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Personality- and Memory-Based Software Framework for Human-Robot Interaction

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***Abstract*—The synergic orchestration of the cognitive and psychological dimensions characterizes human intelligence. Accordingly, carefully designing this mechanism in artificial intelligence can be a successful strategy to increase human likeness in a robot, enhancing mutual understanding and building a more natural and intuitive interaction. For this purpose, the main contribution of this work is a psychological and cognitive architecture tailored for HRI based on the interplay between robotic personality and memory-based cognitive processes. Indeed, the artificial personality manifests itself not only in various aspects of the behavior but also within the action selection process, which is closely intertwined with personality-dependent hedonic experiences linked to memories. Within this paper, we propose a task- and platform-independent framework, evaluated in a multiparty collaborative scenario. Obtained results show that a robot connected to our proposed framework is perceived as a cognitive agent capable of manifesting perceivable and distinguishable personality traits.**

***Index Terms*—Artificial personality; Human-Robot Interaction; Personality-adaptive architecture; Social Robotics**

I. Introduction

Humans define their model of the world through the actions they execute. Indeed, the human brain naturally encodes how actions are performed allowing a proper anticipatory reaction when other individuals are performing the same activity [1]. Establishing a shared vocabulary of actions allows for a mutual understanding of agents acting in a shared environment by perceiving and predicting what other individuals intend to do. Therefore, the development of cognitive skills of an artificial agent can be exploited to improve the interaction.

On the other hand, personality, from a psychological point of view, is a driver of the action-selection process since it manifests itself in people's characteristic patterns of thoughts, feelings, and behaviors [2]. The implementation of an artificial model of personality can be not only a strategy to further investigate the role of this psychological construct during the interaction between two parties but it can also be used to drive the robot's behavior to be much more appealing to the human. Related scientific literature highlights how a proper design of the robot's personality can possibly improve humans' likeability, enjoyment, knowledge acquisition, engagement, and trust [3], [4], [5], [6]. Furthermore, the use of artificial personality has been identified as a strategy to prevent communication with the user from becoming boring or no longer engaging over time, especially when a prolonged interaction is required [7]. Finally, adaptive architectures that adjust the robot's personality to the user can be exploited, following the similarity/complementary attraction theories [8], [9], [10], possibly with the aim to persuade the user to take certain decisions [11], [12]. The correct design of behavioral parameters, which can be driven by personality, can also improve collaboration, psychological safety, and trust toward the robot in a collaborative (possibly industrial) scenario [13], [14], [15] [16].

From the technical point of view, a possible solution to model personality is to exploit a psychological taxonomy such as the Myers-Briggs Personality Type Indicator [17], the PEN model [18], the Cattell's model [19], and the Big Five Factor model [20]. The latter is called also OCEAN for the name of the five dimensions along which it is organized: Openness to experience, Conscientiousness, Extroversion, Agreeableness, and Neuroticism. Its intuitiveness and self-explanatory are the main reasons for its large adoption in robotics [21], [8], [9], [22]. Anyway, the computational effort of dealing concurrently with five dimensions results in a fragmented literature where only one or two traits are explored. To overcome this limitation, we propose a *personality model specifically conceived for social robots*, based on the CEA taxonomy, composed of the corresponding three traits of the OCEAN model (Conscientiousness, Extroversion, Agreeableness) [23].

Furthermore, personality interacts closely with cognition. Physiological evidence suggests that cognition is inseparable from emotional components [24], and personality influences how memories are stored and retrieved to guide appropriate actions [25]. Several cognitive architectures have incorporated personality taxonomies, such as the OCEAN model, as a social factor in decision-making, but these have primarily been tested in simulations, likely due to the complexity of implementation [26], [27], [28], [10]. In addition, within all possible cognitive components, prospection refers to the brain's ability to use episodic memories to simulate the future and its related hedonic experience [1]. Regrettably, many cognitive architectures lack this component [29], [26].

