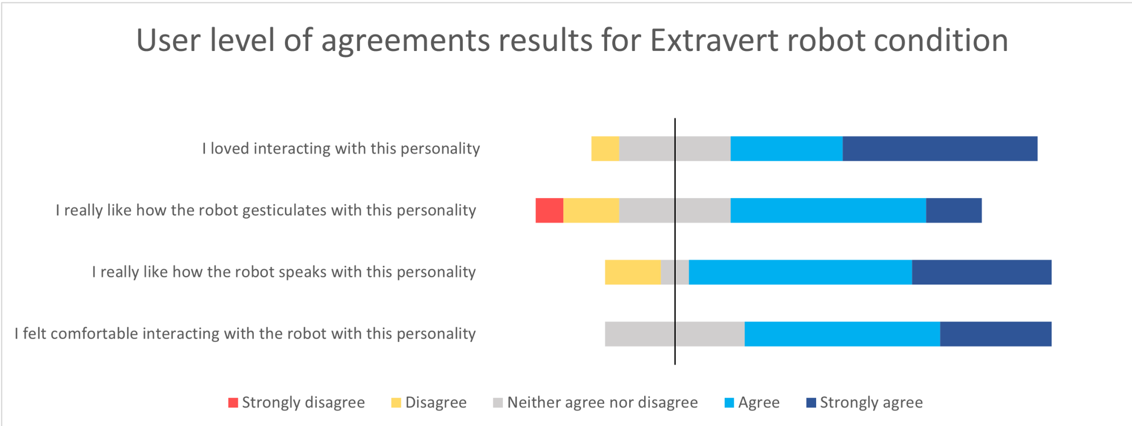
6.1 RQ1 Robot personality can influence the user experience of MCI older adults?

6.1.1 Influence robot personality on user engagement. Table 1 displays the UES scores obtained by the robot during the first interaction. Internal reliability of the user response was evaluated by calculating Cronbach's alpha coefficient for both interactions ($1st$ interaction $\alpha = 0.88$, $2nd$ interaction $\alpha = 0.86$). The scale that yielded better results for both robot conditions during the first interaction was Perceived Usability (PU). Overall, participants reported higher engagement with the introvert robot, as indicated by the higher overall engagement score of 4.63 (see Table 1).

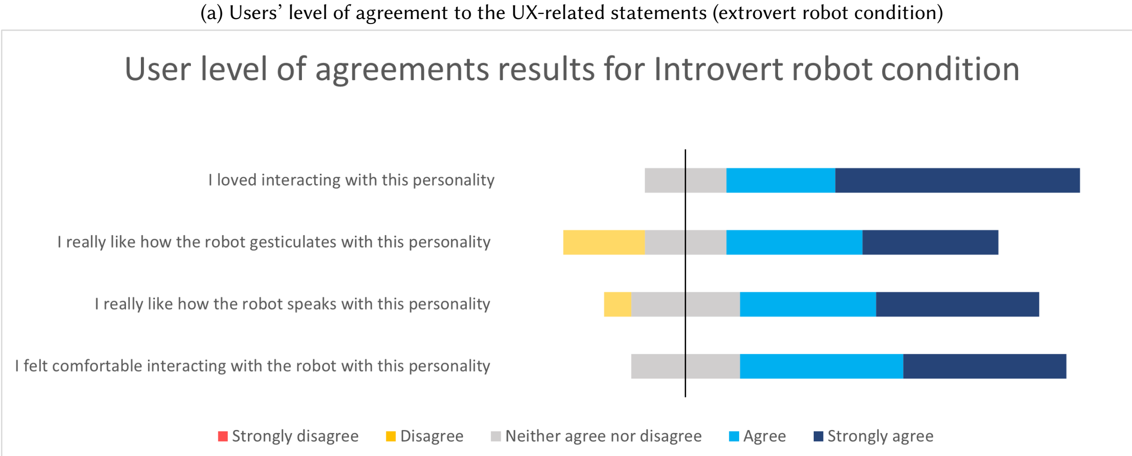
Similar results were obtained during the second interaction, where perceived usability remained on the scale with the highest scores for both the extravert and introvert robot conditions. Once again, participants reported higher engagement with the introverted robot, as indicated by the higher overall score of 4.45. These findings suggest that the quiet and calm behaviour exhibited by the introverted robot had a positive effect on participants' engagement level, as compared to the extraverted robot.

