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Personality Psychology

Influence of User Personality Traits and Attitudes on Interactions With Social Robots: Systematic Review

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Social robots are robots that can interact and communicate with people in accordance with social norms. They are increasingly implemented in various environments including healthcare, education and the service industry. Individual differences, such as personality traits and attitudes are drivers of human social behaviours and interactions. As robots are increasingly developed as social agents, the drive to develop more socially acceptable, user-centered robots calls for a synthesis of existing findings to improve our understanding how user traits and attitudes influence human-robot interactions (HRI). Understanding the role of individual differences, and their impact on lived experience, is crucial for designing interactions that are better tailored to users. Currently, it is unclear whether or how personality traits and user attitudes affect HRI, which interaction modalities are being investigated and what is the quality of existing evidence. To address these questions, we conducted a systematic search of the literature, yielding 56 articles, from which we extracted relevant findings. As some of the studies included qualitative outcomes, we used a mixed methods meta-aggregation, in which findings were grouped into categories to form more general synthesized findings. We found evidence that user personality traits and attitudes are indeed correlated with social HRI outcomes, including extraversion being associated with preferred distance from the robot, preference for similar robot personality traits, users' impressions of robots and behavior towards robots. Our analysis also revealed that existing evidence has limitations which prevent us from drawing unambiguous conclusions, such as disparate interaction outcome measures, lack of comparison between different robots and small sample sizes. We provide a comprehensive summary of the existing evidence and propose that these findings can guide the development of research hypotheses to extend knowledge and to provide clarification where the existing literature is ambiguous or contradictory. Findings that warrant future investigation include different preferred robot behaviours based on extroversion and introversion, the impact of user traits on perceived robot anthropomorphism and social presence of the robot.

The growing interest in introducing social robots into various environments such as healthcare (Dawe et al., 2019; Kachouie et al., 2014) and education (Belpaeme et al., 2018), is accompanied by a need for a better understanding of which factors contribute to successful and beneficial human-robot interactions (HRI). For this study, we used the definition of social robots based on a review by Sarrica et al., which identified features most commonly attributed to social robots. By this definition, a social robot is autonomous; has a physical body; identifies and responds to cues from the environment; is capable of social interaction and execution of social rules (Sarrica et al., 2019). We selected this definition as it emphasizes the embodiment of the robot, its existence within the environment and ability to socially interact with users.

Social robots share features of technological artifacts and social agents, and as such are compelling target for investigations of dyadic human-robot interactions. This work commonly applies the Computers Are Social Actors (CASA) framework, which is centered around the idea that humans interact with computers in a manner similar to interacting with other agents (Nass & Moon, 2000). Since robots are

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technological artifacts like computers, CASA proposes that interaction with robots will follow the same patterns as interaction with computers. For instance, studies within this framework suggest that social biases that humans have extend to their treatment of machines. Since people's relationship with technology and the technology itself have changed since CASA was first proposed, new iterations of the framework suggest expanding it to account for unique human-media interaction scripts that are likely to be different from human-human interactions (Gambino et al., 2020) and there is growing evidence that computers alone no longer elicit social behaviours from humans (e.g.,Heyselaar, 2023). Since the available technology has become more prevalent, interactive and customizable it is more likely that people have developed unique ways of interacting with devices, that cannot be directly attributed to treating machines like social actors. Alternative theories are emerging seeking to explain human interactions with social robotics, such as "social robots as depictions of social agents" (Clark & Fischer, 2023).

Designing robot interactions that are tailored to users is important for social robot acceptance and sustained use. To be successful, social robots not only need to functionally address particular user needs in an application area (Robillard & Kabacińska, 2020), but also be responsive and adaptive to user characteristics and emotions, due to the nature of social interactions they provide. A good fit between the robot and user is especially important for assistive social robot applications, which is evidenced by a growing interest in creating emotionally-aligned assistive technology (Ghafurian et al., 2020; Robillard & Hoey, 2018). Thus, the quality of interaction with a social robot is dependent on their ability to accommodate specific users. Ultimately, the right robot-user fit will facilitate social robots' effectiveness, usefulness and have a positive impact on interaction outcomes in domains such as health (Pu et al., 2019) and education (Belpaeme et al., 2018).

One potentially influential factor of interest in HRI that plays a central role in human-human interactions are human personality traits. The American Psychological Association defines personality as "individual differences in characteristic patterns of thinking, feeling and behaving"(*Personality*, n.d.). This study focuses on personality traits, as they are a dimension of personality that is measurable by a variety of questionnaires and thus comparable. Additionally, since certain social behaviours are associated with well-defined personality traits, it is also feasible to endow social robots with behaviour patterns that are consistent with certain personality traits. However, as McAdams (1995) points out, comparability and nonconditionality of personality traits also constitute limitations to this approach of personality description, as traits do not capture the full nuance of personality that cannot be described in terms of traits alone. McAdams (1995, 2013) proposed a three-domain model, in which together with traits, personality is described by characteristic adaptations and integrative life narratives. While social robots can exhibit or simulate certain personality traits, which in turn could likely impact social interaction, the possibility of existence (or simulation) of the other two dimensions of personality is much less likely. Characteristic adaptations would require a social robot to have goals, values, plans and thus individual agency (McAdams, 2013). Whether social robots can have agency is a debated topic (Alač, 2016; Ziemke, 2023), however, social robots will not have integrative life narratives. As such, for this systematic review, the focus is on personality traits which are the most relevant for social HRI, as they can be manipulated and measured.

While many models for personality traits have been established, the dominant model is the Big Five, developed through a factor analysis of personality traits. The Big Five posits that the traits are clustered in five broad domains: extraversion, agreeableness, conscientiousness, neuroticism and openness (Goldberg, 1993). Other models that have been put forward include Eysenck's personality dimensions and Cloninger's psychobiological model of temperament and character. Both these models were aimed at providing an explanation of the biological underpinnings of personality, rather than a descriptive taxonomy. Eysenck's model is based on three factors – extroversion, neuroticism and psychoticism, and Cloninger's model includes novelty seeking, harm avoidance, reward dependence, persistence, self-directedness, cooperativeness and self-transcendence (Boyle et al., 2008; Cloninger et al., 1993). As researchers in HRI attempt to model user-robot interactions to make robots more responsive and acceptable to different users, modeling personality, in particular using quantitative metrics, is a compelling research area.

Attitudes towards robots are a second factor of interest in the present review, as they are frequently linked to behavioural intention to interact with robots (de Graaf & Ben Allouch, 2013; Nomura et al., 2008). In fact, both the Almere Model (Heerink et al., 2010) and Model of Domestic Social Robot Acceptance (de Graaf et al., 2019) identify attitudes as potentially contributing to social robot acceptance. A review by Naneva et al., which consolidates the evidence regarding attitudes, acceptance and trust towards social robots, suggests that generally, people have moderately positive attitudes towards robots (Naneva et al., 2020). It is unclear, however, how individual variation in user attitudes may impact the quality and outcome of interaction with social robots. Additionally, it is uncertain whether attitudes towards social robots are meaningfully related to user personality traits.

A recent review provides a broad overview of personality traits research in HRI and divides the topics of interest into 1) robot personality traits, 2) human personality traits, 3) interactions between human and robot personality traits and 4) facilitating robot personality traits (Robert, 2018). The authors also proposed a Human-Robot Integrative Personality Model, which conceptualized the relationships between these topics of interest and HRI outcomes. While this work provides a useful foundation for understanding of personality traits in HRI, a synthesis of findings is needed to establish whether personality traits are likely to influence a person's interaction with a robot and what role attitudes towards robots play in these interactions. Further, the use of different methods and models makes it challenging to rapidly compare and synthesize existing work into a foundation for future work. In this review, we aimed to address the following questions:

1. How do human personality traits impact social HRI?
2. How do attitudes towards robots impact HRI?
3. What modes of HRI interaction have been investigated?
4. What interaction outcome measures are commonly used?
5. What personality trait measures are used in HRI research?
6. What is the quality of existing evidence regarding the impact of personality traits and user attitudes on interactions with social robots?

To address these questions and to establish a detailed view of human personality traits as a factor in HRI, we conducted a systematic review of the literature focused on 1) individual differences (traits) of the users, 2) user's attitudes towards robots and their impact on the interaction with social robots.

Methods

We conducted a systematic review of the literature on user personality traits and attitudes as predictors of human-robot interaction. We registered our review protocol in the PROSPERO database [CRD42021233557].

Eligibility Criteria

We considered English-language peer-reviewed journal articles and conference proceedings, with no restrictions based on date. To be included, we required that studies contain a quantitative measure of personality traits or attitude, and report outcomes (either quantitative or qualitative) related to an interaction between a person and a social robot. To reduce the variability of the interaction outcome measures and to improve our ability to compare between the studies, our sample only included research that involved direct human-robot interaction; studies were excluded if they involved the participant observing a third party interacting with a robot, or viewing photos or video. Included studies could feature participants of any age or diagnostic group.

Literature Search

The literature search was conducted on November 14, 2020 using the following electronic databases: MEDLINE®, IEEE (including ACM), EMBASE, PsycINFO, and Web of Science. Search strategy was developed in consultation with a research librarian. Exact search terms varied slightly across databases, but included: *(robot*),* AND *(interaction*)* OR *(relationship*),* AND *(personality)* OR *(attitude*).* Full details are available in Supplementary Text S1.

