Virtual Human Characteristics Impact on User Emotion

A Comparative Analysis of EEG Patterns Elicited by VH Visual Characteristics

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This study examines the impact of human-like characteristics of VHs on user reactions. By analyzing EEG data in response to differences in voice modulation, eye contact, and facial expressions in VHs, we investigate the emotional dimensions of human-to-VH interactions. Participants interact with VHs while wearing the NeuroSky Mindwave Mobile 2 EEG headset, allowing the measurement of user reactions through EEG data. This method enables the quantification of emotional responses, providing a unique insight into the dynamics of these interactions. The study highlights the critical role of human-like characteristics in VH design, suggesting that such features may improve user experience by fostering trust. These insights have important implications for the development of empathetic VH technologies across various applications. Future research should explore the impact of these interactions in professional domains where trust is essential.

CCS CONCEPTS •

Additional Keywords and Phrases: VHs, Human-Computer Interaction, Trust, Brainwave Data, Emotional Response.

1 INTRODUCTION

Virtual Humans (VH) are graphical representations usually available in various gaming scenarios. Specifically, we are concerned with highly realistic 3D VH representations and the focus is on the facial representation [1]. Brain-Computer Interfaces (BCIs) using dry sensor technology are systems that allow electroencephalogram data collection. Several biometric devices such as Electroencephalography (EEG), Electromyogram (EMG), and functional magnetic resonance imaging (fMRI) facilitate the measurement of brain activity. In recent years, the development of dry sensor technology capable of sensing human brain activity led to the employment of Brain-Computer Interfaces (BCI) in various fields ranging from rehabilitating stroke victims [2] to allowing pelagic people access to forms of competition [3]. BCI enables data collection regarding brain activity. BCI technology may change the way that humans interact with the environment and each other. It has the potential to connect internal human predilection under the form of EEG data with external devices, enabling seamless communication between the human and the computer. BCI technology can be invasive, semi-invasive, or non-invasive [5]. Non-invasive wearable headsets using dry-sensor technology [12] are utilized to objectively collect brain waves, which can lead to emotion classification.

Levels of trust, comfort, or emotions of a user may be assessed qualitatively through self-report questionnaire data, however, there is no obvious way to quantitatively measure user trust, comfort, or emotions. We intended to convert abstract brainwave data into quantified emotional responses from users, thereby pushing the boundaries of how VHs can interact and relate to users in a more human-like manner. This study contributes to knowledge in human-computer interaction and also paves the way for more empathetic and responsive VH technologies in the future. By examining the influences of voice modulation, eye contact, and facial expressions, we seek to uncover deeper insights into the psychological and emotional dimensions of human-to-VH interactions. These findings could have significant implications not just for enhancing user experience in virtual environments but also for advancing the development of VHs in various professional and personal contexts.

2 Related Works

2.1 Virtual Humans

A virtual human (VH) is a type of virtual assistant embodied in a digital representation of a human. It may be implemented in several ways, including visually as a human-like avatar or audibly as a voice [5]. Intelligent assistants are becoming more commonplace and are employed in a variety of fields such as software, mechanics, architecture, medical services, legal services, aerospace, and education, in addition to personal assistants for private use [2]. VHs may be driven by complex data and algorithms that give them intelligent behavior, transforming them into AI characters trained for content-specific conversations. They listen, respond, and engage in dialogue with learners [8].

Users can be skeptical about intelligent VH assistants. In a phenomenon known as “algorithm avoidance,” people are inclined to trust human judgment over the judgment of an algorithm, which can lead to incorrect results as algorithms often perform better than humans. Users are also more comfortable with the concept of algorithms being used for analytical work than for work described as requiring emotion [3].

Several factors can influence the trust a user has towards a VH based user interface. Increasing ease of use, usefulness, anthropomorphism, perceived intelligence, and perceived animacy can improve a human’s attitude toward a VH [4]. Specifically, an increase in the accuracy of human-like characteristics possessed by a VH produces an increase in the social responses a human has to the VH [5]. For our research, we chose to focus on the effects of various levels of anthropomorphism and animacy.

