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"I Know How You Feel": The Importance of Interaction Style on Users Acceptance in Entertainment Scenario *

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Abstract

In this article, we aim to evaluate the role of robots' personality-driven behavioural patterns on users' intention to use in an entertainment scenario. Toward such a goal, we designed two personalities: one introverted with an empathic and self-comparative interaction style, and the other extroverted with a provocative and other-comparative interaction style. To evaluate the proposed technology acceptance model, we conducted an experiment (N=209) at a public venue where users were requested to play a game with the support of the TIAGo robot. Our findings show that the robot personality affects the acceptance model and three relevant drivers: perceived enjoyment, perceived usefulness, and social influence. The extroverted robot was perceived as more useful than the introverted, and participants who interacted with it were faster at solving the game. On the other hand, the introverted robot was perceived as more enjoyable but less useful than the extroverted, and participants who interacted with it made fewer mistakes. Taken together, these findings support the importance of designing proper robot personalities in influencing users' acceptance, featuring that a given style can elicit a different driver of acceptance.

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Keywords— Robot personality, Robot communication style, Robot acceptance, Technology acceptance model

1 Introduction

Social robots are robots designed to interact socially with humans in their environment. Research has shown that social robots have been used in healthcare (Andriella et al. (2020b, 2022)), education (Clabaugh et al. (2019)) and entertainment (Andriella et al. (2019b)). As social robots are meant to work closely with humans, offering appropriate support and assistance is key to developing mechanisms of interaction and communication that reflect human-social behaviour. Personality has been identified as a characteristic of paramount importance in understanding and shaping the interaction between humans and robots (Robert (2018); Sverre Syrdal et al. (2006)).

Thus, the capability of the robot to embody different personality traits has a fundamental role in the development of robotic solutions that can be accepted and trusted. However, robot personality, because of its multifaceted nature, seems to be dependent on numerous factors such as context (Joosse et al. (2013)), sample size (Esterwood et al. (2021)), robotic platform (Robert et al. (2020)), robot's role (Staffa et al. (2021)), individuals' expectations (De Graaf and Ben Allouch (2014)), and their attitude (Anzalone et al. (2017)), among others. Hence, it is very hard to draw any general conclusion from previous studies. A very interesting insight from Robert *et al.* literature review about personality (Robert et al. (2020)) is the importance they ascribed to the robot's behaviour in terms of communication style.

Previous work has investigated how human personality can predict the robot's acceptance and intention to use, showing that the more agreeable, extroverted, and open individuals are, the more inclined they are to accept the robot (Esterwood et al. (2021)). For instance, Conti et al. (2017) discovered that openness to experience and extroversion personality traits affected teachers' acceptability and intention to use the robot during teaching activities. On the other hand, some studies also explored how robot personality can predict humans' acceptance of it (De Ruyter et al. (2005); Meerbeek et al. (2008); Tay et al. (2014)). Tay et al. (2014) argued that robot personality did not monotonically influence user responses; instead, it depended on the corresponding role stereotypes, which in turn affected their acceptability. Similarly, Staffa et al. (2021) found that users overall preferred to interact with an extroverted robot, but this was highly dependent on their occupational roles. However, very few works have investigated the impact of communication style with respect to the robot personality on users' acceptance.For instance, Maggi et al. (2020) discovered that the robot's interaction style (authoritarian or friendly) related to participants' acceptance and trust of the technology.

In this work, we are interested in evaluating the effect of robots personality-driven behavioural patterns on user' acceptance of the robot in an entertainment scenario, regardless of the user personality. We build upon the pioneer work of Tapus et al. (2008) and our previous work (Andriella et al. (2021)), to design two personalities: one more introverted, empathic (Leite et al. (2014)) and self-comparative (Schneider and Kummert (2016)) and the other more extroverted, provocative and other-comparative (Swift-Spong et al. (2015)). We modelled such personality traits in terms of verbal and non-verbal social cues as well as of vocabulary and stereotypical expressions in a TIAGo robot.

Next, we evaluated the robot personality traits through a pre-study with 21 subjects. As in the pre-study, participants were able to distinguish between the two personalities, we carried out a field experiment with 209 subjects at an international fair, in which untrained participants were asked to play a game with the assistance of a robot endowed with one of the two personality traits (see Figure 1).

To measure the users' Intention To Use (ITU) the robot, we used a modified version of the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al. (2003)). The UTAUT showed that Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Social Influence (SI) and Perceived Enjoyment (PENJ) of the model explained the users' ITU, regardless of the robot personality. However, the model reached different degrees of fit when the robot displayed a personality, which was higher in the case of the introverted robot and lower in the case of the extroverted, meaning that the introverted robot increased the overall user's ITU. Furthermore, the robot equipped with an extroverted personality was perceived as more useful than the introverted, which in turn, was perceived as more enjoyable and less useful. Additionally, both robots were perceived by participants to have social influence. Finally, we found that participants who interacted with the extroverted robot were capable of finishing the game in a shorter time than those who interacted with the introverted. On the other hand,

Figure 1: A participant plays with the assistance of a robot that can exhibit either an extroverted or introverted personality.

we discovered that participants who interacted with the introverted robot made fewer mistakes than those who played with the extroverted.

1.1 Research Questions

This work aims to extend our previous findings on robot personality (Andriella et al. (2021)), investigating what role the communication style plays on the users' intention to use the robot in an entertainment scenario in which a social robot is programmed to aid participants to solve a game.

Based on previous work, in which robots with an empathic communication style were deemed more friendly (Leite et al. (2014)), and more engaging (Rossi et al. (2020)) and robots with a more provocative style and other-comparative feedback decrease users' task performance (Swift-Spong et al. (2015)) and break their expectations (Paetzel-Prüsmann et al. (2021)), we hypothesise that overall a robot endowed with a more empathic interaction style will increase the participants' intention to use it and their performance on the task than a robot with a more provocative communication style. Therefore, we formulate the following research questions:

RQ1: *To what extent, if any, would the robot, provided with an introverted personality and empathic communication style, be more accepted than an extroverted robot with a provocative communication style in an entertainment scenario?*

RQ2: *To what extent, if any, would the participants interacting with a robot provided with an introverted personality and empathic communication style, perform better than those who interact with an extroverted robot and a provocative communication style in an entertainment scenario?*

1.2 Hypotheses

In light of the aforementioned research questions, we defined the following hypotheses (see Figure 2):

H1: PU is a more important precedent of ITU for participants who interact with an empathic robot than for those who interact with a provocative robot.

H2: PEOU is a more important precedent of ITU for participants who interact with an empathic robot than for those who interact with a provocative robot.

H3: PENJ is a more important precedent of ITU for participants who interact with an empathic robot than for those who interact with a provocative robot.

H4: SI is a more important precedent of ITU for participants who interact with an empathic robot than for those who interact with a provocative robot.

H5: PEOU is a more important precedent of PU for participants who interact with an empathic robot than for those who interact with a provocative robot.

H6: Participants who interact with the extroverted robot will perform worse than those who interact with the introverted robot.

Specifically, H1-H5 help us to address RQ1, namely, to evaluate whether and to what extent a robot endowed with an empathic personality would be more accepted than a provocative one. On the other hand, H6 tackles RQ2, speculating that the robot's behavioural pattern related to the two personality traits can affect the participants' performance.

1.3 Contributions

In addressing the research questions, we make the following contributions:

- Modelling the two personality-driven behavioural patterns in terms of verbal and non-verbal social cues in a fully autonomous robot.