For this reason, this work proposes and tests a personality-based cognitive architecture to bridge the gap between cognitive and psychological agents. Its main innovation lies in the development of a comprehensive model designed to capture the complexity of personality while remaining applicable in robotics. One distinctive aspect of this framework is how the interaction among personality, internal simulations, and

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internal motivations empowers the agent to determine both the selection and execution of actions. Furthermore, this work introduces a groundbreaking implementation of *prospection*, a concept not yet practically incorporated into cognitive architectures, despite its significant role in human intelligence.

The overall work is organized as follows: Section II describes the proposed framework mostly focusing on the definition and implementation of personality and the personality-affected cognitive processes. Section III shows the experimental setup used to validate the overall architecture. Section IV shows and discusses the obtained results. Finally, Section V concludes and speculates about future improvements.

II. Material and Methods

A. Framework

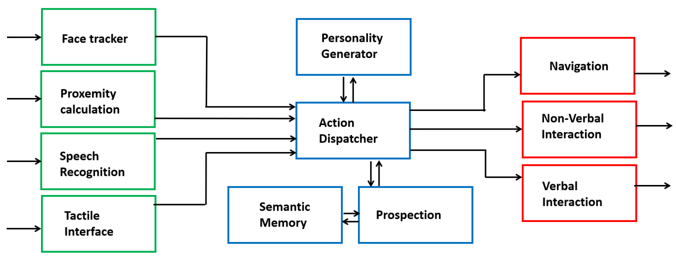

Fig. 1. Personality-based software architecture. Three different modules can be identified: perception (green), reasoning (blue), and actions (red).

The modular personality-based framework for cognitive agents, shown in Figure 1, is explained within this section.

The green-shaded perception blocks exhibit platform and task dependency, serving to facilitate precise human-robot interaction within a given context, and they are closely linked to the robot's sensory inputs (laser, tactile, visual, and audio). Nonetheless, the architecture's modularity enables effortless integration of new blocks.

In blue, three reasoning nodes can be identified. Among them, Semantic Memory is a cognitive component implemented through an ontology to represent and update the actual state of the world with predicates whenever it is necessary, remaining unaffected by personality factors [1]. Prospection is a cognitive component involved in goal-directed behavior, aimed at anticipating future actions. The core of this module is a personality-dependent planning strategy, managed with an LPG planner [30] (Section II-D). The Personality Generator module is the psychological core of the architecture: it is platform- and task-agnostic and it is constructed around the aforementioned CEA taxonomy customized for HRI. It employs language generation techniques, in particular BERT attention-based architecture, to simulate personality-related behaviors (Section II-B). Notably, this approach stands out from previous research as it enables the simultaneous management of behaviors associated with three distinct personality traits.

The Action-Dispatcher (Section II-C) coordinates the flux of information through the architecture making the Prospection module aware of the actual robot's personality. Additionally, any time a new action needs to be executed, it is responsible for retrieving the behavioral parameters from the Personality Generator, triggering the action execution. The execution blocks, in red, are implemented with three classes: navigation, verbal interaction, and non-verbal interaction. Given one general action chosen from the reasoning nodes, the Action-Dispacher forwards it to the related class. Each class is capable of updating the behavioral parameters and executing the actions. The system is adaptable to several tasks, with customization required for the specific robotic platform, such as the humanoid robot Pepper, in our case.

The architecture uses the ROS middleware to be adaptable to the majority of the platforms. Anyway since not all robots are compatible with ROS and may require different programming languages (e.g., python2.7 for Pepper), we improved the usability of the architecture by implementing a Rest-API-based server compatible with multiple programming languages.

