Finding "H" in HRI:
Examining Human Personality Traits, Robotic Anthropomorphism, and Robot Likeability in Human-Robot Interaction

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ABSTRACT

The study examines the relationship between the big five personality traits (extroversion, agreeableness, conscientiousness, neuroticism, and openness) and robot likeability and successful HRI implementation in varying human-robot interaction (HRI) situations. Further, this research investigates the influence of human-like attributes in robots (a.k.a. robotic anthropomorphism) on the likeability of robots. The research found that robotic anthropomorphism positively influences the relationship between human personality variables (e.g., extraversion and agreeableness) and robot likeability in human interaction with social robots. Further, anthropomorphism positively influences extraversion and robot likeability during industrial robotic interactions with humans. Extraversion, agreeableness, and neuroticism were found to play a significant role. This research bridges the gap by providing an in-depth understanding of the big five human personality traits, robotic anthropomorphism, and robot likeability in social-collaborative robotics.

KEYWORDS

Agreeableness, Big Five, Conscientiousness, Extroversion, HRI, HRI Implementation, Neuroticism, Openness, Robot Likeability, Robotic Anthropomorphism, Social-Collaborative Robotics, Uncanny Effect

INTRODUCTION

Technology has been improving our lives dramatically and drastically in the last several decades. COVID-19 pandemic and the changing landscape presents a testimony to the above statement. Technology is playing an important role in our lives today, and we are trying to find a new normal during the present world crises through technology usage. The 'new normal' emerging out of the current turbulent times will subsequently need more technology usage and enhancement whether it means connecting students online; schools and Universities experimenting more with online/hybrid classes; continuous and consistent sanitation requirements of high touch areas in both developed and emerging economies; remote work possibilities for people who are sick, unwell, elderly or sensitive; reduced face-to-face interaction for increasing productivity, and much more. For achieving all this, we will need 'social robots' in our everyday lives to meet the new demands of the ever-changing

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global world. Social robots provide comfort to the elderly and have shown to improve their well-being (Wada & Shibata, 2007). People who feel lonely, tend to anthropomorphize robots more than others (Samuel, 2019). These social robots may serve as tools and agents to alleviate their loneliness (Eyssel & Reich 2013) and additionally decrease their stress levels (Wada et al. 2004). Social robots are known to have been used in a variety of situations including (but not limited to) patients suffering from dementia, therapeutic applications for children with autism, adults with health issues, mental health issues, and in stroke patients' recovery processes (Tapus, Ţăpuş, & Matarić 2008; Ab Aziz 2015; Libin & Libin 2004).

Human-robot interaction (HRI) is a research domain dedicated to understanding communication between robots and humans (Kaplan, 2019). This research area is gaining popularity and attention in the diverse fields of study – science, technology, engineering, and mathematics (STEM), along with business and management (Arora & Arora, 2020). One of the early contributions to HRI study is artificial intelligence research. Artificial Intelligence (AI) is a term used for robotic technologies, which refers to the ability of computers/robots to acquire knowledge and think like humans (Arora & Arora, 2020). With the advancement in AI technology and the expansion of HRI, social-collaborative robots have emerged in HRI space in the past few years (Lungarella et al., 2003). According to the Big Five trait taxonomy, personality can be broadly classified as being comprised of five significantly different traits. These five characteristics are Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness (Goldberg, 1981), and the generalizability of the Big Five dimensions remains constant across all cultures (McCrae & Costa, 1997; Pulver *et al.*, 1995; Salgado, 2002). 'Extraversion' is a trait that is energetic and enthusiastic to social settings, and typically emotionally positive. 'Agreeableness' can be described as affectionate, altruistic, modest, and sympathetic. 'Conscientiousness' refers to an organized, responsible, reliable, goal-oriented, and controlled personality style. 'Neuroticism' is characterized as tense, anxious, fearful to the world around, and typically, emotionally negative and sad. The 'Openness' characteristic is described as open-minded, having broad interests, insightful, and curious (John & Srivastava, 1999). People utilize such personality variables in describing themselves and others as well as in how they perceive the world around them (John & Srivastava, 1999). In this new era of social-collaborative robots where robots are continuously assuming roles of family members, teammates, and/or therapists, Big Five traits can be a strong predictor of differential reaction to robots, and play a crucial role in successful HRI implementations. Given the current turbulent times and the emerging focus on adapting to humanless touch technology, there is a dire need to study and examine Big Five human personality dimensions to understand the field of HRI through the lenses of robotic anthropomorphism, robot likeability, and successful HRI implementation. Our research aims to fulfill this gap.

Robotic anthropomorphism refers to the attribution of human form, behavior, or characteristics to robots (Bartneck et al., 2009). In addition to employing human personality traits or Big Five to understand human/consumer behavior towards robots, we conceptualize that anthropomorphism (along with the Big Five) will help researchers understand HRI. Previous research has examined the impact of anthropomorphism in the field of social robotics (Kaplan, Sanders, and Hancock, 2019). Still, not much literature is available on the role of the Big Five personality traits in the context of robotic anthropomorphism. Robot likeability refers to a positive initial impression (usually within seconds) of robots, and the concept of robot likeability significantly influences our positive or negative judgments about social-collaborative robotics (Bartneck et al., 2009).

There is a dearth of human psychology and consumer behavior research in the field of human-robot interaction. The success of HRI between humans and social-collaborative robotics cannot be assessed without recognizing human judgment towards different levels of robotic anthropomorphism and its subsequent influence on robot likeability. Social-collaborative robotics exhibits social characteristics that are more human-like than traditional artificial intelligence designs. Therefore, developers utilize both robotic anthropomorphism and likeability into account when designing social-collaborative robots for consumers of all ages with either emotional (therapeutic) or physical needs. In order to bridge the identified research gaps in HRI space pertaining to the Big Five, Robotic anthropomorphism, robot likeability, and overall HRI implementation, our research addresses the following questions:

1. Do the Big Five personality traits (Extroversion, Agreeableness, Conscientiousness, Neuroticism, and Openness) impact robot likeability in human-robot Interaction (HRI) situations?
2. Will the degree of human-like attributes in robots (a.k.a., robotic anthropomorphism) influence the likeability of robots?
3. Will robotic anthropomorphism influence the relationship between human personality variables and robot likeability in varying (industrial versus social) HRI situations?