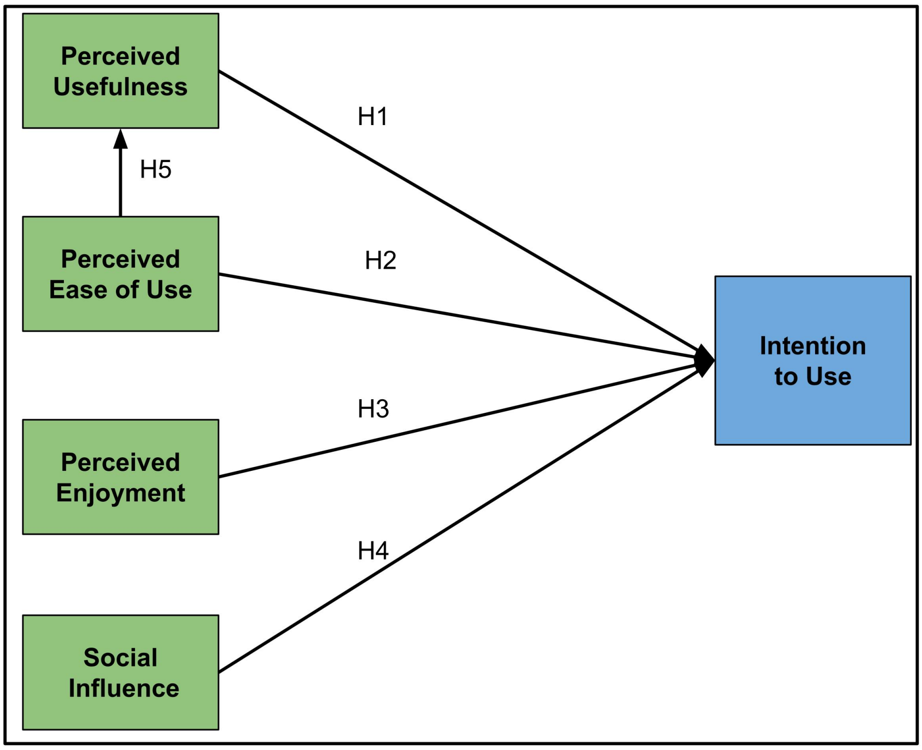


Figure 2: Proposed UTAUT for assessing users' intention to use the robot.

- Evaluation of it in a real-world use-case with 209 untrained participants.

With these results, we aim to contribute to the current state of the art on robot personality showing that, if modelled properly, robot behavioural patterns can impact the user's intention to use. Therefore, by potentially manipulating these features, we could turn on or amplify different drivers of the technology acceptance model.

2 Related Work

Our work focuses on modelling personality traits with their respectively communication styles on a TIAGo robot and evaluating the participants' intention to use it in a real-world setting. In Section 2.1, we present the most relevant work on robots' communication styles and their impact on the users' performance and perception. In Section 2.2, we introduce the state of the art with respect to the robot personality focusing on the extroverted/introverted trait, which is the trait modelled on the robot in this work. Finally, in Section 2.3, we describe the technology acceptance models and their specific usage in assessing users' intention to use the robot.

2.1 Robot Communication Style

A communication protocol is defined as the set of rules that allow establishing a communication process between two systems, whether technological or human (Bochmann and Sunshine (1980)). The production of communication protocols through language includes three elements: what it is said, how it is said and to whom it is said (Brennan and Hanna (2009)). In Human-Robot Interaction (HRI) what is said is usually programmed in the script and how it is said is determined by the use of text-to-speech programmes combined with non-verbal language expressions (Chidambaram et al. (2012)). Regarding the last factor, a general rule to establish effective communication with an audience is to follow the cooperative principle. For a speaker to apply the cooperative principle, they must have precise expectations about what listeners already know about the topic or about their ability to understand what is being explained to them. Principles that have also been followed in advertising communication, as for a message to be persuasive, the listener must be motivated and have sufficient ability to process the information correctly (Petty and Cacioppo (1986)).

Very few works in socially assistive robotics have explored the effect of communication style in providing feedback and motivation to users. Maggi et al. (2020) investigated how two interaction styles, one more friendly and the other more assertive could affect the participants' performance in a cognitive assistive task. Results showed that the assertive robot seemed to be more appropriate to improve the performance when the task required high cognitive demand. Also, that the highest increase in terms of acceptance and intention to use was observed in the authoritarian condition. Paetzel-Prüsmann et al. (2021) similar to our work, modelled the robot communication style, defining one more optimistic and engaging and the other more impatient and provocative. They found that the robot displaying a provocative communication style did not change the perception of the users when interacted with it over time. On the other hand, for those who interacted with the robot endowed with an encouraging style the uncanny feelings toward the robot diminished while being exposed to it. Schneider and Kummert (2016) evaluated how different motivational styles can influence users to persist longer on a planking task. They found a motivational gain when the robot was providing acknowledging feedback. Swift-Spong et al. (2015) explored the effect of comparative feedback, defined as self-comparative and other-comparative, provided by a robot coach which provided guidance to post-stroke patients in an arm reaching task. They found that participants who interacted with the other-comparative robot took more time to respond in comparison with those who interacted with the self-comparative robot. Akalin et al. (2019) examined how different feedback defined as positive (praise), flattering (over-praise) and negative (challenging), provided by a robot affected older adults acceptance and intention to use. Results highlighted that when the robot provided flattering and positive feedback was more accepted by the older adults than when it provided negative feedback. Tapus et al. (2008) investigated the role of robot personality in hand-off therapy process. In particular, they focused on two different styles one more nurturing linked to the introverted personality and the other more challenging linked to the extroverted personality. The results showed that by adapting the robot personality to that of the user, the latter can improve their performance.

However, none of these works has explored which are the factors that affect the users' intention to use. An exception is the work presented by Ghazali et al. (2020) in which they designed a new acceptance model for persuasive robots evaluating the factors that influenced their acceptance in a charity donation scenario. Results showed that trusting beliefs and liking towards the robot were the main drivers for predicting the acceptance of the robot. Despite the findings, the experiment was conducted in a laboratory setting and the robot was controlled using a Wizard of Oz (WoZ) paradigm.

In this study, inspired by the work of Tapus *et al.* and the findings of Ghazali *et al.*, we evaluate how robot personality-driven behavioural patterns affect the users' intention to use by using a modified version of the UTAUT. To do so, we endow the robot with two different communication styles: one more empathic and self-comparative and the other one more provocative and other-comparative and evaluate the user's intention to use as well as their performance when exposed to one of the two styles in a game scenario. Additionally, we validate our approach in a real-world setting with 209 untrained users who had no prior experience with robots.

2.2 Robot Personality

An inherently human characteristic is the uniqueness of each individual, which can be reflected in their personality, which designers would like to adapt in social robots to improve HRIs (Robert et al. (2020)). A personality trait is a set of psychological attributes that configures a pattern of behaviour in different situations and that lasts over time (Hall and Lindzey (1957)). Therefore, being able to model it may be beneficial to improve HRI and technological acceptance.