One of the most significant human-like characteristics that a VH can possess is a facial embodiment. A facial embodiment may or may not include non-verbal expressions that can imply emotion. Prior research shows that interactions between a human and a VH are more positive when the VH has an expressive facial embodiment than when the VH has no facial embodiment [5]. Personal bias can also play a role in how a human perceives a VH, with preference given to VHs who share characteristics with the human user [6].

Figure 1 features how long it took for participants to complete an assortment of puzzles in the presence of different digital human representations, with the controls being a human presence and no presence. The vertical values represent the average distance from the mean in standard deviations, with the lower and higher values representing faster and slower completion, respectively[5].

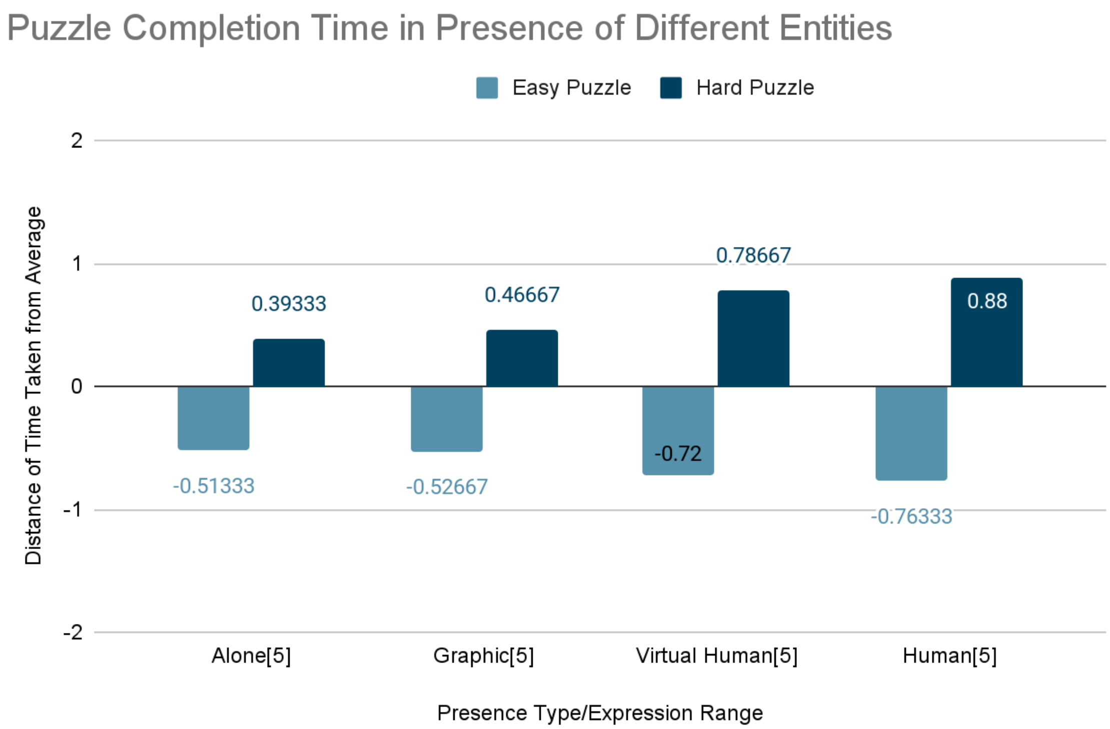

Figure 1.

Studies on trust related to eye contact explore a critical aspect that influences user experience and trust dynamics. In exploring the significance of eye contact with VHs, one psychophysiological study conducted in virtual reality sought to ascertain whether similar attention and emotion-related responses could be elicited in a virtual environment as in face-to-face interactions. This investigation analyzed participants' physiological responses, including heart rate (HR) and skin conductance responses (SCR), in reaction to avatars displaying direct or averted gaze in a virtual reality setting. The findings suggest that while eye contact with a live person elicits substantial attention and emotion-related psychophysiological responses, the physiological effects of eye contact are diminished in virtual reality (VR) environments [9].

Figure 2 displays the mean valence levels of participants after direct and indirect interactions with humans and VHs. In the graph “valence” represents the level of positive emotion a participant may be experiencing, while “direct” and “indirect” represent the type of interaction between a participant and human or VH. In the first study, valence was measured using SCR [9]. In the other study, valence was measured using self-reported data from surveys [5].

