Shaping Gestures to Shape Personalities: Interplay Between Gesture Parameters, Attributed Personality Traits and Godspeed Scores

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***Abstract*— This work explores the role of personality as a mediation variable between observable behavior of a robot - gestures of different energy and spatial extension in the experiments of this work - and experience of its users according to the Godspeed questionnaire. The results show that, at least to a certain extent, the Big Five personality traits that the users attribute to a robot are predictive of the Godspeed scores, i.e., of the quality of the interaction they have with it. In other words, robots that are attributed different personality traits tend to be perceived differently when it comes to the quality of the interaction.**

I. INTRODUCTION

Social Cognition shows that '*people make social inferences without intentions, awareness, or effort, i.e. spontaneously*" [1]. This means that the very presence of others activates cognitive processes that take place outside conscious awareness and aim at deriving "*evaluations and impressions of a target*" [2], i.e., aim at making sense of others while identifying the best way of interacting with them. These processes are so pervasive and spontaneous that they take place not only in face-to-face interactions [3], but also in technology mediated settings (e.g., when observing people in a video [4]) and during interactions with machines that can display human-like behaviors (e.g, during the interactions between people and talking machines [5]).

The goal of this work is to investigate a particular aspect of the phenomenon above, namely the association between the personality traits that people attribute to a robot and the gestures that this latter displays. In other words, this work tries to show whether the synthesis of gestures with a humanoid robot makes it possible to perform *Automatic Personality Synthesis* (APS), the task of conveying personality impressions with machines [6]. The main reason for focusing on gestures is that these convey messages more effectively than speech when the level of acoustic noise is high [7], [8], one of the main characteristics of the public spaces where the gestures investigated in this work will actually be adopted for Human-Robot Interaction (HRI). The main motivation behind the focus on personality is that people have been shown to evaluate more positively the machines to which they attribute more desirable traits [5] or traits more similar to their own [9], [10], [11].

The attempts of conveying personality impressions via Embodied Conversational Agents have made use of a wide spectrum of nonverbal behavioral cues, including head pose [12], facial expressions [13], [14], speech [13], [15], [16], gaze patterns [14], [15], gestures [14], [16] and back-channel [14], [17]. Overall, the results show that changing the nonverbal behavior or the appearance of the agent changes the traits that its users attribute to it, but to a different extent and for different traits.

In particular, the works presented so far show that the trait the users are more sensitive to - meaning that its attribution changes more clearly with the observable behavior - is Extraversion [12], [15], [16], possibly in conjunction with other traits. In the case of [12], the experiments show that the attribution of Extraversion is associated with the head pose of the agent, even when it is presented in static stimuli, i.e., stimuli in which the agent does not actually move. The experiments presented in [16] show that there is an interaction between bimodal behavioral displays that involve gestures and speech, but it it this latter channel that seems to play the most important role in the attribution of the Extraversion. On the other hand, a similar approach proposed in [15], shows that all the cues involved in a multimodal behavioral display (gaze patterns, speech and facial expression) actually interplay with the attribution of the trait. In other works, observed effects account not only for changes in Extraversion, but also for changes in other traits [13], [14], [17]. However, to the best of our knowledge, this is the first work that takes into account not only the interplay between behavior and traits, but also how much these are predictive of interaction quality. This is important because the ultimate goal of a social robot is to interact with its users and, hence, its perceived personality should be compatible with its interactional goals.

The experiments of the work have been performed over 45 gestures that have been synthesized by changing *amplitude* and *speed* of 5 core gestures (see Section II-A for more details). Each of the 45 gestures has been shown to 30 human observers - the same for all 45 gestures - that have been asked to rate the robot in terms of the *Big-Five* [18], the five personality dimensions known to capture most observable individual differences (see Section II-B for more details) [19]. The results show that, at least for some traits, there is a statistically significant association between, on the one side, amplitude and speed of the gesture and, on the other side, the personality scores assigned by the observers. Furthermore, the results show that there is a relationship between the attributed personality traits and the Godspeed scores [20] assigned by the same observers, thus confirming that the traits are predictive of the interaction quality between people and robots.