Although personality is a key aspect in shaping the nature of social relationships (Dryer (1999)) and forging intuitive responses in HRI (Lee et al. (2006)), a limited number of works have investigated this topic (Aly and Tapus (2013); Tay et al. (2014)). Furthermore, the HRI literature lacks a clear and wide understanding of this key factor (Robert et al. (2020)). One of the main reasons for this shortage of literature is that while giving, for instance, gender attributes to a robot might be easier since any sign such as the name is already capable of awakening the perception of gender, endowing it with personality trait attributes is much more complex due to the multiple factors and dimensions that make it up (McCrae and John (1992)). Thus, studies that analyse personality traits in robots are limited to considering only a few dimensions. For example, Dryer (1999) considered two factors of the Big-Five Personality Traits (Soldz and Vaillant (1999)): extroversion (two extreme poles: extroverted-reserved) and agreeableness (two extreme poles: cooperative-competitive) while Aly and Tapus (2013), and Tay et al. (2014) and Andriella et al. (2021) only used one: extroversion, also in the two extreme poles (introverted and extroverted). To recreate these traits, the researchers manipulated language and kinesthetic signals and measured either the degree of credibility of their interpretation or the degree of satisfaction they generated.

In summary, previous works have shown that applying personality traits had a strong influence on users' acceptance of social robots (Tay et al. (2014)), perception of enjoyment, perceived intelligence and attractiveness of the robot (Lee et al. (2006)). Furthermore, robot personality can affect participants' performance during cognitive exercises (Andriella et al. (2021)). Finally, some studies highlight that according to the tasks to be performed, some personality traits seem more effective than others. For example, Lee et al. (2017), showed that the perceived level of courtesy of a social robot negatively affects the perceived benefit of following medical prescriptions and therefore of complying with treatment. In this article, we extend our previous work in which we modelled robot personality in terms of extroversion and introversion traits (Andriella et al. (2021)) by enriching them with two different communication styles to assess whether and to what extent robot personality-driven behaviours elicit different drivers of acceptance of the UTAUT model.

2.3 Technology Acceptance Model

To analyse the process of acceptance of social robots, researchers have been using models derived from previous technologies (computers, internet, smartphones, etc.). One of the best known and that has served as the basis for subsequent developments is the Technology Acceptance Model (TAM), designed by Davis (1989). The TAM was proposed in the early stages of computer technology in workplaces after showing the resistance of workers to use them. Davis's proposal, based on theories from social psychology such as Theory of Reasoned Action (Icek Ajzen (1980)) and the Social Cognitive Theory (Bandura (1986)), considered that prior to starting the implementation of new technologies it was necessary to know their degree of acceptance, which could be measured by asking workers about their future intention. TAM predicts users' intention to use technology based on several social constructs, such as perceived usefulness and perceived ease of use. Furthermore, the effect of external variables on intention to use was mediated by perceived usefulness and perceived ease of use.

A decade later, a new version called TAM2 was proposed by (Venkatesh and Davis (2000), which incorporate new theoretical constructs such as social influence and cognitive instrumental processes (experience and voluntariness). Due to the rapid expansion of new technologies, consumers acquired increased experience and greater familiarity with them, which made the more utilitarian elements of new technologies give way to a greater effect of subjective norms on technological acceptance.

In 2003, Venkatesh et al. (2003) synthesised these models into the UTAUT. This last model considers four precedents that explain the intention to use new technology in organisational contexts (i.e., performance expectation, effort expectation, social influence, and facilitation conditions) that are regulated by four moderators (i.e., age, gender, experience and voluntariness). UTAUT was designed with the purpose: i) to serve for a more advanced state of technological development and ii) to integrate the TAM model (Venkatesh et al. (2016)).

However, TAM, TAM2 and UTAUT and their new versions had some limitations when being adopted as a model for estimating user acceptance for social robots. Several alternatives have been used, for example, the Almere model (Heerink et al. (2010)), an adaptation of the UTAUT, the Service Robot Acceptance Model proposed by Wirtz et al. (2018) or the Robot Acceptance Model for care presented by Turja et al. (2019). Differently from other technological innovations, users have a perceived familiarity with social robots due to their presence in literature, films and popular culture for a century. The science-fiction play of Karel Capek, Rossum's Universal Robot, produced in 1921 in Czechoslovakia, introduced robots as slaves and was not a simple science fiction fantasy, but rather a prophetic look at the future of humanity (Hampton (2015)). This type of behaviour, based on the perception of familiarity towards objects we have never had real experiences, has been studied in psychology, called the illusion of familiarity, and is explained by the fluency theory (Whittlesea (1993)). This illusion of perceived familiarity operates as a mental shortcut, allowing researchers to consider more advanced models of technological acceptance despite robotics being an emerging technology. In this article, we propose a modified UTAUT model, to measure the participants' intention to use a social robot with different personality traits in an entertainment context. This model has been already employed in our recent work, in which Forgas-Coll et al. (2021) proposed a model to estimate the intention to use a social robot in an entertainment context, focusing on the impact that participants' gender and rational thinking can have on their acceptance of the robot. The next section explains in more detail such a model.

3 The Proposed Model of Acceptance

Taking into account that social robots can solve complex cognitive problems but with low social-emotional complexity (Wirtz et al. (2018)), and that users manifest different attitudes depending on whether the experience with the robot is real (positive and approving attitude) or hypothetical (negative and ambivalent attitude) (Savela et al. (2018)), in this article, we consider that one way to equip the robot with emotional and social skills is by displaying its personality. Among the Big-Five Personality Traits (McCrae and John (1992)), this study focuses on extroversion/introversion in its two endpoints: introversion with an emphatic and self-comparative communication style and extroverted with a provocative and other-comparative communication style. Thus, we propose to evaluate users' acceptance of the robot personalities using a modified version of the UTAUT model (see Figure 2) presented already in our previous work (Forgas-Coll et al. (2021)).

The proposed model takes into account three essential elements from psychology proposed by Gerrig (2014) and adapted to the technological acceptance of social robots. The three elements are: functional, socio-emotional and relational. The model considers that the intention to use a social robot with different personality traits in an entertainment context can be explained by four constructs: PU, PEOU (functional elements), SI (socio-emotional element) (Venkatesh et al. (2003)), and PENJ (relational element) (Wirtz et al. (2018)). This last factor replaces the "facilitating conditions" construct from the UTAUT. The reason for the change is that this construct refers to those elements of the environment that facilitate the use of the system, which is not applicable in our context, as social robotics is still at an early stage and, although there is some familiarity, people do not have yet experience of interacting with real robots. Therefore, we replace this element with PENJ, since one of the constructs that gives social robots more acceptance is their ability to entertain, as proposed by Heerink et al. (2010) and Turja et al. (2019).

Within the context of the proposed study, PU is defined as the degree to which people believe that a robot would be of support for them in making the correct action during the game. The term PEOU refers to the degree to which participants believe that using a robot would be free of effort for them. PENJ refers to the pleasant feeling that participants had experienced while playing with a robot. SI refers to the degree of acceptance that individuals receive from their social environment when using new technology, in this case, the robot. Finally, ITU is defined as the degree to which participants like or dislike playing with the robot (Heerink et al. (2010); Wirtz et al. (2018); Turja et al. (2019)).

4 The "Guessing the Nobel Prize Winner" Game

To evaluate our research questions (See Section 1.1), we devised a game scenario, in which participants were asked to solve it with the assistance of the TIAGo robot. The task consisted of composing the name of a Nobel Prize Winner with the tokens available on the board (see Figure 1), trying to minimise the number of mistakes and the completion time. With the letters available on the board, three names were possible solutions: "CURIE", "GODEL" or "MORSE". The task was defined as complex enough to foster as many interactions as possible with the robot but not so that the participants became frustrated at not being able to complete it. For this reason, after four consecutive mistakes, the robot provided the participant with the correct token. Thus, in the worst-case scenario, the number of possible mistakes were 15.

