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A Systematic Review of the Personality of Robot: Mapping Its Conceptualization, Operationalization, Contextualization and Effects

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ABSTRACT

Robots are becoming prevalent as they could socially interact with humans and provide service or companionship. As people attribute personality traits to machines, the personality of robot (POR) has attracted considerable scholarly attention from researchers of human-robot interaction. However, due to the complexity of personality, the ways to design personality into robotics vary on a wide range. This systematic review attempts to map the approaches to designing the personality of robot and understand its effects on human-robot interaction. Following the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses, a review of 40 peer-reviewed publications was conducted. The conceptualization, operationalization, contextualization and effects of POR were summarized in the review. In general, positive POR was preferred and associated with desirable social responses. Suggestions on future design of robotics were discussed. Specifically, it is recommended that the design of POR should match users' expectations in different social contexts. Social cues such as eye gaze, gestures, and voice should be applied at a self-explanatory level to help users efficiently predict and engage with the behaviors of social robots.

1. Introduction

Against the backdrop of the fast development of artificial intelligence, intelligent machines are on the rise. Robots are becoming prevalent in homes, restaurants, hospitals, shopping malls, and other locations where they can socially interact with humans and provide service or companionship (Kanda & Ishiguro, 2013). In 2005, service robots outnumbered industrial robots for the first time (United Nations, 2005). The global robotics market was expected to be worth $1.5 billion by 2019 (The Guardian, 2016).

The terms *social robot, sociable robot, socially intelligent robot, socially interactive robot, socially assistive robot*, and *service robot* are often used interchangeably. For parsimony, we use the term *social robot* in this study. Although virtual agents are sometimes counted as social robots, in this study, we only include physically embodied robots as the approaches to designing these two types of technologies are remarkably different. We rely on Dautenhahn's (1998) definition of social robots and refer to them as embodied agents that are individuals as part of a heterogeneous group, which can "recognize and interact with each other and engage in social interactions", "explicitly communicate with each other", and "contribute to the dynamics of the whole group" (p. 103). These physically embodied robots were found to be critical in eliciting users' responses (Tapus, Mataric, & Scassellati, 2007). To become fully useful in human-centered environments, social robots are expected to satisfy two criteria (Dautenhahn et al., 2005; Syrdal, Dautenhahn, Woods, Walters, & Koay, 2006). First, they must be able to perform tasks or functions useful to humans. Second, they must behave in a socially acceptable and effective manner to ensure that humans feel comfortable with them.

Social psychologists have long corroborated that personality plays a crucial role in human–human interactions, as personality provides consistency that helps individuals interpret and predict each other's behaviors (DiCaprio, 1983). In a similar vein, the personality of robot has attracted considerable scholarly attention from researchers of human–machine interaction, as people indeed attribute personality traits to machines (Lee, Peng, Jin, & Yan, 2006). The personality of robot (POR) refers to the assigned personality traits of social robots. As its significance has been recognized, an increasing number of human–robot interaction researchers and designers have tried to synthesize POR and implement it into social robots.

Despite the significance of POR, because of the complexity of this concept, the ways to design personality into social robots vary on a wide range. Practically, researchers from diverse academic disciplines and geographic regions have attempted to implement POR from visual, linguistic, vocal, and behavioral perspectives. Moreover, the effects of the implemented POR also remain to be explored and documented. If the literature on POR is charted and synthesized, researchers may benefit from the review and use it as a guide to improve the design of social robots. Although some reviews on the general design and use of social robotics have shed some light on the overall human–social robot interaction (e.g., Dautenhahn, 2007a; Fong, Nourbakhsh,

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Table 1. Summary of the reviewed articles on the implemented personality of robot.

Author (Year)	Region	Robot	POR	Operate	Task/Context	Effect
Lee et al. (2006)	US	AIBO	Big Five	VO, M	Simple interactions using 17 verbal commands	Social attraction, Social presence, Enjoyment, Parasocial relationship
Bartneck et al. (2007)	NL	iCat	Agreeableness	L	To play the Mastermind game	Hesitation to switch off the robot
Heerink et al. (2007)	NL	iCat	Expressiveness	L, M	One-on-one conversation	Conversational expressiveness
Mower et al. (2007)	US	ActivMedia Pioneer 2DX	Positive, Negative, Neutral	L, M, VO	Wire puzzle game	Users' engagement
Woods et al. (2007)	UK	PeopleBot	PEN model	M	Interaction tasks in which the robot either negotiates with or help a user	Perception of POR
Kim et al. (2008)	KR	AMIET	MBTI model	M	Robot speaking and listening	Impression of familiarity, enjoyment, activity, and performance
Lohse et al. (2008)	DE, UK, SE	BIRON	EXT-INT	L, M	Watched videos of robot interacting with a user in a robot apartment	Rating on robot's behaviors, such as "active", "interesting" and "talkative"
Meerbeek et al. (2008)	NL	iCat	Big Five: extraversion, agreeableness, conscientiousness	L, M, C, VO	Simple interaction, and TV assistant	Perceived user control, willingness to use, recommendation appreciation
So et al. (2008)	KR	I-Robi	MBTI model	L, VO	To ask people do something + To provide useful info to people	Users' preference
Tapus et al. (2008)	US	Mobile robot	EXT-INT	HIP, VO, L	Post-stroke rehabilitation therapy	Interaction time
Walters et al. (2008)	UK	PeopleBot	Big Five	VA, M	Watching videos of robot's attention-seeking behavior	Acceptance of robot
Groom et al. (2009)	US	Lego Mindstorm NXT, car robot	Friendliness, integrity, malice	VA, HIP	Assembled a robot	Extension of self-concept
Kim et al. (2009)	KR	ROLLY	Ball and Breese's personality types	M, VO	Watching robot's motions	Perceived friendliness
Walters et al. (2009)	UK	PeopleBot	Big Five	VA	Meeting robot at the robot house	Users' preference
Hendriks et al. (2011)	NL	Robot vacuum cleaner	Big Five	VO, M	Cleaning floor	Users' preference
Walters et al. (2011)	UK, DE, SE	BIRON	EXT-INT	M, L	Simple interactions in an apartment	Perceived usefulness of the robot
Jung et al. (2012)	KR, US	KMC-EXPR	EXT-INT	C	To express three facial expressions	Perceived friendliness and likability of robot
Ludewig et al. (2012)	DE	TOOMAS	EXT-INT	L, M, C, VO	Supported customers of a hardware store	Social acceptance
Park et al. (2012)	KR, SP	Facial expression robot	EXT-INT	C	To read a funny story to the robot	Comfortableness, social presence
Weiss et al. (2012)	NL	NAO	EXT-INT	M, VO	Robot as teacher, pharmacist, CEO	Users' preference
Aly and Tapus (2013)	FR	NAO	EXT-INT	L, M	Restaurant info request	Users' preference
Broadbent et al. (2013)	NZ, US	PeopleBot	Asch's checklist	VA	Assisted the participants to take blood pressure	Perceptions of robot's mind and eeriness
Hiah et al. (2013)	NL	Walk-in closet	Dominant, submissive	M	To find a particular item of clothing	Users' perceived dominance, preference
Hwang et al. (2013)	KR	Robot prototypes or visual image	Big Five	VA	Evaluated the prototypes of robots	Emotions
Joosse et al. (2013)	NL	NAO	Big Five	VO, M	Tour guide, cleaner	Users' preference
Kim et al. (2013)	KR	Nettoro	Not specified	L	Having a conversation	Perceived friendliness of robot, response and distance to robots
Kishi et al. (2013)	JP	Humanoid robot	Miwa mental model	HIP, M	Simple interaction	Social attraction
Niculescu et al. (2013)	NL, SG	Olivia	EXT-INT, rational-emotional, strong-weak, assertive-submissive	L, VO	5 receptionist scenarios	Social attraction
Tay et al. (2014)	SG, KR	Humanoid robot	EXT-INT	VA, M, VO	Healthcare robot, Security robot	Social acceptance

(*Continued*)

Table 1. (Continued).

