



HAL
open science

The influence of extraversion on a robot developmental learning in a human robot interaction

Hakim Guedjou, Sofiane Boucenna, Laurence Chaby, David Cohen, Mohamed Chetouani

► **To cite this version:**

Hakim Guedjou, Sofiane Boucenna, Laurence Chaby, David Cohen, Mohamed Chetouani. The influence of extraversion on a robot developmental learning in a human robot interaction. IEEE International Conference on Development and Learning (ICDL), May 2024, Austin (TX), United States. hal-04590176

HAL Id: hal-04590176

<https://hal.science/hal-04590176v1>

Submitted on 28 May 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

The influence of extraversion on a robot developmental learning in a human robot interaction

1st Hakim GUEDJOU
ETIS-UMR8051
CY Cergy Paris Université
Cergy, France
hakimguedjou@gmail.com

2nd Sofiane BOUCENNA
ETIS-UMR8051
CY Cergy Paris Université
Cergy, France
sofiane.boucenna@ensea.fr

3rd Laurence CHABY
ISIR-UMR722
Sorbonne Université
Paris, France
laurence.chaby@parisdescartes.fr

4th David COHEN
ISIR-UMR722
Sorbonne Université - GH Pitié-Salpêtrière, APHP
Paris, France
david.cohen@aphp.fr

5th Mohamed CHETOUANI
ISIR-UMR722
Sorbonne Université
Paris, France
mohamed.chetouani@sorbonne-universite.fr

Abstract—Social robotics continues to expand as a prominent area of research due to the increasing use of robots in settings involving social interactions. In this paper we study the social dimension of human robot interaction during a posture imitation game. We discuss how human personality traits influence a learning robot. A neural architecture is used to enable autonomous and interactive learning. We address this issue by linking the performance of the robot algorithms (learning trajectory, convergence, recognition score...) to the personality traits of its partners (extraversion and anxiety).

As results of this work we noticed the emergence of pattern related to the extraversion trait of individuals interacting with the robot but no evidence for anxiety. By analyzing the robot's learning with each partner, we observe that the acquisition time of the partner's visual representation was correlated with the extraversion trait. The results show that even in a simple posture imitation game, we observe a fluctuation in a robot's learning based on the personality traits exhibited by its human partner.

Index Terms—Social robotics, developmental learning, human-robot interaction, personality traits, extraversion

I. INTRODUCTION

Due to the increasing use of robots in healthcare, education, domestic assistance and assistive technologies, we see a higher interest for social robotics. Research is progressively exploring how robots can engage in social interactions with people. Various approaches are employed to address this question. Some studies assess the acceptance of robots as social partners [1], while other aim to imbue robots with behaviors to simulate specific personality traits [2]. In healthcare some studies assess human-robot interaction in the context of pathology either by developing improved models for effective interaction with disabled individuals or using robots as tools to study these

pathologies [3]. However few studies tend to assess human-robot interactions with an emphasis on human personality traits. To our knowledge, the prevalent method in these studies involves using scripted or teleoperated robots ("Wizard of Oz" experiment) [4], [5]. Here, it's presumed that the robot acts as an extension of the human operating it. Consequently, any changes in how the partner interacts with the robot can be attributed solely to the operator involvement in the interaction process.

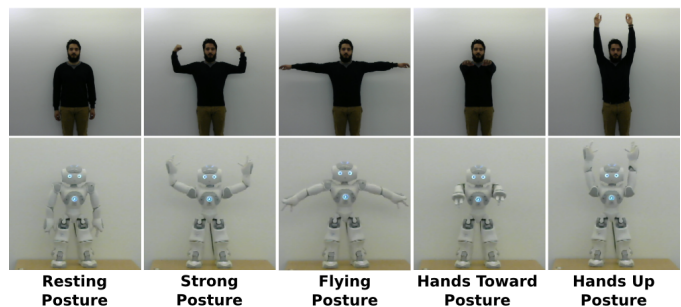


Fig. 1: The five postures of the human-robot imitation game

Contrary to this studies we aim to follow a developmental learning approach to build an effective social interaction between the human and the robot and those by taking inspiration from the learning mechanism and social construction in human. The social cognitive theory by Bandura [6], [7] assumes that part of a child's social learning can be achieved through direct instruction, where the social partner explicitly tells children what is expected of them, modulating behavior through reward and punishment mechanisms. Nevertheless, personality models also are acquired by the child using imitation mechanisms (imitation of parents, relatives or other