5 Modelling Robot Personality-driven Behaviour Patterns

In this section, we describe how the personality has been modelled in terms of extroversion/introversion traits on the TIAGo robot (See Section 5.1). Furthermore, we describe for each personality trait the communication style adopted: empathic and self-comparative for the introverted robot and provocative and other-comparative for the extroverted robot (See Section 5.2).

5.1 Modelling Robot Personality

To model the robot personality in terms of extroversion and introversion traits, we refer to our previous work (Andriella et al. (2021)). There, we modelled the introverted and extroverted traits of a robot after carrying out a user study in which the behaviour of introverted and extroverted people, acting as assistants in a cognitive game, was observed and labelled.

Specifically, three verbal cues were deemed relevant: loudness, speech rate and pitch. Those features are the most effective according to the pioneering work of Lee et al. (2006). In the present work, we used Loquendo[1] text-to-speech to generate the voice. We were able to tweak the voice using the parameters reported in Table 1 according to the defined personality profile.

Additionally, we extended our previous work by providing the robot with facial expressions as non-verbal social cues. The robot was capable of reproducing seven facial expressions:

[1] www.loquendo.com

Robot personality	Communication style	Communication type	Feature
introverted	empathic	verbal	Voice: - loudness: 85 Hz - speech rate: 140 words/min - pitch: 250 Hz
		non verbal	Facial expression: - excited - happy - neutral - sad - confused
extroverted	provocative	verbal	Voice: - loudness: 120 Hz - speech rate: 190 words/min - pitch: 350 Hz
		non verbal	Facial expression: - neutral - angry - disappointed

Table 1: The table summarises the verbal and non-verbal social cues employed by the robot to show an introverted or extroverted personality.

neutral, sad, confused, happy, excited, disappointed and angry (see Figure 3).

On the one hand, the introverted robot was capable of expressing itself through the following five facial expressions: neutral, happy, excited, sad, and confused. The introverted robot was happy when the correct token was picked (d), very excited when a token was correctly placed (e), sad when a token was incorrectly placed (b), and confused when the wrong token (c) was grasped by the user. Finally, during the game, its default expression was neutral (a). On the other hand, the extroverted robot was capable of expressing itself through the following three facial expressions: neutral, disappointed, and angry. The extroverted robot did not change its facial expression when a correct move was performed (a), it was disappointed when participants grasped the wrong token (f), and angry when the token was placed in the wrong location (g). We decided to not include happy and excited facial expressions, as this personality profile should have reflected challenging and antagonistic behaviour with a cold temperament in contrast to the introverted robot.

5.2 Modelling Robot Assistive Communication Style

Once defined the two robot personality traits, we designed two communication styles according to them. We revised the current state of the art as presented in Section 2.1. We decided to model two communication styles: one more empathic and self-comparative that will relate to the introverted robot and the other more provocative and other-comparative that will relate to the extroverted robot. The robot assistive communication style is reported in Table 2. We defined four increasing levels of assistance: *Encouragement*, in which the robot cheers the user

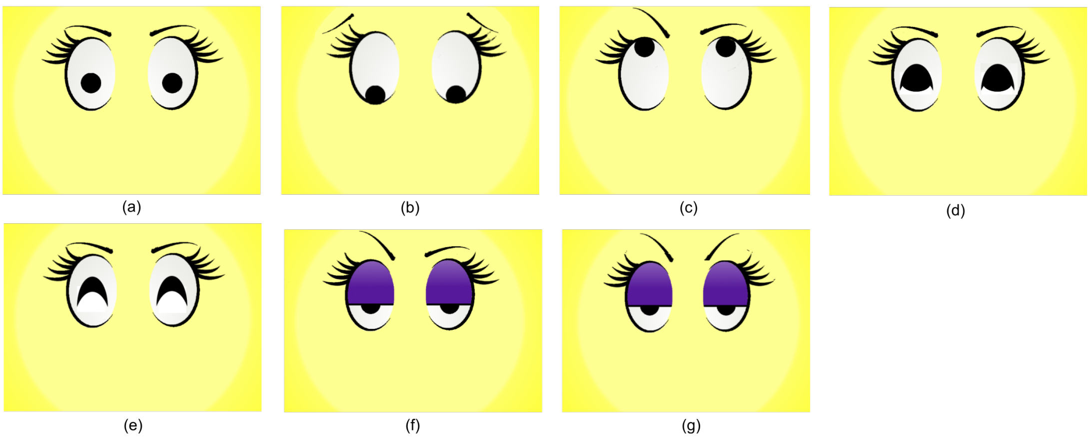


Figure 3: Example of female robot facial expressions: (a) neutral , (b) sad, (c) confused, (d) happy, (e) excited, (f) disappointed, (g) angry. Note the same expressions were designed for the male robot.

to make a move, *Suggest line*, in which the robot suggests the line of the board in which the correct token is located, *Suggest subset*, in which the robot suggests three adjacent tokens, one of which is the correct, and finally, *Suggest solution*, in which the robot suggests the user the correct token to move. Furthermore, depending on whether the user made a correct or wrong move the robot could congratulate or reassure the user. As unexpected events can happen, if the robot could detect that, it asked the user to move the token back and repeat the move. Finally, the robot was capable to provide backchannelling behaviour using SOCIABLE (Andriella et al. (2020a)), a kind of feedback given by combining robot verbal and non-verbal social cues when a token was just picked. For each one of these assistive behaviours two communication styles were defined.

Regarding the empathic communication style, we designed it in a way that can resemble a very supportive and cheerful assistant. We followed the principles defined by Cutrona and Suhr (1992). In their work, they specified five categories to model pro-social behaviour: i) informational, ii) emotional, iii) appraisal, iv) social network support, and v) tangible support. Inspired by Leite et al. (2014) work which proved this behaviour to be effective in child-robot interactions, we decided to reshape the robot's assistance according to it. Additionally, to model the robot's empathic style we also referred to Tapus et al. (2008) and Rossi et al. (2020), in which the introverted robot was programmed to have more praise and nurturing personality. Finally, according to the work of Swift-Spong et al. (2015), we introduced what was called "self comparative" assistance, that is, providing the user with feedback on their current performance. Overall, the empathic robot got very excited whenever a user moved a token to its correct

Level	**Assistive Behaviour**	**Introverted Robot**	**Extroverted Robot**
1	Encouragement	"Come on.... I know you can do it" "I believe in you!!" "Don't be afraid to make a mistake"	"The guy before was performing better, try to be more concentrated" "You need to be faster as the guy before" "This is a child's play, try to not make mistakes as the previous guy"
2	Suggesting line	"I will provide you a hint, look at the right" "Ï will provide you a hint, look at center" "I will provide you a hint, look at the left"	"Do you really need more assistance? look at the right" "Do you really need more assistance? look at the center" "Do you really need more assistance? look at the left"
3	Suggesting subset	"The solution can be A, C, F"	"I can't believe I need to help you more, look at tokens A, C and F"
4	Suggesting solution	"Why don't your try with letter C"	"Really?! Do I need to provide you with the solution? Pick token C"
	Congratulation	"Well done, you're playing as I expected" "You're so good" "Congratulations that's the correct letter"	"I have higher expectations from you" "Well, you can do better" "That's the best you can do?"
	Reassurance	"No worries sometimes happens" "I know how you feel I've been in this situation before" "People say lucky in love unlucky in gaming"	"Come on, really? That's so easy, I don't know how to help you" "I don't understand what you're doing, the guy before was so fast" "Really? That's completely wrong already more mistakes than the average"
	Unexpected action	"Could you move the token back, please?"	"You have to follow my rules not yours, move the tokens back now"
	SOCIABLE (Andriella et al. (2020a))	"Nope, Are you sure? "Think about it?" "Huhu", "Cool", "Well done"	"No, no", "Very bad", "You're wrong" "Trivial", "Ok, but too slow"

Table 2: Example of communication style modelled on the introverted and extroverted robot.

location and responded very positively in any situation especially in those in which the user failed to pick (or place) the correct token.