Data Collection

A data extraction template was developed and piloted by K.K and J.A.D. Following piloting and discussion, the following data were extracted from each paper: bibliographic information (publication type, year of publication, etc.), country of study, relevant research aims, study design, human-robot interaction protocol, robot used and its characteristics (humanoid/non-humanoid, speaking/non-speaking, etc.), mode of robot control, predictive and outcome measures, participant characteristics, and findings.

To assess risk of bias, we used a modified version of an existing assessment tool which has been previously used to evaluate the literature on attitudes and anxiety directed at social robotics (Naneva et al., 2020). The quality measure assessed each paper in two broad domains 1) Study validity and 2) Outcome measure quality. The assessment includes three questions to evaluate study validity focusing on existence of alternative explanations, sampling bias and representativeness of the sample. These dimensions should be measurable during review of the paper and are important for gauging the quality of the reported results. We chose to evaluate outcome measure quality because it is vital for determining whether or not there was an effect of personality traits or attitudes towards robots on the HRI. Thus, for outcome measures we have asked questions regarding validity, test-retest reliability and internal consistency. Additionally, we have added the size of the sample to the quality criteria. The full instrument used for quality assessment, including the definitions user for "Low" and "High" assessment, is included in Supplementary Text S2.

Data analysis

The sample obtained in this study was not suitable for meta-analysis due to the heterogeneity outcome measures, both qualitative and quantitative, and robot-interaction protocols. As a result, based on guidance from the Joanna Briggs Institute (JBI) on mixed methods systematic reviews, we took a convergent integrated approach to analysing the data (Stern et al., 2020). This approach allows for combining qualitative and quantitative data to perform a synthesis. As recommended by JBI, we transformed all quantitative results from reviewed studies into qualitative statements. Once all data was in qualitative form, we performed meta-aggregation of all findings. In this process, the statements describing results from all included studies were categorized. The resulting categories were then combined to form synthesized findings (Pearson et al., 2011). This process was collaborative, with two authors (K.K and J.A.D.) reaching consensus through discussion.

Results

Search Outcomes

An initial pool of 5267 references was obtained (Figure 1). These materials were managed using Covidence, an online software platform (Veritas Health Innovation, n.d.). First, duplicate results were removed. Then, authors K.K and J.A.D. each screened the titles and abstracts of all works against the inclusion/exclusion criteria. Disagreements were resolved through discussion. The two authors then independently examined the full text of the remaining potentially eligible studies, with further discussion of any dis-

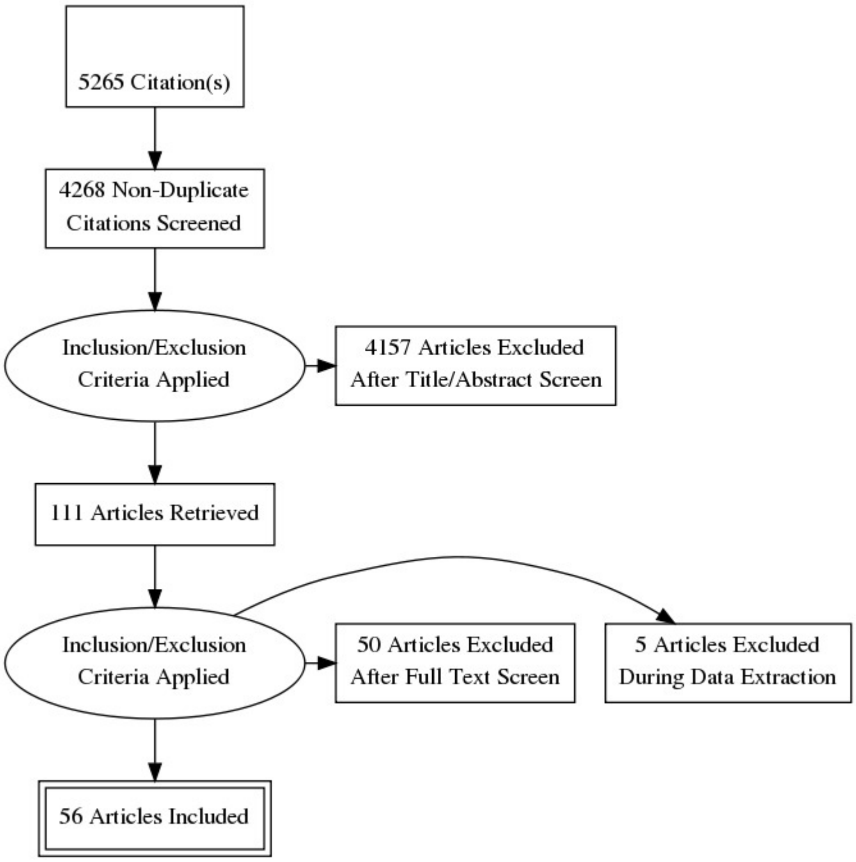

Figure 1. PRISMA diagram of systematic search process.

crepancies. A final set of fifty-six eligible studies were identified and subjected to extraction.

Study Characteristics

The characteristics of studies included in this review are summarized in Table 1. The number of participants in the studies ranged from 3 to 164 (mean = 46).

Full summary of included studies is shown in Table 2. Number of publications by year is depicted in Figure 2.

After data extraction and qualitization of the findings, we obtained 102 individual findings that related to our guiding questions (see introduction).

The findings were subsequently grouped into 31 categories and formed 11 synthesized findings. Two findings remained ungrouped. Supplemental Table S1 contains all the findings, categories and synthesized findings.

Quality Assessment of Included Studies

The summary of quality assessment is available in Table 3. The overall assessment is based on the total rankings a study has received. If a study scored *High*, *Low* or *Unsure* in at least half (4/8 or more) of assessment areas, the overall score was the same as the majority of the scores. If no clear majority of assessments could be established, the overall ranking of the study was rated as *Unsure*. There were 8 studies in the sample that received an overall *High* quality score, 35 studies received an overall *Low* score and for 13 studies we were unable to establish a quality assessment score with the information available in the publications.

User Personality Traits

The most frequently used measure of personality traits in the reviewed studies was the Big Five Personality Inventory e.g., (Gosling et al., 2003; Rammstedt & John, 2007) (k=17). One specific measure based on this model was NEO Personality Inventory-3 (Costa & Mccrea, 1992). The second most frequently used measure were the Eysenck Personality Inventory and Questionnaire (Eysenck, 1991; Eysenck & Eysenck, 1965) used in 5 studies. The detailed information on user trait measures is summarized in Table 4.

The Association Between User Traits, Robot Traits and HRI Assessment. Establishing the association between user traits and general interaction outcomes such as interaction length, preference for the robot, engagement with the robot and evaluation of the robot was the dominant theme in 17 extracted study findings (Agrigoroaie & Tapus, 2020; Aly & Tapus, 2013, 2016; Andrist et al., 2015; Celiktutan et al., 2019; Celiktutan & Gunes, 2015; Correia et al., 2019; Craenen et al., 2018; Cruz-Maya & Tapus, 2017; K. M. Lee et al., 2006; Park et al., 2012; So et al., 2008; Tapus et al., 2008).

For some users, interacting with robots matching their traits led to more positive human-robot interaction outcomes. Users tended to prefer robots that match their traits