B. Personality

The lack of a complete taxonomy for robotic personalities [31] has been tackled in this work by developing a comprehensive model applicable to robots of different sizes, shapes, and purposes. Indeed, establishing a robotic personality is not straightforward, even if the large adoption of the OCEAN model in literature [22], [21], [9] suggests the usage of this taxonomy, especially for human-like agents [32]. In this work, We have considered a subset of the OCEAN model, the CEA taxonomy, based on three Big Five traits: Extroversion, Conscientiousness, and Agreeableness. This model, whose definition is based on psychological literature [23], represents each personality as a vector within a three-dimensional space.

$$Personality = W_eE + W_aA + W_cC \tag{1}$$

E,A, and C correspond to the versors of the three axes. W_e, W_a, and W_c are the three corresponding coordinates and express the degree to which each trait is expressed. This taxonomy allows us to define infinite personalities within the three-dimensional space, overcoming the common limitation linked to the usage of a single trait to express a synthetic personality. Our solution allows us to reflect the complexity of this psychological concept, rather than merely depicting a stereotype of a trait that exhibits a fixed set of behaviors. On the other hand, this solution is practically testable and applicable in robotics.

To efficiently map these three traits into different robot behaviors, both psychological and robotic literature has been taken as a reference [23]. These research findings, associating a specific value of each behavioral feature with each semiaxis of the mentioned dimensions, are detailed in Table I. Their practical integration into the robotic platform is discussed in Section II-C

To practically use these results in a robotic context, we have designed a specific component capable of simulating how human personality activity influences all these behavioral patterns. For this purpose, a BERT model [33] has been fine-tuned to learn how to associate an action and a personality to

TABLE I
PERSONALITY TRAITS AND ROBOT'S PARAMETERS.

Trait	E +	E -	C +	C -	A +	A -
Language	Verbose, excited	Neutral, non verbose	Scrupulous	Unscrupulous	Polite	Rude
Pitch	High	Middle	Middle	Low	Low	Middle
Volume	Very dynamic	Middle	Middle	Low	Dynamic	Dynamic
Velocity	High	Middle	Low	Rather high	Middle	Rather high
Gaze	Mutual	Avoid	No active	No active	Mutual	Avoid
Head movements	Shaking	Little shaking	Tilt up shaking	Tilt down shaking	Nodding	Little shaking
Gestures amplitude	High	Low	Middle	Middle	Middle	Middle
Gesture speed	High	Low	Middle	Middle	Middle	Middle
Navigation Speed	High	Low	Middle	Middle	Middle	Middle
Proxemic	Near	Far	Middle	Middle	Near	Far

the set of related behavioral parameters (Table I) required in the action execution. The input employs conditional generation techniques, following the format $personality < |sep| > action$, where the personality condition guides the action to perform, and $< |sep| >$ is the special token for separation. An example input may be *Extrovert* $< |sep| >$ *speak about Italian food*. Through fine-tuning [23], the attentional model learns a multilabel-multiclass classification task, providing the related parameters, finally specifying how a given action should be executed when the agent should exhibit a particular personality.

The significant advantage here lies in the task- and platform-independent nature, which allows us to model personality as an abstract concept applicable universally across platforms, rather than merely mapping personalities to behaviors. Moreover, the fine-tuned BERT model not only learns a compact representation of each particular action but also generates a set of parameters that can ideally be employed with any conceivable action. For instance, when presented with a contextualized action like *take a book from the desk* the fine-tuned BERT model accurately predicts the required parameters, because it has learned how to deal with that specific action within various, often distinct, contexts.

Since personality is a vector within the three-dimensional space, two different poles of a personality can generate contrasting parameters. The choice of the trait that will be expressed is taken by extracting it randomly from the normalized distribution of weights (Eq. 1). Therefore, when performing different tasks, the robot's behavior may have a non-deterministic variation between the traits of its personality, providing a flexible approach.

C. Action Dispatcher

The Action Dispatcher module interacts with the Personality Generator module and, for each action, receives behavioral parameters linked to a randomly selected trait from the personality weights distribution. As anticipated, actions are subdivided into three main execution blocks: navigation, verbal interaction, and non-verbal interaction. The Action Dispatcher checks which parameters, from the list provided by the Personality Generator, are actually active in the specific action, and triggers the corresponding execution block. For example, in the case of a navigation action, the Action dispatcher triggers the navigation blocks with the corresponding limited set of meaningful parameters (speed, proxemics).

Concerning the parameters to be implemented, the values of verbal cues corresponding to all the possible levels of pitch, volume, and velocity have been chosen. Changing the vocal cues during the interaction should result in uncanny feelings, hence these are set only at the beginning.