interactional partners) [8]. Meltzoff and Moore demonstrated that imitation was innate in humans, finding that this ability was found in babies aged between 42 minutes and 72 hours [9], [10]. Imitation in the newborn provides a tool for the construction of social cognition and is fundamental in the development of a theory of mind mechanism and empathy for others [19]–[21]. Imitation is seen as a dynamic embodied process of interpersonal coordination that allows both psychological connectivity and differentiation between self and other [22].

This paper delves into the dynamics of imitation interactions between humans and robots, with a specific focus on the interplay between a human and an autonomous robot. In these interactions, the robot learns to imitate postures through an interactive loop with its human counterpart. The primary objective of this research is to investigate the impact of human personality traits on the robot’s learning process. From robot-centric approach ¹, our study tackles to unravel the central question: How does the human behavior, shaped by individual personalities, influence a robot’s learning?

II. STATE OF THE ART

Before delving into how personality might affect a robot’s learning during human-robot interaction, it’s essential to first examine studies exploring the impact of personality on human behavior within human-human interactions. Understanding how personality traits shape human interactions provides a foundational understanding of how these traits might manifest or influence interactions involving robots.

Hauschild et al. conducted a comprehensive experiment involving the congruence effect [15]. Their investigation primarily focused on examining the relationship between borderline personality disorder, loneliness, and their impact on mimicry. The results showed two findings: a) a heightened prevalence of mimicry in individuals with borderline personality disorder, and b) a distinctive pattern emerged in the influence of loneliness on mimicry when comparing borderline and typical participants. Specifically, the study revealed that heightened loneliness in individuals with borderline personality disorder correlated with a reduced tendency to engage in mimicry, while in typical participants, an inverse relationship was observed — increased loneliness was associated with a greater likelihood of mimicry. Dijk et al. demonstrated that the mimicry of an individual’s smile becomes more pronounced when experiencing social anxiety. The experiment featured an interactive scenario between an actress and a participant [14]. The actress narrated a story and incorporated specific facial expressions at strategic points. Notably, this study revealed a crucial insight: the heightened mimicry effect manifested during face-to-face interactions but did not occur when the individual was exposed to a video. This distinction underscores the nuanced nature of the impact of social anxiety on smile mimicry, emphasizing the importance of real-time interpersonal dynamics in eliciting such responses.

¹By robot-centric approach, we mean an analysis of the robot’s learning carried out during the interaction with the human partner [11]–[13]

Studying the influence of personality on the handshake Orefice et al. tried to generalize their observations from a human-human interaction to a human-robot interaction [16]. In their study of human-human interaction they placed pressure and speed sensors on different parts of the hands of individuals as they performed the task. These individuals also completed personality questionnaires. The results of this study showed that a set of characteristics linked to the way individuals performed a handshake, including firmness, pressure and inclination of the grip, were indicative of gender as well as anxiety. However, the results concerning gender differentiation were indeed generalizable to the level of Human-Robot interaction. Nevertheless, no results were found regarding the influence of personality on human-robot interaction.

In a study on social personal distance, Walters et al. showed that the majority of participants maintained the same interaction distance whether interacting with a human or a robot [4]. They also showed that this interaction distance depended on social traits such as proactivity.

Anzalone et al. designed an experiment enabling spontaneous interaction between a human and a robot [5]. A human is positioned in front of a robot controlled by an operator. The robot hands an object to the human without any instructions. Using non-verbal features describing the interaction such as amount of movement, distance between human and robot, synchrony of behavior, they were able to detect anxiety levels of the individual interacting with the robot.