Overall, the findings above suggest that the quality of

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Human-Robot Interaction is a matter of personality, both when it comes to the self-assessed traits of the users and the traits that these latter attribute to the robot. In other words, personality can act as a mediation variable between the observable behavior of the robot - amplitude and speed of the gestures in the experiments of this work - and the experience of the users in terms of the dimensions assessed by the Godspeed questionnaire. This seems to confirm that social robots are capable to interface with the psychology of their users and to activate the same processes as those observed in human-human interactions. The main implication for the design of HRI is that this is likely to be as complex as human-human social exchanges and are likely to be governed, at least to a certain extent, by the same underlying principles and laws.

The rest of this article is organized as follows: Section II presents the data used in this work, Section III presents the methodology adopted in the experiments, Section IV reports on the results and the final Section V draws some conclusions.

II. The Data

This section describes the data adopted in the experiments, including the gestural stimuli (Section II-A) and the approach adopted to measure self-assessed and attributed personality traits (Section II-B).

A. The Stimuli

The process for the generation of the 45 gestures - the *stimuli* hereafter - starts with the selection of 5 seed gestures - the *core stimuli* - among the standard animations available on *Pepper*, the robot used for the experiments [1]:

- Disengaging / Send-away;
- Engaging / Gain attention;
- Pointing / Giving Directions;
- Head-Touching / Disappointment;
- Cheering / Success.

The motivation behind the adoption of the animations above is that they are relevant to the setting in which the gestures will be used, namely a public space where the level of the acoustic noise is significant, the number of people is high and the robot is expected to attract attention while proactively starting the interaction with its users.

In the rest of the process, the speed λ and the amplitude α are changed to produce 9 variants per core stimulus, thus leading to the final $9 \times 5 = 45$ stimuli. For each core stimulus, three different values of λ are used, namely 15, 25 and 35 *frames per second* (fps), where 25 fps is the original speed of the core stimuli. Then, for every stimulus and for every value of λ, the amplitude is changed by multiplying the difference $\Delta\theta_i(t) = \theta_i(t) - \theta_i(t-1)$ by a factor α, where $\theta_i(t)$ is the angle between the two mechanical elements connected by joint i at frame t. The value of $\Delta\theta_i(t)$ is multiplied by α for all values of t and i, i.e., for the entire duration of the stimulus and for all joints. The values of α adopted in the experiments are 0.50, 0.75 and 1.00, where the adoption of $\alpha = 1.00$ corresponds to leaving the amplitude of a core stimulus unchanged.

[1]The animations associated to the core stimuli are available on the version 1.6B of Pepper in the following directories: "`animations/Stand/Gestures/No_3`" (Disengaging), "`animations/Stand/Gestures/Hey_2`" (Engaging), "`animations/Stand/Emotions/Negative/Hurt_1`" (Pointing), "`animations/Stand/Gestures/Far_3`" (Head-Touching) and "`animations/Stand/Emotions/Positive/Happy_1`" (Cheering).

I ...	The robot ...
am reserved	is reserved
am generally trusting	is generally trusting
tend to be lazy	tends to be lazy
am relaxed, handles stress well	is relaxed, handles stress well
have few artistic interests	has few artistic interests
am outgoing, sociable	is outgoing, sociable
tend to find fault with others	tends to find fault with others
do a thorough job	does a thorough job
get nervous easily	gets nervous easily
have an active imagination	has an active imagination

TABLE I

THE BFI-10 QUESTIONNAIRE USED IN THE EXPERIMENTS OF THIS WORK. THE VERSION REPORTED HERE IS THE ONE THAT HAS BEEN PROPOSED IN [23]. THE LEFT COLUMN IS THE FIRST PERSON VERSION ADOPTED FOR SELF-ASSESSMENT, THE RIGHT COLUMN IS THE THIRD PERSON VERSION ADOPTED FOR THE ATTRIBUTION OF THE TRAITS TO THE ROBOT.

B. Personality and its Measurement

Personality is the latent construct that accounts for "*individuals' characteristic patterns of thought, emotion, and behavior together with the psychological mechanisms - hidden or not - behind those patterns*" [21]. In other words, while not necessarily corresponding to any observable characteristics - this is the sense of the adjective "*latent*" in the definition above - personality can explain and predict observable individual differences and, in particular, important life aspects such as "*happiness, physical and psychological health, [...] quality of relationships with peers, family, and romantic others [...] occupational choice, satisfaction, and performance, [...] community involvement, criminal activity, and political ideology*" [22].