The research makes the following contributions. First, the study focuses on the Big Five human personality traits and how they are linked to positive and/or negative reactions to robots. Previous research (e.g., Eysenck, 1950; Donnellan et al., 2006) has provided evidence of extraversion and how it is linked with robot likeability through strong communication preferences and low communication apprehension (Nomura et al., 2008; Kaplan, Sanders and Hancock, 2019); however there is not much research available on how different human personality traits can be associated with positive and/ or negative reactions towards social robots in varying HRI settings. Kaplan et al. (2019) utilized the Mini International Personality Pool (Mini-IPIP; Donnellan et al., 2006) and examined Big Five personality traits for social robots, yet their research focus was on extroversion-introversion trait and its relationship with anthropomorphism and robot likeability. They did not investigate the entire breadth of Big Five personality traits, and the subsequent impact of Big Five on a positive and successful HRI implementation. Our research aims to fulfill this gap. Second, there is limited research conducted on how these human personality traits are associated with anthropomorphic tendencies, and human's ability to anthropomorphize robots by attributing human-like characteristics to robots (Woods et al., 2007; Letheren et al., 2016; Kaplan, Sanders and Hancock, 2019). Furthermore, the following question arises: Does robotic anthropomorphism acts as a bridge (or mediator) between human personality traits and our reactions and likeability for robots. Our research explores this question and fulfills the research gap through an in-depth examination of robotic anthropomorphism and its relationships with the Big Five human personality traits, along with robot likeability and overall positive/successful HRI implementation. Last but not least, most HRI research focused on any social robot without getting into details of the robot's appearance and its real usage in industry and home settings. The issue of robot morphology plays a significant role in human perception of robots, especially in the context of "two robots of differing appearance, even if they worked in the same job domain" (Kaplan, Sanders, and Hancock, 2019, p. 135) since varying robots' appearances will yield different results with respect to human personality traits and their reactions (likeability) towards robots. In our research, we tried to overcome this research gap by examining two different robots (one social robot used in therapeutic situations called PARO Baby Seal robot, and another industrial robot called KUKA robot generally used in organizations, as a supplier of intelligent automation solutions) through the lenses of Big Five human personality traits; and investigating how anthropomorphism mediates the relationship between Big Five and robot likeability leading to a successful HRI implementation. To the authors' knowledge, this is the one-of-its-kind HRI research attempted in the interdisciplinary areas of Big Five personality traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to experience), robotic anthropomorphism, robot likeability, and successful HRI implementation by utilizing two different robot settings from home and industry.

This article consists of four sections. First, we focus on defining and describing social-collaborative robotics in HRI. Second, we examine how Big Five human personality traits impact social-collaborative robotics either directly or through the mediating effect of robotic anthropomorphism. Thereafter, we investigate the effects of Big Five and robotic anthropomorphism on robot likeability, and the subsequent impact of these HRI interrelationships on the success of HRI implementation. Next, we propose our Personality – Anthropomorphism – Likeability framework and utilize SmartPLS methodology to investigate the impact of our framework on consumers and businesses through human personality traits, robotic anthropomorphism, robot likeability, and (successful) HRI implementation in the context of social-collaborative robotics and HRI.

THEORETICAL FRAMEWORK

Social-collaborative robots possess skills related to cognition (reasoning, planning, manipulation, navigation, etc.), and collaboration through their interaction with human-supported HRI environments (Lungarella et al., 2003). According to Arora and Arora (2020), social-collaborative robots can be classified in multiple categories in the HRI domain – therapeutic robots, physically-assistive robots, robot interrogators, Wizard-of-Oz (WoZ), and industrial robots with human interaction capabilities. Social-collaborative robots not only possess cognitive skills (i.e., logical thinking, decision- making, and consciousness, problem-solving, etc.) but are also equipped with the ability to understand and exhibit social and ethical norms by displaying socially acceptable behaviors (Arora & Arora, 2020). Social-collaborative robots can assist humans in various situations, both therapeutically (emotionally) and physically. Human-robot interaction (HRI) focuses on the interaction between humans and robots (Kaplan et al., 2019). Therefore, it is crucial to understand the human side of personality differences in order to implement HRI successfully. An important question arises here. Do different human personality traits influence (and change) a person's attitudes about and their behavior towards robotic technology? The answer may lie in the extensive research literature available on human personality traits that suggests that all personality measures may be categorized under the umbrella of a 5-factor model of personality, also called the "Big Five" (Goldberg, 1990).