Even if these studies show that the human modulates his behavior according to his social traits while interacting with a robot. They have some limitations. The robot being teleoperated by a human operator (wizard of Oz technique), we can assume that the robot is an extension of the human who controls it, and that if the partner exhibits a variation in behavior towards the robot, it is only due to the presence of a human in the interaction loop. The study by Boucenna et al. addresses this limitation by using an autonomous learning robot [11], [17]. In this study, a new ”robot-centric” approach was introduced, making it possible to evaluate and quantify behavioral differences in the robot’s partners. This approach consists of an architecture that enables the robot to learn interactively and autonomously with a human partner through imitation. The architecture was tested in interaction with three different groups: healthy adults, typically developing children and children with autism spectrum disorders [12], [13], [18]. By analyzing metrics assessing robot learning, different patterns emerged according to each group, showing that the nature of the group has an impact on robot learning.

This paper builds upon previous research, extending its focus from pathology to personality traits. By utilizing an autonomous learning robot, we aim to delve into the intricate dynamics of human-robot interaction, specifically examining how human personality traits impact the learning mechanisms of a robot. This shift in focus from pathology to personality traits allows for a more comprehensive understanding of how individual characteristics affect the human-robot interactions.

III. METHODOLOGY

Using a mirroring paradigm, a robot learns by interacting with a human partner. The robot learns to recognize simple postures and reproduce them. Considering this imitation game, we want to see if human personality traits influence robot's learning. The choice of imitation as a paradigm is motivated by the aforementioned multidisciplinary studies that link child development and social traits.

A. Experimental protocol

The task performed in this protocol is a posture imitation game between the robot and a human partner. The protocol consists of two phases :

Learning phase: During the first phase, the robot performs pre-coded postures randomly (figure 1). While the robot performs these postures, the human partner imitates it. Using its visual perception and proprioception, the robot associates what it sees with what it does achieving a sensory-motor coupling between the visually perceived human partner and its motor proprioception (the posture it is performing). The robot can learn, in real time, in less than two minutes to recognize pre-coded postures (figure 1) and reproduce them to imitate the human partner. During this phase, images of the partner and the robot's internal states are recorded for subsequent simulations.

Validation phase: In this second phase, the robot is able to recognize its partner's postures. So it's the human partner's turn to perform one of the preceding postures, and the robot recognizes and reproduces it. By performing a succession of postures, a game of imitation led by the human partner is established. This phase assesses the robot's recognition of the partner's postures.

IV. PARTICIPANTS

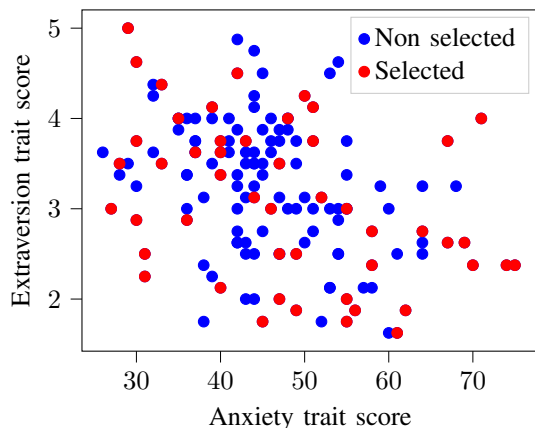


Fig. 2: distribution of 146 participants and 51 selected on anxiety and extraversion scores

The study was carried out within the INSEAD-Sorbonne Université Behavioural lab (INSEAD stands for "Institut Européen d'Administration des Affaires"). The INSEAD-Sorbonne Université Behavioural lab is a structure that facilitates the performance of certain behavioral studies. This

structure takes care of recruiting individuals and provides an experiment room. The final experiment took place in two stages:

a) 146 people completed questionnaires at home on a computer via an INSEAD platform (BFI-Fr and STAI-Y).

b) The number of people we could involve in the experiment was set around 50, due to logistical and material constraints. To evaluate the influence of a personality trait, it is preferable to have a sample of participants representative of the entire spectrum of that personality trait. With a population of 50, we choose to focus on anxiety and extraversion during the selection of participants (these two traits having given good results during pilot experiments). 55 of the 146 participants were therefore selected on the basis of their anxiety and extraversion scores². The distribution of these people's scores for the anxiety and extraversion traits covered the whole spectrum of these two traits (figure 2). The 55 people were invited to visit the INSEAD behavioural lab within two weeks of the first phase. At the INSEAD behavioral lab, the participants carried out interactions with the robot. The participants receive a compensation of 10 euros for their participation at the end of the interaction. Of the 51 participants, 22 were women and 29 men. The average age is 23.25 years and the standard deviation is 3.31 years.

