Human-Robot Interaction: Mapping Literature Review and Network Analysis

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Abstract

Organizations increasingly adopt social robots as additions to real-life workforces, which requires knowledge of how humans react to and work with robots. The longstanding research on Human-Robot Interaction (HRI) offers relevant insights, but the existing literature reviews are limited in their ability to guide theory development and practitioners in sustainably employing social robots because the reviews lack a systematic synthesis of HRI concepts, relationships, and ensuing effects. This study offers a mapping review of the past ten years of HRI research. With the analysis of 68 peer-reviewed journal articles, we identify shifting foci, for example, towards more application-specific empirical investigations, and the most prominent concepts and relationships investigated in connection with social robots, for example, robot appearance. The results offer Information Systems scholars and practitioners an initial knowledge base and nuanced insights into key predictors and outcome variables that can hinder and foster social robot adoption in the workplace.

Keywords: Human-Robot Interaction, cross-disciplinary literature review, network analysis, social robots, research developments

1. Introduction

The research field of Human-Robot Interaction (HRI) gained increasing attention over the last years. Since 2012, publications on HRI have almost doubled (2012: 22,500 vs. 2021: 39,400 publications[1]). HRI researchers investigate any form of interaction between humans and robots to understand the varying factors influencing such interactions and their consequences. While a lot of HRI research has accumulated, only a few literature reviews exist that synthesize the collected knowledge across the different research disciplines (e.g., Diederich et al., 2022; Fink, 2012; Malinowska, 2021). However, they often lack a synthesis of empirically supported relationships between key concepts, which hinders the convergence of theory. Additionally, the Information Systems (IS) research field has only recently started investigating the impact of robots – specifically socially interacting robots (i.e., social robots) – in the work context (e.g., Ge et al., 2021; Stock & Nguyen, 2019). In the core IS journals, not even a handful of articles cover research on social robots so far. With the increasing adoption of social robots in real-life work contexts, e.g., robotic concierges in hotels (Yam et al., 2021), we require a better understanding of how the adoption of social robots into our work environment changes human perception and their ensuing consequences for their human counterparts and organizations.

To close this gap, this work identified shifts in HRI topics and synthesized key theoretical concepts and relationships of past HRI research to offer researchers more nuanced insights into the existing HRI literature across disciplines on social robots. Thus, our research questions are: *How did the HRI research develop over the last 10 years? What are the key theoretical concepts and relationships employed in the HRI literature?*

Our HRI review contributes an overview of the technological and application-specific developments of social robots and a systematic identification of key concepts and relationships from the past 10 years by adopting a network analysis approach. The network analysis allowed us to quantitatively analyze the complex and interwoven effects discovered in HRI research to uncover the dynamics of the research field (Strozzi et al., 2017). The following sections are structured as follows. First, a background on the HRI field is given, followed by a description of the methods we employed for mapping and analyzing the literature. We then present the results of our study and end with

[1] Based on Google Scholar (scholar.google.com) search on the 11.06.2022

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contributions for theory and practice, limitations, future research, and a conclusion.

2. Background on HRI

The HRI research field first gained popularity in the late 1990s but dates back to the early 1930s. HRI specifically investigates the emerging effects when humans come into contact with robots. Robots can be understood as physically embodied artificial technologies with virtual and physical capabilities (You & Robert, 2018).

HRI is a multi-disciplinary field (Diederich et al., 2022), comprising computer science, that investigates the technical development and design of artificial technologies and algorithms (e.g., Baumgartl & Buetter, 2020; X. Li et al., 2017), operations research, which studies the industrial and logistic applications of robots, psychology, which analyses the socio-emotional consequences of interactions (e.g., Stenzel et al., 2012; Wiese et al., 2019), but also medicine, investigating healthcare and medical applications for robots (e.g., Atashzar et al., 2017; Ison & Artemiadis, 2015), and other fields such as sociology or education, investigating pedagogic benefits and potential knowledge gains of learning with robots (e.g., Leyzberg et al., 2018). More recently, business use cases, such as robots in the retail and hospitality sector (Chuah & Yu, 2021; de Kervenoael et al., 2020) have emerged, which have also been studied from an IS angle, investigating the effects of service robots in investment handling (Ge et al., 2021), as a home assistant (Benlian et al., 2020) or as part of a team collaboration (You & Robert, 2018).