Personality is an essential human attribute for human social interaction, and researchers (e.g., Dicaprio, 1983; Woods et al., 2005; and Tapus and Matarić, 2008) defined personality as: "the pattern of collective character, behavioral, temperamental, emotional and mental traits of an individual that has consistency over time and situations" (Aly and Tapus, 2015, p. 186). Several personality models can be utilized in the human social interaction context, of which the predominant ones are: Big Five (Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism) (Goldberg 1990, 1999); Eysenck Model of Personality (PEN) (P: Psychoticism, E: Extraversion, and N: Neuroticism) (Eysenck 1953, 1991); and Meyers-Briggs (Extraversion-Introversion, Sensation-Intuition, Thinking-Feeling, and Judging-Perceiving) (Myers-Briggs and Myers 1980; Murray 1990). We use the Big Five personality traits for our HRI research, as "it is the most descriptive model of human personality" (Aly and Tapus, 2015, p. 186). The 5-factor structure of Big Five personality model has been analyzed in various languages, integrated into existing personality inventories (McCrae & John, 1992; Judge et al., 1999); assimilated and generalized across all cultures (McCrae & Costa, 1997; Pulver et al., 1995; Salgado, 2002), and has maintained stability and consistency over time (Costa & McCrae, 1992). The big five personality traits are: (1) *Extraversion,* which "implies an energetic approach toward the social and material world and includes traits such as sociability, activity, assertiveness, and positive emotionality"; *Agreeableness,* which "contrasts a prosocial and communal orientation toward others with antagonism and includes traits such as altruism, tender-mindedness, trust, and modesty"; *Conscientiousness,* which describes a "socially prescribed impulse control that facilitates task- and goal-directed behavior such as thinking before acting, delaying gratification, following norms and rules, and planning, organizing, and prioritizing tasks"; *Neuroticism,* which "contrasts emotional stability and even-temperedness with negative emotionality, such as feeling anxious, nervous, sad, and tense"; and *openness to experience,* which measures "the breadth, depth, originality, and complexity of an individual's mental and experiential life" (John et al., 2008: 120).

The current study focuses on extraversion-introversion as strong predictors of diverse reactions towards robots in HRI contexts. Individuals who score high on the extraversion trait tend to be enthusiastic about social settings and are more open to new experiences or entities, typically describing then as likable and/or positive. Extraverts exhibit positive responses to technologies and robots due to low communication apprehension and their inherent ability to demonstrate strong preferences for communication, while introverts portray negative reactions and attitudes towards robots due to their need for higher levels of communication apprehension (Nomura et al., 2008). Since robotic anthropomorphism is linked with human-like characteristics in robots (e.g., facial features of robots like big eyes, smiling face, interactive voice, speech, hand and body gestures integrated into robots like ASIMO, Nao, Kirobo Mini, Pepper, etc.), the ability to anthropomorphize robots is strongly linked to attributing these specific personality traits related to user's personality (Kaplan et al., 2019) leading to robot likeability. Individuals with a high extraversion trait are predicted to show more positive attitudes in HRI settings. Furthermore, since extraversion integrates strong anthropomorphic tendencies (Letheren et al., 2016), we hypothesize that extroversion will be strongly related to robot anthropomorphism in addition to direct relationships and associations with robot likeability in HRI situations. Therefore, we posit the following hypotheses:

H_{1A}: Extraversion will be positively associated with robotic anthropomorphism.
H_{1B}: Extraversion will be positively associated with robot likeability.

Agreeableness is another trait that can be expected to demonstrate a favorable reaction in HRI. This is because agreeableness includes characteristics such as favorable to others, sympathetic and altruistic. Agreeable people are likable, caring, cooperative, good-natured, cheerful and gentle, along with their ability to trust others easily (Judge et al., 1999). Research has shown that the trait of agreeableness is associated with less need for physical distance between robots compared to other traits (Takayama & Pantofaru, 2009). With all the positive traits of agreeable individuals, the cooperative nature of agreeable individuals may lead to more successful careers in life; however, high levels of agreeableness may pose a problem sometimes as they may tend to sacrifice their success in pleasing others (Judge et al., 1999). Conscientiousness is a characteristic that follows social rules and norms dedicated to the achievement of goals, and consists of three significant orientations or facets – (a) dependability orientation (responsible and careful), (b) achievement orientation (hardworking and persistent), and (c) orderliness (planned and organized) (Judge et al., 1999). Once the human's interaction with a robot is accepted as a goal, conscientiousness will strive to achieve the goal of successful HRI. Both agreeableness and conscientiousness demonstrate higher levels of robot likeability and anthropomorphism (Kaplan, Sanders, and Hancock, 2019). Thus, we posit the following hypotheses:

H_{2A}: Agreeableness will be positively associated with robotic anthropomorphism.
H_{2B}: Agreeableness will be positively associated with robot likeability.
H_{3A}: Conscientiousness will be positively associated with robotic anthropomorphism.
H_{3B}: Conscientiousness will be positively associated with robot likeability.

Neuroticism, unlike the other Big Five traits, is likely to demonstrate an adverse reaction in HRI. Neuroticism refers to a lack of positive emotional stability and psychological adjustment. It, therefore, may be related to two characteristics: anxiety (instability and stress proneness), and one's well-being (personal insecurity and depression) (Judge et al., 2019; Takayama & Pantofaru, 2009). The trait of neuroticism is characterized as nervous, tense, fearful, and exhibiting a tendency to see the world negatively. Costa and McCrae (1992) differentiated among six facets of neuroticism: anxiety, depression, self-consciousness, hostility, vulnerability, and impulsiveness. In the HRI context, neuroticism is associated with adverse attitudes towards robots (Takayama & Pantofaru, 2009) and robotic anthropomorphism.

On the contrary, openness to experience is characterized by philosophical and intellectual abilities, along with unconventionality (imaginative, autonomous, and nonconforming) attributes (Judge et al., 1999). The openness personality trait is characterized as having a high level of curiosity for new entities and being open-minded to novel objects. Therefore, individuals with a high level of openness will be more likely to see robots as new entities, be able to anthropomorphize robots positively, and will be more willing to accept them in HRI situations. Therefore, we posit the following hypotheses:

H_{4A}: Neuroticism will be negatively associated with robotic anthropomorphism.
H_{4B}: Neuroticism will be negatively associated with robot likeability.
H_{5A}: Openness to Experience will be positively associated with robotic anthropomorphism.
H_{5B}: Openness to Experience will be positively associated with robot likeability.