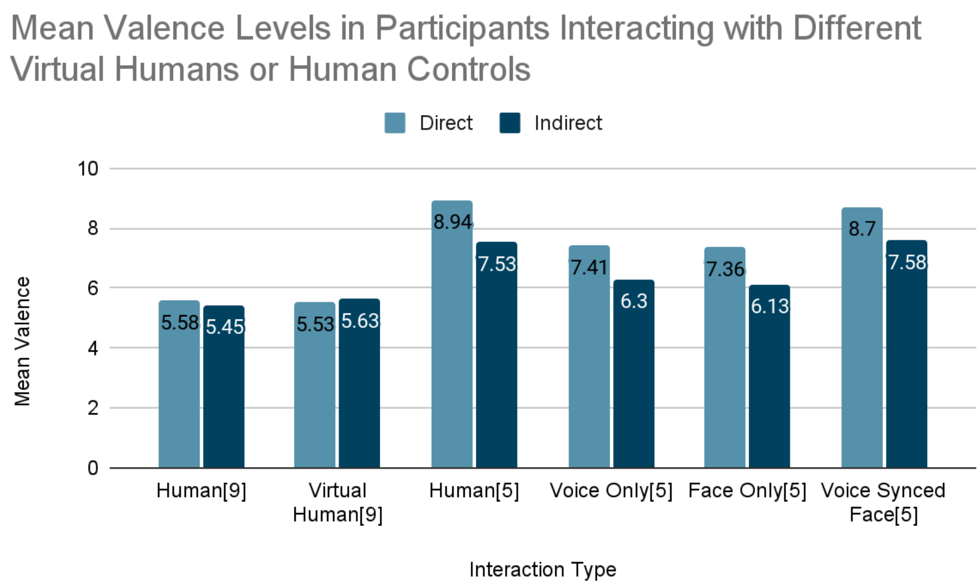

Figure 2.

The exploration of eye contact in VR with another user's avatar can create an impression of bidirectional visual interaction between two people, potentially evoking a sense of being akin to eye contact with a live person. Notably, the SCR, indicative of physiological arousal, exhibited a larger response to direct gaze compared to averted gaze only in the Live condition, suggesting that while eye contact with a live person evokes significant attention and emotion-related psychophysiological responses, the impact of eye contact is somewhat attenuated in VR settings. These findings underscore the nuanced nature of trust dynamics in virtual interactions, where factors such as eye contact play a crucial yet complex role in shaping user experience and perceptions of trustworthiness.

Voice quality is vital for human trust during VH interaction. During a study conducted on student participants, statistically, the participants described the text–to–speech voice as boring, eerie, and supernatural [7]. The participants believed the recorded voice was easier to understand [7]. This could contribute to the feelings of mistrust from a human or poor voice quality of the VH.

In another study, participants went through two experiments. The first had a voice-synced facial appearance VH and the voice-synced facial appearance conveying emotion VH produced stronger social facilitation than the other VH types and had no statistical difference compared to performance in the human presence condition [5]. The second experiment tested for politeness, and the participant's statistical responses were the same as the first experiment [5]. Research seems to show that an increase in human-like characteristics in a VH does more strongly elicit social responses in humans [5].

Figures 3 and 4 both feature data from the same studies. Figure 3 shows the decrease in negative emotional states in participants after interacting with a VH. Figure 4, similarly, illustrates the increase of positive emotions of participants after interacting with a VH. Figure 4 also includes participants' willingness to engage in study groups before and after interacting with the VH.