Author (Year)	Region	Robot	POR	Operate	Task/Context	Effect
Andrist et al. (2015)	US, FR	Humanoid robot	Big Five	C	The Tower of Hanoi puzzle solving	Users' engagement
Celiktutan and Gunes (2015)	UK	NAO	EXT-INT	L, M, VO	Multiparty conversation	Users' attention and other interaction behaviors
Gu et al. (2015)	KR	NAO	EXT-INT	M, VO	Museum tour guide	Users' experience and attitude toward the exhibition
Salam et al. (2017)	FR, UK	NAO	EXT-INT	M, VO	Triadic interactions	Users' engagement
Sundar et al. (2017)	US, SG, HK	HomeMate	Playful vs. Serious	VO	To recommend music	Perceived robots' social attractiveness, intelligence, anxiety and eeriness
Ullrich (2017)	DE	NAO	Positive, neutral, negative	L	Four different interaction scenarios: Train ticket purchase, etc.	Users' preference
Chang et al. (2018)	TW	ElliQ	EXT-INT	VO	Viewed a video, listened to and evaluated 8 voices	Perceived likability
Craenen et al. (2018)	UK	Pepper	Big Five	M	Simple interactions	Users' preference
Ogawa et al. (2018)	JP, NL	Geminoid robot	Property-based adjective measurement	HIP	To present a persuasive message of advertising a bluetooth headset	Persuasiveness
Martínez-Miranda et al. (2018)	MX	Lego Mindstorms EV3	Agreeableness	L, M	To guide robot through a maze while collecting sweets and avoiding obstacles	Children's affective reactions and preference toward the robots
Yamashita et al. (2018)	JP	Affetto	Personality Impression Questionnaire	HIP	To look at the forearm of the robot and touch it with their dominant hand	Users' preference

1) For region, DE = Germany, FR = France, HK = Hong Kong, JP = Japan, KR = Korea, MX = Mexico, NL = Netherlands, NZ = New Zealand, SE = Sweden, SG = Singapore, SP = Spain, TW = Taiwan, UK = United Kingdom, US = United States of America.
2) For POR, EXT-INT = Extroversion-Introversion.
3) For operationalization, VA = Visual appearance, L = Language, VO = Vocal feature, M = Movement, C = Countenance, HIP = Haptics, Interaction, and Proxemics.

& Dautenhahn, 2003), there has been no systematic review on the POR. This paper aims to map the existing approaches to designing POR, to understand the effects of POR on human–robot interaction, and to provide suggestions for future robotics design. Specifically, this systematic review attempts to seek answers to how POR has been defined (RQ1) and operationalized (RQ2), what effects POR has exerted (RQ3), and what factors influence the effects of the implemented POR (RQ4).

2. Method

This systematic review was conducted following the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA). The PRISMA protocol was developed by a group of medical researchers to ensure that systematic reviews can be fully and transparently reported so that readers can assess the strengths and weaknesses of the investigation (Liberati et al., 2009). It is notable that due to the heterogeneity in the definitions of our key term *personality* and the manifestation of POR, a meta-analysis has not been conducted.

The terms and syntax of "('personality') AND ('robot' OR 'machine' OR 'agent')" were used to search four academic databases: Web of Science, Science Direct, IEEE Xplore, and ACM Digital Library. The searches were performed on article themes, titles, keywords, and abstracts. Although industrial robots are widely used, we did not include them in this review, as their primary functions are not socially embedded.

Literature that met the following three inclusion criteria was selected. First, only empirical studies published in print or online within the past 12 years (2006–2018) were included. Second, only peer-reviewed studies (including peer-reviewed journal articles, conference proceedings, and conference papers) were included; hence, theses, dissertations, and book chapters were excluded. Third, only English-written papers were considered. As a result, 3,930 articles were identified in this stage, along with 10 additional articles through other sources, including the broad search engine Google Scholar. After removing 3,648 irrelevant articles based on titles and abstracts, textual analysis was conducted with the remaining 292 articles.

The eligibility criteria included empirical studies that investigated the effect of the implemented POR. Hence, eight reviews or opinion pieces were screened out, along with 38 articles that did not consider POR, 126 articles that did not consider the implementation of POR, and 33 articles that did not consider the effect of the implementation of POR. A further 47 duplicate articles were filtered out. Ultimately, 40 articles were included in the final sample for review (see the PRISMA flow diagram for study inclusion in Figure 1).

3. Results

In this section, we first summarize the definitions of POR in previous research, followed by the discussion about the lack of conceptualizations of POR. After that, six approaches of operationalizing POR are elaborated. These approaches include visual appearance, language, vocal features, movement, countenance,

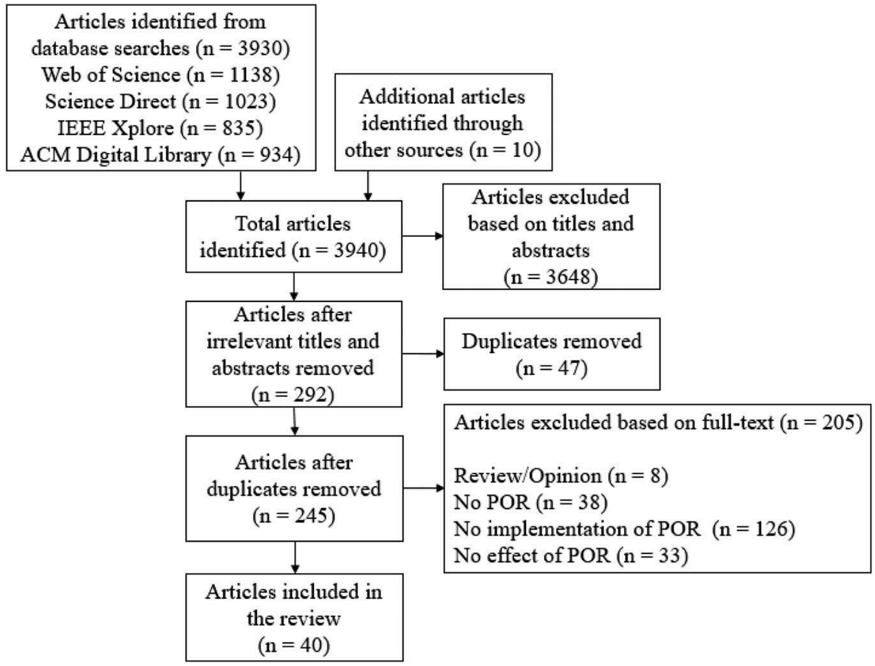

Figure 1. The PRISMA flow diagram for study inclusion.

and others. Next, the effects of implementing POR on users' attitudinal, perceptional, and behavioral responses are reviewed. Last, the roles of users' own personalities, demographics, task contexts, and cultures are discussed as they have been found to moderate the effects of POR (see Table 1).