As defined earlier, robotic anthropomorphism is the human-like attribution of human behavior and characteristics in robots (Bartneck et al., 2008). Prior research has shown some significant results on robotic anthropomorphism in HRI (Kaplan et al., 2019; Woods et al., 2007; Epley et al., 2007; Reich and Eyssel, 2013). Robots with higher anthropomorphism or stronger attribute-similarities and characteristics with humans in both appearance and behavior may facilitate constructive and natural HRI (Duffy, 2003; Złotowski et al., 2015; Strait et al., 2017). Robotic anthropomorphism increases comfort levels for users (humans) during their interactions with robots (Sauppé & Mutlu, 2015; Strait et al., 2017). A robot exhibiting a high degree of anthropomorphism is often perceived to be intelligent and more likable (Bartneck et al., 2008). Therefore, we posit:

H_6: Robotic Anthropomorphism will be positively associated with robot likeability.

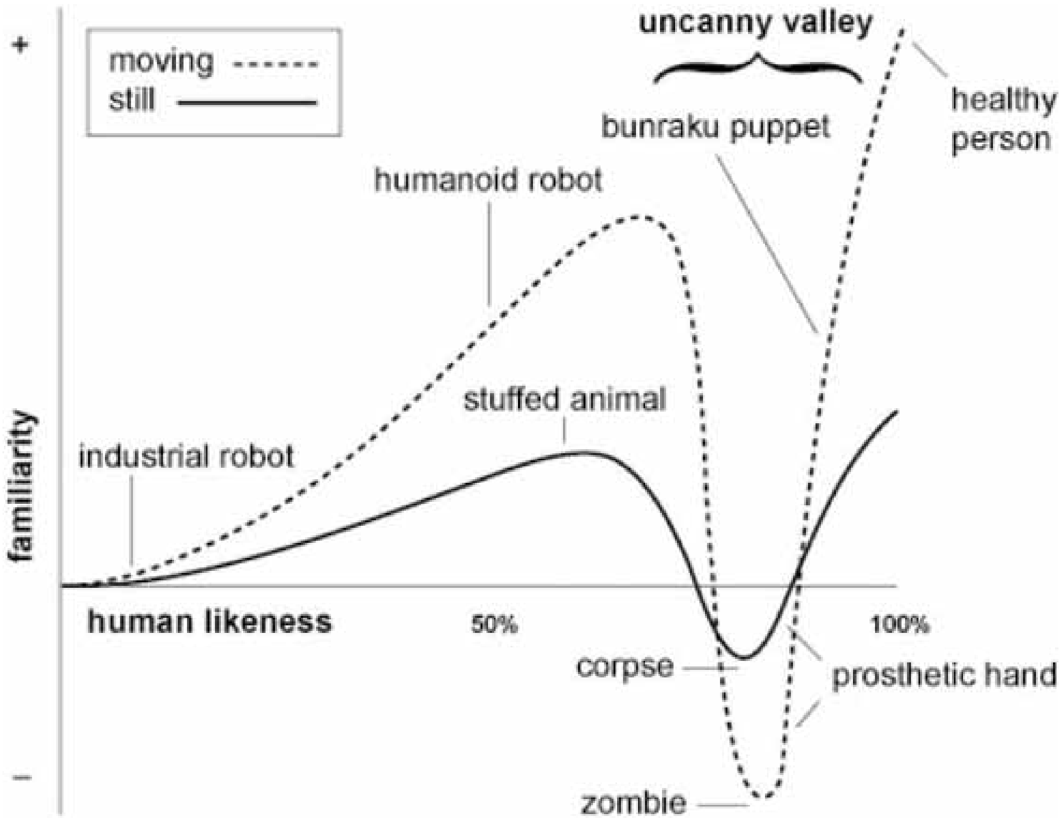
Robot likeability is usually determined within seconds during social-collaborative robots' interactions and, thus, the impression of likeability significantly influences (positive or negative) HRI implementation (Kaplan et al., 2019; Bartneck et al., 2008). While human-like robots have resulted in positive outcomes, such as increased feelings of familiarity or ease in working with robots (Sauppé & Mutlu, 2015), researchers have also identified adverse (negative) feelings (Mori et al., 2012) of consumers towards robots. This psychological phenomenon is referred to as 'the uncanny valley effect,' originally described by Japanese robotics professor Masahiro Mori in the 1970s (Mori et al., 2012).

Figure 1 describes the 'uncanny valley' as a dip between a humanoid robot and a healthy person. The graph shows that robot likeability increases to a highly human-like robot up to a point, and then drops if the robot becomes too human-like. In short, people respond more adversely to robotic anthropomorphism as the degree of human-like attributes increase. Consequently, the uncanny valley effect is another factor to consider in designing social-collaborative robotics, to remember that if robots are too human-like, they may be viewed less positively (Arora and Arora, 2020). Robot likeability is particularly interesting because the amount of information that humans process within seconds is limited to very few variables. For instance, it may be the robot's appearance and one or two of its motions. Therefore, it is vital to design robots with consideration to appearance and behavior, (or robotic anthropomorphism), for the purpose of a successful HRI implementation. The more likable a robot is, the more successful its implementation in practical, real-world settings (Zheng et al., 2013). Therefore:

H_7: Robot likeability will be positively associated with a successful HRI implementation.

Figure 2 demonstrates our Personality – Anthropomorphism – Likeability conceptual framework. Figure 2 exemplifies relationships among the constructs of Big Five personality traits, robotic anthropomorphism, and robot likeability, leading to a successful and positive HRI implementation, as described in H_{1-7}.