All 146 participants received information about the experiment and gave written consent prior to participation. The protocol was approved by the ethics committee of the INSEAD-Sorbonne University Behavioural lab.

A. Personality assessment

To assess the participants' personality traits, each of them completed the following questionnaires.

- The big five inventory (BFI-Fr) : a personality questionnaire based on the "big five" model, widely used in the study of personality. The model is based on five independent dimensions (Openness, Conscientiousness, extraversion, Agreeableness, Neuroticism) [23]
- The State-Trait Anxiety Inventory (STAI) (Form Y) : a questionnaire which allows the assessment of two characteristics (state anxiety which is immediate anxiety corresponding to the moment of the questionnaire and trait anxiety which assesses anxiety as a stable characteristic) [24]

V. NEURAL ARCHITECTURE

We used a sensory-motor architecture that enables perception-action conditioning to be learned. It consists of a visual perception module and a learning one. The learning part is made up of a set of artificial neural network layers. During learning, the robot performs a posture in a predefined alphabet (figure 1). Simultaneously, the robot learns the visual input and associates it with the performed posture.

²Due to a material problem during the experiment, four of the 55 recordings have been discarded

A. Visual perception

The aim of this part of the architecture is to build a representation of the robot's partner using an attentional vision mechanism. This representation, referred to as visual patterns in the following, will be learned and evaluated by the different layers of neurons (see section V-B). We start by searching for points of interest³ on the visual field of the robot. Firstly, the image perceived by the robot is transformed into a grayscale image. This image is then subjected to gradient extraction. The resulting gradient image is convolved by a difference of Gaussians. Once the difference of Gaussians has been calculated, we search for points of interest by calculating local maxima through competition between adjacent points. For each of the previously retrieved points of interest, a visual pattern is extracted. The visual pattern is a small image of the point of interest's neighborhood which undergoes a transformation from Cartesian space to polar logarithmic space.

B. Visual patterns learning

The characteristic patterns of each image are learned and recognized by the VF (Visual features) neural layer. VF is a variant of the k-means algorithm, which allows the number of clusters (in this case neurons) to be modified during the learning process. This algorithm is called a SAW (selective adaptive winner). The VF output is calculated as follows:

$$VF_j = net_j \cdot H_\gamma(net_j) \text{ with } net_j = \frac{1}{N} \sum_{i=1}^N |W_{ij} - I_i|$$

VF_j is the activation of neuron j of group VF . N is the size of the vector representing each thumbnail(pattern) I . H_γ is the thresholding function (Heaviside):

$$H_\gamma = \begin{cases} 1 & \text{if } \gamma < x \\ 0 & \text{otherwise} \end{cases}$$

γ is a vigilance parameter. It is chosen empirically. This parameter is a threshold for pattern recognition by the VF layer. If pattern recognition is below γ , a new neuron (corresponding to a new cluster) is recruited (incremental learning) to represent it. The learning rule enables both "one-shot" learning when a new pattern appears, and long-term averaging when a similarity with an existing pattern is observed. The change in W_{ij} weights is calculated as follows:

$$\Delta W_{ij} = a_j(t)I_i + \mu(1 - \delta_j^k)(I_i - W_{ij})(1 - VF_j) \quad (3)$$

$$k = \text{ArgMax}(a_j) \text{ et } a_j = \begin{cases} 1 & \text{if new neuron} \\ 0 & \text{otherwise} \end{cases}$$

³Salient points or points of interest are points considered interesting in the image (whose neighborhood carries information). For this search, we use filters inspired by the center-off cells of the visual system in certain animals species

