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Assessment of Distraction and the Impact on Technology Acceptance of Robot Monitoring Behaviour in Older Adults Care

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***Abstract*—People's successful coexistence with robots strictly depends on people's acceptance of robots' presence in their daily activities. This is particularly relevant when the robot's actions may interfere with or intrude on people's activities, creating discomfort and a possible rejection of the robot. We believe that people's acceptance of a robot may vary depending on the activities they are involved in. In this study, we investigate the impact of a robot's actions on people's engagement in an activity while the robot has the task of monitoring them. We observed the behaviours of 18 older adults with respect to the robot while they were carrying out tasks that require different cognitive workloads (e.g., working at the PC, talking on the phone). We used subjective and objective metrics, such as social cues, to evaluate people's engagement in the robot and their disengagement in their own task. We observed that people were distracted by the robot's behaviours based on the cognitive loads required by their activity. Our results show that variation in people's engagement in the robot and the task is affected by their perception of usefulness of and trust in the robot, and by individuals' personality traits and acceptance of the robot. People's with higher trust in the robot, and a higher degree of conscientiousness and emotional stability, tend to continue with their task, paying less attention to the robot. We observed, in contrast, that a robot perceived as a social entity caught more easily their attention when people have a higher extroverted personality. Our findings also showed that variations in the affective and emotional demeanour of the participants are a predictor of their distraction to an external observer.**

***Index Terms*—Distraction and disengagement, emotional reactions, technology acceptance.**

I. Introduction

Robotic applications in human-centred environments, such as private homes [1], hospitals [2], and caring homes [3], have become extremely important since the late pandemic. In particular, older and vulnerable people were the most affected by the isolation [4]. Social isolation among older individuals can have negative consequences on both physical and psychological health, and, in general, on their quality of life [5], [6]. For example, some studies suggested that isolation may have an impact that is comparable to the effects of smoking [7]. Isolation was also observed to be a factor in decreased quality of life of older adults [5], [8], causing emotional distress and highlighting the need for coping strategies [9]. In response to such emergency, roboticists' recent efforts are directed towards the deployment of autonomous robots to assist and collaborate with people in situations where humans cannot be present or are elsewhere engaged. Several studies support the choice of adopting social robots for helping, supporting, and completing tasks in human-centred environments, and how such robots can mitigate the negative consequences of social isolation [10]–[12]. One important task for autonomous robots is monitoring older people's well-being and safety in private and caring homes [13]. Assistive robots can improve older people's quality of life by adapting their own behaviours and interactions to human habits, needs, and physical or mental impediments based on the level of engagement of the person [1], [14]–[16].

People's perception of robots is not always positive and welcomed in situations in which humans and robots live in long and close contact [17]. For example, people might not trust a robot that occasionally makes errors or that might make them uncomfortable [18]. A robot's behaviour may be annoying and disturbing to people if they are engaged in other activities, even if the robot is carrying on a collaborative task. For example, a vacuum cleaner robot should not start its cleaning task while people are sleeping or on the phone. In the same way, a robot should not distract people's attention while they are watching a movie unless it is necessary. The personalisation and the need for context-awareness of the robot's behaviours and characterisation for non-interactive tasks have gained significant importance in the service robotics community [19]. Particular emphasis is placed on the information needed by a robot to recognise people's

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emotional, cognitive and social state in the surroundings before it decides to operate. Such information can be even more relevant when the "utility" of the robot's behaviour is not easily perceived. For example, in a monitoring activity, a robot needs to actively observe a person by moving, looking at and approaching them to improve the observation without engaging them in any interaction. These robot behaviours can be perceived as non-social, or even anti-social, annoying and intrusive, leading people to reject the robot and frustrating its efforts to carry out the task.

People's acceptance of robots in their environments can be enhanced by adopting socially intelligent robots [20]. A robot needs to be able to recognise the situational context of human activities, in terms of the level of engagement and criticality in their task. This is crucial for letting the robot adapt to a person's individual differences, such as their personality traits. While several studies investigated how to measure people's engagement in an interaction [21], [22], understanding when a person is disengaged is still a challenge. Detecting people's engagement and disengagement is a complex process that includes the monitoring and processing of several social cues when the user is about to lose engagement and when the user is not engaged anymore with the robot [14], [23]. These changes in social cues can be used as indicators of behavioural, affective, and cognitive states to assess users' engagement [24]. Facial emotions have been observed to be effective for measuring users' engagement [25]. In particular, variations of facial features (i.e., action units) can be used to establish if the people's expressions are of happiness, joy or amusement. Positive emotions are associated with a state of engagement, while negative emotions or the absence of an emotion would be an indicator of disengagement. While the presence of a person's affective reaction can easily be an indicator of engagement, it is more challenging to correlate a negative or neutral emotional state with an episode of disengagement. A person who is frustrated or bored during a task is not necessarily disengaged [26]. Nevertheless, we believe that facial affective expressions, or more the lack of them, can be still a very good indicator for evaluating people's engagement in a task or in the robot [27]. In our specific case, we believe that this can be used as a non-invasive way to assess the variation in the affective dimension of engagement of the user, relying on cameras' data. While this kind of measurement provides a naive way to evaluate the participants' emotional variation, and why these occur, it allows us to visually identify these specific types of users' deviation from the task.