The results indicated that the introvert robot received higher scores for all the categories in the questionnaire. Conversely, the extravert condition obtained lower scores for the FA and AE categories than the introvert condition. We analysed the median of the scores. The introvert condition had a median of scores equal to 4.7 for categories AE, FA, and RW, while the score was 5 for the PU category. On the other hand, the extravert condition had a median score of 4.7 in the categories AE, PU, and RW. In general, the majority of the users indicated a preference towards introversion over extraversion.

6.1.2 Influence of robot personality on UX. We evaluated users' UX through additional four statements on which they had to rate their level of agreement on a 5-point scale about how much they liked: interacting with the robot on a general level, how the robot uses gestures, how the robot speaks, and comfort in interacting with it. Those statements,



(a) Users' level of agreement to the UX-related statements (extrovert robot condition)



(b) Users' level of agreement to the UX-related statements (introvert robot condition)

Fig. 2. Users' level of agreement to the UX-related statements for an introvert (Figure 2b), for extravert personality (Figure 2a)

for the 1st session obtained internal consistency of $\alpha = 0.75$, while for the 2nd one $\alpha = .85$. Figure 2a and 2b show related results. In general, users felt slightly more comfortable interacting with the introverted robot, and they slightly preferred interacting with the introverted robot. Regarding the robot's vocality, both robots scored similarly. There is no significant difference in the vocal aspects of the two robot's behaviour.

6.2 RQ2 Is there any relationship between participants' personalities and their preferences for a specific robot personality?

Table 2 considers two aspects: the personality of the robot (Introvert Robot and Extravert Robot) preferred by the user and the user's personality (Introvert User and Extravert User, as per the results of the Mini-IPIP questionnaire). The data are presented in a two-way table with the preference for a specific robot personality (Introvert Robot and Extravert Robot) in the columns and the user personality (Introvert User and Extravert User) in the rows of the table. The numbers in the table indicate the number of participants who preferred a specific robotic personality. From Table 2,

Table 2. User Personality and Robot Personalities Preferences

	Extravert Robot	Introvert Robot
Extravert User	5	3
Introvert User	3	5

the number of participants who preferred the introverted robotic personality is higher among introverted users (5) compared to extraverted ones (3). Conversely, the number of participants who chose the extraverted robotic personality is greater among extroverted users (5) than introverted ones (3). Thus, it appears that introverted users preferred the introverted robotic personality, while extroverted users preferred the extroverted robotic personality. Due to the limited sample size, we performed a Fisher exact test which did not provide any statistically significant result.

6.3 RQ3 Were the users able to detect differences between introvert and extrovert robot behaviour, according to how they perceived some aspects associated with their interaction with the robot?

To analyse the relationships between the two robot personalities (as implemented in the robot through various combinations of speech, gestures etc.) and the perception of the human-robot interaction as experienced by the users (and expressed through their answers to the GodSpeed questionnaire, which measures participants perceptions of a robot's anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety, we analysed the means and SD. Each category's mean and standard deviation are presented separately for extraverted and introverted robots (see Table 3). The internal consistency of the Godspeed questionnaire was assessed for both sessions with Cronbach's alpha (1st sessionα = .92; 2st sessionα = .95). For anthropomorphism and animacy, the means are very similar for extraverted and introverted robots, indicating that participants perceived both types of robots to have similar human-like qualities and lifelike movements. Regarding likeability, the introverted robot had a slightly higher mean score than the extraverted robot, suggesting that participants found the introverted robot more pleasant to interact with. The perceived intelligence scores for both types of robots were very close, with the extraverted robot having a slightly lower mean score than the introverted robot. For perceived safety, the introverted robot had a higher mean score than the extraverted robot, indicating that participants perceived the introverted robot as being safer to interact with. Overall, these results suggest that participants did not strongly prefer extraverted or introverted robots regarding anthropomorphism, animacy, and perceived intelligence but they tend to prefer the introverted robot for likeability and perceived safety.

6.4 Qualitative Analysis

We performed a thematic analysis based on the observation made during the study and particularly on the analysis of what users said during the sessions. Three main themes have been identified: perceptions of robot personalities (Theme 1), the effect of robot's personality on user experience (Theme 2) and perception of robots as human-like (Theme 3). This analysis provided additional information to address RQ1 and RQ3.