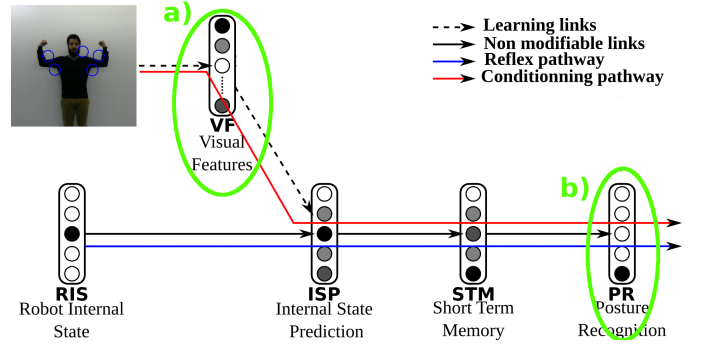


Fig. 3: Neural layers corresponding to the evaluated metrics: a) number of VF layer neurons and time of convergence, b) human partner posture recognition score

and δ_j^k is Kronecker's symbol :

$$\delta_j^k = \begin{cases} 1 & \text{if } j = k \\ 0 & \text{otherwise} \end{cases}$$

The μ parameter is the learning speed. It is chosen empirically. This parameter plays an important role in the recognition task: as with the threshold γ , if μ is too large, too much memory will be used and the system's generalization will decrease, but if μ is too small, the averaging will be too great and the recognition score will fall.

C. Posture learning and prediction

During the learning phase, the VF layer learns the visual patterns that the robot receives. VF neurons are activated according to the patterns detected in each image (the robot's visual stimuli). Posture learning corresponds to a classification of active VF neurons according to the robot's internal state. The robot's internal state is indicated by the RIS (Robot Internal State) layer. Each neuron in the RIS layer corresponds to a pre-coded robot posture. The layer that performs the classification mentioned above is the ISP (Internal State Prediction) layer. The ISP layer functions as a conditioning mechanism. It builds a conditioning signal that will be used during the validation phase, using a reflex signal corresponding to the simultaneous activation of neurons in the VF and RIS layers. To summarize, during the learning phase, the ISP (Internal State Prediction) layer links simultaneously active VF and RIS neurons using Widrow and Hoff's least-squares learning rule:

$$\Delta w_{ij} = \mu \cdot VF_i \cdot (RIS_j - ISP_j) \quad (4)$$

During the validation phase, it is no longer the RIS layer that controls the robot's motricity, but the output of the ISP layer after some filtering (figure 3). The output of the ISP layer is calculated as follows:

$$ISP_j = \sum_{i=1}^N VF_i \cdot w_{ij} \quad (5)$$

Final filtering: During the validation phase (see section III-A), sudden changes in robot posture may occur due to the human partner, or wrong recognition of a given image. This creates both physical instability for the robot, and confusion in the interaction between the robot and its human partner. To overcome this problem, a low-pass filtering mechanism is used in the STM (Short Term Memory) layer over a given time (N iterations). The formula is as follows:

$$STM_i(t+1) = \frac{1}{N}ISP_i(t+1) + \frac{N-1}{N}STM_i(t) \quad (6)$$

Finally the PR(Posture Recognition) neural layer uses a "winner take all" mechanism on the STM layer to determine the posture that best responds to the visual stimulus.

D. Assessed metrics

We carried out this investigation on each learning level of the architecture (figure 3). Firstly, the VF neuron layer recruits neurons to learn a representation of the robot's visual stimuli. Each neuron learns a pattern characterizing the postures of the human partner. The number of neurons in VF can be seen as a measure of learning complexity and partner imitation variability. The second metric is the time it takes to achieve this variability representation (The time for the VF layer to reach a maximum number of neurons when all the multiple patterns of a partner visual representation are learned). Third, to assess learning of the imitation task as a whole, posture recognition scores are used.