In this paper, we explore the impact of robots' tasks on people's engagement in their everyday activities and, consequently, to what extent people's acceptance of robots is negatively affected by their disengagement. We chose for this investigation a monitoring task carried out by a social robot. We explored people's acceptance and perception of the robot based on their disengagement as evaluated by the measurement and observation of emotional and cognitive cues, both as externally observed and subjectively perceived. Finally, we addressed the feasibility of affective engagement cues as a predictor of participants' distraction.

The remainder of this article is structured as follows: Section II discusses the related background that motivated our research approach; Section III presents the user study conducted for investigating people's engagement and disengagement in the robot and the task; Sections IV and V present and discuss respectively the novel results obtained by the investigation with older adults, and discuss future research directions; Section VI summarises the work presented.

II. Background

Social robots are a promising solution to complement the efforts of families and caregivers in offering support to vulnerable populations or to those requiring specialised assistance, such as older individuals with motor or cognitive difficulties (e.g., [1], [28], [29]).

The UPA4SAR project [1] is an example of humanoid social robots deployed in the homes of older adults diagnosed with a mild neurocognitive disorder, providing monitoring (e.g., of instrumental activities of daily living) and entertainment (e.g., playing favourite music) functionalities through a daily assistive plan. Long-term performance and acceptability of a system integrating smart objects, environmental sensors, and service robots, were investigated for monitoring older participants and providing them with social, cognitive, and physical stimulation in MoveCare project [28]. D'Onofrio et al. [29] deployed a robotic system across three countries (Ireland, Italy and England) in a residential care, in a hospital and in a community, equipped with applications providing cognitive stimulation, social engagement and health assessment. In these kinds of applications, which are directly introduced in the everyday life environment of older people, the participants showed appreciation towards the robot's presence, and social and entertaining capabilities. The authors argue that the approach could be a useful solution to help lower older adults' loneliness, providing at the same time tools to enhance social connection [29]. Some assistive behaviours include having robots that providing support by reminding an older adult to perform activities or, for example, to follow

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correct medication intake [30], [31]. In such applications, emotional characterisation has been also shown to make the robot more engaging and pleasant [32].

A. Human Engagement and Disengagement in HRI

Monitoring and stimulating human engagement in activities being carried out can be a key factor for the successful interaction of people with a Socially Assistive Robot (SAR). In such scenarios, robots need to be able to detect the cues that show people's declines of their attention in the task and robot, and correctly evaluate users' distraction and disengagement. SARs have been employed for encouraging older adults to perform physical exercises, and play memory games with arm movements [33]. Fatola and Mataric [33] showed that participants generally preferred a more engaged and praising robot that elicited them to complete the exercises . Fan et al. [34] integrate a humanoid robot and a virtual reality platform to engage older adults in multi-modal tasks, characterised by physical, cognitive, and social stimuli, and to promote social communication. In such work [34], different stimuli, such as game interaction, audio, visual, and electroencephalography responses of the participants, are used by the robot to teach participants how to interact with the virtual environment, while evaluating social and activity engagement. Authors assessed the engagement by monitoring the interaction, and estimated the state of the people by using supervised machine learning strategies [35].

Rossi et al. [16] assessed participants' distraction caused by the robot's presence, and their results suggest that they were more disengaged or distracted from the task during activities whose completion requires low cognitive demands. A robot's presence, movements or attempts at giving feedback to a human carrying out a task, that requires a certain amount of attention and focus, might be detrimental and cause distraction from the activity (e.g., while reading a story) [36]. Body language (e.g., the pose or posture of the human) and face orientation are useful indicators of people's attention which can be used to establish if a person is distracted or available for being approached by the robot [37]. Understanding which robots' behaviours cause distraction is a very relevant issue for a successful and non-disruptive coexistence of robots and humans. Correctly assessing the distribution of the human's attention can be important to deploy strategies for robot monitoring and motion planning that are non-distracting for the user [38].

B. Robots' Acceptability during Non-Interactive Tasks

Successful human-robot interactions require the robot's behaviour to be appropriate and effective. Therefore, it is necessary to understand how different characterisations impact the user's perception. Depending on the type of task, different robot profiles might be more appropriate. Maggi et al. [39] observed that a more authoritarian robot behaviour might lead to better performance in a cognitive evaluation task with a higher cognitive load compared to neutral and friendly characterisations, while a neutral behaviour would score higher in attention-measuring tasks compared to authoritarian and friendly personalities. In scenarios where the robot and the human might have unaligned interests, such as in a turn-taking dice game, a socially engaged robot personality was, instead, rated higher in likeability and animacy compared to a competitive one, and can lead to a higher acceptance of the robot [40]. The personality of the person interacting with the robot has also been shown to be an important factor in robot acceptance, with extroversion, openness, and agreeableness resulting to have a strong positive relationship [41]. Participants who scored higher on openness personality also appear to have greater trust in robots compared to those with a lower score [42].