3.1. How has POR been defined?

Defining POR is as difficult as, if not more difficult than, defining human personality, as no consensus on the definition of personality has been reached (Ewen & Ewen, 2014). Of the 40 articles, 29 did not provide definitions of personality in their literature reviews. The rest marked individual differences or dispositions. For instance, Tapus and colleagues referred to personality as "the pattern of collective character, behavioral, temperamental, emotional and mental traits of an individual that have consistency over time and situations" (Aly & Tapus, 2013, p. 2; Tapus, Ţăpuş, & Matarić, 2008, p. 5). Similarly, personality was generally described as "a set of distinctive qualities that distinguish individuals" (Kim, Kwak, & Kim, 2008, p. 494), "the most important ways in which individuals differ in their enduring emotional, interpersonal, experiential, attitudinal, and motivational styles" (Joosse, Lohse, Pérez, & Evers, 2013, p. 2134), or "a collection of individual differences, dispositions and temperaments that have consistency across situations and time" (Woods et al., 2007, p. 282). Only Hwang, Park, and Hwang (2013) loosely referred to POR as the perception by humans "when looking at the overall shapes of robot" (p. 464). Hence, although POR was implemented and evaluated in all of the literature reviewed in this study, the scholars generally failed to offer a conceptual explication of personality in their work.

Personality has long been a subject of interest among psychologists (Ewen & Ewen, 2014). Since the late 1980s, McCrae and John's (1992) five-factor model, widely known as the Big Five model, has been the mainstream conceptualization of personality. The five factors are extroversion, conscientiousness, agreeableness, neuroticism, and openness to experience. In a more parsimonious form, Eysenck's (1991) Psychoticism–Extroversion–Neuroticism (PEN) model has also been widely used. In line with the popularity of the Big Five and the PEN models in social psychology, 24 out of the 40 studies reviewed here had adopted or partially adopted either the Big Five or the PEN model in their implementation of POR. However, the factors in each model were not equally used. The bipolar dimension of extroversion-introversion shared by both models was the most used factor. For example, one article described the extrovert personality as sociable, friendly, talkative and outgoing, whereas introverts are introspective, and they prefer to be with small groups of people (Walters et al., 2011). As extroversion is the most accurately observable and influential dimension and has the highest agreement among observers (Kenny, Horner, Kashy, & Chu, 1992; Lippa & Dietz, 2000), most studies focused on this dimension.

The third taxonomy of personality is the Myers–Briggs Type Indicator (MBTI). The four dichotomies of MBTI comprise extroversion–introversion, sensing–intuition, thinking–feeling, and judging–perceiving. Those four dimensions reflect an individual's attitude to gather energy, function to collect information, function to make decisions, and lifestyle to adapt to circumstances, respectively (Funder & Sneed, 1993). Compared with the PEN and the Big Five personality dimensions, MBTI is less sensitive to social desirability as it contains no negative aspects of personality (Jeong, 2003). Two groups of Korean researchers chose to manifest POR based on MBTI (Kim et al., 2008; So, Kim, & Oh, 2008). Both groups re-categorized the four dimensions into four types of personality: extraversion–thinking, extroversion–feeling, introversion–thinking, and introversion–feeling.

As the abovementioned personality classifications can be difficult to operationalize, other less-documented personality types were also considered in prior studies. Kim, Kwak, and Kim (2009) used Ball and Breese's (2000) two-dimension personality model. With dominance and friendliness as the two axes, 11 personalities were positioned in a coordinate system, including dominant, arrogant, gregarious, irritable, hostile, skeptical, considerate, friendly, aloof, submissive, and unassuming. Operationally, Asch's (1946) checklist of characteristics has also been used to rate POR. This list consists of 18 pairs of traits that make up three categories of factors: sociable factor (sociable, popular, imaginative, warm, humorous, good-natured), amiable factor (good-looking, happy, humane, generous), and trustworthy factor (persistent, wise, honest).

In addition to borrowing ideas from psychology, robotics researchers have also proposed their own technology-oriented models of personality. Kishi et al. (2013) applied Miwa, Umetsu, Takanishi, and Takanobu's (2001) mental model of robot personality. The robot personality in this mental model consists of a sensing personality and an expressing personality. The sensing personality is shaped by the inward information flow from external stimuli to the robot's emotional state. The expressing personality is determined by the relationship between the robot's emotional state and its actual behavior. The robot's emotion is co-determined by the three dimensions of activity, pleasantness, and certainty.

Besides the well-established models of personality or POR, personality has been defined in nonsystematic ways. For instance, the traits of being friendly, aggressive, shy, bossy, integrate, malicious, and dominant have been equated to personality in studies conducted by, Groom, Takayama, Ochi, and Nass (2009), and Hiah et al. (2013). In two other studies, personality was simplified into three modes: positive, negative, and neutral (Mower, Feil-Seifer, Mataric, & Narayanan, 2007; Ullrich, 2017).

3.2. How has POR been operationalized?

As personality is multifaceted, robotics researchers have sought to implement POR using diverse approaches. In this review, we classify the approaches identified in the 40 studies into six categories (see Figure 2).

3.2.1. Visual appearance

A robot's visual appearance is one of the main factors that influence users' perceptions at first sight, as the robot's overall appearance affects people's expectations when they interact with it (Woods, 2006). Fong et al. (2003) classified the robot's appearance into four categories: anthropomorphic, zoomorphic, caricatured, and functional. In general, anthropomorphic robots are preferred in social settings. Humans tend to treat mechanical-looking robots (or *mechanoids*) less politely and more assertively than human-looking robots (or *humanoids*) (Hinds, Roberts, & Jones, 2004). However, other studies found no significant preference between anthropomorphic and zoomorphic robots, and people liked zoomorphic robots more than machine-like robots (Li, Rau, & Li, 2010).

Of the 40 studies, six manipulated the visual appearance of robots to manifest different dimensions of POR. Broadbent et al. (2013) investigated how a robot's facial appearance affected users' perception of POR. Thirty participants had their blood pressure measured with the assistance of a Peoplebot healthcare robot under three conditions in a randomized order: a robot with a humanlike face, with a silver face, and with no face on the display screen. The robot with the humanlike face display was the most preferred and was rated as the most humanlike, alive, sociable, and amiable; the robot with silver face was the least preferred and was rated as the most eerie, but was perceived as moderately amiable. The robot with no face display was rated least sociable and amiable. Therefore, the humanlike face display was associated with positive perceived personality traits.

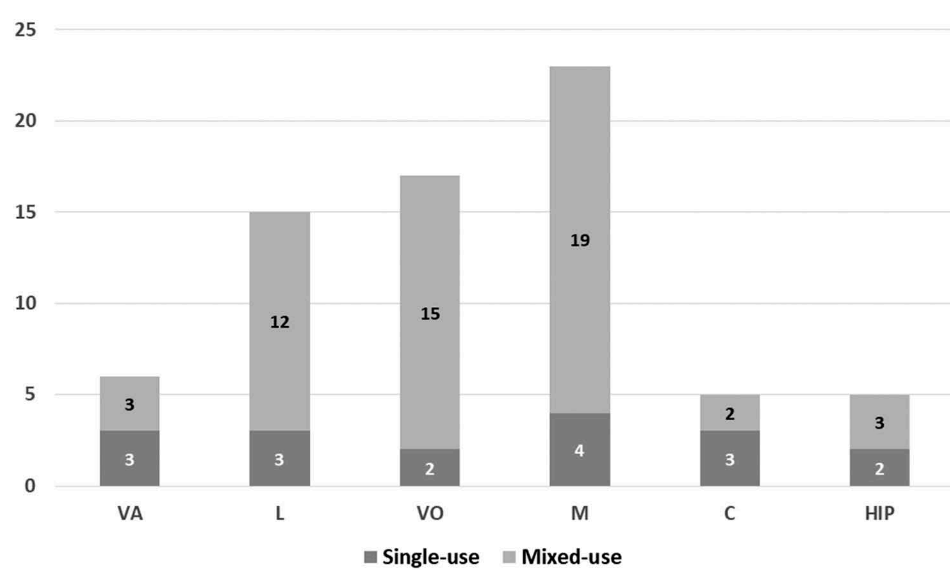

Figure 2. Use of six approaches to operationalize POR.
1) VA = Visual appearance, L = Language, VO = Vocal feature, M = Movement, C = Countenance, HIP = Haptics, Interaction, and Proxemics.2) The y-axis represents the number of studies.