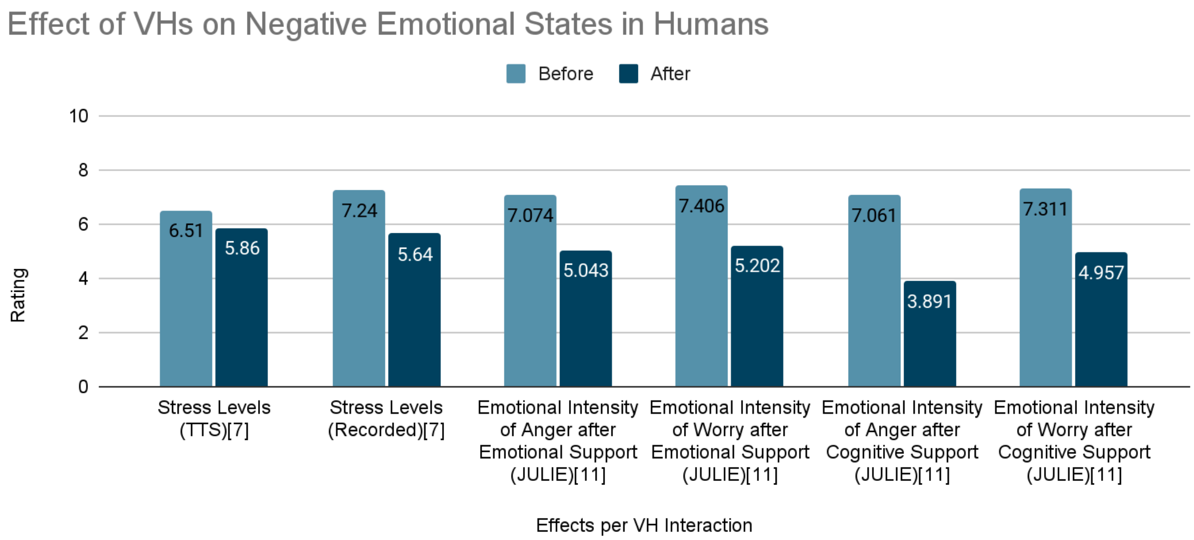

Figure 3.

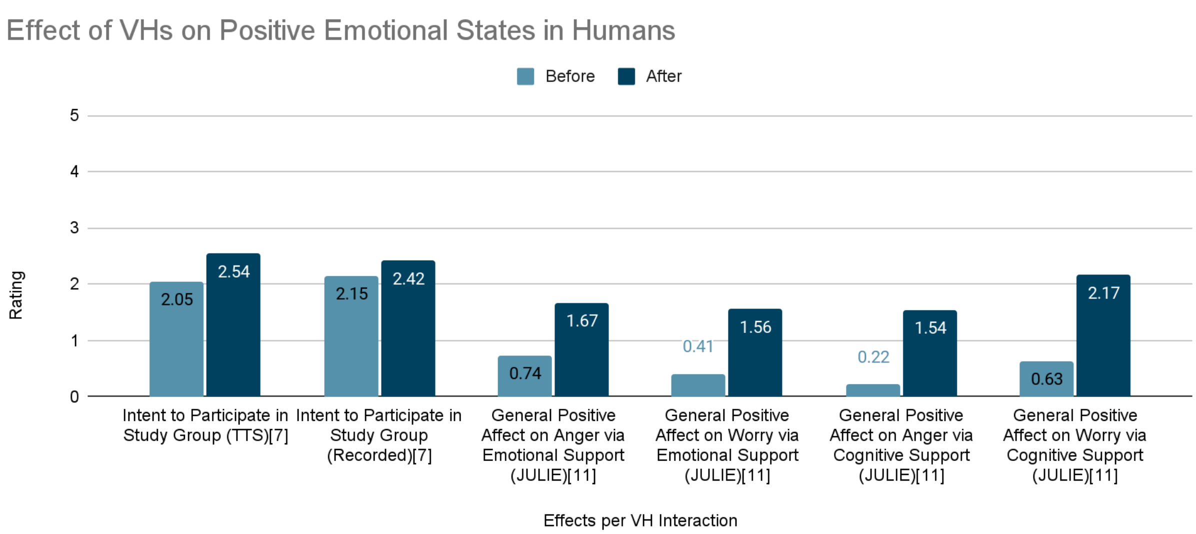

Figure 4.

Figure 5 displays the levels of co-presence participants experienced when interacting with various VHs. One study used a VH named JULIE who was designed to show more emotional support or cognitive support towards the participants, depending on the version [11]. The other study, however, divided its different VHs by whether they were 2D or 3D, and whether they were Verbal or Non-Verbal [12].