The literature proposes different personality models (see [19] for an extensive survey), but this work is based on the *Big-Five* [18], the most commonly adopted and effective personality model both in psychology [24] and computing [6]. The main advantage of the model is that it represents personality as a five-dimensional vector where each component corresponds to a *trait*, i.e., an observable tendency that different people can display to a different extent. When the component corresponding to a trait is large, it means that a person tends to display the associated tendency more frequently or more intensely than the others. Vice versa, when the component is small, it means that an individual displays the tendency less frequently or less intensely than the others.

The Big-Five traits are as follows:

- *Openness*: tendency to be artistic, curious, imaginative, insightful, original, to have wide interests, etc.
- *Conscientiousness*: tendency to be efficient, organized, reliable, responsible, thorough, etc.

- *Extraversion*: tendency to be active, assertive, energetic, outgoing, talkative, etc.
- *Agreeableness*: tendency to be appreciative, kind, generous, forgiving, sympathetic, trusting, etc.
- *Neuroticism*: tendency to be anxious, self-pitying, tense, touchy, unstable, worrying, etc.

Measuring the personality means to quantify the tendencies above in such a way that individuals that display them more frequently or more intensely receive a higher score than the others. The most common way to perform such a task is to use questionnaires where every item is associated to a Likert scale, the answers can be mapped into numbers and these, after applying appropriate algorithms, provide the scores corresponding to the traits. The questionnaire adopted in this work is the *Big Five Inventory 10* (BFI-10) [23], an instrument that has the advantage of providing reliable measurements while including a limited number of items and, hence, requiring only a limited time to perform an assessment.

The BFI-10 can be used in two ways (see Table I). The first corresponds to using the questions in first person and its result is the personality that individuals attribute to themselves (the *self-assessed* traits). The second corresponds to using the questions in third person and the result is the personality that individuals attribute to others (the *attributed* traits). In the experiments of this work, the BFI-10 in the second way to obtain the traits that the observers attribute to the robot when it performs the 45 stimuli described in Section II-A (one assessment for each stimulus).

The agreement between the observers can be measured in terms of *effective reliability* R [25]:

$$R = \frac{Nr}{1+(N-1)r}, \tag{1}$$

where N is the total number of observers and r is the average of the correlations between individual observers:

$$r = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=i+1}^{N} r_{ij}. \tag{2}$$

In the equation above, r_{ij} is the correlation between the personality scores attributed by observers i and j. In the experiments of this work, the effective reliabilities are 0.96 for Openness, 0.95 for Conscientiousness, 0.91 for Extraversion, 0.90 for Agreeableness and 0.89 for Neuroticism. All values are above the threshold of 0.80 that the literature considers to be the minimum for the judgments to be considered acceptable [26].

III. Methodology

This section presents the two main questions that have been addressed in the experiments of this work and the methodologies that have been adopted for the purpose.

A. Analysis of Attributed Traits

The first question that this article addresses is whether there is an association between the gestures that a robot displays - represented in terms of amplitude α and speed λ - and the traits that human observers attribute to it. During the experiments, $N = 30$ human observers have filled the assessment version of the BFI-10 questionnaire [23] (see Section II-B) after watching each of the 45 stimuli described in Section II-A (all observers have assessed all stimuli). This means that, for a given stimulus, the assessment process leads to a matrix A such that the element a_{ij} is the score that subject i has assigned in correspondence of trait j, where the value of i ranges between 1 and N and the value of j ranges between 1 and 5 (the number of traits in the Big-Five personality model).

For a given trait j, the following sum t_j can be thought of as the total score that a given stimulus (s, α, λ) has received (the index s is omitted for clarity):

$$t_j^{(\alpha,\lambda)} = \sum_{i=1}^{N} a_{ij}^{(\alpha,\lambda)}. \tag{3}$$

Correspondingly, the following sum can be thought of as the total score that the variants of a given core stimulus have received for the trait:

$$T_j = \sum_{\alpha} \sum_{\lambda} t_j^{(\alpha,\lambda)}, \tag{4}$$

where the sums run over all values of α and λ. The expressions above allow one to define the following χ^2 variable [27]:

$$\chi^2 = \sum_{\alpha} \sum_{\lambda} \frac{(t_j^{(\alpha,\lambda)} - E)^2}{E} \tag{5}$$

where $E = T_j/9$, i.e., the total score accumulated along trait j by the 9 variants of the same core gesture. The probability density function $p(\chi^2)$ of the χ^2 variable is known when the null hypothesis is true, namely when the scores distribute uniformly across the variants of the same core gesture. Thus, it is possible to estimate the probability of the χ^2 variable to be at least as much as the value observed in the data and, if such a probability is lower than a given confidence level (typically 0.05), it is possible to say that there is a statistically significant association between, on the one side, the trait j and, on the other side, amplitude and speed of the gestures.