Robot acceptability is also influenced by its proxemics and the way it moves in a shared environment with humans, depending on their personal profile and preferences [43]. Besides people's personality traits and preferences, cultural factors, social dynamics and norms can also influence the appropriateness of robot use [44]. In the case of older adults, preference and acceptance of robots could depend on the tasks and the extent to which these are involved. For instance, Smarr et al. [45] noted that older adults were more likely to accept robot assistance in less physically invasive activities of their daily living, such as housekeeping, medication reminders or entertaining activities. On the contrary, they were less inclined in accepting robots in the case of more invasive activities like shaving.

III. Experimental Approach

In assistive scenarios, especially when targeting older adults, it is fundamental for the novel technologies being introduced in their everyday environment to be non-disruptive and cause as little unwarranted distraction as possible. For these types of applications, it might be necessary to carry out their intended tasks, regardless of whether they are addressed or engaged by the human. For instance, a robot that is tasked to monitor an older individual (such as in our application domain) must be able to conduct its activity in the most seamless way possible, even if people are already involved in other activities.

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In this work, we are particularly interested in the users' engagement towards the task and towards the robot. We considered engagement a multidimensional construct consisting of affective, behavioural and cognitive components [24], [46]. Based on the current literature, we believe that facial expressions and human postures can be used as indicators of engagement and disengagement [32], [37]. We decide to map the eye gaze to the cognitive engagement, the user's pose to the behavioural, and the smiles to the affective engagement. While this might be a simplified characterisation of these three aspects, we believe it provides us with a straightforward way to analyse the impact of the robot's presence on the participants' perception and demeanour. We also argue that, while it might be clear to an external observer that in some cases the robot's presence may distract the person, this might not reflect the perception of those involved in the human-robot scenario. Moreover, we considered the user's personality to also be a relevant factor for people's engagement, impacting their perception of the robot's behaviour [47], [48].

Based on these considerations, we designed a user-study to answer the following Research Questions (RQ) for measuring the impact of a robot's monitoring behaviour on participants' perception and engagement:

RQ1: "How does the robot's presence affect the participants affective, cognitive and behavioural engagement?". This research question is addressed as a direct extension of the findings of [16]. We analyse the number of smiles, pose changes and gazes of the users, the duration of the actual interaction and the distraction perceived by the participant during the activities for measuring the different engagements.

RQ2: "What is the impact of the robot's presence on users' subjective and objective distraction and disengagement?". We aim to assess to which degree the subjective perception of the distraction of the participants varies from the objective disengagement rated by an expert. We wonder whether people could perceive less their distraction during activities that require high-cognitive demands to be completed.

RQ3: "Is there a correlation between users' acceptance of the robot and their affective, behavioural and cognitive engagement?". We argue that the robot's presence during non-interacting activities might be moderated by the user's trust and perception of usefulness and ease of use of the robot.

RQ4: "How are individuals' personality traits associated with the engagement process?". We expect that more extroverted people are more easily distracted by the robot's presence, as they might attracted by the prospect of interacting with it. In the case of individuals with high scores in consciousness, instead, we expect them to be very focused on the task, and to be less distracted by the robot.

A. Methodology

We designed a within-subjects study, recruiting older adult volunteers among researchers' friends and relatives at the Department of Psychology of the University of Campania "Luigi Vanvitelli". Participants were admitted to the study based on the following inclusion criteria: 1) absence of cognitive decline defined by age- and education-adjusted score on the Italian version of the Montreal Cognitive Assessment (MoCA > 15.5) [49]; 2) absence of a history of neurological disorders; 3) absence of major depression according to DSM-5 (Diagnostic and Statistical Manual of Mental Disorders, fifth edition) [50], or other neuropsychiatric disorder.

We collected demographic information (i.e., gender, age, years of schooling) for each participant. The study was conducted in accordance with the latest version of the Declaration of Helsinki (October 2013), approved by the Ethical Review Board of the University of Naples Federico II, and participants gave written informed consent.

At the beginning of each session, participants filled out the Italian version of the NEO Personality Inventory-3 (NEO-PI-3) to evaluate their personality trait (i.e., Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness) [51]. The NEO-PI-3, contrary to other tests (e.g., the Big Five [52]) offers greater granularity to investigate each personality traits. For instance, Extraversion is described by a series of measures, such as Warmth, Gregariousness, Assertiveness, Activity, Excitement Seeking, and Positive Emotion. We chose this test to be able to assess the correlations with different aspects of the personality traits with greater granularity.