Table 1. Study characteristics

Study characteristic	Number of studies	References
Conference proceedings	33	(Cruz-Maya & Tapus, 2016a; Andrist et al., 2015; Bechade et al., 2015; Craenen et al., 2018; Cruz-Maya & Tapus, 2017; Cruz-Maya & Tapus, 2016b; de Graaf & Ben Allouch, 2013; Haring et al., 2013; HeeSeon Abe et al., 2017; Bernotat & Eyssel, 2017; Brandstetter et al., 2017; Celiktutan & Gunes, 2015; Haring et al., 2015; Hwang & Lee, 2013; Jeong et al., 2020; Jung et al., 2012; Kanero et al., 2018; Kimoto et al., 2016; N. Lee et al., 2011; Li et al., 2020; Nitsch & Glassen, 2015; Nomura et al., 2007; Nomura & Kawakami, 2011; Obaid et al., 2016; Rossi et al., 2018; Salem et al., 2015; So et al., 2008; Stafford et al., 2010; Takayama & Pantofaru, 2009; Tapus et al., 2008; Woods et al., 2005; Wullenkord et al., 2016)
Journal articles	23	(Agrigoroaie et al., 2020; Aly & Tapus, 2013, 2016; Bjorling et al., 2020; Celiktutan et al., 2019; Correia et al., 2019; Dziergwa et al., 2018; Gaudiello et al., 2016; Ivaldi et al., 2017; Ke et al., 2020; K. M. Lee et al., 2006; Leichtmann & Nitsch, 2021; Looije et al., 2010; Nomura et al., 2008; Park et al., 2012; Rossi et al., 2020; Salam et al., 2017; Spatola & Wudarczyk, 2021; Stafford et al., 2014; Tay et al., 2014; Thepsoonthorn et al., 2018; Xu, 2019)
Country of origin	**Number of studies**	**References**
France	12	(Aly & Tapus, 2013; Cruz-Maya & Tapus, 2016a; Agrigoroaie et al., 2020; Agrigoroaie & Tapus, 2020; Aly & Tapus, 2016; Bechade et al., 2015; Cruz-Maya & Tapus, 2017; Cruz-Maya & Tapus, 2016b; Gaudiello et al., 2016; Ivaldi et al., 2017; Salam et al., 2017; Spatola & Wudarczyk, 2021)
Japan	8	(Abe et al., 2017; Haring et al., 2013; Kimoto et al., 2016; Nomura et al., 2007, 2008; Nomura & Kanda, 2012; Nomura & Kawakami, 2011; Thepsoonthorn et al., 2018),
USA	7	(Andrist et al., 2015; Bjorling et al., 2020; Jeong et al., 2020; K. M. Lee et al., 2006; Takayama & Pantofaru, 2009; Tapus et al., 2008; Xu, 2019)
South Korea	5	(HeeSeon Hwang & Lee, 2013; Jung et al., 2012; N. Lee et al., 2011; Park et al., 2012; So et al., 2008)
United Kingdom	5	(Celiktutan et al., 2019; Celiktutan & Gunes, 2015; Craenen et al., 2018; Salem et al., 2015; Woods et al., 2005)
Germany	4	(Bernotat & Eyssel, 2017; Leichtmann & Nitsch, 2021; Nitsch & Glassen, 2015; Wullenkord et al., 2016)
New Zealand	4	(Brandstetter et al., 2017; Obaid et al., 2016; Stafford et al., 2010, 2014)
The Netherlands	2	(de Graaf & Ben Allouch, 2013; Looije et al., 2010)
Italy	2	(Rossi et al., 2018, 2020)
Portugal	1	(Correia et al., 2019)
China	1	(Li et al., 2020)
Hong Kong	1	(Ke et al., 2020)
Poland	1	(Dziergwa et al., 2018)
Australia	1	(Haring et al., 2015)
Turkey	1	(Kanero et al., 2018)
Singapore	1	(Tay et al., 2014)
Study design	**Number of studies**	**References**
Between-subjects design	28	(Cruz-Maya & Tapus, 2016b; Agrigoroaie et al., 2020; Andrist et al., 2015; Craenen et al., 2018; Gaudiello et al., 2016; Haring et al., 2013; HeeSeon Abe et al., 2017; Bernotat & Eyssel, 2017; Brandstetter et al., 2017; Celiktutan & Gunes, 2015; Hwang & Lee, 2013; Ivaldi et al., 2017; Jung et al., 2012; Kanero et al., 2018; K. M. Lee et al., 2006; Leichtmann & Nitsch, 2021; Li et al., 2020; Nomura et al., 2007, 2008; Nomura & Kanda, 2012; Nomura & Kawakami, 2011; Park et al., 2012; Salem et al., 2015; So et al., 2008; Spatola & Wudarczyk, 2021; Tay et al., 2014; Wullenkord et al., 2016; Xu, 2019)
Within-subjects design	15	(Agrigoroaie & Tapus, 2020; Aly & Tapus, 2013, 2016; Bechade et al., 2015; Correia et al., 2019; Cruz-Maya & Tapus, 2017; Cruz-Maya & Tapus, 2016a; Kimoto et al., 2016; Looije et al., 2010; Obaid et al., 2016; Rossi et al., 2020; Stafford et al., 2014; Tapus et al., 2008)
Other designs and mixed designs	11	(Celiktutan et al., 2019; Chen et al., 2020; de Graaf & Ben Allouch, 2013; Haring et al., 2015; Jeong et al., 2020; K. M. Lee et al., 2006; Nitsch & Glassen, 2015; Rossi et al., 2018; Salam et al., 2017; Stafford et al., 2010; Takayama & Pantofaru,

Study characteristic	Number of studies	References
		2009)
Qualitative design	2	(Bjorling et al., 2020; Dziergwa et al., 2018)
Robots used in the studies	**Number of studies**	**References**
Humanoid robots	39	(Aly & Tapus, 2013; Cruz-Maya & Tapus, 2016a; Agrigoroaie & Tapus, 2020; Andrist et al., 2015; Bechade et al., 2015; Chen et al., 2020; Craenen et al., 2018; Cruz-Maya & Tapus, 2017; Cruz-Maya & Tapus, 2016b; de Graaf & Ben Allouch, 2013; Haring et al., 2013; Salam et al., 2017; HeeSeon Abe et al., 2017; Bernotat & Eyssel, 2017; Celiktutan et al., 2019; Celiktutan & Gunes, 2015; Haring et al., 2015; Kimoto et al., 2016; Leichtmann & Nitsch, 2021; Nitsch & Glassen, 2015; Nomura et al., 2007, 2008; Nomura & Kanda, 2012; Nomura & Kawakami, 2011; Obaid et al., 2016; Rossi et al., 2018, 2020; So et al., 2008; Spatola & Wudarczyk, 2021; Stafford et al., 2010, 2014; Thepsoonthorn et al., 2018; Xu, 2019)
Abstract robots	8	(Agrigoroaie et al., 2020; Bjorling et al., 2020; Jeong et al., 2020; Salem et al., 2015; Takayama & Pantofaru, 2009; Tapus et al., 2008; Tay et al., 2014; Woods et al., 2005)
Head-only robots	5	(Correia et al., 2019; Dziergwa et al., 2018; Jung et al., 2012; Li et al., 2020; Park et al., 2012)
Animal-like robots	4	(Hwang & Lee, 2013; K. M. Lee et al., 2006; N. Lee et al., 2011; Looije et al., 2010)
Interaction type	**Number of studies**	**References**
Conversation with the robot	18	(Aly & Tapus, 2013, 2016; Bjorling et al., 2020; de Graaf & Ben Allouch, 2013; Salam et al., 2017; HeeSeon Brandstetter et al., 2017; Celiktutan et al., 2019; Celiktutan & Gunes, 2015; Jeong et al., 2020; Kimoto et al., 2016; Leichtmann & Nitsch, 2021; Li et al., 2020; Nomura et al., 2008; Nomura & Kanda, 2012; So et al., 2008; Spatola & Wudarczyk, 2021; Stafford et al., 2010, 2014; Xu, 2019)
Free interaction	7	(Abe et al., 2017; Bernotat & Eyssel, 2017; Chen et al., 2020; Dziergwa et al., 2018; Haring et al., 2015; Hwang & Lee, 2013; K. M. Lee et al., 2006)
Playing a game	6	(Andrist et al., 2015; Bechade et al., 2015; Correia et al., 2019; Haring et al., 2013, 2015; Nitsch & Glassen, 2015)
Proxemics task	3	(Nomura et al., 2007; Obaid et al., 2016; Takayama & Pantofaru, 2009)
Administration of assessment or questionnaires by the robot	2	(Agrigoroaie & Tapus, 2020; Rossi et al., 2018)
Robot giving a speech	2	(Agrigoroaie & Tapus, 2020; Nomura & Kawakami, 2011)
Observation of the robot	2	(Craenen et al., 2018; Cruz-Maya & Tapus, 2017)

(Aly & Tapus, 2013, 2016; Andrist et al., 2015; Correia et al., 2019; Craenen et al., 2018; HeeSeon Park et al., 2012; So et al., 2008) have longer interactions with robots that have traits similar to theirs (Agrigoroaie & Tapus, 2020; Andrist et al., 2015; Tapus et al., 2008) and tended to be more engaged and perform better in interactions with robots similar to them (Andrist et al., 2015; Celiktutan et al., 2019; Celiktutan & Gunes, 2015). While these findings support the similarity principle, some of the reviewed studies also provided evidence to support the complementarity principle. In these studies, participants preferred the robots that exhibited traits different from their own, or enjoyed the interaction with these robots more than with those matching their traits (Craenen et al., 2018; Cruz-Maya & Tapus, 2017; K. M. Lee et al., 2006). These findings tended to be specific to particular user groups. For instance, in a study by Cruz-Maya and Tapus (Cruz-Maya & Tapus, 2017) extroverted female participants were found to prefer the distance of the introverted robot in an interaction (0.8m distance, as opposed to 0.6m distance of the extroverted robot).

User Traits Are Related to Their Impressions of Robots. Another focus of investigation was whether user traits are associated with perceptions or impressions of robots. Extroversion was the most frequently investigated human trait in this context. The reviewed studies found that extroverted participants tend to anthropomorphize the robots more (Park et al., 2012; Salem et al., 2015), report higher psychological closeness to robots (Salem et al., 2015) and perceive them as more friendly (Park et al., 2012). One study reported findings providing evidence against positive association between user extroversion and perceived anthropomorphism of the robot (Haring et al., 2015).

Other user traits such as emotional stability, attachment style and trait loneliness were related to perceived anthropomorphism of the robot (Dziergwa et al., 2018; Haring et al., 2015; Li et al., 2020; Salem et al., 2015). Two findings reported an association between user traits and perceived