B. Personality and Godspeed

The second question that the article addresses is whether personality can act as a mediation variable with respect to the quality of interaction, i.e., whether the attributed traits are predictive of it. For this reason, the observers have been asked to fill not only the BFI-10, but also the Godspeed questionnaire [20]. Such an instrument measures the following tendencies associated to the interaction between people and robots:

- *Anthropomorphism*: tendency of human users to attribute human characteristics to a robot;
- *Animacy*: tendency of human users to consider the robot alive and to attribute intentions to it;
- *Likeability*: tendency of human users to attribute desirable characteristics to a robot;

	Ope		Con		Ext		Agr		Neu	
Core Stimulus	α	λ	α	λ	α	λ	α	λ	α	λ
Engaging					$\uparrow$	$\uparrow$			$\uparrow$	$\uparrow$
Disengaging							$\downarrow$	$\downarrow$	$\uparrow$	$\uparrow$
Pointing					$\uparrow$	$\uparrow$			$\uparrow$	$\uparrow$
Head-Touching					$\uparrow$	$\uparrow$				
Cheering					$\uparrow$	$\uparrow$			$\uparrow$	$\uparrow$

TABLE II

THE SYMBOLS "$\uparrow$" AND "$\downarrow$" ACCOUNT FOR STATISTICALLY SIGNIFICANT EFFECTS ($p < 0.05$ ACCORDING TO A χ^2 TEST AFTER APPLYING THE FALSE DISCOVERY RATE CORRECTION [28]). THE SYMBOL "$\uparrow$" MEANS THAT INCREASING AMPLITUDE OR SPEED CORRESPONDS TO OBSERVING HIGHER PERSONALITY SCORES. THE SYMBOL "$\downarrow$" MEANS THAT INCREASING AMPLITUDE OR SPEED CORRESPONDS TO OBSERVING LOWER PERSONALITY SCORES. EMPTY CELLS CORRESPOND TO CASES IN WHICH NO STATISTICALLY SIGNIFICANT EFFECTS HAVE BEEN OBSERVED.

- *Perceived Intelligence*: tendency of human users to consider intelligent the behavior of a robot;
- *Perceived Safety*: tendency of human users to consider safe the interaction with a robot.

The association between the attributed traits and the Godspeed scores has been measured with the *Spearman's Rank Correlation Coefficient* [27].

$$r = 1 - \frac{6\sum_{k=1}^{M} d(t_k, g_k)}{M(M^2-1)} \tag{6}$$

where t_k and g_k are the average trait and Godspeed scores, respectively, assigned by the 30 observers to stimulus k, and $d(t_k, g_k)$ is the difference between the rank of t_k and the rank of g_k in the ordered lists of the t_is and g_is assigned to the 45 stimuli, respectively. The main advantage of the Spearman coefficient with respect to other measures of correlation is that it is based on the ranking of the variable values observed in the data. In this way, the coefficient is more robust to possible outliers. When the correlation between a personality trait and a Gospeed score is statistically significant, it means that the former is actually predictive of the other.

IV. Experiments and Results

The experiments of this work have involved $N = 30$ observers (20 female and 10 male) that have been asked to watch the 45 stimuli described in Section II-A and, for each of them, to fill the BFI-10 questionnaire in third-person form. Furthermore, the subjects have been asked, for each stimulus, to fill the Godspeed questionnaire. All observers have rated all stimuli during three sessions held in three consecutive days (15 stimuli per session). The subjects have been selected randomly from a pool of assessors available at the University of Glasgow, where the experiments have been performed. The participants have been paid according to the law of the UK. The rest of this section presents the results obtained during the experiments. The observers involved in the same session have filled the questionnaires while sitting in front of the robot at a distance of roughly 1.5 meters. The questionnaires have been filled through a software interface running on a tablet.