Regarding the provocative communication style, we designed it in a way that can resemble a very demanding and challenging assistant. To do so, we referred to the work of Mota et al. (2018) and Paetzel-Prüsmann et al. (2021) by designing a robot that was very impatient and overreacted to any event. Finally, according to the work of Swift-Spong et al. (2015), we introduced what was called ”other-comparative” assistance, that is, comparing the current user's performance with previous users. Overall, the provocative robot got more upset and disappointed if the incorrect token was picked or placed, but it also did not react to any correct move by the user; instead, it was pushy and impatient, always understating participants' performance with respect to others.

6 Experimental Design

The experiment was designed as a between-subject in which each participant played either with the empathic or the provocative robot. In order to address our research questions, two dependent variables were measured: the intention to use the robot (see acceptance model presented in Section 2.3) and the user's performance (number of mistakes and completion time) in the cognitive game. In order to evaluate them, we manipulated the robot personality-driven behavioural patterns (independent variable) defined in Section 5. Concerning the intention to use, the Structural Equation Modelling (SEM) technique was used to validate scales and estimate the causal relationships with all the data. The procedure, based on variance and covariance matrices, is adjusted by maximum likelihood according to Bentler (1989). Regarding the two robot's personality profiles, taking into account the sample size once segmented, they were adjusted by ordinary least squares (Hayes (2014)). Regarding the users' performance, the Mann-Whitney test was used to assess the significance of the dependent variables with respect to the two different robot's personality profiles.

It is important to note that the two personality-driven behavioural patterns were designed with the objective of measuring the effectiveness of the robot's communication style on participants' attitude and performance. The two personality profiles were linked to the two corresponding communication styles and considered as two distinct behavioural patterns. Evaluating the effect of both by combining the independent variables, personality traits (introverted and extroverted) and communication style (empathic and provocative), was out of the scope of this work. Finally, to avoid any stereotypical effect associated with the robot gender, both the voice and facial expressions of the robot were generated with male and female characteristics and counterbalanced during the evaluation.

6.1 Metrics

In order to assess the participant's intention to use, we employed a questionnaire which consisted of 19 statements of five scales (see Table 3). Each statement had to be evaluated according to a 5-point Likert scale, ranging from 1, which corresponded to "I totally disagree", up to 5, which corresponded to "I totally agree". The five scales were: ITU as dependent variable (Palau-Saumell et al. (2019)), PU as mediating variable, PEOU, PENJ and SI as independent variables according to Heerink et al. (2010). These scales, taken from previous studies, were translated into Catalan and Spanish.

Concerning the user's performance, the participants' mistakes during the session as well as the game's completion time were defined as dependent variables.

6.2 Apparatus

A TIAGo [2] robot was endowed with the ability to provide assistance according to the two different personality profiles as defined in Section 5. That is to say, that while the degrees of assistance offered were the same, (column "Assistive Behaviour" of Table 2), they were implemented according to the personality profile (columns "Introverted Robot" and "Extroverted Robot" of Table 2). It is important to note that the assistance level was changing according to the mistakes of the participant. That is to say, every time the user made a mistake additional

[2]https://pal-robotics.com/robots/tiago/

Code	Construct	Items
PENJ	Perceived Enjoyment	It's fun to talk to the robot It's fun to play with the robot The robot looks enjoyable The robot seems charming The robot seems boring
PEOU	Perceived Ease Of Use	I immediately learned how to use the robot The robot seemed easy to use I think I can use the robot without any help I think I can use the robot with someone's help I think I can use the robot if I have some good instructions
PU	Perceived Usefulness	I think the robot is useful to entertain It would be nice to have the robot to entertain I think the robot could be used to entertain me and do other things
SI	Social Influence	I think my friends would like me to use the robot I think it would give a good impression if I played with the robot I think that people whose opinion I value would look favourably upon me playing with the robot
ITU	Intention to Use	If the robot was available, I would try to use it If the robot was available, I would try to use it whenever I could in my spare time If the robot was available, I would sometimes think about using it

Table 3: Constructs and items of the modified version of the UTAUT.

assistance was given eventually suggesting the correct token at the fourth attempt.

In order to foster human-robot interaction and better model the two robot personality profiles, we replaced the robot's head with an LCD screen (see Figure 1) to display the robot faces (Figure 3). Additionally, in order to avoid any effect related to gender, half of the participants interacted with an introverted (extroverted) robot with a female face and voice and the other half with an introverted (extroverted) robot displaying a male face and voice.

Regarding the detection of the tokens on the board, we used an electronic board based on RFID technology (see Andriella et al. (2019a) for more details). As a result, we were able to detect not only when a token was placed in a different location on the board but also when it was just picked up with 100% of reliability.

6.3 Pre-test: Validating Robot Personality

A personality manipulation pre-test was carried out to verify that the two different personality profiles with the corresponding communication style were perceived correctly. Twenty-one participants recruited at the University of Barcelona were requested to watch two videos of a TIAGo robot interacting with the experimenter while he was playing the cognitive game. In one video the robot interacted displaying an introverted personality and in the other, the robot interacted displaying an extroverted personality as defined in Table 2. Participants were then asked to rate the robot's perceived personality with four items: "The robot seems competitive (supportive)" and "The robot seems empathic (provocative) on a five-point scale (1 = "I strongly disagree" and 5 = "I strongly agree"). The results revealed that the two personalities were clearly identified. Participants considered that the introverted robot was less competitive (M = 2.41, SD = 1.24) than the extroverted (M=3.90, SD=1.51; F(1, 21)=6.74, $p < 0.05$) and, vice versa, more supportive (M=4.25, SD=0.62) than the extroverted robot (M=2.81, SD=1.53; F (1,21)=8.86, $p < 0.01$). Finally, participants judged the introverted robot less provocative (M = 2.58, SD = 1.31) than the extroverted robot (M=3.90, SD=1.09; F (1, 21)=7.10, $p < 0.05$) and, vice versa, more empathic (M=3.83, SD=1.02) than the extroverted robot (M=1.81, SD=1.16; F (1, 21)=19.34, $p < 0.01$). These results are in line with our previous work (Andriella et al. (2021)), in which we demonstrated that by manipulating the robot verbal and non-verbal social cues it was possible for the users to recognise the robot's personality trait. Same results were obtained by Meerbeek et al. (2008), who argued that by properly modelling robot social cues, it was possible to convey to humans the robot's overall personality.

6.4 Procedure and Sample

The experiment was carried out at an international fair in Barcelona. We installed a booth with two separate areas, one to welcome the participants and fill in the consent form and the questionnaire, and another in which to play the game with the robot.