VI. RESULTS

A. Personality assessment

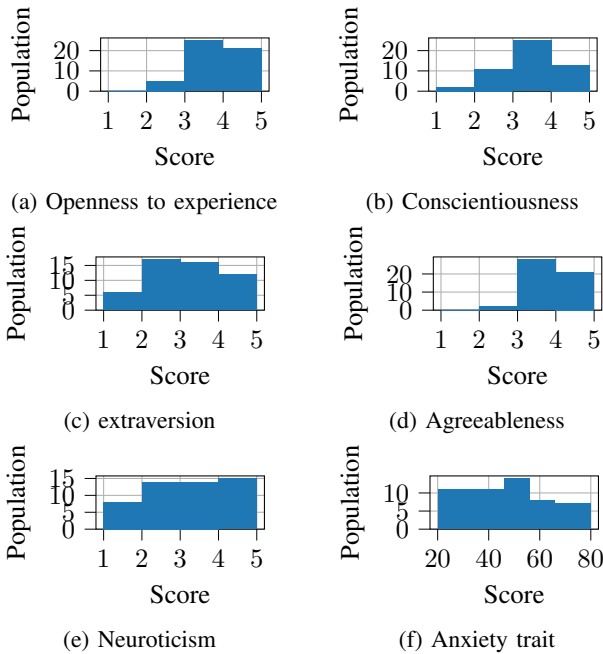


Fig. 4: Histogram of participants' scores

Given our sample we first check the BFI and anxiety traits distribution. As we can see on the figure 4 all extraversion and

anxiety scores are represented in our sample. Even if we didn't reach the uniform distribution, the less represented scores ($x \in [1, 2]$) for the extraversion have more than 10% participants of the sample. The difficulty of achieving a uniform distribution on our sample can be explained by the real distribution of the Big5 across general population which is a normal one [23].

B. Influence of social traits on robot learning

	Extraversion	Anxiety
Number of VF neurons	($r = -0.21, p = 0.14$)	($r = 0.12, p = 0.39$)
Posture recognition scores	($r = 0.05, p = 0.72$)	($r = -0.19, p = 0.20$)
Visual representation learning time	($r = 0.23, p = 0.03$)	($r = -0.08, p = 0.56$)

TABLE I: Pearson correlation results and p-values between personality traits scores and the robot centric metrics

To assess the influence of the human's partner social traits on the robot's learning we evaluated Pearson's correlation for each learning metrics with the extraversion and anxiety trait scores. By analyzing the needed time for the robot to build a complete representation of each participant, we were able to observe, as shown in table I and figure 5.a, that the acquisition time of the partner's visual representation is correlated with the extraversion trait. The correlation is positive, ($r = 0.30, p = 0.04$). In other words, the robot needed more time to build a visual representation of extrovert partners. However the difference in learning time inter individuals is less than one second (corresponding to 20 images : the frame-rate of the camera). Note that even after removing the points that appear to be outliers, we still obtain a correlation ($r = 0.32, p = 0.03$)(figure 5.b). Contrary to the previous result the Pearson correlation for the anxiety trait gave a non significant negligible correlation of ($r = -0.08, p = 0.56$)

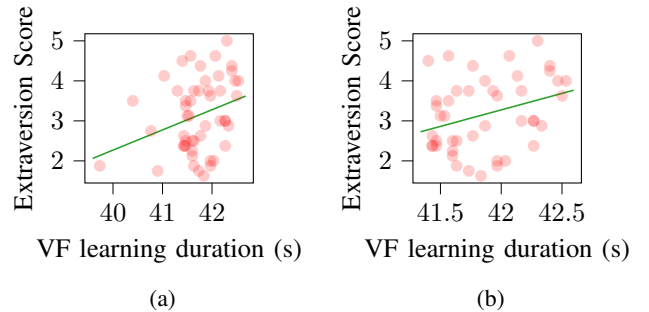


Fig. 5: Correlation between extraversion score and time required to learn the VF layer. a) Correlation for all participants. b) Correlation with outliers removed

Using the same approach of our previous papers [12], [13], [18], we calculated the correlations between the number of neurons recruited on VF layer with the extraversion and anxiety traits scores. However the evolution of this metric didn't give significant results as we can see on the table I. The results for extraversion trait and anxiety trait are respectively ($r = -0.21, p = 0.14$) and ($r = 0.12, p = 0.39$). There was no observed correlation between the posture recognition scores and the personality traits. The results for extraversion and

anxiety were ($r = 0.05, p = 0.72$) and ($r = -0.18, p = 0.19$), respectively.