Table 2. Summary of included studies

#	Authors	RQs, goals, hypotheses	Intervention type	Length/ frequency of intervention	Robot used	Robot type	Mode of robot control	N	Age	Gender
1	Tapus et al. (2008)	Q1: Will users prefer a physical therapy robot that matches their personality?	Robot as a motivation during stroke rehabilitation.	20 mins per robot personality	ActivMedia Pioneer 2-DX	non-humanoid	Pre-programmed behaviours supporting the interaction	12	18-30	8 males, 4 females
2	Nomura et al. (2007)	Q1: What are the relationships between negative attitudes and anxiety towards robots and allowable distance of a robot?	Robot proxemics task	One-time interaction	Robovie-M	humanoid	Pre-programmed behaviours selected by robot operator	17	mean 19.0	12 males, 5 females
3	Haring et al. (2013)	H1: Individuals with extravert personality traits would make higher offers in the trust game	Economic trust game	One-time interaction	Actroid-F	humanoid	Some pre-programmed behaviours with some teleoperation	55	18-66, mean 22.6	18 males, 37 females
4	Park et al. (2012)	Q1: What is the relationship between the human's personality and his or her immersive tendency, anthropomorphism, friendliness, preference, and social presence? Q2: What is the relationship between the robot's personality and its immersive tendency, anthropomorphism, friendliness, presence, and social presence?	Reading a story to a robot	Not given	A facial expression robot KMC-EXPR	head only	Pre-programmed behaviours supporting the interaction	120	19-32, mean 24.9	60 males, 60 females
5	Looije et al. (2010)	G1: To find behavior for an electronic personal assistant that improves the self-care capabilities of older adults.	Robot as an interviewer	30 mins	iCat	animal	Wizard-Of-Oz operation	24	45-65	12 males, 12 females
6	Kimoto et al. (2016)	Q1: What is the relationship between personality and robot's interaction strategies in object recognition contexts in conversations?	Object recognition conversations	One-time interaction	Not named	humanoid	Other: Not fully described	20	mean 35.5	10 males, 10 females
7	Cruz-Maya and Tapus (2016a)	H1: Close interaction (at the limit of interpersonal distance) will be preferred by extroverted people and far interaction (1.5 times the limit of interpersonal distance) will be preferred by the introverted people in the task reminder.	Robot as a motivation/ reminder at work	One-time interaction	Meka M1	humanoid	Pre-programmed behaviours supporting the interaction	16	21-32	12 males, 4 females
8	Bechade et al. (2015)	G1: To explore the relationships between audio cues, mental states, and personality traits in order to discover cues and correlations that can be exploited to build useful participant profiles for social Human-Robot Interaction (HRI).	Emotional recognition game with the robot, robot-directed social interaction	2 sessions, averages of 2:46 mins and 2:26 mins	Nao	humanoid	Pre-programmed behaviours supporting the interaction	37	21-62, mean 35.1	62% males, 38% females

#	Authors	RQs, goals, hypotheses	Intervention type	Length/ frequency of intervention	Robot used	Robot type	Mode of robot control	N	Age	Gender
9	Andrist et al. (2015)	H1: Matching the robot's personality to the user's personality will improve the user's subjective ratings of the robot's performance. H2: Matching the robot's personality to the user's personality will improve compliance with the robot's requests to engage in the task for a longer period of time. H3: The user's intrinsic motivation for the task will interact with the personality-matching effect on compliance. Users with low intrinsic motivation will be more affected by personality-matching than users with high intrinsic motivation.	Playing a game with the robot	Not given	Meka	humanoid	Pre-programmed behaviours supporting the interaction	40	20-58, mean 30.6	24 males, 6 females
10	Stafford et al. (2014)	Q1: Are participants' attitudes towards robots and drawings of robots associated with their evaluations of a conversational robot and their BP and heart rate, after interacting with the robot?	Conversation with the robot	5 mins per each of the 6 display conditions	ELIZA programme on a Peoplebot robot	humanoid	Pre-programmed behaviours supporting the interaction	20	55-71, mean 64.5	7 males, 13 females
11	Aly and Tapus (2016)	H1: The robot behavior that matches the user's personality expressed through combined speech and gestures will be preferred by the user.	Conversation with the robot	Average duration was 3 to 4 mins	Nao	humanoid	Pre-programmed behaviours supporting the interaction	21	21-30	14 males, 7 females
12	Craenen et al. (2018)	G1: To verify whether the similarity-attraction effect — the tendency of people with similar personality to like one another applies in the case of synthetic (robotic) gestures.	Observing robotic gestures	One-time interaction	Pepper	humanoid	Pre-programmed behaviours supporting the interaction	30	Not given	10 males, 20 females
13	Correia et al. (2019)	G1: To assess the participants' preferences regarding the choice of a robotic partner.	Playing a game with the robot	Not given	EMYS	head only	Pre-programmed behaviours supporting the interaction	61	17-32, mean 23.66	38 males, 23 females
14	Spatola and Wudarczyk (2021)	Q1: Do implicit attitudes towards robots predict explicit attitudes towards robots, semantic distance between robots and humans, anthropomorphic evaluations, and behaviour towards a real robot? Q2: Are they better predictors than explicit attitudes?	Conversation with the robot, followed by turning off the robot.	Not given	Nao	humanoid	Pre-programmed behaviours supporting the interaction	37	mean 19.4	18 males, 19 females
15	Leichtmann and Nitsch (2021)	G1: The effect of tendency to anthropomorphize on robot behavior evaluation	Conversation with the robot	One-time interaction	Nao and Pepper	humanoid	Pre-programmed behaviours	107	19-46, mean 23.28	79 males, 28 females

#	Authors	RQs, goals, hypotheses	Intervention type	Length/ frequency of intervention	Robot used	Robot type	Mode of robot control	N	Age	Gender
							selected by robot operator			
16	Rossi et al. (2020)	G1: To evaluate the personality and emotional aspects as factors affecting the interaction with the robotic platform during cognitive assessment. G2: To evaluate the older adults' intention to accept the robotic platform as a psychometric tool.	Robot monitoring participant behaviour.	Not given	Pepper	humanoid	Pre-programmed behaviours supporting the interaction	21	53-82, mean 61	8 females
17	Agrigoroaie, Ciocirlan and Tapus (2020)	G1: To determine how do individuals (based on their RFT type) react when a robot appears at their doorway to ask them to perform a short questionnaire.	Questionnaire administered by the robot.	Not given	Tiago	non-humanoid	Pre-programmed behaviours supporting the interaction	42	23-52, mean 36.42	21 males, 8 females
18	Björling et al. (2020)	G1: To better understand how the robot should behave such that users feel heard	Conversation with the robot.	Not given	EMAR V4, Blossom	non-humanoid	Wizard-Of-Oz operation	62	14-18, mean 16.77	24 females, 32 males, 5 non-binary
19	Li et al. (2020)	Q1 (study 3): What is the correlation between trait loneliness, robot anthropomorphism and acceptance (of robot)?	Conversation with the robot	5 mins	Social robot prototype	head only	Pre-programmed behaviours supporting the interaction	51	mean 19.82	32 males, 19 females
20	Agrigoroaie and Tapus (2020)	Q1: Can the ME-type of an individual influence the performance on a cognitive task with a robot? Q2: What is the role of personality and sensory profile?	Robot delivering stressing or encouraging speech during a task.	Not given	Tiago Robot	humanoid	Pre-programmed behaviours supporting the interaction	24	Mean 27.38	19 males, 5 females
21	Xu (2019)	Q1: How will users' attitudes toward robots interact with the social cues in predicting users' social responses?	Conversation with the robot	2-mins	Alpha	humanoid	Pre-programmed behaviours supporting the interaction	110	18-34, mean 20.4	55 males, 55 females
22	Nomura et al. (2008)	G1: To clarify the relationship between negative attitudes, anxiety toward a robot, and behaviour towards it.	Conversation with the robot	Not given	Robovie	humanoid	Pre-programmed behaviours supporting the interaction	38	Mean 21.3	22 males, 16 females

#	Authors	RQs, goals, hypotheses	Intervention type	Length/ frequency of intervention	Robot used	Robot type	Mode of robot control	N	Age	Gender
23	Aly and Tapus (2013)	H1: The robot's behavior that matches user's personality expressed through speech and gestures will be preferred by the human user. H2: The robot's personality expressed through speech and gestures will be perceived more expressive than the robot's personality expressed just through speech by the human user.	Conversation with the robot	Not given	Nao	humanoid	Pre-programmed behaviours supporting the interaction	21	21-30	7 females
24	Jung et al. (2012)	Q1: Will personality affect facial interactions between humans and robots? Q2: Do people prefer robots with similar personalities to themselves?	Robot mimics participants' facial expressions	135 seconds	KMC-EXPR	head only	Pre-programmed behaviours supporting the interaction	40	Mean 23.2	Not given
25	Lee, Shin and Sundar (2011)	Q1: How do perceptions of hedonic (for fun) and utilitarian (designed to complete a task) robots differ?	Not specified	5 mins	PLEO and Roomba (not a social robot)	animal	Other: No info given	48	Not given	24 males, 24 females
26	Nitsch and Glassen (2015)	Q1: How do attitude toward technology and robot behaviour influence interaction with a robot (in an ultimatum game)?	Playing a game with the robot	Not given	NAO Next Gen	humanoid	Wizard-Of-Oz operation	48	Not given	35 males, 13 females
27	Celiktutan, Skordos and Gunes (2019)	Q1: Does interacting with a robot 1-on-1 versus with another person impact prediction of a person's personality? Q2: Are an acquaintance's predictions of someone's personality easier to predict than self ratings of personality?	Conversation with the robot	10-15 mins	Nao	humanoid	Wizard-Of-Oz operation	18	Not given	9 males, 9 females
28	Celiktutan and Gunes (2015)	Q1: How do participant personality and robot personality (extroversion/introversion) affect the participants' interaction experience with the robot?	Conversation with the robot	10-15 mins	Nao	humanoid	Wizard-Of-Oz operation	Not given	Not given	Not given
29	Salam et al. (2017)	G1: To analyse the role of personality in the prediction of human participants' engagement states in Human-Human-Robot Interactions.	Conversation with the robot	Not given	Nao	humanoid	Pre-programmed behaviours selected by robot operator	18	Not given	Not given
30	Bernotat and Eyssel (2017)	G1: To investigate the influence of user characteristics (positive affect, technology commitment, Big 5 factors) on the evaluation of interaction with an intelligent robot (H2).	Free interaction with the robot while completing daily tasks in a robotics apartment	On average four interactions during the study	Meka Mobile Manipulator M1	humanoid	Wizard-Of-Oz operation	47	15-50	21 males, 26 females
31	Stafford et al. (2010)	Q1: Do attitudes and emotions towards a healthcare robot change after meeting the robot? Q2: Do attitude and emotions, and changes in these variables, predict better robot ratings?	Conversation with the robot	Not given	Healthbot	humanoid	Pre-programmed behaviours supporting the	53	68-92, mean 80.1	28.1% male residents, 4.8% male staff (n = 1)