Participants were conducted in an experimental room and left alone with a robot Pepper, whereas the investigators monitored the interaction from an adjacent room through video and the robot's cameras. The robot had the task of monitoring participants' state, without actively engaging them, while they were occupied in different activities (e.g., watching the TV, talking to their phone).

The experimental sessions were evaluated with subjective and objective measures: participants were asked to complete the Unified Theory of Acceptance and Use of Technology (UTAUT) questionnaire [53]; their behaviours were evaluated by a clinician to measure their disengagement from the carried-out activity and

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the distraction caused by the robot; and we collected participants' gaze, smiles, postural changes during the completion of their task and the robot's approach for its monitoring task.

B. Experimental Procedure

Participants first completed the prestudy questionnaires, which included the demographic and personality traits questions. Then, they were conducted in a room furnished as a robot home, including a fridge, a coffee machine, iron and ironing table, a working phone, a desk on which there was a PC laptop, and a couch placed in front of a TV. The session continued with a familiarisation phase, in which the robot administers the psychometric evaluation based on the MoCA test for reducing the novelty effect. In this phase, the robot explains the instructions, registers the answers and computes the scoring of the MoCA test [54]. After the familiarisation phase, the participants were asked to perform four activities, one at a time, and in randomised order, while the robot was left idly wandering in the room. The activities chosen are characterised by an increasing degree of cognitive involvement required, and different postures assumed by the participants while performing them (see Figure 1):

i) Watching TV. In this activity, we considered sitting posture and low-level of cognitive load required (see Figure 1a). The participant is sitting on a couch watching the news on the TV.
ii) Making coffee. We considered in this activity standing posture and medium level of cognitive load required (see Figure 1b). The participant needs to prepare coffee by using a moka pot, water and powder coffee.
iii) Talking on the phone. This activity included standing posture and medium-high level of cognitive load required (see Figure 1c). The participant is engaged in a real phone call with a family member.
iv) Working at the PC. In this activity, we considered a sitting posture and high level of cognitive load required (see Figure 1d). The participant was sitting at a desk while browsing a news website on the laptop.

The robot's task consisted of approaching the participants to monitor their current state. For each activity, after a brief casual navigation around the room, the robot would approach the participant to monitor their activity, stopping for 10 seconds while looking in the direction of the participant. More specifically, the robot stopped to monitor the users twice per activity, respectively at 2.5m and 1.5m from the participant. The robot's approaching strategies were implemented based on previous literature [43], [55]. In particular, high relevance was given to proxemics which can influence significantly the perception and acceptance of a social robot [43]. Different types of activities, with varying degrees of cognitive involvement required, might allow different approaching distances [55]. Based on these works, distances above 2m can be perceived as public space, while between 1.5m and 2m can be perceived as social space [56].

The investigators monitored each session from an adjacent area of the room separated by dividers. The experimental sessions were timed and video-recorded, using an external camera and the robot' 2D camera. The robot recorded a 10-second RGB video with its camera from each approaching distance; and two external cameras placed in two different positions in the room captured the activities being carried out across the entire room.

Once the interaction phase was concluded, the participants left the robot room and were asked by the experimenters to complete the post-experiment UTAUT questionnaire. The entire experimental session lasted approximately 45 minutes.

C. Disengagement Evaluation

In this work, we aim to evaluate the user's engagement/disengagement based on the impact of the robot's presence in a scenario simulating real-world everyday activities. To this extent, we used three types of evaluation:

1) Subjective evaluation: after the completion of each of the four activities, the participants were asked to rate the subjective perceived distraction caused by the robot on a scale from 0 (no distraction) to 100 (high-level distraction). The scale was presented to the users printed on paper as a vertical line with 100 steps, numbered every 10.
2) Objective evaluation: a two-item brief disengagement assessment was conducted by a clinician using two 5-point Likert scales (rating from 0 to 4) to quantify the disengagement from the current activity (item 1) and the distraction caused by the robot's movements (item 2). For the first item, the scale translates to *not at all*, *to a sufficient extent*, *to a moderate extent*, *to a good extent*, *to a great extent*, while for the second item, it was reversed, so a lower score would reveal a higher level of distraction caused by the robot. The two items are formalised as:
   - "*How much was the subject focused on the task?*", Engagement to task (item 1) in Table I.

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(a) *Participant during a Watching TV activity.*

(b) *Participant during a Making coffee activity.*

(c) *Participant during a Talking on the phone activity.*

(d) *Participant during a Working at the PC activity.*

Fig. 1: Snapshots of the participants' activities taken from the robot's camera during the study.

- "*How much was the subject distracted by the robot?*", Engagement to robot (item 2) in Table I.

The two items are subsequently used to compute a composite score to reflect the total engagement towards the task, taking into account the distraction caused by the robot. This is obtained as the sum between the scores for *item 1* and *item 2*.