VII. DISCUSSION

In this paper we study how the diversity of human behavior based on their personalities influences a robot's learning during human-robot interaction. We study an imitation interaction between a human and a robot where the robot is a perfectly autonomous entity. The robot automatically learns an imitation task in an interactive loop with a human partner. We focused our study on anxiety and extraversion traits and follow a robot centric approach to assess the influence of the human's personality traits on the robot learning. In this paper we use different metrics underlying the robot learning which are the needed time for the robot to build a visual representation of its partners, the number of neurons needed to achieve this representation (maximum number of neurons on VF layer) and the posture recognition scores.

Assessing the needed time for the robot to build a complete representation of each of its human partners during the interaction, we observe a fluctuation in the robot's learning based on the personality traits exhibited by its human partner. This fluctuation is characterised by a correlation of 0.3 between the partner extraversion trait and the needed time for the robot to build a visual representation of its partner. This meaning that the robot needed more time to build a complete representation while interacting with more extrovert people. However the evaluation of the anxiety trait using this metric didn't show any significant result.

In contrast to our previous studies we assessed the influence of pathology and age on the developmental learning of a robot and showed that for each interaction of the robot, the learning phase duration, the number of recruited neurons and the posture recognition scores depends on the different groups the partner of the robot belongs to (children with ASD, typical child, adults) [12], [13], [18], we didn't see any significant influence of the extraversion or anxiety on those metrics. One hypothesis is that contrary to ASD population where state of the art addressed some motor impairment, the motor behaviour variations according to personality traits doesn't variate enough to affect the scores of recognition.

This study being in an initial stages, the limited results can be due to the imitation task being too simple (only five postures). The task is maybe too contrenious and doesn't allow the partners a high degree of freedom to express their personality over their behaviour. Studies show that imitation is deeply linked to the notions of purpose and intention [20], [25], one solution could be the integration of the imitation game in a goal directed task, by offering the human a goal to achieve during the interaction, the human's influence on the robot's learning might be more pronounced.