#	Authors	RQs, goals, hypotheses	Intervention type	Length/ frequency of intervention	Robot used	Robot type	Mode of robot control	N	Age	Gender
							interaction			
32	de Graaf and Allouch (2013)	G1: To explore the relation between people's negative attitude and anxiety towards robots and human behavior in an interaction with a robot.	Conversation with the robot	5-10 mins	Nao	humanoid	Pre-programmed behaviours supporting the interaction	60	18-28	28 males, 32 females
33	Woods et al. (2005)	Q1: What is the relationship between human personality and perceived robot personality?	Robot wanders around the room while participant performs tasks	Total testing took 1 hour.	PeopleBot	non-humanoid	Wizard-Of-Oz operation	28	18-55	14 males, 14 females
34	Chen et al. (2020)	G1: To examine the change in technology acceptance after a direct interaction with a humanoid social robot.	Free interaction	ABAB design with each phase lasting 8 weeks	Kabochan	humanoid	Autonomous robot	103	67-108, mean 87.2	21 males, 82 females
35	Thepsoonthorn, Ogawa and Miyake (2018)	Q1: How do a robot's nonverbal behaviours affect likability and how does this interact with user personality (introvert/extravert)?	Robot gives a speech	2 mins per trial x 2 trials	Nao	humanoid	Pre-programmed behaviours supporting the interaction	30	22-35, mean 26	18 males, 12 females
36	Takayama and Pantofaru (2009)	G1: To explore factors that influence proxemic behaviour around a robot.	Robot proxemics task	One-time intervention	PR2 (personal robot 2)	non-humanoid	Robot either teleoperated or autonomous	30	19-55, mean 28.9	14 women, 16 men
37	Cruz-Maya and Tapus (2017)	H1: The robot's behavior generated after interactions with individuals of different personalities and genders will best match with the preferences of new users than by using fixed behaviors based on the theories of Similarity attraction or Complementarity attraction	Observing robotic gestures/ behavior	One-time intervention	Pepper	humanoid	Pre-programmed behaviours supporting the interaction	26	20-47	9 females
38	Nomura and Kanda (2012)	G1: To assess the impact of robot evaluations on human learning.	Conversation with the robot	Not given	Robovie-R2	humanoid	Wizard-Of-Oz operation	155	mean 20.5	82 males, 75 females
39	Nomura and Kawakami (2011)	Q1: What is the effect of robot self-disclosure on human anxiety towards robots?	Robot gives a speech	Not given	Robovie-X	humanoid	Wizard-Of-Oz operation	39	Not given	17 males, 22 females
40	Rossi et al. (2018)	G1: To explore the influence of personality factors on psychometric assessments by a robot	Robot administers assessments	Test session 45 mins	Pepper	humanoid	Pre-programmed behaviours supporting the	21	53-82, mean 61.16	11 males, 8 females

#	Authors	RQs, goals, hypotheses	Intervention type	Length/ frequency of intervention	Robot used	Robot type	Mode of robot control	N	Age	Gender
							interaction			
41	HeeSeon So et al. (2008)	G1: To test preferences in robot's personality based on people's own personalities.	Conversation with the robot	Not given	I-Robi	humanoid	Pre-programmed behaviours supporting the interaction	80	Mean 23	Not given
42	Haring et al. (2015)	Q1: Based on people's personality and perception of the robot, what are their touch patterns when they interact with an android robot.	Free interaction followed by economic trust game	One-time interaction	Actroid-F	humanoid	Pre-programmed behaviours supporting the interaction	46	Mean 28.5	21 males, 25 females
43	Salem et al. (2015)	H1: Personality will affect perception of robot, interaction, and willingness to collaborate with robot	Robot acts as a host of a lunch gathering	10 mins	University of Hertfordshire (UH) Sunflower Robot	non-humanoid	Pre-programmed behaviours supporting the interaction	40	19-60, mean 38	18 males, 22 females
44	Abe et al. (2017)	G1: To develop a method for estimating a child's personality from behavioural observation during interaction with a robot.	Free interaction	One-time 30 mins	LiPRO	humanoid	Wizard-Of-Oz operation	39	Mean 5.75	25 males, 14 females,
45	Obaid et al. (2016)	H1: Humans with a higher tendency to anthropomorphize non-human agents will prefer a greater interaction distance with the robot than people with a low general tendency to anthropomorphize.	Robot proxemics task	4 person/ robot approach trials	Nao	humanoid	Wizard-Of-Oz operation	22	19-56, mean 28.6	14 males, 8 females
46	Hwang and Lee (2013)	G1: To investigate the role of personality matching in behaviour	Free interaction	5 mins	Pleo	animal	Autonomous robot	31	Mean 24.03	20 males, 11 females
47	Cruz-Maya and Tapus (2016b)	H1: Neuroticism trait is positively related with the test score of the multimedia learning.	Robot as a health coach	A single intervention	Kompai	humanoid	Pre-programmed behaviours supporting the interaction	45	21-64	21 females
48	Kanero et al. (2018)	G1: To examine how individual differences in attitudes towards robots and personality traits may be related to learning outcomes.	Robot as a teacher	One-time lesson, 20 mins	Nao	humanoid	Wizard-Of-Oz operation	24	18.41-24.73, mean 20.18	8 males, 16 females
49	Wullenkord et al. (2016)	H1: Touch will increase negative attitudes among people who already hold prior negative emotions towards robots H2: Touch will enhance positive attitudes towards robots for people who like casual touch	Robot showing hand signs to participants	The study took 40 mins	Nao	humanoid	Wizard-Of-Oz operation	100	17-66, mean 24.03	47 males, 50 females
50	Brandstetter et	Q1: What role is played by personality traits in lexical entrainment	Robot	One-time	Nao	humanoid	Wizard-Of-	40	18-45, mean	55% males,

#	Authors	RQs, goals, hypotheses	Intervention type	Length/ frequency of intervention	Robot used	Robot type	Mode of robot control	N	Age	Gender
	al. (2017)	to robots? Q2: How does this compare in lexical entrainment to other humans?	introduces new words in a lexical entrainment task	interaction			Oz operation		23.7	45% females
51	Jeong et al. (2020)	G1: To test whether a "positive psychology intervention" via in-dorm robot can improve students' psychological wellbeing, mood, and readiness to change behavior.	Conversation with the robot	3-6 mins daily interaction for 7 days	Jibo	non-humanoid	Pre-programmed behaviours supporting the interaction	35	Not given	7 males, 27 females, 1 other
52	Dziergwa et al. (2018)	Q1: How do people with different styles of attachment establish a relation with a social robot during cohabitation? Q2: Can they become emotionally attached?	Free interaction	10 days	EMYS	head only	Autonomous robot	3	25-30	All females
53	Ivaldi et al. (2017)	G1: To determine whether the extroversion dimension is related to the frequency and duration of gazes directed towards the robot's face. G2: To determine whether the extroversion dimension is related to the frequency and duration of utterances addressed by the human to the robot. G3: To determine if the negative attitude towards robots is related to the frequency and duration of the utterances addressed by the human to the robot G4: To determine If the negative attitude towards robots is related to the frequency and duration of gazes directed towards the robot's face G5: To determine If the negative attitude towards robots is related to the frequency and duration of gazes directed towards the areas of contacts between the human and the robot.	Cooperation task with the robot	One-time interaction, average 246.10 s	iCub	humanoid	Wizard-Of-Oz operation	56	19-65 mean 36.95	37 women, 19 men
54	Gaudiello et al. (2016)	Q1: Which individual and contextual factors (desire for control, negative attitudes towards robots, collaborative vs. competitive scenario are likely to influence trust in robot?	Decision-making tasks with robot as fellow participant	30 mins	iCub	humanoid	Wizard-Of-Oz operation	56	19-65, mean 36.95	37 women 19 men
55	Tay, Jung and Park (2014)	Q1: Will users' (a) attitudes, (b) subjective norms, (c) perceived behavioral control, and (d) perceived trust of a social robot positively affect their acceptance of the robot?	Robot performs healthcare or security tasks	20 mins	Unnamed robot	non-humanoid	Wizard-Of-Oz operation	164	20-35, mean 22.4	84 males, 79 females, 1 undisclosed
56	Lee et al. (2006)	G1: To determine whether people would develop complementarity-based attraction or similarity attraction towards a social robot.	Free interaction	25 mins	AIBO	animal	Pre-programmed behaviours	48	19-34, mean 22.46	"balanced between the

#	Authors	RQs, goals, hypotheses	Intervention type	Length/ frequency of intervention	Robot used	Robot type	Mode of robot control	N	Age	Gender
							supporting the interaction			conditions"