3) Observable measures: several objective and observable parameters, including social and behavioural cues, were analysed to quantify the human-robot interaction to evaluate the subjects' engagement towards the robot. These measures were computed to allow us to make considerations on the basis of more granular observations of the distraction caused by the robot. We chose the specific measures employed to have a direct mapping to the three types of engagement: cognitive, behavioural and affective. We considered:
   - the number of eye gazes toward the robot (number of gazes), which can be related to cognitive engagement.
   - the number of smiles the subjects directed towards the robot during each activity (number of smiles), which refers to the affective engagement. When the participants smiled at the robot, for that amount of time they moved the focus of their attention from the task to the robot. It is important to note that, in this work, we do not investigate the *quality* of this shift in attention, as we are specifically interested in the *presence* of such variation.
   - the number of postural changes triggered by the robot's presence or approaching behaviour (number of pose changes), describing the behavioural engagement.

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To investigate the overall impact of the presence of the robot, we defined an aggregate score to consider the total amount of time (in seconds) the subjects looked, smiled or turned to the robot during each activity. This is obtained as the sum between these three measures.

These ratings were obtained through a behavioural analysis conducted by a clinician on the video recordings collected with the internal camera of the robot and the external cameras mounted in the environment.

IV. Results

We recruited 18 participants (11 males and 7 females) who completed cognitive and personality assessment and the experimental session with Pepper. As demographic features, we considered age ($MIN = 53, MAX = 82, M = 60.28$, $SD = 7.19$) and years of education ($MIN = 8, MAX = 18, M = 12.39$, $SD = 3.91$).

All analyses were conducted with the IBM SPSS-26 [57] statistics software with α level set at .05. We used a non-parametric Friedman test to compare engagement variables across the four different activities (i.e., Making Coffee, Talking on the phone, Working at the PC, Watching TV) [58]. Post-hoc pairwise comparisons were assessed to identify any occurred differences. We ran Spearman's rank-order correlation tests to evaluate [59]: *i.* the relationship between the subjective perceived distraction obtained with the participants' scores and the objective engagement scores measured by a clinician using the external cameras' recordings, and *ii.* the relationship between engagement scores measured using the external camera recordings and the level of technology acceptance (i.e., UTAUT) and participants' personality (i.e., NEO-PI-3).

A. Comparison of Engagement Parameters During the Execution of Different Activities

The comparison between engagement parameters reported during different activities showed significant differences in item 1, item 2 and the total score of the engagement evaluation, on the number of gazes, on the duration of the human-robot interaction, and on subjective perceived distraction rate (see Table I). No significant differences between different activities on the number of smiles and pose changes were found.

As shown in Table I, a post hoc analysis highlighted that subjects were significantly less focused on the task *(see Engagement to task (item 1))* during the Watching TV activity compared to Making Coffee and Working at the PC activities. Participants were also significantly less focused on the robot (see *Engagement to robot (item 2)*) during the activities Watching TV compared to Making coffee and Working at the PC. Moreover, they reported a higher distraction caused by the robot (*Subjective perceived distraction*) for Talking on the phone compared to Making coffee. Regarding the total engagement score (see *Engagement Total)*, we found that participants showed lower levels of engagement in the task during Watching TV compared to Making coffee and Working at the PC activities, whereas they were more engaged in the task during Making coffee than during Talking on the phone.

Participants looked (see *Number of gazes*) towards the robot for the least amount of time during the Making coffee activity. This is consistent with how this activity was defined, with the participants giving their back to the robot, and facing a table on which they need to add coffee powder in a Moka pot. It is interesting to note that we did not observe a similar result for Talking on the phone task, where participants held a less static pose and turned more often towards the robot when this was approaching. Watching TV was the task with the higher distraction of the participants and more attention to the robot (in terms of gaze time directed to the robot). We believe that this reflects the low level of cognitive load required by this activity. The Working at the PC task, which requires a higher cognitive investment, resulted to be the second with the least gazes directed at the robot.

A similar trend can be also observed in general for the entire duration of the session (*Duration of HR interaction*). The participants interacted with the robot for a significantly lower amount of seconds during Making coffee, followed by Working at the PC, Talking on the phone and Watching TV.

Finally, the *Subjective perceived distraction* shows that participants perceived the robot to be the least and most distracting for Making coffee and Watching TV tasks, respectively. They, overall, perceived the robot to be more distracting during the Working at the PC activity, compared to the Talking on the phone task.

B. Association Between Engagement Parameters and the Subjective Perceived Distraction

No significant correlation was found between the engagement levels rated by the clinician and the participants' subjective perceived distraction for the Making coffee and Working at the PC activities. The subjectively perceived distraction caused by the robot while the participants were performing the Talking on the phone activity was found to be positively correlated to the number of gazes directed to the robot ($r = 0.489$; $p = 0.040$). The subjective perceived distraction rated

TABLE I: Comparisons between engagement parameters across different activities.