Besides facial appearance, height has also been considered as an indicator of robot personality. In a study by Walters, Koay, Syrdal, Dautenhahn, and Te Boekhorst (2009), commercially available Peoplebot platforms were redesigned into humanoid and mechanoid robots. Humanoids had a humanlike face with eyes and mouth; mechanoids had a camera instead of a face. The findings revealed that humanoid robots tended to be perceived as more intelligent than mechanoid robots, but when combined with short height (1.2 m tall), the humanoid robots were seen as less conscientious and more neurotic, and the taller robots (1.4 m tall) were perceived as more humanlike and conscientious.

The robot's shape also has an influence on people's perception of POR. Hwang et al. (2013) presented visual images and real prototypes of 27 robot shapes to participants. It was found that the robot shape with a cylindrical head and a humanlike trunk was associated with a conscientious personality. The robot shape with a cylindrical head, a humanlike trunk, and humanlike limbs was associated with an extroverted personality. The one with a cylindrical head, cylindrical trunk, and cylindrical limbs was associated with an anti-neurotic personality.

In three other studies, the robots' visual appearances were manipulated in conjunction with factors such as movement. After watching three videos of human – robot social interaction in a domestic home environment, viewers rated a humanoid as more extroverted, agreeable, conscientious, and intelligent (substituted for open to experience) than a basic robot and a mechanoid (Walters, Syrdal, Dautenhahn, Te Boekhorst, & Koay, 2008). Similar to the design of the research reported by Walters et al. (2009), the humanoid had a face and was fitted with two arms, each with seven degrees of freedom (DoF) to make a more humanlike waving gesture. In contrast, the mechanoid had no face and had a simple one-DoF gripper that was only able to move up or down. The basic robot had a simple one-DoF arm fitted with a compound movement that allowed the robot to lift its arm and make a pointing gesture. However, Groom et al. (2009) found that the car robot was more likely than the humanoid robot to be perceived by the participants as an extension of self-concept with a favorable personality.

In studies in which the robot's overall appearance could not be easily modified, subtle changes in visual appearance were used as complements to manifest personalities. A shiny red color was used on an extroverted robot and matte gray was used on an introverted robot by Tay et al.'s (2014) study. These colors were in tandem with different movements and vocal characteristics to reflect the extroversion–introversion personality dimension.

3.2.2. Language

Language is another powerful tool to manifest POR. Indeed, 15 of the 40 studies reviewed here designed specific language styles to express robots' personality traits. Three studies relied merely on language to manifest different personality traits. In the study reported by Bartneck, Van Der Hoek, Mubin, and Al Mahmud (2007), when playing a cooperative game with the iCat robot, participants experienced varying levels of the robot's agreeableness. In the high agreeableness condition, the robot kindly asked if it could make a suggestion, whereas in the low agreeableness condition, the robot insisted that it was its turn (Bartneck et al., 2007). The robots that called the participants by their names were rated friendlier than those who did not call the participants by their names. For the robots calling participants by name, the robots' speech style (familiar vs. honorific) was used to shape the participants' perception of the robot's friendliness (Kim, Kwak, & Kim, 2013). Different language was used to fit the profiles of positive personality (being nice, friendly, and enthusiastic about everything, complimenting people, and being inconsolable after making a mistake), neutral personality (acting like a robot or a computer in the classical sense – focusing on efficiency and doing exactly what is asked), and negative personality (being sarcastic, a bit stubborn, and unpredictable) (Ullrich, 2017). Below are example responses of the three robot personalities in a ticket purchase scenario.

> Positive: "Hi! I wish you a good day. You're looking exceptionally well today! How many tickets may I print for you?"
> Neutral: "Please name the amount of tickets."
> Negative: "Not so fast! My break lasts exactly eight more seconds, and I surely won't change that for you! [8 seconds later…] Alright now. How many tickets?"

Another eight studies implemented POR via language joint with vocal features. In post-stroke rehabilitation therapy, the effect of extroverted and introverted robots was examined (Tapus et al., 2008). The extroverted challenging personality was expressed by strong and aggressive language (e.g., "You can do it!" "You can do more than that, I know it!" "Concentrate on your exercise!"), higher volume, and faster speech. In contrast, the introverted nurturing script was composed of gentler and supportive language, such as "I know it's hard, but remember that it's for your own good," "Very nice, keep up the good work," and "You did a very nice job," in a voice of lower volume and pitch. Similarly, positive, outgoing, and enthusiastic styles of language were operationalized to express extraversion, and timid, inward, and impersonal styles for introversion, along with different vocal features, in the studies of Celiktutan and Gunes (2015), Ludewig, Döring, and Exner (2012), Meerbeek, Hoonhout, Bingley, and Terken (2008), Mower et al. (2007), Niculescu, van Dijk, Nijholt, Li, and See (2013), and So et al. (2008). Walters et al. (2011) also chose brief sentences to shorten interactions for introverted robots.

The combination of language and movement was another popular means to demonstrate different personality traits, as nine studies adopted this approach. Besides the extroversion dimension of personality, agreeableness was expressed via language. For instance, in Martinez-Miranda et al.'s research (2018), via voice commands, children guided agreeable or disagreeable robots through a maze to collect sweets and avoid obstacles. Both personality traits were designed with predefined phrases. For instance, an agreeable robot would welcome participants by saying, "Hello, my name is Paulina. I am a robot, and I am here to help you collect as many sweets as possible. What is your name?" In contrast, a disagreeable robot would say, "Hello, my name is Ever and I am here to win sweets. I hope you are good enough to give me useful instructions and achieve that." In addition to the dialog, actions were simulated to model these personality traits. The agreeable robot correctly executed all of the movements instructed by the children (walk, stop, turn left, and turn right), whereas some of the children's commands were ignored or delayed intentionally by the disagreeable robot.