A. Attributed Traits

Table II shows the interplay between personality traits and parameters adopted to change the shape of the core stimuli, namely amplitude α and speed λ. Statistically significant effects are observed for Extraversion, Agreeableness and Neuroticism, but not for Openness and Conscientiousness. One possible explanation is that these latter traits are less socially oriented than the others (the BFI-10 questions related to them do not revolve around interpersonal behaviour like the questions related to the other traits). This means that the adoption of communicative gestures (see Section II-A), inherently targeting a scenario of interpersonal interaction, is likely to reduce their chances to emerge clearly. In other words, according to the terminology of personality science, Openness and Conscientiousness are less *relevant* [29] than the others to the setting.

In the case of Extraversion - the trait that people tend to attribute more consistently and coherently across different contexts [30] - there are statistically significant effects for the variants of all core stimuli except Disengaging. The probable reason is that Extraversion accounts for the tendency to attract social attention [31], while the main communicative goal of the Disengaging gesture is to reject social attention. For all other core stimuli, the Extraversion ratings tend to become higher when α and λ increase. In the case of α, the positive correlation between the spatial extension of gestures and Extraversion has been observed earlier both in the case of people [32] and artificial agents [16]. When it comes to λ, higher speed corresponds to higher energy and such a term is often adopted as a synonym of Extraversion (see, e.g., [33], [34]). The association between the two concepts - observed since the earliest studies on the Big-Five based on lexical approaches - is the probable explanation of the effect.

Higher α and λ values tend to be associated with lower Agreeableness scores for the Disengaging core stimulus. The probable reason is that the main communicative goal of the gesture is to avoid interaction or reject users (the tags that the robot manufacturer assigns to the animation are "*negative*", "*no*", "*oppose*", "*refute*" and "*reject*"), two messages that are not aligned with the main tendency Agreeableness accounts for, i.e., to do what others like [18]. Increasing spatial extension and energy is likely to be interpreted as a more resolute attempt to avoid interaction and, hence, as a less agreeable attitude towards others.

Finally, Table II shows that there are statistically significant effects for Neuroticism in correspondence of all core stimuli except Head-Touching. In all cases, the tendency is to observe higher scores for the trait when amplitude and speed increase. One possible explanation is that the literature reports on relationships between emotional expressiveness and Neuroticism (see [35], [36] for a survey), the reason being that such a trait is often referred to as *Emotional Stability* and it accounts for the tendency to be stable (or unstable) from an emotional point of view. This suggests that Higher spatial extension (higher α) and energy (higher λ) of gestures are probably interpreted in terms of higher emotional arousal

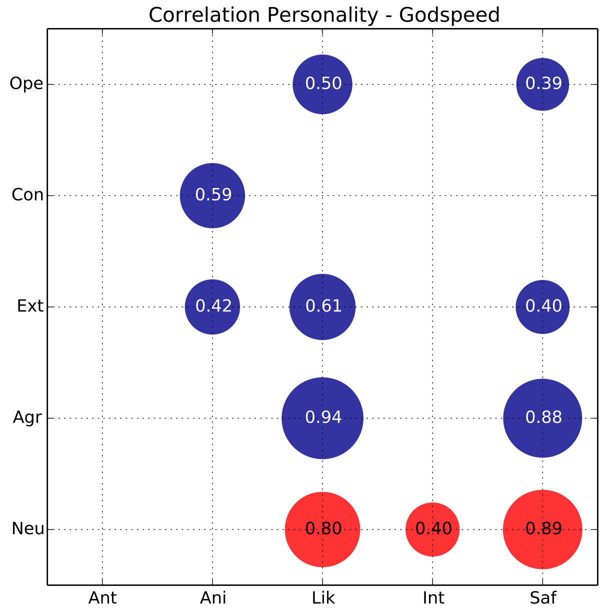

Fig. 1. Correlation between personality traits and Godspeed scores. The size of the bubble is proportional to the absolute value of the correlation, blue and red bubbles correspond to positive and negative correlations, respectively. The plot includes only statistically significant correlations ($p < 0.05$ after applying the False Discovery Rate correction [28]).

and, hence, lower emotional stability or, equivalently higher Neuroticism.