Research fields differ mostly based on their interest in the types of robots. The most commonly known and most applied robots are industrial robots. In the past operations research, industrial robots followed rule-based instructions, so that pre-programmed movements could be utilized on assembly lines. Current research utilizes more advanced cobots, i.e., collaborative robots, which triggered more research on the collaborative and cooperative 'nature' of robots (Liu & Wang, 2021). In parallel, medical research investigated the utilization of companion robots, wearable robots, and surgical robots in health care, rehabilitation (e.g., J. Fong et al., 2019), and medical procedures (e.g., Buzzi et al., 2017). Especially companion robots emerged as effective means to stimulate comfort and pain relief in patients (e.g., Carros et al., 2020; J. Fong et al., 2019). In psychology, a particular focus was set on social robots, which describe any form of a robot with social interaction capabilities to converse with humans in a human-like manner (Appel et al., 2021; Breazeal, 2004; B. Tay et al., 2014). This sparked interest as research recognized the impact that human-like and interactive robots had on humans.

A large amount of research has accumulated on HRI, yet a broader synthesis is missing. With the corpus of knowledge being fragmented, it can prove challenging for newcomers, such as researchers from the IS field, to gain an overview of the socio-emotional and interpersonal effects of robots. Yet, such a synthesis is relevant for improving our understanding of the effects of robots being increasingly adopted in practice and for designing the addition of robots to the workforce. Especially with their gaining popularity and technical potential, social robots increasingly become reality in the business context, even beyond the industrial setting (e.g., Yam et al., 2021). Therefore, it is essential to build a broad overview of the theoretical concepts and relationships that past HRI research has investigated and could provide IS researchers with a foundation and future research directions.

3. Method

We adopted a mapping review methodology, as a specialization of a scoping review, to capture the extent of the existing HRI literature (Paré et al., 2015). Relevant literature was searched in six academic databases (ACM Digital Library, IEEE Xplore, EbscoHost, Science Direct, AIS Electronic Library, and Wiley Online Library) and all Basket of 8 IS journals (Lowry et al., 2013). The broad search terms (to adhere to a mapping review) were *Human-Robot Interaction, Human Robot Interaction,* and *HRI* in the title, abstract, or keywords. Articles had to be written in English and be published between 2012 and April 2022 resulting in 3,218 accessible articles.

We performed three rounds of exclusions. The first iteration excluded papers that were off-topic, had less than 3 pages, or were duplicates, resulting in 2,697 articles. Articles focusing on robots other than social robots, in a medical setting with patients, theoretical articles, and technical specifications of algorithms, were excluded in the second round, because they did not fit the topic, could bias results for healthy people, or did not offer insights on tested relationships. This iteration resulted in 390 papers. The third iteration excluded articles focusing on children, infants, and the elderly, due to similar reasons (e.g., infants and small children react differently to robots than adults (Okanda et al., 2021) biasing the relationships). Finally, we excluded all articles not published in journals ranked in the VHB[2] or ABS[3] lists, two widely used lists of journals recognized as high-quality outlets with a focus on the business and management communities including information systems, to keep the review manageable, resulting in a final set of 70 articles published across 22 journals (see Table 1).

Two authors coded the constructs and relationships in several rounds to ensure consistency in coding. Only significant main effects between two constructs were included (i.e., edges), which cover independent, mediating, dependent, or control variables. Moderating effects, time-series/within-subjects, clustering analyses, and most correlation analyses had to be excluded as they could not have been visualized. The final data set included 68 papers, resulting in the collection of 226 nodes and 306 edges.

4. Results

The results are presented in two parts: we first describe the shifts that occurred in HRI research in the last 10 years, and then we present the key theoretical constructs and relationships that were identified based on a network analysis.

4.1. Shifting Focus in HRI

Several developments in the HRI research field in the last 10 years are reflected in the examined robot types, robot embodiment, and application areas (see Figures 1 and 2). It should be noted that the drop in 2022 is due to the fact that our study included articles published until April 2022 and thus does not include a full year.