Figure 1. Masahiro Mori's (2012) 'Uncanny Valley Effect' curve (Adapted from MaDorman et al. (2015)



METHODOLOGY

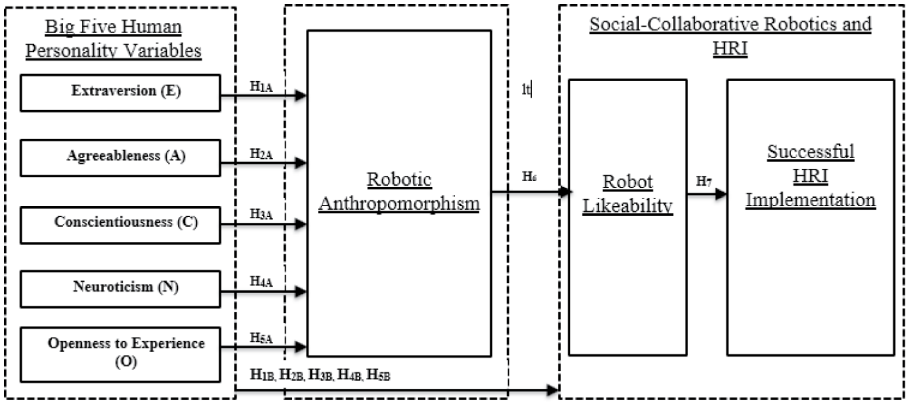
To test the conceptual framework, the X-Culture project was used to collect the data. *X-Culture* (www.X-Culture.org) is a large-scale international business collaboration and consulting project, which in a given semester attracted about 5,000 business students and working professionals from all six continents across the globe. The project is run twice a year on a semi-annual basis. The participants work in global virtual teams, typically six to seven people per team, each from a different country. The project participants rely on such as tools as Google Docs, Dropbox, WhatsApp, Facebook, Twitter, Snapchat, Google Hangouts, Skype, and the for communication and collaboration.

Sample

About 37 percent of the participants were graduate MBA and EMBA students, and the rest were business students in their last or second to last (senior or junior) year of studies. The average age was 23.3 years, and 39 percent were male. The vast majority of the participants had at least some work experience (average of 3.2 years), and many (31.1 percent) were employed at the time of the project. Some even ran their own businesses or held managerial positions (5.1 percent). The X-Culture project teams submitted weekly deliverables, and all project participants completed weekly progress surveys. The average response rate was 97.2% resulting in a sample size of 308 usable fully-completed questionaries.

Admittedly, the present sample is comprised of students and certain concerns about the generalizability of the findings exist. However, the threat to the validity and generalizability of the

Figure 2. Human Personality – Robotic Anthropomorphism – Robot Likeability HRI Framework



findings is likely minimal. The concern is that students differ from the general population in terms of their demographic characteristic, particularly age. However, the fact that students are typically younger is of little concern if the maturation effect does not influence the effects studied. For example, in the case of the present study, some organizations offered post-market commissions to the students, as well as prospects of internships and job offers. So the stakes and motivation were high and closer to those in the real world, rather than a typical symbolic bonus that professors offer to their students for participating in a study. The participants, the project settings, and the inter-member differences were real, and the work design was closely reminiscent of the real business world. Therefore, the threat that the findings of the present study would not generalize to the real world consumer population is minimal.

In subsequent sections, measures used in the framework, data collection process, and data analysis are discussed. The X-Culture participants watched 3 videos (2-3 minutes each) of social robots in industrial (e.g., KUKA Industrial Robot - https://www.youtube.com/watch?v=lv6op2HHIuM) and personal, social- collaborative (e.g., PARO – Personal Assistive Robot – Seal Robot - https://www.youtube.com/watch?v=2ZUn9qtG8ow) situations before being exposed to the final questionnaire. The idea was to get the participants to understand and enjoy the field of industrial and social robotics through videos. Research in social sciences and interpersonal communication has revealed that messages/communications can be made more persuasive and compliant by cueing humans' involvement with objects and behaviors (Clark 1998; Cleveland, Kalamas, and Laroche 2005). Thus, for the respondents to understand the field of social-collaborative robotics, we used video messages/advertisements as cues to understand social behaviors in varying HRI situations. Once the respondents felt connected to the topic (after multiple exposures to industrial and social robots through videos), an electronic Web-based questionnaire was provided to the X-Culture participants with questions focusing on two robots: (a) KUKA Industrial robot [1]used by manufacturing companies for automation and digitization, turnkey production facilities, and smart software solutions; and (b) PARO Seal Therapeutic Robot[2] – a personal assistant social robot helping humans to reduce anxiety, depression, and loneliness, while also stimulating, collaborating and engaging with people who are living with dementia (Pu et al., 2020).

Measures

The questionnaire consisted of measures from existing literature that were adapted to this study. Godspeed questionnaires using 5-point semantic differential scales were utilized as measures for robotic anthropomorphism, robot likeability, and HRI implementation (Bartneck et al., 2008). Big Five human personality traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience) were assessed on a 5-point Likert scale using measures from John & Srivastava (1999). All eight constructs in the conceptual model constitute latent variables requiring indirect measurement (Churchill, 1979; Bagozzi and Phillips, 1982). As the constructs in our research reflect (i.e., cause) their indicators, they were specified to be reflective (Diamantopoulos and Winklhofer, 2001; Diamantopoulos et al., 2008). All indicators were selected based on an extensive literature review as well as evidence from academicians. A 5-point Likert scale was used to measure the items. We conducted Harman's single-factor test (Podsakoff and Organ, 1986), the most widely used method to evaluate the possibility of common method variance (Podsakoff et al., 2003). We did not find any general factor that accounted for the majority of the variance in these variables. Therefore, we conclude that common method variance is not a problem in our study (Podsakoff and Organ, 1986).

Data Analysis

We validated our measures and tested our hypothetical model using partial least squares (PLS), and more specifically, SmartPLS version 3.2.8 (Ringle et al., 2015). PLS is a structural equation modeling tool that employs a fixed point or component-based least squares estimation procedure to obtain parameter estimates. PLS uses a series of interdependent OLS regressions to minimize residual variances, placing minimal demands on data in terms of measurement scales, sample size, and distributional assumptions (Chin, 1998; Fornell and Bookstein, 1982; Wold, 1982). Therefore, it is preferable to approaches that employ covariance-based maximum likelihood methods (e.g., Lisrel, EQS, etc.) in examining data where the sample size is relatively small (Bagozzi et al., 1991; Hulland et al., 2010). PLS is also a conservative modeling approach that tends to underestimate rather than overestimate path coefficients (Dijkstra, 1983), reducing the likelihood of Type 1 errors in hypothesis testing (Bagozzi et al., 1991).