Dealing with language, this framework takes advantage of generative network capabilities and uses conditional text generation techniques to write utterances as already done managing extroversion in different research works [34], [9]. Differently from the previously existing literature, this work exploits the generative power of Chat-GPT [35] to take into account concurrently the whole CEA taxonomy. More in detail, Chat-GPT is used to rewrite a specific sentence with a desired personality. The prompt sent as input to Chat-GPT is: *Rewrite this sentence in Italian in a **fashion** way "sentence"*. The fashion corresponds to the generated language parameter (e.g. verbose, polite, rude...) or to a randomly extracted synonym of that. Furthermore, for personalities with multiple traits, the model facilitates the simultaneous use of multiple adjectives to convey the style. Additionally, multiple versions of each sentence have been generated offline, with the robot selecting one randomly during interactions. The choice of adopting Italian language has been taken to make participants able to interact with the robot and fully understand the personality-generated lexical facets. Anyway, the use of Chat-GPT allows for changing the language by simply updating the prompt. For each personality to test, one script is generated offline to avoid errors that can arise during the generation (such as the inversion between the first and the second person verbs) could compromise the meaning of the instruction that the human has to perform. In addition, offline sentence generation reduces latencies during the interaction. To enable real-time chatting and direct user interaction, sentences are generated online by relying on the text-davinci-003 model [36]. The dialogue starts with generating personality-specific questions in Italian on a randomly selected topic, followed by dynamic responses that consider the conversation history, creating a more natural mixed-initiative dialogue. This adaptable language generation implementation aligns with the framework's task- and platform-independent concept and enables the concurrent handling of multiple personality traits.

Concerning the gaze, a face tracker may be enabled or disabled, so as to implement mutual or avoiding behavior. Head movements have been controlled through pitch and yaw angles.

Concerning gestures, since they seem to be affected only by extroversion, this trait has predominance on the other. When the personality presents an intermediate level of extroversion, the middle values of velocity and amplitude are used. The speed of gesture is synchronized to the speaking velocity, respecting the match between speaking and gesture speed for extroversion. Dealing with the amplitude, a set of possible speaking gestures has been considered, splitting all possible gestures into three categories: low, high, and medium amplitude. During the conversation, these are randomly selected according to the amplitude and performed during speaking. To generate gestures not dependent on speech, e.g., indicating a specific object, relevant joints' velocities are suitably controlled to model the amplitude and the overall speed of the gesture.

Dealing with navigation, the approaching distance is computed as the human position minus a certain length which is set according to the three proximity zones defined for different personalities. Concerning the navigation speed, this has been set in real-time according to the generated parameters (i.e., high, medium, and low speed).

D. Prospection

Emotions are a crucial factor in cognitive behavior, shaping our action choices by driving them toward the pursuit of pleasure, with each personality trait associated with distinct actions linked to diverse hedonic experiences. More in deep, each personality trait has been correlated with specific brain regions [37] that get more excited when specific motivational goals are achieved [38], [39], [40], since these satisfy the personality-dependent hedonic needs. Table II shows the relationship between personality and associated motivational goals. All these variables are predictors of action tendencies and are combined during the action selection process in a single system of predictive regulation and feedback in a manner that is similar to allostasis [1].

The robot, through the Prospection module, acquires the capability of planning in advance the sequence of actions keeping its hedonic feeling above a certain threshold. The Prospection is implemented through the LPG planner and models the allostasis-regulated control loop affected by personality.