Participation in the experiment was opened to all visitors over 18. On arrival, participants were informed of the procedure and asked to sign in a consent form. The experimenter would then introduce the robot to the participants, providing them with enough information to play the game with its assistance. No clues were provided to the participants neither on the degrees of assistance the robot could give them nor on its personality, they were only told to wait after each move for possible aid from the robot. The session lasted on average 222 secs with 7.6 mistakes. After completing the game, participants were asked to fill in the questionnaire reported in Table 3. Data were collected from 209 participants (46.1% female) ranging in age between 18 and 67 (M=35, SD=11.77). 110 participants interacted with the introverted robot (52 with the male and 52 with the female) and 109 interacted with the extroverted robot (52 with the male robot and 53 with the female robot). None of the participants had prior experience in interacting with the robot. Participation in the study was voluntary and no material incentive was provided, and only controls for gender and age were established (Mende et al. (2019)).

7 Results

To analyse the users' intention to use the robot a modified version of the UTAUT was estimated from the responses of the questionnaire administered to the participants (Section 3). Before examining the model, the psychometric characteristics of dimensionality, reliability and validity of the constructs were analysed (See Section 7.1). Next, we analyse the general structure model (see Section 7.2) and those in which the robot was endowed with introverted and extroverted personality traits (see Section 7.3). Finally, we estimate the effect of robots' communication style on users' performance (see Section 7.4).

7.1 Psychometric Characteristics

We examined the psychometric characteristics of dimensionality, reliability and validity of the constructs following procedures proposed by Fornell and Larcker (1981). As a result of this analysis, of the 19 items (see Table 3), four of them were removed, leaving fifteen items, three items per construct. The results are reported in Table 4.

The average variance extracted (AVE) is a measure of the degree of convergence of the set of items that made up a construct. In other words, it represents the amount of variance explained by the construct in relation to the variance explained by measurement errors. This value must be greater than 0.5. In our experiment, all constructs met the criteria. The other two measures, composite reliability (CR) and Cronbach's alpha, both very similar, appraised the internal consistency of the scale items (Netemeyer et al. (2003)). The reason for internal consistency is that all individual items must measure the same construct and therefore be highly correlated. Values of these measures should be greater than 0.70. In addition, the factor load of each item that makes up each scale should be greater than 0.6, as recommended by the literature, and all items included exceed this value (Hair et al. (2010)).

Finally, the discriminant validity of the scales was also analysed according to the Fornell-Larcker criterion, using the cross-loading matrix. According to this criterion, the square root of the AVE of each construct (represented on the diagonal of the matrix) must be greater than

	Factor loading	T	M	SD
Perceived Enjoyment (AVE: 0.66; CR: 0.82; Alpha: 0.82)				
It's fun to talk to the robot	0.79	15.21	3.18	1.28
It's fun to play with the robot	0.87	15.96	3.65	1.15
The robot looks enjoyable	0.67	12.18	2.96	1.31
Perceived ease of use (AVE: 0.60; CR: 0.78; Alpha: 0.77)				
Immediately I learned how to use the robot	0.80	10.53	4.03	1.05
The robot seemed easy to use	0.75	9.49	4.21	0.93
I think I can use the robot without any help	0.64	10.79	3.82	1.10
Perceived usefulness (AVE: 0.65; CR: 0.82; Alpha: 0.82)				
I think the robot is useful to entertain	0.66	9.17	3.97	1.17
It would be nice to have the robot to entertain	0.88	19.59	3.15	1.22
I think the robot could be used to entertain me and do other things	0.78	12.16	3.47	1.16
Social influence (AVE: 0.70; CR: 0.85; Alpha: 0.85)				
I think my friends would like me to use the robot	0.75	11.66	2.99	1.20
I think it would give a good impression if I played with the robot	0.90	18.94	2.94	1.20
People whom I value your opinion I think they would look good that I play with the robot	0.78	14.49	3.17	1.22
Intention to use (AVE: 0.67; CR: 0.83; Alpha: 0.82)				
If the robot was available I would try to use it	0.71	11.15	3.45	1.10
If the robot was available I would try to use it whenever I could in my spare time	0.88	19.39	2.78	1.23
If the robot was available I would be thinking sometimes when using it	0.77	13.18	2.20	1.16

Table 4: Analysis of the dimensionality, reliability and validity of the scales (factor loading represents the correlation between the items and the scale, T is the coefficient divided by its standard error, M is the mean and SD is the standard deviation).

	PENJ	PEOU	PU	SI	ITU
PENJ	0.81				
PEOU	0.25**	0.78			
PU	0.68***	0.19**	0.81		
SI	0.66***	0.05 (ns)	0.66***	0.84	
ITU	0.63***	0.16 (ns)	0.69***	0.63***	0.82

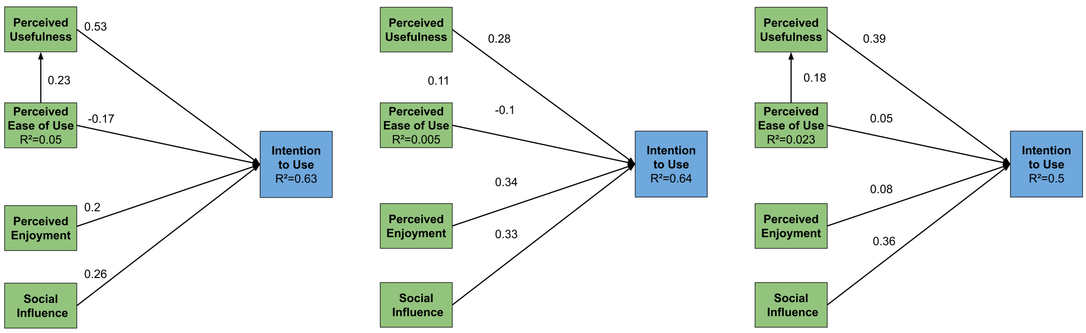
Table 5: Discriminant validity of the scales. Below the diagonal the correlation estimated between the factors (ns denotes no significance, * denotes $.01 < p < .05$, ** denotes $.001 < p < .01$, and *** denotes $p < .001$)

its correlation with the other constructs (represented by the rest of the values in each row). These results are reported in Table 5.

7.2 General Structure Model of the modified UTAUT

In order to analyse the causal relationships between the constructs of the model represented in Figure 4a, a SEM model was estimated. SEM calculates the effect that different constructs have on the dependent variable. Furthermore, it also measures the amount of variability explained by the relationship model through the R^2 coefficient which defines how close the data are to the fitted regression model.

The obtained R^2 values are in line with the sample size used, a R^2=0.63 for ITU and a R^2=0.05 for PU (see Table 6). Regarding the weight of the factors of the general model, all factors reached significant values, with $p < 0.05$. The main factor is PU ($\beta = 0.53$, $p < 0.001$), followed by SI ($\beta = 0.26$, $p < 0.01$), and PENJ ($\beta = 0.20$, $p < 0.01$). As a controversial result, PEOU reaches a negative value ($\beta = -0.17$, $p < 0.05$) and, in addition, PEOU has an indirect effect, mediated by PU, which was also significant ($\beta = 0.23$, $p < 0.05$).



(a) General structure model (b) Introverted model (c) Extroverted model

Figure 4: (a) shows the General Structural Model of the modified version of the UTAUT according to Table 6. (b) and (c) show the Structural Models that aim to address H1-H5 for a robot manifesting an introverted personality and an extroverted personality, respectively.