3.2.3. Vocal features

Besides the robots' language style, vocal features were used to express POR in 17 studies. Common vocal features included volume, speaking speed, pitch, and the amount of speech. In the ten studies that manipulated the extroversion dimension of personality, extroversion was expressed with higher volume, faster speed, higher and varied pitch, and a larger amount of speech; introversion was expressed with lower volume, slower speed, lower and monotonous pitch, and a smaller amount of speech (Celiktutan & Gunes, 2015; Chang, Lu, & Yang, 2018; Gu, Kim, & Kwon, 2015; Joosse et al., 2013; Lee et al., 2006; Ludewig et al., 2012; Niculescu et al., 2013; Tapus et al., 2008; Tay et al., 2014; Weiss, van Dijk, & Evers, 2012). For instance, Lee et al. (2006) specified their calibration of parameters of the Sony AIBO robot in manipulating the AIBO personality. For an extrovert AIBO, the voice was set with a 140 Hz fundamental frequency, a 40 Hz frequency range, 216 words per minute speech rate, and the volume level at 3; but for an introvert AIBO, the voice was set with an 84 Hz fundamental frequency, a 16 Hz frequency range, 184 words per minute speech rate, and the volume level at 1. Similar vocal features were used to express more dimensions of the Big Five personality, including extroversion, openness, and neuroticism in the study by Hendriks, Meerbeek, Boess, Pauws, and Sonneveld (2011); extraversion, agreeableness, and conscientiousness in the study by Meerbeek et al. (2008); and all of the five factors in the study by Salam, Celiktutan, Hupont, Gunes, and Chetouani (2017).

In the four studies in which personality was defined with other models other than the Big Five model, similar vocal features were manipulated and found to associate with personality traits. Kim et al. (2009) found that volume was negatively related to friendliness. In Mower et al.'s (2007) research, the positive personality case used a bright tone of voice and provided strong encouragement, whereas the negative personality case used a scornful tone of voice and provided little encouragement. As for robots designed for senior citizens in a retirement home, the serious robot featured a female voice that spoke with limited inflections in pitch and tone, whereas the playful robot featured a female voice with frequent inflections in pitch and tone (Sundar, Jung, Waddell, & Kim, 2017).

The most difficult personality traits to express are probably those of the thinking–feeling dimension in the MBTI model. In the study by So et al. (2008), the extrovert and thinking robot had a fast and direct speech rate, spoke loudly, and had a high pitch and monotone voice; the extrovert and feeling robot had a fast and impromptu speech rate, spoke loudly, and had a high and varied pitch; the introvert and thinking robot had a slow and fixed speech rate, spoke quietly, and had a low pitch and monotone voice; and the introvert and feeling robot had a slow and gentle speech rate, spoke quietly, and had a low and soft pitch.

3.2.4. Movement

Given that robots are machines that can move independently, movement was the most commonly used approach to the synthesis of POR. Indeed, 23 studies applied POR this way. Due to the wide range of robot forms, the movements the robots were capable of performing were different.

For the robots with arms and/or hands, the amplitude and speed of hand gestures are widely used to express POR. For instance, in Celiktutan and Gunes (2015) and Salam et al.'s (2017) research, the extroverted NAO robot displayed hand gestures and shifted posture, whereas the introverted NAO robot exhibited a static posture during the course of the interaction. As the gesture is constrained by an arm's DoF, adding more DoFs changes the gestures remarkably. In Walters et al.'s (2008) study, the two arms of a robot had seven DoFs each and were able to make a more humanlike waving gesture. In contrast, the simple one-DoF arm of the basic robot and the mechanoid robot could only move up and down. Thus, through the attributes associated with robot design, the robots displayed the Big Five personality traits. Besides the Big Five personality traits, the MBTI trait of thinking versus feeling was implemented via the size, velocity, and frequency of gestures, such that the feeling robot moved its hands fast and frequently, whereas the thinking robot moved its hands less frequently (Kim et al., 2008).

In a similar vein, for the robots with a movable head, the head and neck motion can be used to display personality traits. Meerbeek et al. (2008) designed two versions of personality for the iCat robot. The introverted, polite, and conscientious iCat robot moved its head more slowly and less frequently, nodded reservedly, and kept its head tilted slightly downward. In comparison, the extroverted, friendly, and somewhat careless iCat robot turned its head and nodded faster with more playful movements, kept its head up, and turned its head away during conversation. For robots whose heads can move less, nodding is the most expressive way to display personality traits, as demonstrated in Ludewig et al. (2012) and Heerink, Krose, Evers, and Wielinga (2007).

Following the principles of kinesics, the moving angle, moving speed, and moving patterns of a robot generally have POR implications. As a rule of thumb, larger, faster, and more frequent body movements are symbolic of extroversion and dominance. This principle was observed in studies conducted by Gu et al. (2015), Joosse et al. (2013), Lee et al. (2006), Walters et al. (2011), Tay et al. (2014), Aly and Tapus (2013), Lohse et al. (2008), Kim et al. (2009), Craenen, Deshmukh, Foster, and Vinciarelli (2018), and Mower et al. (2007). In addition, the robots' proactive behaviors (e.g., robots did not wait for participants to give instructions) and passive behaviors (e.g., robots waited until instructed) led to different ratings on the robots' personality traits of neuroticism and psychoticism in Woods et al.'s (2007) research, and of agreeableness in Martinez-Miranda et al.'s (2018) research.

Besides those conventional robots, a robot with an abstract shape was used in Hiah et al.'s (2013) study. An intelligent walk-in closet was made to behave either dominantly or submissively using lighting effect. The submissive lighting illuminated shelves closest to the user and followed the user's movements in the closet, whereas the dominant lighting directed the user toward a specific shelf by using a sequential flickering of lights.

3.2.5. Countenance

For robots with humanlike faces, eye contact can be designed to express different personality traits. As extroverts generally engage more with the gaze of their conversational partners than introverts do, gaze is closely tied to personality. In an experiment reported by Andrist, Mutlu, and Tapus (2015), in which a socially assistive robot guided users in a puzzle-solving task, the gaze behavior was controlled to make the robot extroverted or introverted.

The robot KMC-EXPR is a commercial face robot with a pair of eyes, a mouth, and lips, and has been used in two studies. To make the robot's appearance and behavior extroverted, Jung, Lim, Kwak, and Biocca (2012) and Park, Jin, and Del Pobil (2012) designed active facial characteristics such as big eyes and a frequently moving gaze. In a shopping environment, the shopping assistant TOOMAS's eyes winked frequently for the extrovert version, in addition to having more eye contact (Ludewig, Döring, & Exner, 2012).

Other countenance can also express dimensions of personality. For instance, in Meerbeek et al. (2008), a smile with eyes wide open and brows up was symbolic of agreeableness, whereas a frown implied conscientiousness.

3.2.6. Haptics, interaction, and proxemics

Besides the five commonly used robot characteristics, robot texture has also been examined as a factor influencing POR. Humans perceived different POR when touching the soft part of a childlike android robot named Affetto who was made of different textures (Yamashita, Ishihara, Ikeda, & Asada, 2018). The preferable touch sensations were associated with the robot's likable personality impressions.

The role that the user plays in a human–robot interaction can affect the perception of POR. A significant effect of the robot's assembler has been found on perceived robot malice, such that participants rated the robots assembled by others more malicious than those assembled by themselves (Groom et al., 2009). In a persuasion study, a persuasive message was presented via a Geminoid (an android that greatly resembles a human) of the Japanese robotics scientist Hiroshi Ishiguro, a video of the scientist, or the scientist himself (Ogawa et al., 2018). While the Geminoid was found to be as persuasive as the scientist and the video of him, the Geminoid was rated as more open than the scientist or the video of him.

Since the seminal work by Hall (1996), proximity has been widely studied in social contexts. According to Hall's personal space theory, space is divided into four zones: intimate (up to 0.25 m from the body), personal (between 0.3–1 m), social (about 1–3 m), and public (beyond 4 m). Robotics researchers have begun to use proxemics to express POR, one example being the robot's sensing personality in the study reported by Kishi et al. (2013), in which the distance between the robot and an object determined the robot's emotional state, which further shaped its expression personality. For instance, if the object moved far away, pleasantness decreased; if the object moved closer and entered an area within a distance of 45 cm to 75 cm, pleasantness increased until activation increased if the object got closer than 45 cm.