REFERENCES

- [1] O'Reilly, Z., Navare, U., Marchesi, S. & Wykowska, A. Does Embodiment and Interaction Affect the Adoption of the Intentional Stance Towards a Humanoid Robot?. *Social Robotics*. pp. 357-366 (2022)
- [2] Lalioti, V. & Ionescu, I. Designing Robotic Movement with Personality. *Companion Of The 2023 ACM/IEEE International Conference On Human-Robot Interaction*. pp. 217-220 (2023)
- [3] Saleh MA, Hanapiah FA, Hashim H. Robot applications for autism: a comprehensive review. *Disabil Rehabil Assist Technol*. 2021 Aug;16(6):580-602. doi: 10.1080/17483107.2019.1685016
- [4] Walters, M., Dautenhahn, K., Boekhorst, R., Koay, K., Kaouri, C., Woods, S., Nehaniv, C., Lee, D. & Werry, I. The influence of subjects' personality traits on personal spatial zones in a human-robot interaction experiment. (2005,9)
- [5] Anzalone, S., Varni, G., Ivaldi, S. & Chetouani, M. Automated Prediction of Extraversion During Human-Humanoid Interaction. *International Journal Of Social Robotics*. **9**, 385-399 (2017,6)
- [6] Bandura, A. & Walters, R. Social learning theory. (Prentice-hall Englewood Cliffs, NJ,1977)
- [7] Bandura, A. Social foundations of thought and action. *Englewood Cliffs, NJ*. **1986** (1986)
- [8] Bandura, A. Bandura, A. (1963). The role of imitation in personality development. *Dimensions Of Psychology*. pp. 16-23 (1963)
- [9] Meltzoff, A. & Moore, M. Newborn Infants Imitate Adult Facial Gestures. *Child Development*. **54**, 702-709 (1983)
- [10] Meltzoff, A. & Moore, M. Imitation in newborn infants: Exploring the range of gestures imitated and the underlying mechanisms. *Developmental Psychology*. **25**, 954-962 (1989)
- [11] Boucenna, S., Anzalone, S., Tilmont, E., Cohen, D. & Chetouani, M. Learning of Social Signatures Through Imitation Game Between a Robot and a Human Partner. *IEEE Transactions On Autonomous Mental Development*. **6**, 213-225 (2014,9)
- [12] Guedjou, H., Boucenna, S. & Chetouani, M. Posture recognition analysis during human-robot imitation learning. *2016 Joint IEEE International Conference On Development And Learning And Epigenetic Robotics (ICDL-EpiRob)*. pp. 193-194 (2016,9)
- [13] Guedjou, H., Boucenna, S., Xavier, J., Cohen, D. & Chetouani, M. The influence of individual social traits on robot learning in a human-robot interaction. *2017 26th IEEE International Symposium On Robot And Human Interactive Communication (RO-MAN)*. pp. 256-262 (2017,8)
- [14] Dijk, C., Fischer, A., Morina, N., Eeuwijk, C. & Kleef, G. Effects of Social Anxiety on Emotional Mimicry and Contagion: Feeling Negative, but Smiling Politely. *Journal Of Nonverbal Behavior*. **42**, 81-99 (2018,3)
- [15] Hauschild, S., Winter, D., Thome, J., Liebke, L., Schmah, C., Bohus, M. & Lis, S. Behavioural mimicry and loneliness in borderline personality disorder. *Comprehensive Psychiatry*. **82** pp. 30-36 (2018,4)
- [16] Orefice, P., Ammi, M., Hafez, M. & Tapus, A. Let's handshake and I'll know who you are: Gender and personality discrimination in human-human and human-robot handshaking interaction. *2016 IEEE-RAS 16th International Conference On Humanoid Robots (Humanoids)*. pp. 958-965 (2016,11)
- [17] Boucenna, S., Cohen, D., Meltzoff, A., Gaussier, P. & Chetouani, M. Robots Learn to Recognize Individuals from Imitative Encounters with People and Avatars. *Scientific Reports*. **6** pp. 19908 (2016,2)
- [18] Xavier, J., Guedjou, H., Anzalone, M., Boucenna, S., Guigon, E., Chetouani, M. & Cohen, D. Toward a motor signature in autism: Studies from human-machine interaction. *L'Encéphale*. **45**, 182-187 (2019,4)
- [19] Meltzoff, A. & Keith Moore, M. Early imitation within a functional framework: The importance of person identity, movement, and development. *Infant Behavior And Development*. **15**, 479-505 (1992,10)
- [20] Meltzoff, A. & Decety, J. What imitation tells us about social cognition: a rapprochement between developmental psychology and cognitive neuroscience.. *Philosophical Transactions Of The Royal Society B: Biological Sciences*. **358**, 491-500 (2003,3)
- [21] Meltzoff, A., Kuhl, P., Movellan, J. & Sejnowski, T. Foundations for a New Science of Learning. *Science*. **325**, 284-288 (2009,7)
- [22] Xavier, J., Johnson, S. & Cohen, D. From child-peer similarity in imitative behavior to matched peer-mediated interventions in autism. *Frontiers In Psychology*. **14** (2023)
- [23] Plaisant, O., Courtois, R., Réveillère, C., Mendelsohn, G. & John, O. Validation par analyse factorielle du Big Five Inventory français (BFI-Fr). Analyse convergente avec le NEO-PI-R. *Annales Médico-psychologiques, Revue Psychiatrique*. **168**, 97-106 (2010,3)
- [24] Spielberger, C. State-Trait Anxiety Inventory. *The Corsini Encyclopedia Of Psychology*. pp. 1-1 (2010),
- [25] Calinon, S., Guenter, F. & Billard, A. Goal-Directed Imitation in a Humanoid Robot. *Proceedings Of The 2005 IEEE International Conference On Robotics And Automation*. pp. 299-304 (2005,4)