In the last decade, the advancement of technological capabilities allowed robots to become more autonomous. Several articles in our review build their investigations on such rather autonomous robots (e.g., Akalin et al., 2022; Qin et al., 2022).
Still, many authors relied on images of real or animated robots, (Dang & Liu, 2022; Weis & Herbert, 2022), and videos of real robots (e.g., Cameron et al., 2021; C. S. Song & Kim, 2022) (see Figure 1).

Other research relied on robots in virtual reality (Thimmesch-Gill et al., 2017) or in telepresence (i.e., real-time broadcasted interaction with a real or animated robot at a different physical location (Koulouri et al., 2012; Mollahosseini et al., 2018)). Overall, our review shows that there exists an increasing focus on physically present robots, with a continued usage of images.

Table 1[4]: Overview of journals in the review

Journal	Freq
Computers in Human Behavior	30
International Journal of Human-Computer Studies	12
Cognition	4
Applied Ergonomics	4
IEEE Transactions on Cybernetics	2
Journal of Experimental Psychology: Human Perception and Performance	1
Information Systems Journal	1
Information Systems Research	1
Journal of Experimental Psychology: Applied	1
Journal of Marketing Research	1
Journal of the Association for Information Systems	1
Tourism Management	1
International Journal of Hospitality Management	1
Journal of Business Research	1
The Information Society	1
British Journal of Education Technology	1
Journal of Retailing and Consumer Services	1
Human Factors and Ergonomics in Manufacturing & Service Industries	1
Human-Computer Interaction	1
Revue Europénne de Psychologie Appliquée	1
ACM Transactions on Computer-Human Interaction	1
Total	**68**

The application area of robots has also shifted over the last decade (see Figure 2). Most articles studied social robots in a non-specified context with an experimental design independent of any application field. Although, collaborative robots (e.g., Akalin et al., 2022; Alarcon et al., 2021) and robots in the service industry (e.g., Cameron et al., 2021; Ge et al., 2021) appear to gain an increased interest since 2017/18.

A few studies investigated robots and their interaction with humans as educational robots (e.g., Guggemos et al., 2020), smart home assistants (Benlian et al., 2020), or companion robots (e.g., Delgosha &

[2] https://vhbonline.org/en/vhb4you/vhb-jourqual/vhb-jourqual-3/complete-list, which is particularly recognized in the German-speaking communities.

[3] https://charteredabs.org/academic-journal-guide-2021/, which is particularly recognized in the United Kingdom, Australia, New Zealand, etc.

[4] A detailed author, journal, and frequency table can be found in the supplementary materials at: https://osf.io/d9nz8/

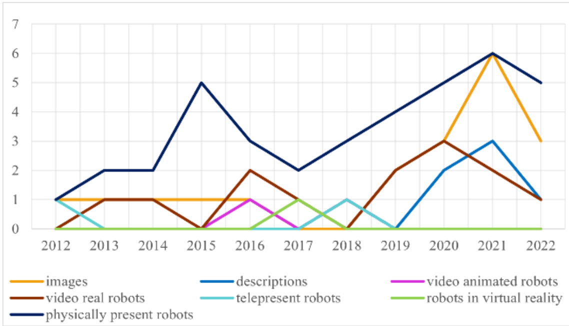

Figure 1: Robot types over the last 10 years

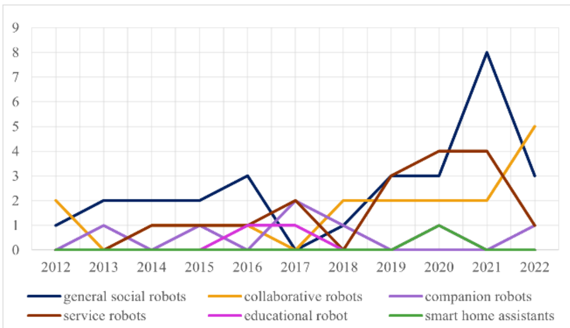

Figure 2: Robot application areas investigated in the last 10 years

Hajiheydari, 2021). However, the latter findings have to be treated carefully, as our inclusion criteria focused on healthy adults, excluding children and the elderly. Likely, even more HRI research on robots for education and companionship exists.