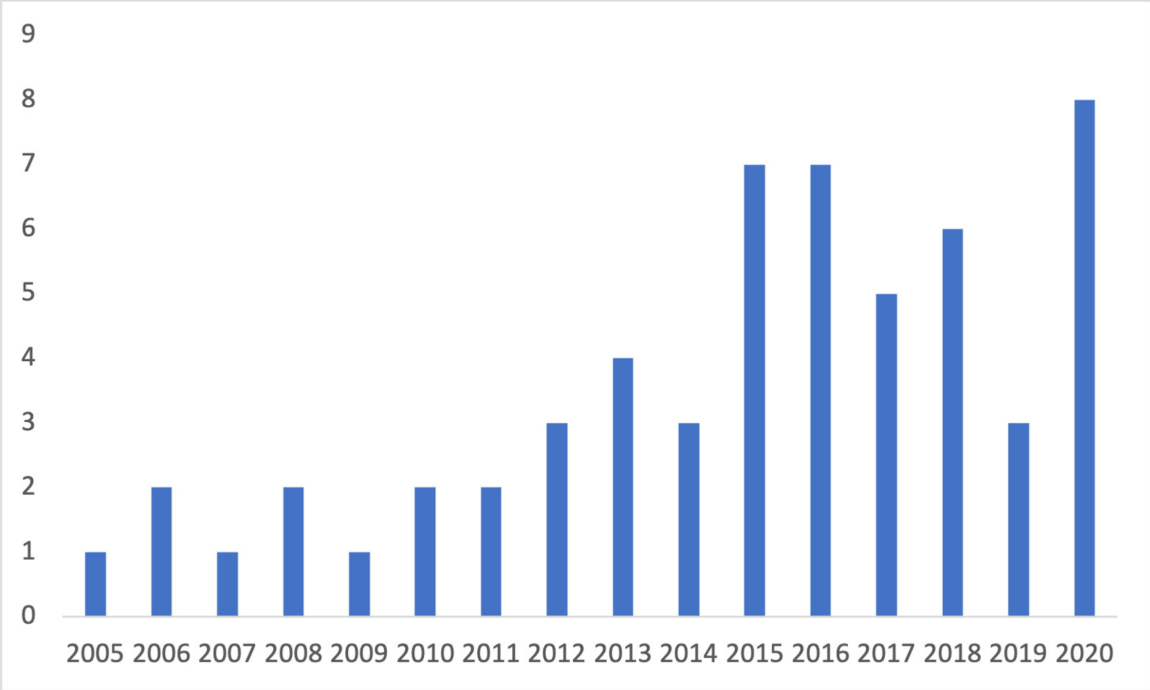

Figure 2. Number of studies included in the review by year of publication

social presence of robots. Park et al. (Park et al., 2012) found that introverted participants perceived the robot as less socially present, while Rossi et al. (Rossi et al., 2020) found that participants with greater ability to recognize the mental states of others rated robot sociability lower. Other correlations included higher perceived positivity of the robot assigned by conscientious participants, higher perceived realism assigned by participants with higher neuroticism, higher perceived positivity and realism of the robot rated by participants with greater openness to experience (Celiktutan & Gunes, 2015). Additionally, participants higher in conscientiousness perceived the robot as more stressful and more expressive in certain conditions (Cruz-Maya & Tapus, 2016a).

User Traits Are Related to Robot Acceptance and Attitudes Towards Robots. User extroversion (Park et al., 2012), agreeableness (Celiktutan & Gunes, 2015) and tendency towards parasocial interaction (N. Lee et al., 2011) were found to be related to greater enjoyment of interaction with the robot and more positive attitudes towards robots. Meanwhile, trait loneliness and avoidant attachment style were associated with lower acceptance of robots (Dziergwa et al., 2018; Li et al., 2020). The higher participants scored in conscientiousness, the less they liked a robot that behaved socially (Looije et al., 2010).

User Traits Are Related to User Behavior Towards Robots. Studies investigating the correlation between the extroversion personality dimension and behavior found that participants who were more extroverted tended to be more engaged in the interaction with the robot and try different types of interactions (Abe et al., 2017; Haring et al., 2013, 2015; Hwang & Lee, 2013; Ivaldi et al., 2017; Salam et al., 2017). Agreeable and conscientious participants tended to be more comfortable and engaged interacting with a robot (Salam et al., 2017; Takayama & Pantofaru, 2009), with the exception of children with high agreeableness who were less likely to maintain eye contact with a robot (Abe et al., 2017). High neuroticism was associated with lower engagement in interaction (Haring et al., 2015; Salam et al., 2017) and greater distance from the robot (Takayama & Pantofaru, 2009). Other traits associated with behaviors towards a robot include introversion correlated with higher head nod synchrony with a robot (Thepsoonthorn et al., 2018) and more monotonous touch (Hwang & Lee, 2013); internal locus of control correlated with greater disclosure during conversation with a robot (Nomura & Kanda, 2012); secure attachment style related to treating the robot like a human being and avoidant attachment style related to treating the robot more like a machine (Dziergwa et al., 2018). Technology competence and enthusiasm for technology influenced the money offers participants made to a robot during a game (Nitsch & Glassen, 2015).

User Traits Are Related to Performance/Outcomes of HRI. Since potential future uses of robots include administering assessments and supporting people during work tasks, the influence of individual differences on outcomes of interaction with a robot is of interest for studies included in this review. Introverts were found to perform better in robot-delivered tasks (Agrigoroaie & Tapus, 2020; Cruz-Maya & Tapus, 2016a). For robot administered tests, openness to experience and extroversion (Kanero et al., 2018; Rossi et al., 2018, 2020), as well as neuroticism (Cruz-Maya & Tapus, 2016b; Rossi et al., 2020)) were linked to higher scores. A study by Jeong et al. found that participants with high conscientiousness and low neuroticism were more ready to change after interacting with a robot (Jeong et al., 2020). Participants with higher conscientiousness were also

Table 3. Quality assessment outcomes for the included studies

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Sample size	Overall
Tapus et al., 2008	High	Low	Unsure	Low	Low	Low	Low	Low	Low
Nomura et al., 2007	High	Low	Low	High	Low	Low	Low	Low	Low
Haring et al., 2013	High	Low	Unsure	High	High	Unsure	Unsure	Low	Low
Park et al., 2012	High	High	Unsure	Unsure	Low	Low	Low	High	Unsure
Looije et al., 2010	Low	Low	Low	High	High	Low	Low	Low	Low
Kimoto et al., 2016	Low	Low	Unsure	Low	Low	Low	Low	Low	Low
Cruz-Maya & Tapus, 2016a	Low	Unsure	Unsure	Low	Low	Low	Low	Low	Low
Bechade et al., 2015	Unsure	Low	Unsure	Unsure	Low	Low	Unsure	Low	Low
Andrist et al., 2015	High	Unsure	Low	Low	Unsure	Unsure	High	Low	Unsure
Stafford et al., 2014	High	Low	Unsure	High	High	Low	High	Low	High
Aly & Tapus, 2016	High	Low	Unsure	Low	Low	Low	Low	Low	Low
Craenen et al., 2018	Low	Unsure	Unsure	High	High	High	High	Low	High
Correia et al., 2019	High	Low	Unsure	Unsure	Unsure	High	Unsure	Low	Unsure
Spatola & Wudarczyk, 2021	High	Low	Unsure	High	Low	Low	High	Low	Unsure
Leichtmann & Nitsch, 2021	High	Low	Unsure	High	High	Low	High	High	High
Rossi et al., 2020	High	Low	Unsure	High	High	High	High	Low	High
Agrigoroaie et al., 2020	High	Unsure	Low	High	Unsure	Unsure	Low	Low	Low
Bjorling et al., 2020	High	Low	High	High	Unsure	Unsure	Unsure	Low	Unsure
Li et al., 2020	Low	Low	Unsure	Low	Low	Low	High	Low	Low
Agrigoroaie & Tapus, 2020	High	Unsure	Low	High	Unsure	Unsure	Low	Low	Low
Xu, 2019	High	Low	Unsure	Low	Low	Low	High	High	Low
Nomura et al., 2008	High	Low	Unsure	Low	Low	Low	Low	Low	Low
Aly & Tapus, 2013	Low	Low	Unsure	Low	Low	Low	Low	Low	Low
Jung et al., 2012	High	Low	Unsure	Low	Low	Low	High	Low	Low
N. Lee et al., 2011	High	Low	Low	High	Unsure	Low	Low	Low	Low
Nitsch & Glassen, 2015	High	Low	Unsure	High	Low	Low	Low	Low	Low
Celiktutan et al., 2019	Low	Low	Unsure	Unsure	Low	Low	Low	Low	Low
Celiktutan & Gunes, 2015	Unsure	Low	Low	Unsure	Low	Low	Low	Low	Low
Salam et al., 2017	Low	Low	Low	High	High	High	High	Low	Unsure
Bernotat & Eyssel, 2017	Low	Low	Unsure	High	High	Low	Low	Low	Low
Stafford et al., 2010	High	Low	Unsure	High	Low	Low	High	Low	Unsure
de Graaf & Ben Allouch, 2013	Low	Low	Unsure	High	Low	Low	Low	Low	Low
Woods et al., 2005	High	Low	Unsure	Low	Low	Low	Low	Low	Low
Chen et al., 2020	High	High	High	Low	Low	High	High	High	High
Thepsoonthorn et al., 2018	High	Low	Unsure	Low	Low	Low	Low	Low	Low
Takayama & Pantofaru, 2009	Low	Low	Unsure	High	High	Low	Low	Low	Low
Cruz-Maya & Tapus, 2017	Unsure	Low	Unsure	Low	Low	Low	Low	Low	Low
Nomura & Kanda, 2012	High	Low	Unsure	Unsure	Low	Low	High	High	Unsure
Nomura & Kawakami, 2011	High	Low	Unsure	High	Low	Low	High	Low	Low