	Making Coffee (A)	Talking on Phone (B)	Working at the PC (C)	Watching TV (D)	Total activities	χ^2 post hoc	p
Engagement to task (item 1)	3.9±0.2	3.6±0.5	3.7±0.8	2.9±1.2	14.1±2.3	19.1 A>D**, C>D*	<**0.001**
Engagement to robot (item 2)	3.7±0.6	2.9±0.9	3.4±1.1	2.4±1.3	12.5±3.2	21.9 A>B*, A>D** C>D**	<**0.001**
Engagement Total	7.7±0.8	6.6±1.3	7.1±1.9	5.3±2.5	26.6±5.3	24.1 A>B*, A>D*** C>D**	<**0.001**
Number of gazes	0.5±0.92	3.2±3.39	1.6±1.79	4.6±3.48	9.9±6.60	20.412 B>A**, D>A*** D>C*	<**0.001**
Number of smiles	0.1±0.24	0.2±0.65	0.1±0.24	0.3±0.77	0.7±1.45	5.667	0.129
Number of pose changes	0.3±0.84	0.6±0.98	0.1±0.32	0.3±0.77	1.3±1.97	5.308	0.151
Duration of HR interaction	0.5±0.92	10.3±16.74	5.4±13.88	15.4±19.85	31.6±38.72	24.980 B>A**, D>A*** D>C*	<**0.001**
Subjective perceived distraction	7.1±16.69	7.5±12.10	9.8±14.83	14.2±17.84	38.5±55.30	9.102 D>A*	**0.028**
***p < .001;	** = p < .01; * = p < .05.						

after the Watching TV activity was negatively associated with the objective score on engagement to the task (i.e., *Engagement to task (item 1)*; $r = -0.499$; $p = 0.035$), and positively associated with the number of gazes towards the robot ($r = 0.555$; $p = 0.017$) and with the duration of the engagement ($r = 0.471$; $p = 0.048$).

C. Association Between Affective Engagement and Distraction

We used a Pearson's correlation coefficient between the number of smiles and the subjective and objective distraction measures to further assess the impact of the robot's presence on the affective engagement variations.

We can observe that affective engagement towards the robot (i.e., measured as the number of smiles) and the participants' subjective perceived distraction were not statistically significant ($R = 0.11, p > 0.05$), as it can be seen in Table II. When we consider the distraction evaluation performed by the clinician, instead, we observed a moderate negative statistically significant correlation with the affective engagement ($R = -0.48, p < 0.001$). This suggests that while participants did not strongly or significantly associate their behaviours with their unconscious emotional reactions, such as smiles, the clinicians observed that frequent smiling might show participants' attentional shifts and disengagement. In particular, smiles can possibly indicate discomfort, politeness, or superficial engagement.

TABLE II: Pearson's correlation between affective engagement (number of smiles) and the subjective and objective distraction evaluations.

	R	p
Subjective Distraction	0.11	0.36
Objective Distraction	-0.48**	<**0.001**
***p < .001;	** = p < .01;	* = p < .05.

D. Association Between Engagement Parameters and UTAUT Scores

We collected participants' responses to the UTAUT questionnaire to evaluate their overall perception and

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acceptance of the robot [53]. We used the following 12 constructs of the UTAUT questionnaire, adapted to fit the context of assistive robotics and older individual care:

- ANX: Anxiety - Evoking anxious or emotional reactions during the HRI.
- ATT: Attitude towards technology - Positive or negative feelings of the robot.
- FC: Facilitating conditions - Factors in the environment that facilitate the use of the robotic system.
- ITU: Intention to Use - The intention to use the robotic system over a longer period of time.
- PAD: Perceived adaptiveness - The perceived ability of the robot to adapt to the needs of the user.
- PENJ: Perceived Enjoyment - Feelings of joy/pleasure associated with the use of the robot.
- PEOU: Perceived Ease of Use - The degree to which one believes that using the robot would be free of effort.
- PS: Perceived Sociability - The perceived ability of the robot to have sociable behaviour.
- PU: Perceived Usefulness - The degree to which a person believes that the robot would be of assistance.
- SI: Social Influence - An individual feels the importance that others believe they should use the robot.
- SP: Social Presence - Perception that the robot has social characteristics.
- Trust: The belief that the robot acts with personal integrity and reliability.

We considered the association between the engagement parameters scored for the entire experimental session and UTAUT questionnaire scores. We found that the Perceived Ease of Use score of the UTAUT was significantly related to the item 1 of the engagement assessment ($r = 0.567$, $p = 0.014$) and the duration of the human-robot interaction ($r = -0.483$, $p = 0.043$). We also found a significant association between the Intention to Use score of the UTAUT and the item 2 of the engagement assessment ($r = 0.468$, $p = 0.050$).

As for the engagement parameters registered within each activity, we did not find any significant correlations between engagement levels and UTAUT scores when participants were Making coffee, and they were Watching TV.