The standard domain permits the planning of action sequences for task completion, with the architecture allowing replanning in the event of action failure. The allostasis control loop has been implemented through personality-dependent functions, i.e., the extroversion level, the agreeableness level, and the conscientiousness level. These functions vary linearly in time in a range [-10,+10] with an angular coefficient that is inversely proportional to the coordinate of that trait (Eq 1.). The threshold is a static fluent set at the start of the interaction. It represents the desired trait level to ensure the robot's comfort, with positive traits aligned to positive thresholds and vice versa (+5 or -5). The whole Prospection process is fully represented in Figure 2. We define here three types of actions that vary the comfort level associated with each trait and make the agent proceed in achieving the goal:

- *standard actions of the plan*, which cause the function's value to vary linearly in time, increasing it or decreasing it according to the sign of the angular coefficient, and anyway decreasing the comfort level.
- *actions linked to specific personality traits*, and associated with motivational goals (Table II). Those actions are activated when the function is below (in case of a positive value of the corresponding personality trait) or above the threshold (in case of a negative value of the corresponding personality trait), signifying the agent's requirement to enhance its comfort level. These actions aim to respectively increase or decrease the standard step function.
- *context-related actions*, which can either positively or negatively affect the comfort level, and in such cases, the planner strives to devise plans that achieve the goal while minimizing the impact on comfort. For instance, actions involving verbal interaction influence extroversion levels, with extroverted personalities enjoying such interactions, while introverted ones prefer less involvement, and hence interacting through the tablet. Additionally, actions affecting the quality of a gesture impact agreeableness, with agreeable robots finding satisfaction in gentle interactions, while disagreeable ones may opt for less courteous approaches (e.g., throwing the object on the floor instead of handling it to the human).

The angular coefficient with which the functions vary depends on how much a trait is expressed. A bigger absolute value of a coordinate corresponds to a higher manifestation of that trait within the personality. This will result in a higher frequency of triggering actions to satisfy motivational goals.

III. Experimental set up

An experiment has been organized to validate the effectiveness of the framework and to specifically check if the proposed system can generate robotic personalities that are accordingly perceived by users. We are also interested in exploring the perceived agency of the robot, hence its capability of planning actions and its perceived social dimension.

The interactive shapes and capabilities of the humanoid robot Pepper are exploited during the experiments to see how each behavioral parameter can impact robot behavior. The task chosen is a two-humans-robot collaborative construction of a tower of blocks (Figure 3). The neutrality of the activity is necessary to avoid biasing the perception of the robotic personality. During the experiment, two people are sitting at two different locations, while Pepper can navigate between them. One participant is required to pick one of the blocks scattered on the table and give it to the robot. The other participant is required to collect the block from the Pepper

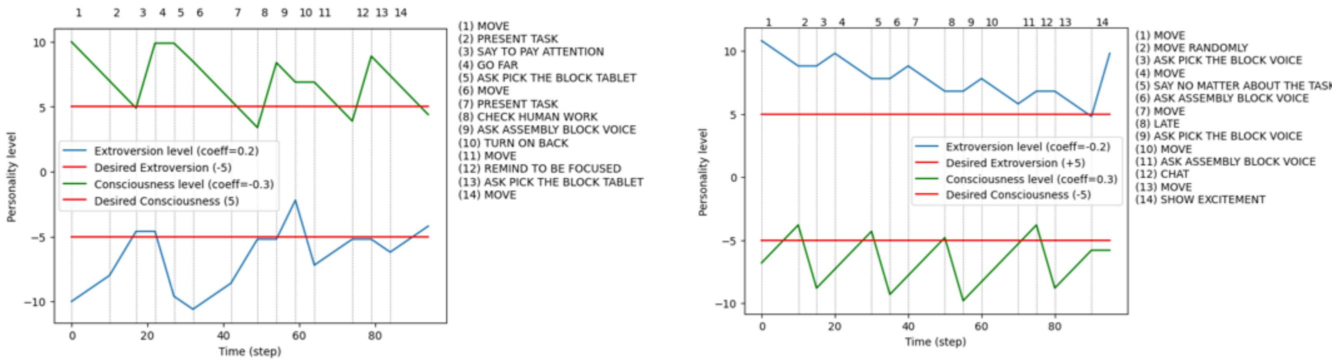

Fig. 2. This image shows the personality-dependent function and how it varies by alternating different actions during the Prospection process. The figure on the left represents a portion of a plan generated for an introverted and conscientious agent. On the right, the plan generated for an extroverted and unscrupulous robot is shown. It may be appreciated how positive and negative poles are required to be kept respectively above or under a certain threshold. In addition, the proportional relationship of the personality coefficients with the frequency of generating motivational goals-related actions can be observed. Finally, the figure shows the effect of complementary actions on the extroversion trait.