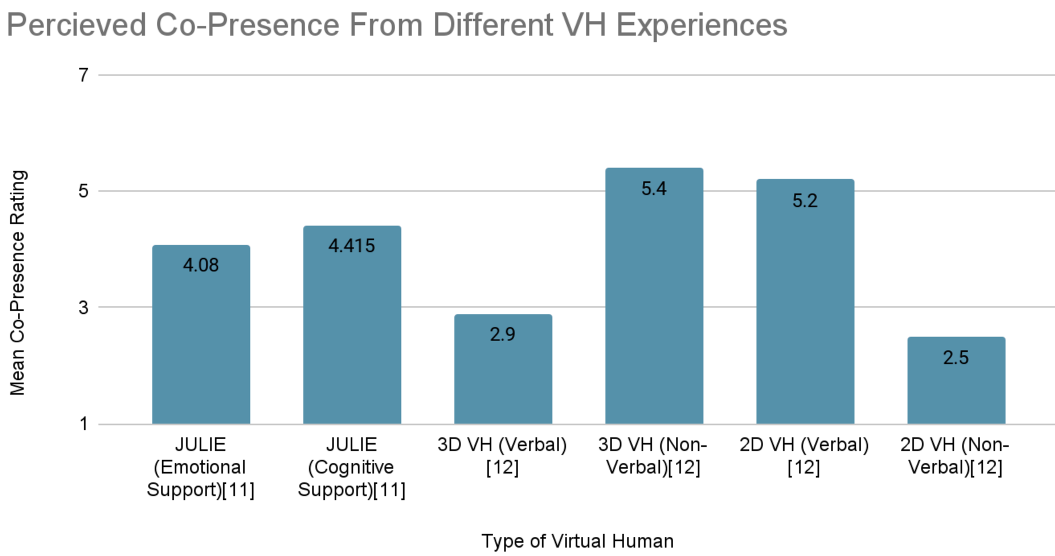

Figure 5.

2.2 Electroencephalography

Human emotions are generated by the mind and an important apparatus is the brain. Some analysis of the electric data generated by the brain (EEG) may provide insights into human emotion. Due to differences in individuals, emotions are complex to decode. Significant research has been conducted into classifying human emotions collected through EEG data using a variety of algorithms [13]. There are two common approaches to classifying brainwaves into emotions. The first approach quantifies valence, arousal, and dominance [14]. Valence is the measure of positivity of the emotion, from happy to unhappy. A higher valence corresponds to a higher sense of happiness. Arousal is used to measure the excitement level of the subject, from a calm state to excitement. Dominance is used to distinguish between emotions that have similar VA measures, such as fear and anger

The second approach attempts to correlate each emotion with a specific pattern of brainwaves. Brainwaves are classified into five groups according to their frequency. Delta waves range from approximately 1-3 Hz, theta waves range from approximately 4-7 Hz, alpha waves range from approximately 8-12 Hz, beta waves range from approximately 13-30 Hz, and gamma waves range from approximately 30-50 Hz. The EEG data loaded is classified using Machine Learning classifier models similar to the method by Lu. KNeighborsClassifier, DecisionTreeClassifier, RandomForestClassifier, AdaBoostClassifier, GradientBoostingClassifier, GaussianNB, LinearDiscriminantAnalysis, and XGBClassifier are the models we utilized for the experiment. The input and output can be a sequence of data. Deep learning neural networks process sequential data on a time axis [14]. Each layer is a combination of several hidden layers with the same weight and bias [14]. The Lu experiment aimed to classify negative, positive, and neutral three kinds of brain wave emotions which have a good average accuracy of 81.26% [13].

3 VH Interaction Experiment

3.1 Experimental Setup

1. Participants are informed on what they will be doing during the experiment.
2. Participants are given a pre-experiment survey to establish a baseline of their emotional state and their previous experiences with VHs.
3. Participants are aided in putting on the Neurosky Brain-Computer Interface (BCI).
4. Participants will sit in a quiet room without distractions to establish a baseline of their encephalographic data prior to VH exposure.
5. Each participant is given 12 trials in a randomized order in which they interact with a VH on a computer while wearing the BCI.
    a. In each trial, the VH will present a different combination of voice, eye contact, and facial animation traits.
    b. Participants will use the computer mouse to answer 10 yes/no questions prompted by the VH while the BCI collects EEG data.
    c. Participants are given a post-trial survey to further assess their reaction to and opinion of the VH.
    d. Repeat until 12 trials are over.
6. Participants are assisted in taking off the BCI.
7. The EEG data collected from the BCI is processed using a Python program to determine significant differences in user reactions.
8. The questionnaire data is analyzed to determine significant differences in user reactions.