Regarding the Talking on the phone activity, we found that the number of smiles directed to the robot was associated with the Social Presence score of the UTAUT ($M = 15.44$, $SD = 4.76$; $r = 0.479$; $p = 0.044$) and that the *Number of pose changes* was related to the Social Influence score of the UTAUT ($M = 6.83$, $SD = 1.50$; $r = -0.600$; $p = 0.008$).

During the Working at the PC activity, the Social Presence score of the UTAUT was significantly related to item 1 ($r = -0.509$; $p = 0.031$), item 2 ($r = -0.536$; p=0.022) and total ($r = -0.542$; $p = 0.020$) scores of the engagement assessment. In this activity, the Social Presence was also significantly related to *Number of gazes* ($r = 0.517$; $p = 0.028$) and to the entire duration of the HR interaction ($r = 0.524$; $p = 0.025$) The engagement to the task item resulted to be associated with Facilitating Conditions ($M = 5.94$, $SD = 1.98$; $r = 0.583$; $p = 0.011$), Perceived Ease of Use ($M = 18.2$, $SD = 3.0$; $r = 0.489$; $p = 0.039$) and Trust ($M = 6.72$, $SD = 2.37$; $r = -0.525$; $p = 0.025$) dimensions.

E. Association Between Engagement Parameters and Personality Traits

Considering the association between individuals' personality traits and engagement parameters observed during the entire experimental session, we found a significant relationship between the agreeableness trait and the Number of smiles ($r = 0.511$, $p = 0.030$). As for the engagement parameters registered within each activity, we found a significant correlation between the extraversion trait ($M = 144.94$, $SD = 21.47$) and the Number of pose changes ($r = 0.497$, $p = 0.036$) during the Making coffee activity. The conscientiousness trait ($M = 178.72$, $SD = 19.79$) was positively correlated with the engagement to the robot item ($r = 0.520$, $p = 0.027$) and negatively correlated with the number of pose changes ($r = -0.490$, $p = 0.039$) during the phone call.

Finally, the number of gazes turned to Pepper resulted to be positively correlated to neuroticism during the Working at the PC activity ($M = 128.78$, $SD = 23.06$; $r = -0.543$, $p = 0.020$).

V. Discussion

In this, study we investigated the distraction and the disengagement caused by a social robot while monitoring older individuals busy in carrying out four different activities that would be commonly undertaken in their everyday lives. We observed different people's disengagement in their activities when these required higher cognitive load (i.e., research question **RQ1**). Indeed, we found higher disengagement during the Watching TV activity compared to the Making coffee and Working at the PC tasks. Working at the PC activity requires more cognitive demands than Watching TV. Indeed, the higher cognitive load required for the completion of a task

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suppresses peripheral processing of task-irrelevant information, and, as a consequence, it decreases distractibility [60]. Moreover, we observed a higher distraction caused by the robot during the Talking on the phone task compared to Making coffee task. Although the Making coffee activity requires a medium level of cognitive load, participants performed this activity with their backs to the robot, explaining the lower level of disengagement compared to Watching TV activity and that they were free to turn around and look at the robot during the phone call.

We did not observe any significant difference between low levels of smiles and pose changes between the four activities. The low number of smiles directed to the robot observed in all proposed activities seems to indicate that the affective dimension of engagement is generally less involved in the interaction. Affective engagement refers to the quality of the relationship in terms of positive emotions and warmth [24] and is reported to be crucial in HRI [61], [62]. Therefore, the mere presence of the robot, in the absence of a real interaction, seems to involve the cognitive dimension of engagement (i.e., attention and concentration) rather than the affective one. It is important to note that, the participants were not socially engaged by the robot. For this reason, we do not deem the lack of higher affective engagement estimates as an effect of an unpleasant robot's behaviour, but rather the consequence of the non-social strategy adopted.

Participants performed a low number of pose changes, but no significant difference emerged between the proposed activities. These findings allow us to hypothesise that the distraction caused by the presence of the robot attracted the gazes of participants rather than pose changes.

Analysing the distraction perceived subjectively by participants (research question **RQ2**), we found that they reported a higher level of disengagement from the task while Watching TV than Making coffee activity. This result is in line with the findings from objective parameters, but highlights the need to evaluate the disengagement from everyday activities and the distraction caused by the robot both from subjective and objective perspectives. This would be a consequence of the participants not being always fully aware of the distraction caused by the robot, especially when they are performing activities that require high-level attention. By considering smiles as an overall predictor of distraction, we observed that they were not a reliable self-reported indicator of engagement, while they can be a valuable cue of disengagement for an external observer. These results also highlight differences in the perception of distraction between participants and clinicians, and how they might be interpreted in a context-dependent way. The investigation of this research question also leads us to the conclusion that the perceived distraction rated by participants was related to objective parameters only in activities with higher levels of distraction, such as Talking on the phone and Watching TV activities.