The conceptual model (Figure 1) was tested by analyzing the data using partial least squares (PLS) following a two-step process. The first step involved assessing the measurement model to evaluate the consistency, reliability, and validity of the measures. The second step involved assessing the structural model to evaluate the significance and strength of the path coefficients between the variables.

Measurement Model

Indicator reliability was tested using a bootstrapping procedure with 1,000 randomized samples taken from the original sample and of original cardinality (Henseler et al., 2009). While checking the estimates of outer loadings of all indicators with their constructs, it was found that the indicators of the construct "Openness to Experience" did not exhibit sufficient outer loadings values. Therefore, the construct "Openness to Experience" was dropped from the final analysis. Finally, the measurement model containing seven constructs was assessed. As shown in Table 1, all estimates of the outer loadings exceed the recommended minimum value of .7 and exhibit sufficient t-values.

When testing for indicator reliability, convergent validity is also assessed, as loadings greater than .7 imply that the indicators share more variance with their respective constructs than with the error variances (Chin, 1998). To assess construct reliability, Cronbach's alpha (α) and composite reliability (CR) were determined. As depicted in Table 1, the α for the constructs are all above the suggested cut-off value of .7 (Cronbach, 1951; Litwin, 1995). Similar results were observed for the CR values, which were all greater than the suggested cut-off value of .6 (Bagozzi and Yi, 1988; Henseler et al., 2009). Convergent validity was assessed using the average variance extracted (AVE). As depicted in Table 1, the AVE is in all cases above the recommended value of .5 (Fornell and Larcker, 1981; Henseler et al., 2009). AVE was also used to evaluate discriminant validity. Table 2 indicates the correlations between the latent variables and the square roots of AVE on the diagonal. As the square root of AVE is in each case greater than the correlation among the latent variable scores with respect to its corresponding row and column values, we can conclude that none of the constructs shares more variance with another construct than with its own indicators, thus exhibiting sufficient levels of discriminant validity (Fornell and Larcker, 1981; Henseler et al., 2009). To assess the structural model's prediction relevance, we applied a blindfolding procedure with an omission distance of 5 (Henseler et al., 2009). All resulting Q^2 values are larger than zero, indicating sufficient predictive power of the structural model (Stone, 1974; Geisser, 1975).

Structural Model

After evaluating and assuring measurement model validity, SmartPLS was employed to test the structural model. The significance of the hypothesized paths was determined using the *T*-statistic calculated with the bootstrapping technique. The explanatory power of the structural model was assessed according to the variance accounted for by the endogenous variables (Oh *et al.*, 2012). Stone–Geisser criterion Q^2 values were obtained by running blindfolding procedures; these ranged above the threshold value of zero, thus establishing the model's predictive relevance (Ringle *et al.*, 2015).

Two structural models were assessed, one with constructs of Anthropomorphism, Likeability and HRI Implementation related to KUKA (industrial robot); and the second model with constructs of Anthropomorphism, Likeability, and HRI Implementation related to PARO (social-collaborative personal assistant robot). Both models included the constructs of Extraversion, Agreeableness, Conscientiousness, and Neuroticism.

Table 3 shows the PLS results of the theoretical model that contains the constructs related to KUKA. The results include standardized path coefficients and significance based on two-tailed *t*-tests. The relationships between extraversion and anthropomorphism ($b = .199, p < .10$), anthropomorphism and likeability ($b = .373, p < .01$), agreeableness and likeability ($b = .123, p < .05$), neuroticism and likeability ($b = -.170, p < .01$), and likeability and HRI implementation ($b = .472, p < .01$) were all significant. On the other hand, the relationships between conscientiousness and anthropomorphism; agreeableness and anthropomorphism; neuroticism and anthropomorphism; extraversion and likeability; conscientiousness and likeability were non-significant.

Table 4 shows the PLS results of the theoretical model that contains the constructs related to PARO. The relationships between extraversion and anthropomorphism ($b = .152, p < .05$), agreeableness and anthropomorphism ($b = .120, p < .10$), anthropomorphism and likeability ($b = .586, p < .01$), likeability and HRI implementation ($b = .752, p < .01$) were significant. On the other hand, the relationships between conscientiousness and anthropomorphism; neuroticism and anthropomorphism; openness to experience and anthropomorphism; extraversion and likeability; agreeableness and likeability; conscientiousness and likeability; neuroticism and likeability were non-significant.

DISCUSSIONS

The COVID-19 pandemic has changed how we perceived the world, and we are gradually adopting a 'new normal' of interacting with others virtually. We are learning that, through social distancing, we are capable of working as a team and be able to learn and study without face-to-face interaction. In contrast, many of us are facing challenges, such as feeling isolated, anxious, or stressed in addition to uncertainty and fear. Individuals will need to take care of their mental health during and after the pandemic without physical interaction with humans. Touchless robotic technology (e.g., social-collaborative robots) has emerged as a critical support system for humans in the present times for automation, digitization, therapeutic and emotional needs.