Study	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Sample size	Overall
Rossi et al., 2018	High	Low	Unsure	High	High	Low	High	Low	High
HeeSeon So et al., 2008	High	Low	Unsure	High	High	Unsure	Low	Low	Unsure
Haring et al., 2015	Low	Low	Unsure	High	High	Low	Low	Low	Low
Salem et al., 2015	High	Low	Unsure	High	Unsure	Low	High	Low	Unsure
Abe et al., 2017	Low	Low	Unsure	High	High	Low	Unsure	Low	Unsure
Obaid et al., 2016	High	Low	Unsure	High	Low	Low	Low	Low	Low
Hwang & Lee, 2013	Low	Low	Unsure	High	High	Low	High	Low	Low
Cruz-Maya & Tapus, 2016b	Unsure	Low	Unsure	Low	Low	Low	Low	Low	Low
Kanero et al., 2018	High	Low	Unsure	High	High	Low	Unsure	Low	Unsure
Wullenkord et al., 2016	High	Low	Unsure	High	Low	Low	High	High	High
Brandstetter et al., 2017	Low	Low	Unsure	High	High	Low	Low	Low	Low
Jeong et al., 2020	Low	Low	Unsure	Unsure	Low	Low	Low	Low	Low
Dziergwa et al., 2018	Low	Low	Unsure	Low	Unsure	Low	Low	Low	Low
Ivaldi et al., 2017	Low	Low	Unsure	High	High	High	Low	Low	Low
Gaudiello et al., 2016	High	Low	Unsure	High	High	Unsure	Low	Low	Unsure
Tay et al., 2014	High	Low	Unsure	High	Low	Low	High	High	High
K. M. Lee et al., 2006	High	Low	Unsure	Low	Low	Unsure	High	Low	Low

Q1: Are there any alternative plausible explanations (as far as the two review team members can detect) that could account for the results presented in the study?
Q2: Is there any evidence of sampling bias?
Q3: How representative is the sample of the target population?
Q4: Have the outcome measures been used in other studies investigating the quality or character of a human-robot interaction?
Q5: What evidence is there for the validity of the outcome measures? Do they measure the quality or character of a human-robot interaction?
Q6: What evidence is there for the test-retest reliability of the outcome measures?
Q7: What evidence is there for the internal consistency reliability of the measures (as defined by Cronbach's alpha)?

more motivated by robot to perform a task, under certain conditions (Cruz-Maya & Tapus, 2016a).

User Attitudes Towards Robots

Two dominant measures assessing users' attitudes towards robots were the Negative Attitudes Towards Robots Scale (Nomura et al., 2006) (12 studies) and Robot Anxiety Scale (Nomura & Kanda, 2003) (7 studies). Other measures used in the studies included Godspeed Questionnaire (Bartneck et al., 2009), Technology Commitment Scale (Neyer et al., 2016), Attitudes Towards Robots Taking Social Roles (Xu, 2019), Unified Theory of Acceptance and Use of Technology Questionnaire (Venkatesh et al., 2003), Technology Affinity (Leichtmann & Nitsch, 2021), Implicit Anthropomorphism Scale (Sundar, 2004), Ezer Scale, Kozak Scale, Demoulin Scale and Cottrell Scale (Wullenkord et al., 2016). Some of these instruments were adapted for individual studies.

Attitudes Towards Robots Are Related to User Behavior and Performance in HRI. Evidence from the analyzed studies suggests that the attitudes that users hold towards robots predicted the allowable distance between the robot and the user. Generally, the more negative the attitudes were, the larger physical distance from robots was preferred (Nomura et al., 2007; Takayama & Pantofaru, 2009). Further, attitudes were reflected in user behavior towards robots. Participants with more negative attitudes were more likely to turn off the robot when it asked them not to (Spatola & Wudarczyk, 2021), looked at the robot's face less (Ivaldi et al., 2017), were less engaged with the robot (Chen et al., 2020) and made emotional utterances towards the robot (Nomura et al., 2008). De Graaf and Allouch found that for women, negative attitudes towards robots explained some variance in how much they talked to a robot (de Graaf & Ben Allouch, 2013). Attitudes were also positively correlated with scores on test following robot-delivered instruction (Kanero et al., 2018) and with robot evaluation (Stafford et al., 2014).

Positive Attitudes Towards Robots Positively Impact User Evaluation And Acceptance. Negative attitudes towards robots at baseline were negatively correlated with robot evaluation following an interaction (Stafford et al., 2010, 2014). Participants who were more comfortable with robots taking social roles had greater intention to use robots in the future (Xu, 2019). Similarly, the acceptance subscale of technology commitment scale was a good predictor of using a robot during an experiment (Bernotat & Eyssel, 2017). The more negative attitudes participants held towards robots, the less safe they felt during an interaction (Takayama & Pantofaru, 2009).

Interaction with the Robot is Related to Change in User Attitudes. There are mixed findings regarding the attitude change following an interaction with a social robot. Björling et al. and Stafford et al. reported an improvement in attitudes following an interaction (Bjorling et al., 2020;

Table 4. User trait measures and studies in which they were used.

Trait Measure	Studies
Eysenck Personality Inventory	Tapus and Mataric (2008)
Eysenck Personality Questionnaire	Haring et al. (2013)
	Agrigoroaie and Tapus (2020)
	Woods et al. (2005)
	Dziergwa et al. (2018)
Big Five Personality Inventory	Looije et al. (2010)
	Kimoto et al. (2016)
	Cruz-Maya and Tapus (2016a)
	Cruz-Maya and Tapus (2016b)
	Bechade et al. (2015)
	Andrist et al. (2015)
	Craenen et al. (2018)
	Aly and Tapus (2013)
	Celiktutan, Skordos and Gunes (2019)
	Celiktutan and Gunes (2015)
	Bernotat and Eyssel (2017)
	Takayama and Pantofaru (2009)
	Cruz-Maya and Tapus (2017)
	Abe et al. (2017)
	Kanero et al. (2018)
	Brandsetter et al. (2017)
	Salem et al. (2015)
NEO Personality Inventory-3	Rossi et al. (2018)
	Ivaldi et al. (2017)
	Rossi et al. (2020)
Myers-Briggs Type Indicator	Lee et al. (2006)
	HeeSeon So et al. (2008)
Wiggings Personality Adjective Items	So et al. (2008)
	Hwang and Lee (2013)
Mini International Personality Item Pool	Jeong et al. (2020)
The Empathy Quotient	Rossi et al. (2020)
Adult Attachment Scale	Dziergwa et al. (2018)
Competitiveness Index	Correia et al. (2019)
Sense of Humor Scale	Bechade et al. (2015)
Regulatory Focus Questionnaire	Agrigoroaie, Ciocirlan and Tapus (2020)
UCLA Trait Loneliness Scale	Li et al. (2020)
Parasocial Interaction Tendency	Lee, Shin and Sundar (2011)
Individual Differences in Anthropomorphism Scale	Obaid et al. (2016)
Fear of Negative Evaluation Scale	Nomura and Kanda (2012)
Locus of Control Scale	Nomura and Kanda (2012)
Bickmore Scale	Wullenkord et al. (2016)
Desire for Control Questionnaire	Gaudiello et al. (2016)
International Personality Item Pool	Jeong et al. (2020)

Stafford et al., 2010), and de Graaf and Allouch found no change (de Graaf & Ben Allouch, 2013). It is also suggested that negative emotions towards robots prior to interaction may predict more negative attitudes towards robots following the encounter, especially if the participant is asked to touch the robot (Wullenkord et al., 2016). Thus touch may be a factor in predicting user attitudes towards robots following an interaction. For instance, Haring et al. found that length of touch predicted higher anthropomorphism scores assigned to the robot while comfort with casual touch did not predict attitudes towards robots (Haring et al., 2015).

Robot Interaction Leads to Increased Anxiety. Five of the studies included in this review showed consistent evidence that participants tend to experience higher anxiety towards robots following the interaction (de Graaf & Ben Allouch, 2013; Nomura et al., 2007, 2008; Nomura & Kawakami, 2011; Rossi et al., 2020). Further, anxiety before the interaction explained how much male participants talked to the robot (de Graaf & Ben Allouch, 2013) and was associated with making negative disclosures to the robot (Nomura & Kawakami, 2011). It is unclear whether the increase in anxiety is attributable to neuroticism.

Discussion

This goal of this systematic review was to characterize how individual differences and attitudes towards robots influence human-robot interaction. The distribution of included studies by year shows a steadily increasing interest in this topic, as social robots become more prevalent and tailoring the interaction to an individual increases in importance. Our novel application of the mixed-methods meta-synthesis in the field of social robotics revealed and described key relationships in HRI and illustrate the variety, complexity and interrelatedness of individual traits and interaction outcomes investigated in social HRI field.

Quality Assessment

We have assessed the quality of evidence, based on 1) Study validity and 2) Outcome measure quality. The assessment included three questions to evaluate study validity focusing on existence of alternative explanations, sampling bias and representativeness of the sample; four questions regarding outcome measure quality, and sample size. Overall, the majority of studies included in this review were assessed to have low quality of evidence, which is not an uncommon finding in social robot research (Kabacińska et al., 2020) given the fast-moving pace of the field and the complexity of factors in the design of an HRI study. Studies tend to have small sample sizes and usually include only one brief interaction with the robot and a single assessment, which increases the risk of bias. It is important to note that not all included studies focused on our topic of interest as the main research question, which limits the usefulness of quality evaluation in these instances. Further, 33 of the studies were conference proceedings. This inherently shorter format results in less detailed reporting and contributes to lower quality scores, which may not reflect the quality of research conducted and is the standard for reporting much of HRI research. Therefore, the quality assessment results should be interpreted with these contextualizing factors in mind. Suggestions on how the quality of the studies could be improved were discussed in Kabacińska et al. (2020) and are relevant to the present study. Publications which were rated as high quality were well-controlled, had larger sample sizes and included thorough descriptions of study designs (e.g., Rossi et al., 2018).