Furthermore, we investigated the possible relationship between disengagement and participants' acceptance of technology (**RQ3**). We found that lower levels of disengagement from the activities were associated with a greater perceived ease of use of the robot. Therefore, participants were less distracted by the robot when they felt it was easy to use. Higher levels of engagement towards the robot were also positively related to the intention to use it.

Studying the associations between the UTAUT questionnaire scores and the disengagement variables for each activity, we found that a higher number of smiles directed at the robot was associated with participants' greater perception of interacting with a social entity. We also observed that a higher number of pose changes were related to higher perceived social influence during the phone call. Participants' engagement in the activity was positively associated with the perceived ease of use of the robot and with the trust in its capabilities during working with a PC activity.

It has been observed that people respond automatically to robots adopting human behaviours and social norms during an interaction [63]. In such cases, social responses, such as smiling, can be used by a robot to positively increase people's perception of the robot as a social entity. We interestingly observed that participants' engagement in their current activity was associated with the perception that the robot is easy to use and with their beliefs that it performs tasks with integrity and reliability. These findings further support that trust plays a crucial role in HRI and confirm that the less trust they have in a robot, the sooner they will intervene as it progresses toward task completion [64], [65].

Analysing the relationship between the specific personality traits of participants and their disengagement from the proposed activities (**RQ4**), we observed a relationship between participants' agreeableness and the number of smiles directed at the robot during the entire experimental session. A significant association emerged between the extraversion trait and the number of pose changes during Making coffee activity. Our results showed that individuals with higher agreeableness adopt friendly and prosocial behaviour to create a positive relationship, which is in line with [66]. We found a relationship between the extraversion trait and the number of pose changes during the Making coffee activity. Due to the nature of the activity, participants had their backs turned toward the robot while carrying the activity. Participants with higher extroversion tended to turn to face the robot more often during the activity. We also found significant relationships between the conscientiousness trait and the engagement with the robot and the number of pose changes during the phone call, and between the neuroticism trait and the number of gazes directed at the robot while working at the PC activity. These results show that the engagement with the robot could be moderated by participants' self-discipline because individuals scoring high in conscientiousness were less distracted by the robot. Individuals with high conscientiousness tend to be more serious, disciplined, and methodical than those with low conscientiousness, and they prefer to focus on task performance rather than act spontaneously [67]. Participants with high levels of neuroticism looked less at the robot, confirming that this personality trait is associated with negative attitudes toward robots [68]. These results further support the findings of Takayama and Pantofarua [68], who analysed human personal space during HRI, showing that more neurotic people tend to increase their personal space by standing further away from approaching robots.

Although we believe the results allowed us to discuss in a consistent and satisfactory way the research questions presented, this study finds its limitations in the small sample size, due to the challenges in recruiting older subjects for experiments set in university laboratories, and in the limited number of everyday activities to be performed by the participants. In this study, we decided to include four activities to keep the duration of the experimental session acceptable for the participants, but we aim to include a wider range of everyday activities in future studies.

VI. Conclusions

In this study, we explored the impact of a robot monitoring older adults while performing everyday activities, with particular interest in the distraction caused by the robot and the effect on the technology acceptance. We conducted a user study with 18 older individuals.

Our analysis revealed that participants were more distracted by the robot during activities that required lower levels of cognitive involvement, such as watching TV. However, participants were cognitively rather than affectively engaged with the robot. We observed that when the robot approach provoked a reaction from the participants, it would translate into gazes towards the robot, rather than smiling at it. The duration of HRI across the activities reflected the overall trends observed for the amount of time in which the participants looked toward the robot. This analysis was obtained from objective external assessments performed by a clinician. In this work, we also intended to study the perception of the participants, who were presented with a subjective perceived distraction scale to rate how much the robot distracted them during each of the tasks. We found that the perception of the participants was in agreement with the objective analyses of the clinician, with the robot being rated slightly more distracting only in one of the activities.

Personality and acceptance of technology assessments were administered to the participants with the objective of studying correlations between the perception of the robot's behaviour and the impact. The trust and the perception that the robot is easy to use seem to be crucial in participants' engagement process since participants were more engaged in their activities when the trust levels were higher. A greater perception of the robot as a social entity was also associated with higher levels of engagement with the robot.

Users' personalities also play a role in the engagement process. More extroverted people tended to be more distracted by the robot, whereas individuals with higher levels of conscientiousness were more focused on task performance rather than the robot's presence. Participants' self-discipline appeared to have an impact in moderating the interaction with the robot, with individuals scoring high in conscientiousness being less distracted by the robot. We noted how, instead, a higher neuroticism corresponded to less attention directed towards the robot.

The results obtained show that a humanoid robot can be used effectively for monitoring older individuals in a home environment, but it is important to consider the cognitive load required by the performed activity, the users' personality and perception of technology, to tailor the behaviour of the robot in a way that is most effective and acceptable.

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