In this new era of diffused humanized technology, social robots have become ubiquitous. Social-collaborative robots have emerged as our pets and/or our family members in some situations. Task-oriented robots improve the quality of human lives. Artificial intelligence (AI) is continuously impacting and changing our globalized landscape, both at the individual (consumer) and organizational levels. Some organizations employ humans and robots as collaborative teams for enhancing productivity. Such teamwork has resulted in significant positive outcomes in the field of Human-Robot Interaction (HRI). While individuals are adopting a new environment and landscape, businesses are

Table 1. Overview of indicators and measures of reliability and validity

Constructs and Indicators		Outer Loadings	
		Point Estimation	*t*-Value
Extraversion (α = .710, AVE = .590, CR = .812)			
ex1	Is talkative		
ex6	Is reserved (reverse scale)		
ex11	Is full of energy	.765	3.346
ex16	Generates a lot of enthusiasm	.730	2.796
ex21	Tends to be quiet (reverse scale)		
ex26	Has an assertive personality	.808	3.368
ex31	Is sometimes shy, inhibited (reverse scale)		
ex36	Is outgoing, sociable		
Agreeableness (α = .697, AVE = .695, CR = .819)			
ag2	Tends to find faults in others (reverse scale)		
ag7	Is helpful and unselfish with others	.751	2.899
ag12	Starts quarrels with others (reverse scale)		
ag17	Has a forgiving nature		
ag22	Is generally trusting		
ag27	Can be cold and aloof (reverse scale)		
ag32	Is considerate and kind to almost everyone		
ag37	Is sometimes rude to others (reverse scale)		
ag42	Likes to cooperate with others	.909	5.566
Conscientiousness (α = .727, AVE = .648, CR = .846)			
Co3	Does a thorough job		
Co8	Can be somewhat careless (reverse scale)		
Co13	Is a reliable worker		
Co18	Tends to be disorganized (reverse scale)		
Co23	Tends to be lazy (reverse scale)	.821	5.678
Co28	Perseveres until the task is finished		
Co33	Does things efficiently		
Co38	Make plans and follows through with them	.724	4.372
Co43	Is easily distracted (reverse scale)	.864	7.123
Neuroticism (α = .767, AVE = .586, CR = .850)			
Ne4	Is depressed	.730	5.919
Ne9	Is relaxed, handles stress well(reverse scale)		
Ne14	Can be tense	.733	6.544
Ne19	Worries a lot		
Ne24	Is emotionally stable, not easily upset		
Ne29	Can be moody	.804	8.047
Ne34	Remains calm in tense situations (reverse scale)		
Ne39	Gets nervous easily	.791	7.632
Anthropomorphism (α = .738, AVE = .548, CR = .829)			
An1	Fake - Natural	.771	17.183
An2	Machine-like – Human-like	.753	19.712
An3	Unconscious - Conscious	.712	12.803
An4	Artificial - Lifelike	.722	14.403
An5	Moving rigidly – Moving elegantly		
Likeability (α = .860, AVE = .643, CR = .900)			
Li1	Dislike - Like	.718	15.516
Li2	Unfriendly - Friendly	.815	34.963
Li3	Unkind - Kind	.839	36.594
Li4	Unpleasant - Pleasant	.848	42.130
Li5	Awful - Nice	.782	23.736
HRI Implementation (α = .868, AVE = .791, CR = .919)			
HR1	Inert - Interactive	.915	51.416
HR2	Stagnant - Lively	.899	35.220
HR3	Failure - Success	.845	29.903

Table 2. Correlations between constructs and Discriminant Validity

Construct	AG	AN	CO	EX	HR	LI	NE	
Agreeableness (AG)	**.834**							
Anthropomorphism (AN)	.074	**.740**						
Conscientiousness (CO)	.360	.122	**.805**					
Extraversion (EX)	.447	.096	.392	**.768**				
HRI implementation (HR)	.111	.282	.050	.017	**.786**			
Likeability (LI)	.148	.374	.101	.064	.472	**.802**		
Neuroticism (NE)	-.208	-.014	-.449	-.236	-.021	-.169	**.765**	

Table 3. Path coefficients and R^2 of structural model (KUKA)

Constructs	Path coefficients		Hypotheses	
	Point estimate	*t*-Value		
AN (R^2=.201)				
EX	.199	1.679	H1a	Accepted*
AG	.018	0.268	H2a	Rejected
CO	.055	0.674	H3a	Rejected
NE	-.056	0.716	H4a	Rejected
LI (R^2=.178)				
AN	.373	6.856	H5	Accepted***
EX	-.049	0.712	H1b	Rejected
AG	.123	1.940	H2b	Accepted**
CO	-.045	0.596	H3b	Rejected
NE	-.170	2.597	H4b	Accepted***
HR (R^2=.071)				
LI	.472	10.057	H6	Accepted***

*p < 0.10; ** p < 0.05; *** p < 0.01

also facing continuous changes in response to disruptive technology advancement and data-driven management. There are many companies utilizing robots in order to implement tasks effectively and efficiently and to provide better service to consumers. For instance, Amazon works with robots that assist in the preparation of customer orders as a team. Similarly, Uber's artificial intelligence assigns human drivers to pick up guests. AI and HRI seem inevitable and essential in this data-driven and ever-changing work environment.

Prior research has shown that human personality traits (especially extraversion) play a crucial role in building robot likeability (Kaplan, Sanders, and Hancock, 2019), however previous researchers did not include constructs of robotic anthropomorphism and HRI implementation. Furthermore, researchers did not include diverse HRI situations (e.g., industrial and social robotics). In our research,

Table 4. Path coefficients and R^2 of structural model (Paro)

Constructs	Path coefficients		Hypotheses	
	Point estimate	*t*-Value		
AN (R^2=)				
EX	.152	2.224	H1a	Accepted**
AG	.120	1.884	H2a	Accepted*
CO	.044	0.676	H3a	Rejected
NE	-.018	0.268	H4a	Rejected
LI (R^2=)				
AN	.586	15.088	H5	Accepted***
EX	-.042	0.566	H1b	Rejected
AG	.009	0.150	H2b	Rejected
CO	-.020	0.253	H3b	Rejected
NE	-.020	0.287	H4b	Rejected
HR (R^2=.565)				
LI	.752	25.161	H6	Accepted***

we aim at understanding human-robot interaction in both industrial and social robots' interactions/situations by examining the constructs of Big Five personality traits (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to experience), robotic anthropomorphism, robot likeability, and HRI implementation. Our research focused on these constructs through KUKA industrial and PARO social robots. We got some noteworthy results that are discussed below.