4 Experimental Results

We expand on previous research by exploring the effects of differences in appearance, eye contact, and voice quality on the perception of a VH by a human user.

Our methodology employs a unique amalgamation of characteristics across different levels, with each trial incorporating a combination of these traits. These trials were carefully constructed to investigate the impact of human-like attributes on the likability of VHs. Specifically, we examined the influence of voice type (Robot, Artificial, and Human), eye contact (Yes or No), and animation (Yes or No) on participants' perceptions. Notably these characteristics were integrated simultaneously in each trial, allowing for a comprehensive exploration of their combined effect. Using a brain-computer interface, we collected quantitative data in an attempt to find a trend in EEG data across users that could be correlated with changes in VH traits. In addition to our EEG analysis, we conducted pre-experiment and post-trial questionnaires to gather qualitative data on participants' perceptions following each interaction level. These questionnaires provided valuable insights into users' subjective experiences and allowed us to complement the EEG findings with rich qualitative data.

4.1 EEG Data

To analyze the EEG data, the mean frequency band for each user was calculated for each trial. These averages were compared across all participants and trials. Additionally, for each participant, the total brainwave voltage difference from their EEG baseline data was compared across all participants and trials.

Despite the robustness of our study design, wherein each trial represented an incremental increase in complexity, the EEG analysis results did not consistently demonstrate discernible patterns in brainwave data across various levels of VH interaction. Based on variations in eye contact, voice quality, and facial animation, there appears to have been no visible uniform trend in EEG data changes across all users. Additional research with a larger sample size and more statistical analysis is required to confirm or negate these findings.

4.2 Questionnaire Data

Analyzing the questionnaire responses across the 12 trials and considering the different configurations of the VH (varying voice type, eye contact, and animation presence), a trend can be observed relating to the perception of the VH by users before and after the interaction.

The responses across the 12 trials and considering the different configurations of the VH (varying voice type, eye contact, and animation presence), a trend can be observed relating to the perception of the VH by users before and after the interaction.

Voice Type: Trials with a human voice (Trials 3, 6, 9, and 12) tend to have more positive responses compared to those with robot or artificial voices, especially when combined with eye contact and animation. Eye Contact: Introducing eye contact (Trials 4-6, 10-12) leads to more positive or very positive responses compared to trials without eye contact (Trials 1-3, 7-9), suggesting that eye contact significantly influences user perception positively. Animation: The presence of animation (Trials 7-12) tends to improve the user's response, moving from neutral or negative to more positive responses, especially when combined with human voice and eye contact (Trial 12), indicating that animation enhances the perceived warmth or liveliness of the VH.The most notable positive shift in responses is observed in trials where all features (human voice, eye contact, animation) are combined (Trial 12), indicating that users respond more positively to the most human-like interactions.

5 Conclusion

In summary, the trend from the qualitative data indicates that features making the VH more human-like (human voice, eye contact, animation) lead to more positive responses. The most favorable responses come from the combination of all three features, underscoring the importance of designing VHs with human-like characteristics for positive user interaction. Interestingly, while the qualitative feedback was clear, the quantitative EEG data did not show a consistent trend, indicating that emotional responses may not always be directly measurable through brain activity alone.

This suggests that subjective measures of user experience are crucial for understanding the impact of VH characteristics. The varying preferences for eye contact, with some users feeling more comfortable without it, point to the need for adaptable interfaces that can cater to individual differences in comfort and familiarity. This finding underscores the potential benefits of customizable VH features to improve user engagement and satisfaction. Overall, the study contributes valuable insights into designing VHs that are both effective and well-received by users. Such designs could reduce algorithm avoidance and increase the acceptance and efficiency of VHs in professional and personal settings, offering a promising avenue for future research and development in human-computer interaction.

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