TABLE II
MOTIVATIONAL GOALS

Trait	Motivational goals	Actions
Extroversion	Achievement, Excitement	Show excitement, Shake hands, Be happy to work together, Express enthusiasm for the future, Chit chat
Introversion	Detachment	Show detachment, Go in a not crowded area, Turn on back, Go far away
Agreeableness	Compassion, Politeness	Ask if the human need help, Express empathy, Say not to worry about mistakes, Be sorry for the fatigue
Disagreeableness	Selfishness	Say that you would perform better, Say that the human should work better, Encourage to work faster, Show disgust,
Conscientiousness	Industriousness, Orderliness	Check human work, Tell the human not to get distracted, Say to pay attention, Remind to be focused
Unscrupulousness	Unreliability	Go in a random position, Delay, Chit chat, Tell the human not to worry about the task

Fig. 3. Experimental setup

robot, finally using it to build a tower. The interaction is repeated until the tower is complete. 24 participants recruited randomly, 12 males and 12 females, with ages ranging from 22 to 63 years old, took part in an interaction of the experiment.

We tested only the extreme poles of each trait, combining two poles at a time assuming that the three traits are not correlated with each other. This results in 12 personalities where each pole appears 8 times. With reference to Eq. 1, traits have been weighted 1 or -1, in such a way that they have the same probability of emerging during the interaction. The coordinates are then multiplied by -0.5 to compute the angular coefficient which affects the Prospection process.

At the end of the interaction, the two participants are required to answer some demographic information and three 5-point Likert scale questionnaires. The first one is the Italian-validated version of the 10-item Big Five Inventory [41], appropriately reversed to the third person to measure the perceived robot's personality. The second one is used to measure the Agency and Experience of the robot [42]. Finally, aspects related to Enjoyability and Sociability are investigated by means of the UTAUT [43] questionnaire. Please notice that the choice of evaluating the framework's ability to generate synthetic personality and cognitive behavior solely through questionnaires is strictly related to the focus of the study, which is on the perception that humans have of the robot, rather than on the human responses.

IV. Results

The responses to the BFI-10 items questionnaire have been analyzed through the Mann-Whitney U test [44]. In the analysis, the two contrasting personality traits expressed by the robot are considered independent variables, while the questionnaire results are the dependent variables. In terms of agreeableness and conscientiousness, we observed a statistically significant distinction between subjects who interacted with a robot displaying a positive trait value compared to those exposed to negative trait values ($p = 0.001$ for agreeableness, $p = 0.003$ for conscientiousness). Dealing with extroversion, subjects detected differences, albeit with a slightly higher chance of confusing the two levels ($p = 0.09$). Indeed, the raincloud plot (Figure 4) reveals distinct distributions for agreeableness and conscientiousness, with minimal overlap.