We also classified the reviewed literature according to the studied robots' embodiment[5]. The two most prominent robot types are human-similar (i.e., humanoid; n=34) or mechanical appearances (n=33). Humanoid robots have a torso, external limbs, a head, eyes, and additional facial features. Nao by Softbank Robotics represents an example studied repeatedly (e.g., Alarcon et al., 2021; Szczepanowski et al., 2020). Mechanical robots do not resemble human bodies and are characterized by being clearly identifiable as machines, such as Baxter by Rethink Robotics (e.g., Zhao & Malle, 2022). It must be noted that the differentiation between humanoid and mechanical robots remains on a continuum so that the "mechano-humanness" remains difficult to interpret. Some authors also investigated androids (n=11), which refer to the most human-similar form of a robot, with its appearance being the 'spitting image' of a human (Złotowski et al., 2018), e.g., Erica by the Japan Science and Technology Agency (JST) at Osaka University (e.g., Zhao & Malle, 2022). Finally, researchers also studied zoological (i.e., animalistic; n=9) (e.g., de Kleijn et al., 2019; Delgosha & Hajiheydari, 2021) or cartoon-like robots (n=3) (Appel et al., 2021). In 6 cases, no clear description of the robot embodiment was provided (e.g., Benlian et al., 2020).

4.2. Network Analysis

In the next step, we visualized the investigated theoretical constructs and relationships as nodes and edges in a network graph. Figure 3 shows the network where (1) the width of edges is calculated based on the frequency a hypothesis was successfully tested, (2) the size of the nodes is determined based on the node total degree (degree centrality). This is representative of how often researchers tested a construct as a predictor, mediator, or dependent variable, and where (3) the direction of the edges is indicated by an arrow based on the ordered node pairs (i.e., predictor and response variable).

Most prominent predictors. The degree-ratio r_i of a node $v \in V$ in Equation 1 was defined as:

$$r_i = \frac{(k_i^{out} - k_i^{in})}{(k_i^{out} + k_i^{in})} = \frac{(k_i^{out} - k_i^{in})}{(k_i^{tot})} \qquad \textit{Equation}\ [1]$$

with in-degree k_i^{in}, out-degree k_i^{out}, and total degree k_i^{tot}. The in-degree and out-degree represent the number of in-going or out-going edges of a node, respectively, and the total degree describes the sum of in- and out-degree (Jackson, 2008). A degree-ratio of 1 suggests that a certain construct (either measured or manipulated) was considered across all reviewed studies as a predictor variable (i.e. only out-going edges; see Table 2). The most frequent predictors, *robot appearance*, *agent type*, and *empathy* will be shortly reviewed in the following:

Robot appearance describes the different robot designs, specifically its embodiment, look, facial design, voice design, and dialogue formulation. It was the most tested predictor construct in our data sample (k^{out}=25) (e.g., de Kleijn et al., 2019; Yam et al., 2021). In this vein, researchers investigated different forms of appearances that spanned different embodiments (e.g., humanoid, mechanical, zoomorphic). Other research on robot appearance focused on certain body parts, such as the head (e.g., Mara & Appel, 2015a; Mollahosseini et al., 2018), the eyes (e.g., Y. Song et al., 2021), or the voice (e.g., Lu et al., 2021). However, the most common manipulation of robot appearance was along the dimensions of human-likeness and machine-likeness (e.g., Lu et al., 2021; Wiese et al., 2019).

Agent type refers to the different types of entities, e.g., humans, robots, and computers. Related research not only tested different robot embodiments, such as Nao or Baxter (Zhao & Malle, 2022) but frequently

[5] A detailed list of all authors can be found in the supplementary material.

directly compared them to humans (e.g., B. T. C. Tay et al., 2016; Wiese & Weis, 2020).

Empathy is defined as the affective and cognitive capability or process of projecting oneself into another person or entity and understanding their reality (Alves-Oliveira et al., 2019; Pereira et al., 2011; Wispé, 1987). In the context of HRI considerable research has concerned itself with the question, of how to ingrain emotional intelligence into robotic behavior and attitudes. Bretan et al. (2015) in their paper developed a system to display emotions through body movement to simulate emotional intelligence. Other articles studied the simulation through empathic speech (Leite et al., 2013) or measured perceived empathy of a non-intentionally manipulated empathic robotic agent (de Kervenoael et al., 2020).