Social HRI Framework is Needed

The CASA framework posits that human-computer interactions can be modelled on human-human interactions, and as such it is not surprising that many of the included studies investigated the complementarity and similarity attraction hypotheses, which are also investigated in human social interactions. While the majority of findings reported in this review support the similarity hypothesis, as is the case for human studies, some studies provided evidence to the contrary. Therefore, it is unclear whether or not there is support for CASA in the HRI space. To better establish which hypothesis holds, there is a need to develop a coherent framework that would allow for efficient synthesis of studies across the field of HRI (Robert, 2018). Social robot-specific interaction framework would allow for development of models for social HRI that could generate testable hypotheses. Better-established outcome measures and more detailed reporting would allow for more quantitative investigation into which hypothesis is supported by direct HRI. Future quantitative studies evaluating these two hypotheses would be valuable in modelling and designing successful HRI. Further, there is a need to investigate other potential factors that could influence users' preferences such as demographic variables (Esteban et al., 2022). The studies analyzed in this review also suggest that attitudes towards robots may be correlated with interaction outcomes and robot evaluation (Bernotat & Eyssel, 2017; Stafford et al., 2010, 2014; Xu, 2019) and that personality traits are associated with user attitudes towards robots (Celiktutan & Gunes, 2015; N. Lee et al., 2011) which adds to the limitations of modeling interaction outcomes based on personality traits alone.

Determining which social rules govern interactions between humans and robots is crucial for better HRI design which will improve interaction quality and robot acceptance. Although individual personality trait differences surely play a role in how people interact with robots, there may be more interaction-specific ways to model behavior, that are less intertwined with other possible variables. One theory that enables modelling of interpersonal interaction is Affect Control Theory (Heise, 2007). Rather than focusing on relationship formation as similarity and complementarity attraction hypotheses do, this theory allows for modelling individual situational interactions which is more appropriate in the context of usually single, brief interactions with robots in the studies. Hoey, Schröder, and Alhothali (Hoey et al., 2013) used the theory to develop BayesAct, which models a two-way interaction for artificial intelligence applications and allows for behavior prediction. This model is being used in development of artificial agents that are emotionally aligned with the users (Ghafurian et al., 2020).

Towards Greater Consistency in Outcome Measures

One of the reasons that prevents us from conducting a traditional meta-analysis of the studies in the sample and thus getting more unambiguous answers is the inconsistency of outcome measures between the studies. The HRI outcomes are often not clearly defined. The exception to this observation is proxemics studies in which allowable distance between the robot and the user is measured between the conditions. Among the studies that used quantitative outcome measures, many chose to design custom, ad-hoc questionnaires to investigate HRI outcomes. To allow for meaningful comparison between studies, there is a need to employ better-defined and more consistent outcome measures. Existing initiatives are working towards more standardized HRI outcome measures. For instance, National Institute of Standards and Technology Performance of Human-Robot Interaction project is focused on developing tests, metrics and databases that will allow for consistent performance measurement, establishment of key performance indicators and thus increase the quality of existing data in the field of HRI (Bagchi et al., 2020; *Performance of Human-Robot Interaction*, n.d.). Continuous work towards creating standard HRI measures is crucial for further development of not only social robotics, but any human-facing robotic technology.

When measuring independent variables, researchers use various forms of Big Five personality trait inventory (Eysenck & Eysenck, 1965) to establish personality traits. To avoid using proprietary measures and achieve greater consistency, resources such as the International Personality Item Pool should be used (Goldberg et al., 2006). It is an open-source collaboration that collects scales assessing personality traits. For measuring attitudes towards robots the Negative Attitudes Towards Robots Scale (Nomura et al., 2007) is being consistently used.

Impressions of Robots, Attitudes and Anxiety

In this review we found evidence that users' personality traits are correlated with their impressions of robots and robot evaluations (e.g., Park et al., 2012; Salem et al., 2015), however, similar findings were also reported when looking at the association between attitudes towards robots and robot evaluation and acceptance (e.g., Xu, 2019). To disentangle the attitude and personality trait findings, it is crucial to conduct HRI studies in the future that control for these two factors.

The consistent results regarding increased anxiety towards robots after interacting with a robot are contradictory to another finding that attitudes towards robots tend to improve after an interaction. It is unclear what contributes to this discrepancy and further research is required to explain this phenomenon. For instance, there is a well-established link between trait anxiety and neuroticism (Knowles & Olatunji, 2020), however the included studies did not investigate whether the increased anxiety following the HRI was linked to trait neuroticism. Based on a study of fifty seven adults, Broadbent et al. found that participants who held more human-like mental representations of robots had greater blood pressure increases when interacting with a robot, compared to participants who held less human-like representations (Broadbent et al., 2011). Therefore, the anxiety difference from pre-to post-interaction may be dependent on user expectations, but also on the type of robot that is being used. The large majority (39/56) of studies in this review used humanoid robots, which could contribute to the increase in anxiety. Researchers should carefully select robots for intended applications. For instance, when using social robots to support mental health (Kabacińska et al., 2020), especially in vulnerable populations like children, using non-humanoid robots could be more suitable to minimize possible increase in anxiety. Similarly, some relationships between personality traits and attitudes (for instance, trait loneliness and avoidant attachment style) may be especially relevant to certain social robot use settings and populations of interest such as older adult care, where robots are designed as companions to mitigate loneliness and provide companionship (Berridge et al., 2023; Dosso et al., 2022, 2023). These context -dependent considerations highlight the critical imperative of involving end-users in social robot development (Martin et al., 2024; Robillard & Kabacińska, 2020). Ultimately, as suggested by Naneva et al., more data is needed to determine whether and how robot design moderates users' anxiety and attitudes towards robots (Naneva et al., 2020).

Different Robots Used

The reviewed studies used a variety of different robots, including research prototypes, which makes it difficult to ascertain to what extent the reported results are robot specific. For the purposes of reporting in the results sections, we categorized the robots into different types (i.e. humanoid, non-humanoid, animal-like, head only and other). Further, there are significant differences in how various robots of a certain type appear. For instance, humanoid robots can be more or less human-like, and can range from android robots, which are aiming at mimicking humans (Haring et al., 2013) to robots with some human-like features (Nitsch & Glassen, 2015). The more humanoid robots resemble humans, the more likely they are to be perceived as eerie or disturbing, as is described by the uncanny valley phenomenon (Zhang et al., 2020). Thus, since different robots are used across studies, it is unclear to what extent the human-likeness of the robot contributes to the results, especially when outcome measures include affective responses or attitudes towards robots. A 2021 study investigated whether this phenomenon could be reduced (Yam et al., 2021). Yam, Bigman and Gray found that this effect is mediated by individual's tendency to dehumanize others but can also be reduced by explaining to participants that humanoid robots do not have mental states and cannot experience emotions. Including this simple procedure in the study design could mitigate undesirable uncanny valley effect in HRI studies. Further, more studies which compare multiple robots are needed to help isolate which robot abilities or features are contributing to HRI outcomes. It is also important to consider that different types of robots, especially robots at different stages of development, have different levels of ability to perform the intended actions. How well individual robots perform, can then affect the outcomes of research studies that are investigating social HRI. Thus, the wide range of robots used in included studies adds a layer of complexity to the synthesis of the findings. For instance, people may treat robots who are abstract differently from robots that attempt to mimic humans due to the negative influence of the Uncanny Valley phenomenon (Wang et al., 2015) and attempts at reducing this effect included de-humanizing of humanoid robots (Yam et al., 2021).

Limitations

The main shortcoming of the present study is the lack of quantitative meta-analysis. While a meta-synthesis provides a thorough overview of the findings collected in this review and novel insights in the relationships that drive HRI, it does not allow for calculating effect sizes and confidence intervals, resulting in less precise, narrative synthesized findings. Additionally, findings included in this review were sometimes different from the main focus of the studies and as a result were reported in less detail.

Further, personality traits in the reviewed studies were largely assessed using the Big Five personality model, which is not fully applicable to all global contexts (Laajaj et al., 2019; Thalmayer et al., 2022). Amber Thalmayer and colleagues propose a new, culturally de-centered personality trait model that would allow for studying personality traits in HRI outside of the western, industrialized context (Thalmayer et al., 2024).

Conclusion

In this systematic review we have captured and evaluated studies investigating the relationship between personality traits, user attitudes and the outcomes of human-robot interaction.

Since the review combined quantitative and qualitative findings, we used a mixed methods approach to data analysis, which allowed for synthesizing diverse studies in the field. Despite low quality of evidence, we identified some emergent categories of findings, including extroversion being tied to better interaction outcomes. The categories and synthesized findings resulting from our research can serve as a guide for refining research designs in HRI and developing further hypotheses in areas where contradictory findings exist.

Contributions

Contributed to conception and design: KK, KV, JAD, JMR

Contributed to acquisition of data: KK, KV, JAD

Contributed to analysis and interpretation of data: KK, JAD, KV, TJP, JMR

Drafted and/or revised the article: KK, JAD, TJP, JMR

Approved the submitted version for publication: KK, JAD, KV, TJP, JMR

Competing Interests

Jill A. Dosso is an associate editor at Collabra: Psychology. She was not involved the review process of this manuscript.

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Data Accessibility Statement

All the data generated in this study is available in the Supplementary Material.

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Supplementary Materials

Table S1

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