3.3. What are the effects of POR?

The underlying assumption in designing personality into social robots is that the POR would elicit users' desirable social responses. This assumption has been validated by the reviewed articles examining the effects of POR. Findings from those studies highlight the affective, attitudinal, perceptional, and behavioral responses elicited by the implemented POR, which could shed light on future social robot designs in securing favorable responses from users.

Under the Computers Are Social Actors paradigm (Nass & Moon, 2000; Reeves & Nass, 1996), the recognition of POR is considered among the first-degree social responses, a term coined by Lee et al. (2006). After the recognition of POR, the subtle and complicated attitudinal and behavioral changes to the machine have been referred to as the second-degree social response, as they are triggered by the first-degree social responses. Borrowing the concepts of first- and second-degree social responses, we reviewed the effects of implemented POR as the consequence of the recognition of POR, even though a substantial number of studies we reviewed did not indicate any causal or temporal relationships between these variables. In this section, we only discuss the main effects of implemented POR. Please see Section 3.4 for the interaction effects between POR and other factors.

3.3.1. The effects of implemented POR on users' affective and attitudinal responses

Hwang et al. (2013) examined the evoked emotions and perceived personalities of a wide range of robot shapes. In a study that showed 27 different robot shapes to 20 college students, the results revealed that the participants' enjoyable and favorable emotions were positively related to the robots' perceived personalities of extroversion, agreeableness, conscientiousness, anti-neuroticism, and openness. Meanwhile the concerned emotion was negatively related to these personality traits.

Likability or preference was a commonly probed attitudinal response in the reviewed studies. The participants generally showed some preference for robots with specific personality traits. For instance, in Hiah et al. (2013), the participants preferred the abstract-shaped robot (intelligent walk-in closet) with submissive characteristics relative to one with a dominant personality. Among senior citizens in Taiwan, a robot's likability was found to be positively related to the robot's degree of extroversion (Chang et al., 2018). On encountering the NAO robot, participants had more enjoyment with an extroverted version than with an introverted one (Celiktutan & Gunes, 2015).

3.3.2. The effects of implemented POR on users' perceptional responses

In addition to affective and attitudinal responses, more studies focused on the effects of implemented POR on users' perceptions. Crucial in social contexts, social acceptance has been deemed a key indicator of the successful implementation of social robots (Ezer, Fisk, & Rogers, 2009; Heerink, Krose, Evers, & Wielinga, 2010). Social acceptance has been examined in a handful of studies. For instance, in shopping scenarios, an extroverted assistant robot (TOOMAS) was more socially accepted by users than a conventional robot (Ludewig et al., 2012).

Moreover, robots with certain personality traits were found to affect, for example, the user's perceived control, the quality of interaction (Niculescu et al., 2013), and the robot's persuasiveness (Ogawa et al., 2018). For instance, in Meerbeek et al. (2008), the iCat robot performed as a television assistant to get information about and recommend television programs.

The participants perceived more user control and had more appreciation for the recommendations with the more extroverted and agreeable robot. Interestingly, the perceived POR was also found to have an influence on the user's extension of self. In Groom et al.'s (2009) study, participants first assembled either a humanoid robot or a car robot. Then they used either the robot they built or a different one in a game. Using the dimensions of friendliness, integrity, and malice to measure personality, the study showed that the participants reported greater extension of self-concept with a car robot and preferred its personality to that of a humanoid robot. Groom et al. (2009) explained that it was because participants perceived the humanoid robot to have a unique identity and were less likely to attribute self-concept to the humanoid.

3.3.3. The effects of implemented POR on users' behavioral responses

Four studies investigated how the implementation of POR affected users' behavioral responses. In Bartneck et al. (2007), the iCat robot cooperated with users in a Mastermind game. Compared to a disagreeable and unintelligent robot with a power switch, participants were more hesitated to shut down an agreeable and intelligent robot. Furthermore, the robot's personality traits influenced the users' interaction with it. The participants showed more expressiveness with a more expressive iCat robot in Heerink et al.'s (2007) study, as the number of users' positive behaviors, such as nodding their head and smiling, was significantly greater when they interacted with the social iCat robot than with the non-social one. Similarly, during social conversations with the Nettoro robot, the participants introduced themselves more actively, paid more attention to what the robot said, asked it more questions, and stayed closer to a friendlier robot that called the participants by their names, than to a less friendly robot (Kim et al., 2013). However, positive personality traits did not always yield better performance. In an exercise-monitoring scenario, the number of participants' fault instances was lower with a negative robot moderator than with a positive or neutral one (Mower et al., 2007).

3.4. What factors influence the effects of implemented POR?

The POR interacts with a variety of other factors to shape the effect of human–robot interaction. Four major factors have been identified: the users' personality, the social context of the task or interaction, culture, and the demographics of the users.

3.4.1. Users' personality

Similarity attraction and complementarity attraction are probably the two most well-documented rules of interpersonal attraction based on personality-based social cues (Infante, Rancer, & Womack, 1997). According to the similarity attraction rule, people are attracted to others with perceived similarities in interpersonal interactions, including similar background and personality (Richard, Wakefield, & Lewak, 1990). The complementarity attraction rule posits that people are more likely to be attracted to those whose personality characteristics are complementary to their own to achieve a balance (Leary, 2004). Whether these two rules stand in human–robot interaction is an open question. The results from the reviewed studies painted a mixed picture.

More studies lent support for the similarity attraction rule. The results of the studies conducted by Tapus et al. (2008), Aly and Tapus (2013), Andrist et al. (2015), Craenen et al. (2018), and Park et al. (2012) indicated that participants preferred or felt more comfortable interacting with a robot with similar personality traits. The complementarity attraction rule was validated by only one study. When interacting with an AIBO robot with complementary personalities to their own, participants enjoyed the interaction more, rated the robot's intelligence and social attraction higher, and felt more social presence during the interaction, than with a robot with similar personalities (Lee et al., 2006).

In addition, two other studies provided more answers than a simple yes or no. Joosse et al. (2013) found patterns that indicated similarity attraction for extrovert participants when the robot was a tour guide, and complementary attraction for introvert participants when the robot was a cleaner. In So et al.'s (2008) study, neither similarity attraction nor complementarity attraction stood out; instead the users preferred a kind robot.

3.4.2. Context of the task/interaction

Due to the technical difficulty, most of the reviewed studies examined only one social context, such as game playing or a social encounter in a domestic environment. However, it is important to consider the role that the orientation of the social scenario plays. Ullrich (2017) differentiated goal-oriented scenarios and experience-oriented scenarios by creating four framing stories: a train ticket purchase (goal-oriented), an amusement park ticket purchase as the millionth visitor (experience-oriented), a tapping test with a possibility to win a prize (goal-oriented), and the first use of a social companion robot (experience-oriented). A NAO robot with positive, neutral, or negative personalities played corresponding roles in these stories. In the goal-oriented stressful situation (train ticket purchase under time pressure), the neutral personality was preferred, and in the experience-oriented scenarios, the positive POR was rated best.