Theme 1. Participants in the study perceived differences in the personalities of the introverted and extroverted robots based on their observed behaviour during interactions. Specifically, participants described the introverted robot as shy, reserved, and insecure, while the extroverted robot was seen as sociable, friendly, and outgoing (ID1, ID3, ID5, ID14, ID15). These descriptions suggest that participants interpreted the robots' behaviour as indicative of distinct personalities and reacted accordingly during interactions. In particular, they highlighted how the nonverbal elements,

Table 3. Godspeed results for extravert and introvert robot

Category	Robot Personality	Mean	SD
Anthropomorphism	E	3.65	1.33
Anthropomorphism	I	3.6	1.42
Animacy	E	3.66	1.42
Animacy	I	3.67	1.36
Likeability	E	4.2	0.83
Likeability	I	4.4	0.86
Perceived Intelligence	E	4.22	0.92
Perceived Intelligence	I	4.24	1.0
Perceived Safety	E	3.31	1.64
Perceived Safety	I	3.55	1.73

such as the robot movement, shaped participants' perceptions of the robots (ID 6). For example, the extroverted robot was described as more sociable and friendly because it "moved more with its arms and head was more agitated it seemed to want to be more natural, in the second it moved less. In both conditions, the robot movements were synchronised with the speech. In both of them, I liked the movements. I did not feel it was false, but his movements were natural. However, the introvert conditions, sometimes the behaviours showed some nervousness or detachment" (ID5). Some participants described the extroverted robot's behaviour as sociable and friendly (ID5, ID15). User ID 5 noticed a marked difference between the two robots, noting that the extroverted robot seemed much closer to his expectations of a robot with intelligence (ID5, ID 8). The introverted robot seems shy and insecure, not very confident (ID3). Another participant, ID 14, noted that "the introverted robot seems very reserved, struggling to approach. The extrovert robot is much more friendly and welcoming" (ID14). While for ID 15, ID 9, and ID 10, the introverted robot seemed more careful and thorough. At the same time, the extroverted was too fast, giving the feeling that it did not care much about the user. In contrast, the introverted seemed calmer, cooperative, and less exaggerated: "I felt like I was talking to a human person". Overall, the users seem to perceive and react differently to introverted and extroverted robots based on their observed behaviours during interactions, highlighting the importance of considering personality traits and nonverbal cues in the design and development of social robots.
Theme 1 provides some indications to address RQ3. It shows that the study participants could detect differences between introverted and extroverted robot behaviour based on how they perceived aspects associated with their interaction with the robot. The theme suggests that participants interpreted the robots' behaviour as indicative of distinct personalities and reacted accordingly during interactions. Specifically, participants described the introverted robot as shy, reserved, and insecure, while the extroverted robot was seen as sociable and friendly. Additionally, the nonverbal elements, such as the robot's movement, shaped participants' perceptions of the robots. Therefore, this theme supports the research question examining whether the users could detect differences between introverted and extroverted robot behaviour based on how they perceived aspects associated with their interaction with the robot.

Theme 2: The user's perceived robot personalities robots affected participants' interaction experiences. Participants reported feeling more at ease and comfortable interacting with the introverted robot, while they felt more engaged and entertained when interacting with the extroverted robot. Some participants (ID 9, ID 6, ID 5) reported that interacting with the introverted robot was less smooth than with the extroverted robot. However, some users (e.g ID 9 and ID 16) noted that the interaction with the introverted robot seemed more natural and spontaneous. In contrast, the interaction

with the extroverted robot seemed more forced and cold. Additionally, ID 16 and ID 14 users noted that the extroverted robot seemed more able to adapt to their needs and provide relevant information than the introverted robot. One participant (ID 5) also speculated that the robot might have intentionally talked fast during their interaction to test them. Overall, Theme 2 suggests that participants' perceptions of the robots' personalities played a role in shaping their experiences during the interactions.
This theme provides evidence that robot personality can influence the user experience of MCI older adults (RQ1). The theme suggests that the robots' perceived personalities affected participants' experiences during interactions. Specifically, participants reported feeling more at ease and comfortable interacting with the introverted robot, while they felt more entertained when interacting with the extroverted robot. Some participants also reported that interacting with the introverted robot was less smooth than with the extroverted robot. However, other users noted that the interaction with the introverted robot seemed more natural and spontaneous, whereas the interaction with the extroverted robot seemed more forced and cold.