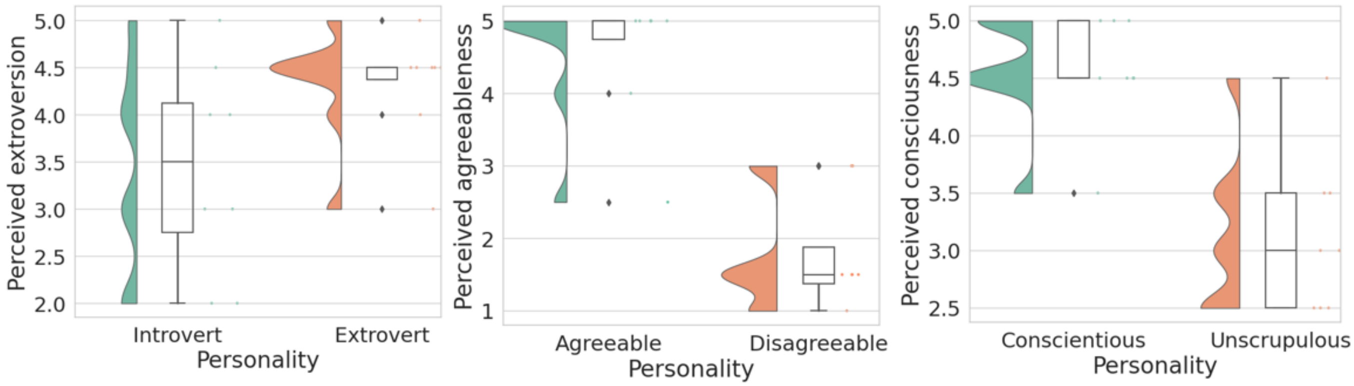

Fig. 4. The raincloud plot concurrently displays data points, a box plot, and a halved violin plot. Each figure is associated with one trait and represents how that trait has been perceived by subjects during the interaction.

Regarding extroversion, interactions with introverted robots led to diverse questionnaire responses, in contrast to the more easily identifiable extroverted behavior. This trend of perceiving introversion with mid-range scale values aligns with prior research findings [45]. Furthermore, we performed a correlation analysis to study if modulating a specific trait, a variation of the other four traits of the OCEAN model is perceived as well. Obtained results show that a variation of agreeableness is perceived along extroversion, emotional stability ($p < 0.001$), and conscientiousness ($p = 0.03$).

The analysis of the Agency and Experience questionnaires using the Mann-Whitney U test [44] across the three personality traits reveals that none of these traits significantly affect how the robot is perceived in terms of its ability to display cognitive behavior or feel emotions. Examining the mean values by using the Wilcoxon signed-rank test [46], $p < 0.001$), we can see how Agency (3.49 ± 0.79) is significantly higher than Experience (2.63 ± 1.026) [42]. Specifically, when focusing on Agency, the item related to the ability to plan actions receives a higher mean (4.54 ± 0.79) across all personality types, suggesting that the robot is perceived as a cognitive agent capable of purposefully carrying out goal-directed actions.

In terms of Enjoyability and Sociability, the UTAUT results reveal that all personality poles are equally enjoyable. However, modulating the level of Agreeableness results in a significant difference in Sociability ($p = 0.045$): the more agreeable the robot, the more it is perceived as sociable. On average, the robot is considered more enjoyable (4.25 ± 0.93) than sociable (3.55 ± 1.2), regardless of the specific personality traits (Wilcoxon signed-rank test [46], $p < 0.001$).

In conclusion, while the implemented synthetic personalities seem to be perceivable by humans, a variation along the traits does not appear to impact how users perceive the agent's cognitive abilities or their overall perception of the robot. Surprisingly, even introverted, disagreeable, or unscrupulous personalities still receive appreciation from users. The significance of considering the agreeableness dimension in the design process is in any case evident, particularly in tasks where social interactions are crucial.

V. Conclusions

This work introduces and validates a software architecture that utilizes a comprehensive taxonomy of robotic personalities. These personalities are represented as vectors within a three-dimensional space defined by Extroversion, Agreeableness, and Conscientiousness, which influence all aspects of the robot's behavior. Additionally, the cognitive and psychological aspects of the agent work in tandem to shape its own experiences. Indeed, we implemented a Prospection module through a personality-based loop, inspired by allostasis, to control the choice of future actions to be executed, so as to achieve a certain goal satisfying the agent's personality-dependent hedonic experience.

In this study, participants engaged with Pepper in a collaborative task involving building a tower of blocks, with the robot displaying concurrently multiple personality traits. The results confirm the validity of our personality taxonomy, demonstrating that variations across the three traits are accurately perceived by humans and that these dimensions are distinct, with extroversion being less prominently recognized.

Future research will explore different tasks and robot types, potentially non-humanoid ones, to consider the impact of embodiment. In addition, the work will enhance the humanization of the framework, allowing it to better understand human behavior, actions, reactions, emotions, and personalities. Consequently, the robot may possibly be able to express emotions based on its internal state and additionally categorize memories as pleasant or unpleasant, thereby constructing its own unique experiences.

VI. Acknowledgement

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