Independent variable	Dependent variable	Beta	T	R^2
PENJ	ITU	0.2	2.70**	0.64
PEOU		-0.17	2.07*	
PU		0.55	5.10***	
SI		0.26	2.84**	
PEOU	PU	0.23	2.39*	0.05

Table 6: Causal relations in the general model (* denotes .01 $<p<$.05, ** denotes .001 $<p<$.01, and *** denotes $p<$.001).

7.3 Acceptance Model based on Robot Personality

Aiming to address the hypotheses H1-H5, the sample was divided between those who received the support of the introverted robot and those who received it from the extroverted. Hence, the two ordinary least squares models were estimated: Scenario 1 (S1, introverted robot with an empathic communication style) and Scenario 2 (S2, extroverted robot with a provocative communication style). The obtained R^2 values are in line with the sample size used, a R^2=0.64 for ITU in an introverted robot (S1, Figure 4b) and a R^2=0.50 for ITU in an extroverted robot (S2, Figure 4c) (see Table 7).

That is, when the robot was endowed with an extroverted personality, the coefficient of determination significantly decreases to explain the ITU (R^2 group S1 − R^2 group S2 = 0.14) as it represents 21.8% of explained variability. Furthermore, when applying Fisher's transformation and estimating the difference in correlations, we found this difference was significant ($z = 1.665$, $p < 0.05$). Therefore, we can conclude that, when the robot displayed an introverted personality, it enhanced the predictive power in explaining the acceptance of it compared to the extroverted.

Regarding the weight of effects, three factors of S1 and two factors of S2 have reached significant values ($p < 0.05$). Of the five proposed hypotheses, only one has been confirmed in the proposed direction, H3. Participants that interacted with a social robot endowed with an introverted personality stated that the intention to use it was mainly driven by PENJ ($\beta = 0.34$, $p < 0.05$), SI ($\beta = 0.33$, $p < 0.05$) and PU ($\beta = 0.28$, $p < 0.05$), given that PEOU did not reach a significant value. On the other hand, when participants interacted with the extroverted robot, the intention to use it was mainly driven by PU ($\beta = 0.39$, $p < 0.05$) and social influence ($\beta = 0.36$, $p < 0.05$), while the other factors did not reach significant values. Therefore, when the robot displayed an introverted personality, only the PENJ had a greater discriminatory effect on the ITU compared to the extroverted robot. Hence, H3 was validated. Differently, when the robot displayed an extroverted personality, PU had a greater weight on the ITU

			S1: Introverted Robot				S2: Extroverted Robot			
Hypothesis	**Independent variable**	**Dependent variable**	**Beta**	**t**	**R^2 Adjusted**	**Sig. ANOVA**	**Beta**	**t**	**R^2 Adjusted**	**Sig. ANOVA**
	Constant	ITU	-0.103	-0.274	0.648	0.000	0.560	1.491	0.506	0.000
H1	PU		0.280	3.612* **			0.399	3.863* **		
H2	PEOU		-0.1	-1.684 ns			-0.058	-0.799 ns		
H3	PENJ		0.347	4.390* **			0.088	0.859 ns		
H4	SI		0.337	4.501* **			0.362	4.200* **		
	Constant	PU	2.965	5.720* **	0.005	0.221	2.648	5.831* **	0.023	0.069
H5	PEOU		0.119	1.232 ns			0.182	1.838 ns		

Table 7: Causal relations for robot personality (ns denotes no significance, * denotes .01 $<p$ $<$.05, ** denotes .001 $<p$ $<$.01).

and, SI on the ITU to a lesser extent, compared to the introverted robot, in contradiction to what was hypothesised in H1 and H4. Additionally, H2 was also rejected as PEOU did not reach significant values in both scenarios. Finally, the same conclusion can be drawn from the indirect effect of PEOU on PU which did not reach significant values in either scenario (H5 was rejected).

7.4 Participants Performance

In order to evaluate whether and to what extent robot personality affects the participants' performance (H6), we computed their number of mistakes and completion time as an estimator of their performance. The results from the Mann-Whitney test indicated that there was a statistical significance in terms of number of mistakes between participants who interacted with the introverted robot (Mnd=7) and those who interacted with the extroverted robot (Mnd=8) (U=22283, $p < 0.04$). Specifically, those who interacted with the introverted robot with an empathic and self-comparative communication style performed better than those who interacted with a provocative and other-comparative robot. Additionally, we found statistical significance in the completion time. Results indicated that participants that interacted with the introverted robot (Mnd=239) took more time to complete the game compared to those who interacted with the extroverted robot (Mnd=208) (U=39679, $p < 0.0001$). Therefore, we can conclude that H6 did only partially stand.

8 Discussion and Conclusion

In this section, we discuss the results of the user-study aiming to provide the social robotic community with useful insights that can contribute to the advance of the field in the understanding of how robot personality and communication style can impact the user's intention to use it.

Aiming to address the RQs defined in Section 1.1, we designed and modelled two personality traits and their respective communication styles on a real robot. The introverted robot was more empathic, supportive, and self-comparative, while the extroverted robot was more provocative, challenging, and other-comparative. The robot was programmed to provide assistance, modulated according to the two personality profiles, to 209 participants playing a cognitive game in a real-world setting.

To address **RQ1**, we proposed estimating the technological acceptance of the social robot using a modified version of the UTAUT (see Section 3), in which the ITU was the dependent variable and estimator. We speculated that the factors that directly affected the ITU were different depending on whether the robot was endowed with an introverted personality and an empathic communication style (S1) or whether it was endowed with an extroverted personality and a provocative communication style (S2). We hypothesised that the robot endowed with an empathic behaviour that offers self-comparative feedback would be the one that would meet the participants' expectations, while the robot with a provocative behaviour that offers other-comparative feedback would break expectations and affect participants' intention to use it, as found by Paetzel-Prüsmann et al. (2021).

The collected results showed relevant differences in the explained variability of both models and in the drivers, which reached positive and significant values, both in the introverted and in the extroverted robot, validating their influence on the ITU. Regarding the differences in the weight of the factors, in some cases, they present similar weights to those collected in the literature, and in others we found different values. Although the lack of standardisation does not allow direct comparisons of the results from different studies, it can help to indicate the degree of consistency of the results (Gerrig et al. (2011)).

Considering the general model (SEM), the PU is one of the most relevant drivers, its weight is in line with the result achieved by Heerink et al. (2010), Lin et al. (2020), and Turja et al. (2019). On the other hand, PEOU, which is a controversial factor, obtained a negative value in line with the results of Lin et al. (2020). Nonetheless, Turja et al. (2019) and Heerink et al. (2010) did not reach a significant value for the same construct, and Lee et al. (2018) reported a positive value. Both PU and PEOU are functional elements, and while the former is more robust with the personality type of robot and scenario, PEOU is greatly affected by these changes. In addition, PENJ, which is the relational element of this model (Wirtz et al. (2018)), is a driver with an intermediate weight, more relevant than in Heerink et al. (2010), but with less weight than in Lin et al. (2020) and Turja et al. (2019). Here, while SI remained robust with respect to the robot's personality, PENJ only achieved significant values with the introverted robot. At the same time, PU had also a mediating role between PEOU and ITU, which was also considered by Heerink et al. (2010) and Lee et al. (2018) with similar effects. However, when the robot's personality is considered, its effect is scattered. Indeed, their dispersion reveals the influence of at least three variables: the type of robot, the target audience, and the context of service provision. For instance, Heerink et al. (2010) used a variety of robotic platforms, controlled in a WoZ manner, in order to evaluate older adults' experience with social robots in the context of elderly care. Lin et al. (2020) proposed theoretical scenarios for the use of robots in a hospitality context aimed at potential clients, in a similar way to Lee et al. (2018), but with restaurant managers as a target audience. Finally, Turja et al. (2019) aiming to evaluate the intention to use a care robot, they conducted a survey collecting data from staff, mostly nurses with experience in the use of four robotic platforms: Double, Nao, Paro, and RIBA.