Theme 3. Perception of robots as human-like. The users had the perception of robots as human beings. In particular, many users (e.g. ID 14, ID 15, ID 9) commented on their ability to perceive the robot's emotions and to feel understood by it. Some users noted differences in the empathic ability of extrovert and introvert robots. User ID 15 found the introverted robot's calm demeanour comforting, saying, "I get along well with calm and tranquil people, and [the robot] transmits a sense of calm to me." Some users reported feeling strongly connected with the robots, even though they knew they were interacting with machines. User ID 8 stated, "I perceived [the robot in general] as if it were a person, even though it is a machine, and I liked it because it is intelligent." User ID 9 reported, "It seemed to me that I was talking to a human person; it was very human-like." User ID 14 initially felt uncomfortable interacting with a robot but reported feeling at ease with the extroverted robot. All users had a positive experience with both robots, but in particular, a user (ID 16) described the extravert robot as charming and human-like. He expressed that he would enjoy having the robot at home as a chat companion and that its behaviour made it likeable and put them at ease. User ID 16 even felt like he was in a fantasy moment with the robot, feeling like it was not just a machine but something real. Overall, user ID 16 enjoyed chatting with the robot and found it a likeable and personable companion. As such, this theme provided additional information related to RQ3. Indeed, from the qualitative feedback provided by users, it was possible to identify a recurrent pattern connected with how users perceived differences in the empathic abilities of introverted and extroverted robots and how their perception of the robots as human-like influenced their interactions with the robots. This aligns with RQ3, which is focused on understanding whether users were able to detect differences in the behaviour of introverted and extroverted robots based on their interaction with the robots.

In conclusion, the thematic analysis indicates that participants perceived differences in the personalities of the introverted and extroverted robots, indicated preferences for interacting with one robot personality over the other, experienced different levels of engagement during interactions and attributed human characteristics to the robots. These findings have implications for designing and developing social robots, as they suggest that personality traits and behaviour can impact user experiences.

7 CONCLUSIONS AND FUTURE WORK

The study aims to investigate the effects of different personalities in a humanoid robot for cognitive training scenarios with older adults with mild cognitive impairment. We combined verbal and nonverbal modalities to represent the robot's personality. We designed two opposite personalities in a social robot based on the Extraversion dimension of the Big Five Factors model. The user study recruited 16 Italian-speaking participants diagnosed with MCI between the ages of 68 and 88. The analysis suggests that robot personality can have an impact on user engagement. The findings indicate that the introverted robot is perceived as more usable and comfortable to interact with. Participants reported higher engagement with the introverted robot than the extraverted robot, as indicated by the higher overall engagement score. Participants also felt more comfortable interacting with the extraverted robot and liked the gestures and vocal components of the extravert personality. This may imply that a robot's personality choice can affect the quality of human-robot interactions and that designers should carefully consider personality design parameters in human-robot interaction scenarios. The second research question explored the relationship between participants' personalities and preferences for a specific robot personality. The results suggest that introverted users preferred the introverted robot, while extroverted users preferred the extroverted robot. Although there were no statistically significant results, the findings highlight the potential importance of considering users' personalities in designing robot personalities. Finally, in the study, we investigated whether users could detect differences between introverted and extraverted robot behaviour. The thematic analysis gives some valuable insight: we found that participants perceived differences in the personalities of the introverted and extroverted robots based on their observed behaviour during interactions. The introverted robot was described as shy, reserved, and insecure, while the extroverted robot was seen as sociable, friendly. The findings suggest that personality traits and nonverbal cues should be considered in designing and developing social robots. This supports the research question of whether users could detect differences between introverted and extroverted robot behaviour based on their interactions with the robot. However, the results of the Godspeed suggest that participants did not strongly prefer one type of robot behaviour over the other regarding anthropomorphism, animacy, and perceived intelligence. However, participants tended to prefer the introverted robot for likeability and perceived safety. However, the study presents some limitations. It was conducted with a relatively small sample size of 16 participants. The study only lasted one interaction session with the robots, which may not capture the long-term effects of robot personality on user engagement and preferences. Future studies will examine the impact of robot personality on user experience over a more extended period, such as several weeks or months, to provide a more comprehensive understanding of the topic using a richer set of games for cognitive training. In conclusion, this study highlights the importance of robot personality in human-robot interaction scenarios. The findings suggest that the choice of robot personality can impact user engagement and preferences and that personality design parameters should be carefully considered in designing human-robot interactions for MCI older adults.

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