B. *Godspeed and Attributed Traits*

The second question addressed in the experiments is whether the attributed traits are predictive of the users' experience. For this reason, Figure 1 shows the correlation between personality traits and Godspeed scores that the observers have attributed to the 45 stimuli used in the experiments. Overall, the plot suggests that the Big-Five traits are predictive, in particular, of Likeability and Perceived Safety. In the first case, the correlation is positive with socially desirable traits (Openness, Extraversion and Agreeableness) and negative with Neuroticism, the only trait of the Big-Five that is not socially desirable. In this respect, the result seems to embody the intuitive tendency to like more robots that convey better personality impressions. Such an evaluative aspect of social perception has been shown to be typical of zero acquaintance judgments like the ones of the experiments [37].

In the case of Perceived Safety, the pattern is the same as in the case of Likeability: positive correlation with socially desirable traits and negative correlation with Neuroticism. A plausible interpretation of such a result is that the observers tend to consider safer those robots that convey socially desirable impressions. One possible explanation, is that higher scores along desirable attributed traits correspond to the expectation of desirable behavioral tendencies (e.g., to be kind and sympathetic in the case of Agreeableness) and vice versa in the case of lower scores (e.g., to be aggressive and hostile in the case of Agreeableness) [21].

In the case of Animacy, there is a positive correlation with Conscientiousness and Extraversion. The probable explanation is that the attribution of personality traits corresponds to the attribution of "*patterns of thought, emotion, and behavior together with the psychological mechanisms - hidden or not - behind those patterns*" [21], i.e., of inner processes allowing the robot to move "*without an external push or pull*" [20], the very property Animacy corresponds to. As both Extraversion and Conscientiousness are socially desirable traits, the finding seems to suggest that the observers tend to consider more life-like the robots that convey good personality impressions and, vice versa, more machine-like those that convey negative personality impressions. Finally, the relationship between Neuroticism and Perceived Intelligence appears to parallel similar effects observed in educational settings (see, e.g., [38]), where more neurotic students tend to be perceived as having lower levels of educational attainment.

V. Conclusions

This work has investigated the role of the Big-Five personality traits [18] as a mediation variable between the observable behavior of a robot - amplitude and speed of gestures in the experiments of this work - and quality of Human-Robot Interaction according to the Godspeed questionnaire [20]. In other words, the experiments of this work have investigated the relationship between the traits that 30 human observers attribute to themselves (the self-assessed traits), the traits that they attribute to the robot (the perceived traits) and the Godspeed scores.

The experiments have shown that there is an interplay between amplitude and speed of the gestural stimuli on the one side and, on the other side, Extraversion and Neuroticism, in line with the experimental observations collected since the earliest experimental studies on nonverbal communication between humans [32], [35]. Higher amplitude and speed are associated with both higher Extraversion and Neuroticism. Hence, any attempt to increase attributed Extraversion - a desirable trait - results into an increase of perceived Neuroticism - a non-desirable trait. One possible solution is to associate the gestural stimuli with other communication channels (e.g., speech or head movements) so that possible *emergence* effects - the observation of effects that are different from those obtained with individual modalities [7], [8] - can avoid the need of a compromise between the two conflicting tendencies above.

Further analysis shows that there are statistically significant correlations between attributed traits and Godspeed scores, especially when it comes to Likability and Perceived Safety. In this case as well, the results appear to be in line with observations made about person perception in the case of humans [37], where it has been shown that people tend to like more others that hold desirable personality traits above the average. Finally, the experiments have shown that the similarity-attraction effect takes place for the majority of the subjects involved in the experiments, but not for all, possibly explaining while the evidence about the phenomenon is contradictory in the literature [6].

The main implication for the design of the interaction with social robots is that, overall, personality acts as a mediation variable between the observable behavior of the robot and the experience of the users. In other words, the traits that the users attribute to the robot are predictive of the quality of the interaction, at least along the dimensions measured by the Godspeed questionnaire. Furthermore, the results of this work suggest that, at least for the cases addressed in the experiments, the observers attribute the traits to the robots following the same patterns as those observed in the literature for the attribution of traits to humans. This suggests that shaping HRI according to the effects observed in the literature for human-human interaction is a safe choice when it comes to the optimization of the Godspeed scores.

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