Some traditional occupations are presumably associated with certain typical personalities in human society (Crowther & More, 1972; Glick, 1991). The same phenomenon may occur in human–robot interactions. Tay et al. (2014) examined the occupation-based personality stereotypes in social robots, using healthcare and security jobs as two examples. Two task scenarios were developed for each occupational role. Largely consistent with their expectation was the finding that people responded more positively to an extroverted healthcare robot and an introverted security robot than the other way around. Users' attitudes, subjective norms, perceived trust, and acceptance of the robot were significantly higher in the extroverted healthcare and introverted security robot conditions than in the introverted healthcare and extroverted security robot conditions. However, this occupation-based stereotype was not validated by Joosse et al. (2013), who expected an extroverted museum tour guide robot and an introverted cleaning robot to be preferred over the opposite. Indeed, the introverted robot was rated significantly less credible than the extroverted robot in both tasks, yielding no support for the proposed hypothesis.

And in Weiss et al. (2012), no significant tendency of preferred POR could be found in three jobs: robot as teacher, pharmacist, and CEO, largely due to the insufficient sample size.

3.4.3. Culture

Weiss et al.'s (2012) study was the only one that explored the effect of culture on the perception of POR. In three stereotypical occupation contexts, a NAO robot played the roles of an introvert teacher, an ambivalent pharmacist, and an extroverted CEO. Twenty-one Dutch and ten German participants evaluated the robot's performance. It was found that Dutch participants were less compliant with the robot, but they trusted it more than German counterparts. German participants, however, were willing to spend more time with the robot in general.

3.4.4. Demographics and technology use experiences

Users' gender, age, and technology use experiences have been identified to play a role in shaping the effect of POR. Martínez-Miranda et al. (2018) examined the affective reactions of 174 children aged 6–11 years old who played a game with Lego Mindstorms EV3 robots with either agreeable or disagreeable personalities. The results indicated a negative relationship between the children's age and their tolerance toward the robot's disagreeableness. Specifically, the children between 6 and 7 years old were more likely to ignore the differences in the two robots' behaviors, feel comfortable and happy with the disagreeable robot, and invite the disagreeable robot to play another mission. The older children were more likely to feel sad and angry while working with the disagreeable robot. One possible reason would be that younger children did not develop the same perception and cognition abilities as older children (Martínez-Miranda et al., 2018), which inhibited them from differentiating robot personalities.

For adults, the pattern of age became complex, depending on their own personality traits. Woods et al. (2007) divided the total 28 participants into two groups: a younger group (< 35 years old) and an older group (> 35 years old). After they socially interacted with a human-scaled PeopleBot in a simulated living room, the participants rated the POR. For the older group, the more sociable they rated their own personality, the more sociable they rated the POR. For the younger group, the more vulnerable, assertive, anxious, and aggressive they rated themselves, the more vulnerable, assertive, anxious, and aggressive they scored the POR. A gender-based difference surfaced as well. For males, their own anxiety level was positively related to the perceived anxiety level of the robot. For females, a similar pattern emerged for assertive and dominant levels. As for technological experience, no significant correlation was found between the participants' own personalities and the perceived POR for the participants without a technological background, but there existed significant correlations for those with a technological background.

4. Discussion

Overall, scholars from different academic fields have documented the conceptualization, operationalization, contextualization, and effects of POR in multiple geographical areas. The results consistently revealed that whereas POR was largely equated with the Big Five or the PEN model of personality, especially the extroversion–introversion dimension, the five approaches of visual appearance, language, vocal features, eye contact, and movement were mainly used to implement POR. The expressed POR not only affected the users' enjoyment and the robots' perceived likability, social acceptance, and persuasiveness, but also elicited different behavioral responses from the users. The users' age, gender, and personality and the task context moderated these effects to varying degrees.

4.1. The issues associated with defining POR

As machines are not living creatures with consciousness (Severinson-Eklundh, Green, & Hüttenrauch, 2003), the design of POR involves designers' assumptions and biases. Fong et al. (2003) classified five common personality types used in social robots: tool-like (operating as a smart appliance), pet or creature (the characteristics associated with domesticated animals such as dogs or cats), cartoon (the exaggerated features to portray personality traits), artificial being (mechanical and machine-like characteristics), and humanlike. Although these five categories have been widely cited (e.g., Joosse et al., 2013; Kim et al., 2008), none of the 40 sampled studies implemented the first four personality types, probably because these personality types have not been operationally defined.

As most of the reviewed studies adopted the human-oriented definition of personality with only a few exceptions (such as Kishi et al., 2013), a mimicry of human personality traits has been widely witnessed. The over-fitting of human personality, however, may introduce some serious validity issues. For instance, in a study, the trait of good-looking was deemed as an aspect of POR. Hence, we question this common assumption made in the reviewed studies that POR should be based on human personality. This human-centered proposition may not hold true. A few studies asked what kind of personalities was desired in social robots and found that people preferred "a calm, polite, and cooperative robot … that works efficiently, systematically and likes routines" (Hendriks et al., 2011, p. 194) or simply "a kind robot" (So et al., 2008, p. 500). A human-oriented personality concept may need alterations to better fit the case of robotics. Some researchers indeed have suggested human-pet interaction as a framework to model human-robot interaction and proposed the idea of implementing the well-liked qualities of companion pets in social robots (e.g., Konok, Korcsok, Miklósi, & Gácsi, 2018).

We also cast doubts to the gold standard of human personality. As the gold standard of human communication has already been questioned (see Spence, 2019), we have reasonable doubt regarding POR matching the bar raised by human personality. Sundar's (2008) machine heuristic can support this idea. If a technology is designed to be machinelike and perform as a machine, it may raise users' perception of the machine as credible, objective, and fair. Thus, if the goal of designing the POR is to increase the perceived trustworthiness of the robot, the assumption that we need a gold standard personality may need to be revisited.

The results further revealed that most of the studies did not provide specific definitions of personality, which may affect how researchers and designers operationalize POR and how they innovate the machines. It is recommended that future research should be more rigorous in conceptualizing the POR as the first step in designing machine personalities.

4.2. The issues associated with operationalizing POR and the effects of POR

Given the advancement level of current robotics, only a handful of social cues have been implemented to manifest POR. While most research has centered on the factors including visual appearances, language, and vocal features, researchers could consider applying more social dimensions to the design of machines. For instance, researchers could focus more on the message manipulation and test the perceived personality based on these message effects. Also, as more modalities have been found to be effective in human-technology interaction (Nam, Shu, & Chung, 2008), future research could factor in haptic cues and emotional cues as manifestations of POR.

Additionally, although it is believed that humans can accurately interpret POR in the intended way (e.g., Lee et al., 2006) in many scenarios, success is not always guaranteed. In terms of the visual appearance of robots, the uncanny valley phenomenon has been well-documented (Mori, 1970), and whether there exists a similar uncanny valley for POR remains an open question. How much of verisimilitude in POR with human personality is too much before we feel eeriness? Studies have yet to address this question.

Although the effects of the perceived POR on users' affective, attitudinal, perceptional, and behavioral responses have been documented, the underlying psychological mechanism between the perceived POR and its effects remains unclear. Because POR is considered first-degree social responses (Lee et al., 2006), the connection between first-degree social responses and second-degree social responses (i.e., the subtle mental and behavioral changes based on the recognition of first-degree responses) could be explored. As more social scientists enter the field of human–machine communication, we expect to see more studies investigating the psychological mechanism behind the effects of POR. To obtain the flow of a user's mind, long-term human-robot interaction is needed. It seems that most previous studies have focused only on short-term or single human–robot interactions with brief zero acquaintance encounters (e.g., Joosse et al., 2013; Jung et al., 2012; Walters et al., 2008). Although it requires much labor, time, and equipment to carry out long-term interaction studies (Dautenhahn, 2007b), it is crucial and beneficial to probe the long-term psychological effects of POR. For instance, Short et al. (2014) found evidence of relationship-building between 26 first-grade children and socially assistive robots Dragonbots over 6-session interactions, and the long-term one-on-one nutrition interventions seem promising in encouraging child learning. Future research may consider incorporating POR and examining its long-term effect (e.g., Goodfellow et al., 2018; Scassellati et al., 2018).