Regarding the communication style employed by the robot to assist and support the participants, this is where the most significant differences occurred, both in explanatory capacity and especially in the weight or importance of each factor. We found that the overall ITU was significantly higher when the robot displayed an introverted personality than when the robot displayed an extroverted robot. We hypothesise that this difference could be considered as a measure of the moderation effect size that different personalities exert on the ITU of a social robot (Hayes (2014)). In line with what Lee et al. (2017) proposed, we found that a robot with a provocative style is perceived as more functional and useful, and a little more socially influential than the empathic one, which, in turn, is perceived as more enjoyable and, to some extent, exerts less social influence. Indeed, the main driver of the ITU for the provocative robot is the perception of usefulness, while for the empathic robot it is its ability to entertain. An interesting finding that would require further analysis is the relevance of SI in both the scenarios and the impact it has on the overall ITU. SI seemed to affect the participant's perception that other people think they should use a robot, the perception that others support their use of a robot, and finally, the perception that the use of the robot is associated with higher societal status. Therefore, we addressed **RQ1**, concluding that a robot endowed with an introverted personality and an empathic communication style increased the overall users' acceptance compared to an extroverted robot with a provocative communication style.

To address **RQ2**, we computed the number of mistakes committed by each participant and their completion time. We found that participants who interacted with the empathic robot performed better compared to those who interacted with the provocative robot, who in turn took more time to complete the game. We speculate that when the robot was endowed with an introverted personality, participants were more at ease and took their time to consider which token to move, while in the other condition, participants got stressed by the pressure of the robot and reacted more impulsively. This result is similar to what was found by Swift-Spong et al. (2015) in which participants who interacted with the introverted robot with self-comparative feedback had overall better performance. Similar results were found by Paetzel-Prüsmann et al. (2021), who discovered that users scored better when they interacted with an optimistic and polite robot compared to those who interacted with a provocative and challenging robot. However, their results were not statistical significance. It is worthwhile noticing that the effectiveness of one personality with respect to the other might depend on the task itself, as indicated by the study of Maggi et al. (2020), who observed that an authoritarian robot could be more appropriate to improve participants' performance when the task required high cognitive demand. Regarding the statistical significance of the completion time, we argue, in view of the findings of the acceptance model, that participants who interacted with the extroverted robot interpreted its behaviour as pushy and impatient to finish the game as fast as possible. This behaviour rushed the participants even though it did not positively impact their performance. On the other hand, the participants who interacted with the introverted robot did not feel this pressure and took on average more time to complete the exercise. This could also be the reason why the main driver for participants who interacted with the introverted robot was PENJ as they were more focused on enjoying the experience with the robot rather than being worried about performing correctly. Hence, we addressed **RQ2**), concluding that a robot endowed with an introverted personality and an empathic communication style improves only partially the participants' performance.

Taken together, these findings highlight the importance of personality-driven behavioural patterns on the perceived intention to use the robot. Specifically, results indicated that a robot endowed with an extroverted personality and a provocative communicative style might be interpreted as more utilitarian, as its approach is recognised as being more helpful for the proposed task than the empathic. On the other hand, the empathic robot was perceived as more hedonic and enjoyable than the provocative, and participants did not pay so much attention to their performance. However, the results of this work need to be carefully interpreted before being considered generalisable and transferable to different assistive domains. Indeed, as we reported in Section 2, personality depends on several aspects. Therefore, these results need further investigation, especially in two different aspects: the context of interaction and the robot's role.

9 Limitation and Future Work

Despite the interesting insights gained from this work, there are a few limitations that should be pointed out and motivate future work. We decided to break them up into methodological limitations, with which we refer to the method and the approach used to validate our research questions, and developmental limitations, which indicate those related to the robotic platform itself and its functionality. Regarding the methodological limitations, we include the following:

(a) *Very opposite personality traits*: the two robot personality profiles were very different from each other. Future work should explore how to design behaviours ranging from empathic to provocative and assess if those can be recognised by humans.

(b) *The robot personality was linked to a given communication style*: introverted with an empathic communication style and extroverted with a more provocative one (1 independent variable with 2 levels). Future work should consider personality as an independent variable from communication style and combine them to assess whether and to what extent they impact on participants' performance and intention to use the robot (2 independent variables with 2 levels conditions).

(c) *Human personality was not considered*: we did not consider assessing the human personality and evaluate it with respect to the robot personality due to the limited number of participants. Future work should analyse whether the human personality might affect any drivers of the intention to use the robot Forgas-Coll et al. (2021).

(d) *Results with limited validity*: despite the number of participants, personality, for its multifaceted nature, highly depends on participants age, background, attitude and also the context. Therefore, results should be considered very carefully and related to the context and the population involved.

(e) *Simple technology of acceptance model*: the proposed model was simple with 4 essential constructs. However, our model was more complex than the TAM but less so than other models that involve more mature technologies. More complex models will be possible when robots will be deployed in society on a larger scale. and thus, people will have more familiarity and experience with them. Only at this stage is will be worthwhile to include more human psychological characteristics in the model, such as liking, attitude and beliefs (Ghazali et al. (2020)).

(f) *Intention to use measured only after the interaction*: we did not evaluate whether the user's acceptance changed after the interaction with the robot. Future work should focus on this aspect and evaluate whether or not the intention to use the robot increased after interacting with it.

Regarding the developmental limitations, we include the following:

(a) *No gesture as interaction modality*: we did not include any robot's movement as from previous work Andriella et al. (2019b), participants did not consider valuable the time spent by the robot providing assistance with its end-effector.

(b) *No speech recognition and dialogue management*: we decided to not implement any speech recognition software as this technology is not ready yet to work in crowded and noisy environments, therefore the robot was not capable of sustaining any conversation with the participants. However, most of them were eager to interact verbally with it.

(c) *No adaptive robot's assistive behaviour*: in order to not have noise and any confounding variable, the robot's behaviour was fixed regardless of the user's performance. Future work could extend our previous work (Andriella et al. (2019b, 2022)) by exploring how the robot's ability to change its behaviour according to the user's needs can affect their intention to use.

Acronyms

AVE average variance extracted. 20

CR composite reliability. 20

HRI Human-Robot Interaction. 7, 9

ITU Intention To Use. 4–6, 12, 17, 21–25

PENJ Perceived Enjoyment. 4, 5, 12, 17, 21, 22, 24, 26

PEOU Perceived Ease of Use. 4–6, 12, 17, 21–24

PU Perceived Usefulness. 4–6, 12, 17, 21–24

SEM Structural Equation Modelling. 16, 21, 24

SI Social Influence. 4, 6, 12, 17, 21–25

TAM Technology Acceptance Model. 10, 27

UTAUT Unified Theory of Acceptance and Use of Technology. 4, 6, 8, 10–12, 19, 21, 23

WoZ Wizard of Oz. 8, 24

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