For both industrial KUKA and social PARO robots, we found strong relationships between robotic anthropomorphism, robot likeability, and HRI implementation. Robotic anthropomorphism was positively associated with (and resulted in) robot likeability, which positively resulted in HRI implementation in both industrial and social HRI situations. This means that the more a robot looks/behaves like a human being, the more it is likable by the humans; and positive robot likeability leads to a positive and successful human-robot implementation, where HRI yields positive results for humans in industry and home (social) settings. The main differences occurred in the way human personality traits relate to robotic anthropomorphism and/or robot likeability. During HRI interactions with KUKA robots, we found extraversion resulted in positive anthropomorphism, and then to positive robot likeability. However, the direct relationship between extraversion and robot likeability was not significant. This means that extraverted individuals like robots which are anthropomorphic or human-like. For KUKA robots, agreeableness resulted in positive robot likeability, while neuroticism resulted in negative robot likeability. Conscientiousness and Openness did not exhibit any significant relationships with either robotic anthropomorphism or robot likeability. Unlike extraversion, we found that agreeableness and neuroticism did not have strong and significant relationships through robotic anthropomorphism to robot likeability. This means that unlike extraverted individuals, agreeable and neurotic individuals like or dislike the robot without experiencing any feelings of anthropomorphism. For these individuals, anthropomorphism has no effect in the context of industrial human-robot interactions.

On the contrary, during social robot interactions with humans, the relationships between human personality traits and robotic anthropomorphism were extremely important. We found that both extraversion and agreeableness resulted in positive anthropomorphism for PARO robots, which further resulted in positive robot likeability. Unlike industrial settings, the direct relationships between personality traits and robot likeability were missing in social HRI; all relationships were channeled through robotic anthropomorphism. Neuroticism, Conscientiousness, and Openness did not exhibit any significant relationships with either robotic anthropomorphism or robot likeability. In both cases of industrial KUKA and social PARO robots, we found that extraverted individuals experienced anthropomorphism first before liking the robot. However, agreeable individuals experienced anthropomorphism before robot likeability in social HRI, whereas they exhibited strong preferences for robot likeability (without experiencing robotic anthropomorphism) in industrial HRI. Neurotic individuals displayed negative feelings for industrial robots and no feelings for social robots. We did not find significant relationships for personality traits of Conscientiousness and Openness (for either KUKA industrial or PARO social robots) in our research results.

Our research has the potential to guide policies regarding designing and implementing robots in industrial and social HRI situations. This is our biggest research contribution. Watson and Clark (1997) pointed out “extraverts are more sociable but are also described as being more active and impulsive, less dysphoric, and as less introspective and self-preoccupied than introverts” (p.769). Our research strengthens this statement because our findings suggest that extraversion results in positive anthropomorphism first, and then leads to positive robot likeability in both industrial and social HRI settings. Extraverts engage with robots more than any other personality traits and form strong anthropomorphism in any HRI situation. While designing robots for extraverts, roboticists and robot designers may need to include stronger anthropomorphic (human-like) attributes in order for the extraverts to like their robots. For example, Toyota’s Kirobo Mini (as part of Toyota Heart Project and a big step in AI for Toyota since it reads a person’s facial expressions and determines his/her mood) is specifically designed with big eyes to attract consumers from all ages, especially Japan’s lonely, elderly and childless (Prosser, 2016). Since neuroticism can be broken down into six factors of anxiety, hostility, depression, self-consciousness, vulnerability, and impulsiveness (Costa and McCrae, 1992); neurotic individuals experience negative feelings for robots. Agreeable individuals are likable, good-natured, and cheerful and gentle, and possess qualities of trust, cooperation, and mutual care for others (Judge et al., 1999); and, therefore, are more prone to like robots than other human personality traits. While designing robots for agreeable and neurotic individuals, roboticists may not need to pay much attention to physical, behavioral, and anthropomorphic details in robots. However, they may need to define stronger non-behavioral, functional robotic features (e.g., robot functionality, control, usage, etc.) in robots. Overall, we found the prominence of three personality traits (Extraversion, Agreeableness, and Neuroticism) in the 5-factor structure of the Big Five traits while examining their interrelationships with robotic anthropomorphism, robot likeability and successful HRI implementation in industrial and social settings.

Our research has some limitations. The nature and composition of the sample can be problematic since it involves students and working professionals examining HRI situations through video messages. It would be beneficial if these HRI interactions can appear in person. However, we would not be able to garner more than 300 surveys in the physical situation. Given that the uncanny valley hypothesis is supported by prior researchers (Strait et al., 2017; Ho & MacDorman 2010), Ho & MacDorman (2010) refer to the likeability (y-axis) as interpersonal warmth, which is the dominant element in human perception to the robotic entities. Although eeriness (uncanny) is almost parallel to the y-axis (likeability) in the graph, the researchers declare the warmth does not correlate with eeriness (Ho & MacDorman 2010). Future researchers and roboticists can include the measures of warmth and eeriness as critical components for designing robots. Similar to warmth and eeriness, attractiveness and humanness (e.g., human-like motion and skin texture, along with certain levels of physical attractiveness that influence various kinds of personal decisions without rationale) can be included in future research for better robotic designs, development, and implementation (Cunningham, 1986; Ho & MacDorman 2010). Future research should attempt to replicate the research results and develop process models that may explain the following: (a) why 'extraversion' has strong relationships with anthropomorphism in all HRI situations, why 'agreeableness' and 'neuroticism' are (positively and negatively) related to robot likeability in industrial HRI and not in social HRI situation, and why 'agreeableness' is positively associated with anthropomorphism (and not likeability) in social HRI; (b) how anthropomorphism becomes a significant factor in social HRI vis-à-vis industrial HRI; and (c) what robot design and implementation will work in different HRI settings while defining situations when all five factors of Big Five personality traits become significant in human-robot interaction.

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ENDNOTES

[1] https://www.kuka.com/en-us/about-kuka/
[2] http://www.parorobots.com/

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