Beyond the moderating effects of age, gender, and technology use in previous POR studies, cultural differences should be a salient influencer in people's perception of robots (Weiss et al., 2012; Woods et al., 2007). However, although researchers from multiple nations and regions have brought their insights into this field, we have seen only one cross-cultural empirical comparisons regarding POR implementation. Based on their affiliations, researchers from 14 countries or regions contributed to the 40 articles (Figure 3). Whereas 11 (27.5%) of the articles were the results of cross-national collaboration, the rest were completed within a single country. However, all those studies in 14 countries or regions showed homogeneity in conceptualization and operationalization of POR to a rather large extent, with little cross-cultural difference looming. Because with a Judeo–Christian tradition, Western societies typically draw a clear line between living and dead entities. In Eastern cultures, such as the Shinto religion-diffused Japanese culture, all things including robots can be deemed as alive and having a soul (Woods et al., 2007). That is probably why humanoid robots have higher acceptance in Japan than in Western countries (Faiola, 2005). As POR is often embedded with designers' cultural perspectives and assumptions, future research may explore how cultural factors influence POR and further affect the effects of POR.

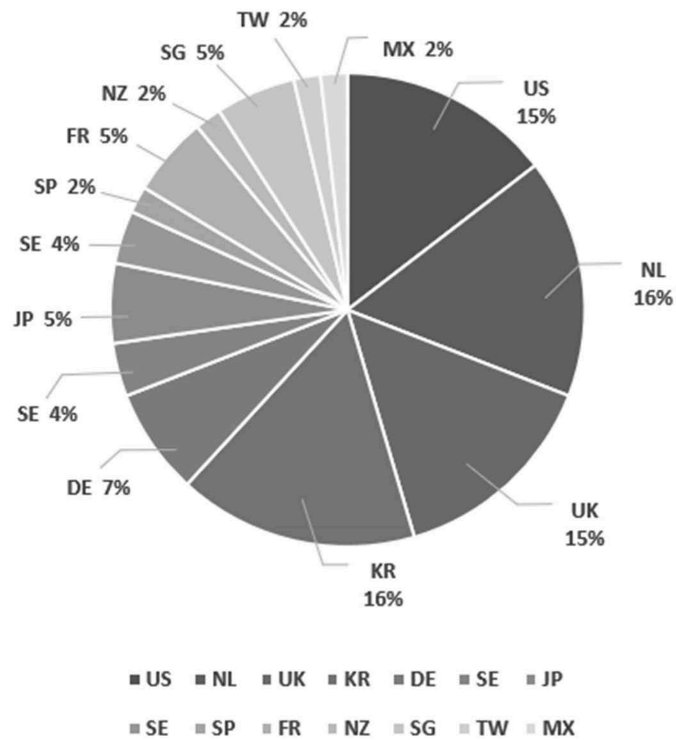

Figure 3. The distribution of the countries or regions of researchers' affiliations. 1) DE = Germany, FR = France, HK = Hong Kong, JP = Japan, KR = Korea, MX = Mexico, NL = Netherlands, NZ = New Zealand, SE = Sweden, SG = Singapore, SP = Spain, TW = Taiwan, UK = United Kingdom US = United States of America.2) For cross-regional collaborations, we counted all countries or regions based on the locations of authors' affiliations.

4.3. Practical implications

This review study has significant practical implications, as it highlights the advantages and disadvantages of various synthesis approaches of POR. Drawing upon the findings of those 40 reviewed studies, three pieces of suggestions should be considered in designing social robot and implementing human-robot social interactions.

First, as an essential social cue that may ultimately affects users' perception, cognition, and emotion, personality plays a significant role in users' interactions with machines. However, a mimicry of human personality may not constantly yield to desirable effects. The extent to which simulation works depends on users' acceptance, attitudes toward machines, and technology use experience. Thus, designers could take user-oriented design principles into consideration and test more interaction effects between individual differences and POR.

Second, projecting POR through multimodal cues is necessary, given the current technological level. Although research has embedded social cues to the countenance, visual appearance, and language of the machines, more subtle cues can be devised and equipped in human-machine communication. Given that robots are becoming more flexible and autonomous, programming gestures, traveling paths, and other social cues would allow the robot to be more human-like and render stronger effects on users' psychological responses.

Third, based on the uncanny valley effects, researchers should be cautious in designing social robots with too much humanness, because it may defeat the robot-aiding-human purpose (Duffy, 2003). It is crucial to match the POR with the social contexts and the task skill level.

4.4. Limitations

This systematic review is subject to several limitations. First, only forty papers have been reviewed in this study. Although it is a small number of articles reviewed, the outcome is based on the guidelines of systematic review protocol; and it is not uncommon to have similar numbers of articles in reviews (e.g., Wong et al., 2019). Admittedly, the way some studies manipulate factors such as robot affect and behavior is substantially similar to the way the reviewed studies implement the POR. For instance, Kennedy, Baxter, and Belpaeme (2015) employed varied verbal content, gestures, gaze, and personalization (using users' names or not) of robots to differentiate a more sociable robot from a less social one. The results in this study paralleled the finding from Mower et al. (2007) research, where users' performance was better with a robot with negative personality than with a positive one. To abide by the selection criteria, however, those studies have been excluded from this review due to their lack of focus on POR. Given that the psychological dynamism of how the POR and robot affect influence users may be similar, it would be enlightening to compare both effects in future research.

Second, given that robotics technology is fast changing, we did not include literature prior to 2006. It may be interesting to take a longitudinal look at how the definition and implementation of POR has evolved over the past decades. Third, although robotic technology is popular in some non-English speaking countries like Japan, only literature in English was reviewed. A review would have more insight if Japanese or other language literature were included. Fourth, we did not assess the quality of the reviewed studies. Instead, we assumed the robustness of the study designs and the correctness of the results. As an example, despite the popularity of the MBTI as a personality indicator, its validity has been questioned in prior research (e.g., Boyle, 1995). Moreover, some experiment studies did not check the success of their manipulation. Hence, our ability to soundly answer the research questions has been constrained.

4.5. Conclusion

This systematic review has provided a panoramic picture of how POR has been conceptualized, operationalized, contextualized, and evaluated over the past 12 years. To fit a human-centered concept of personality, diverse social cues have been used to synthesize POR within the technical constraint. In general, positive POR was preferred and associated with desirable social responses. However, some findings also raised questions about the validity of POR that mirrors human personality. As individuals rely on personalities to predict and interpret each other's behavior, well-designed POR can increase the communication quality between robots and their users. As robots have been applied in various areas, including education and healthcare, pairing robots with a personality that users are comfortable with can augment humans' acceptance of the robots. The study informs us that current research on personality has practical value in human–robot interaction. Specifically, the design of POR should match users' expectations in different social contexts. Social cues such as eye gaze, gestures, and voice should be applied at a self-explanatory level to help users efficiently predict and engage with the behaviors of social robots.

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