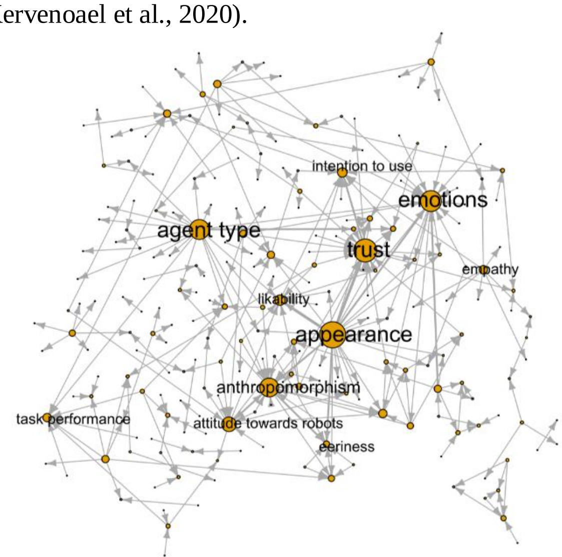

Figure 3[6]: Network graph of confirmed hypotheses

Most prominent outcome variables. A degree-ratio of -1 suggests that a certain construct was considered across all reviewed studies as an outcome variable (see Table 2). The most frequent outcome variables were *task performance*, *intention to use*, and *eeriness*:

Task performance was measured only in six out of 68 articles (Ciardo et al., 2020, 2022; Cohavi & Levy-Tzedek, 2022; Y. Kim & Mutlu, 2014; Wiese et al., 2019; You & Robert, 2018). In the reviewed articles, task performance was, for instance, concerned with the number of mistakes made, the task completion time (Y. Kim & Mutlu, 2014), or the number of successful task achievements.

Intention to use was measured in four out of 68 articles (Cameron et al., 2021; de Kervenoael et al., 2020; Delgosha & Hajiheydari, 2021; Guggemos et al., 2020). In the reviewed articles, intention to use gave an indicator for the adoption in the hospitality industry as a robotic server (de Kervenoael et al., 2020), as a robotic guide in buildings (Cameron et al., 2021), in education as a robotic lecturer (Guggemos et al., 2020) and as companion robot (Delgosha & Hajiheydari, 2021).

Eeriness describes a feeling of discomfort, which acts as an internal warning system (Mori et al., 2012) and was measured in three out of 68 articles (Mara & Appel, 2015a, 2015b; Yam et al., 2021). All these articles build on the idea of the Uncanny Valley (Mori, 1970), which describes the nonlinear relationship that exists between the perceived human-like appearance of a robot and the positive and negative feelings that develop. Against this backdrop, the reviewed studies measured perceived eeriness as a means to better understand, which characteristics (e.g., anthropomorphism, (Mara & Appel, 2015b; Yam et al., 2021)) and behaviors (position and head tilt, (Mara & Appel, 2015a)) of robots foster perceptions of eeriness in humans.

Table 2: Top constructs differed according to the node degree

Construct	k_i^{out}	k_i^{in}	r_i
robot appearance	25	0	1
agent type	19	0	1
empathy	8	0	1
trust	7	16	-0.39
human emotions	5	16	-0.52
anthropomorphism	5	13	-0.44
task performance	0	8	-1
intention to use	0	9	-1
eeriness	0	6	-1

Note: k_i^{in} is the in-degree, k_i^{out} is the out-degree of a node, and r_i is the degree-ratio.

Other prominent variables. Besides the above-mentioned predictor and outcome variables, the review also revealed constructs that were frequently used as independent (IV) and dependent (DV) variables, which were not necessarily solely employed as predictors or outcomes. This is indicated by nodes with high in- and out-degrees in the network and includes *trust*, *human emotions*, and *anthropomorphism*.

Trust refers to the belief that another person acts with integrity and your best interests at heart (Heerink et al., 2010; You & Robert, 2019). Trust is a multi-faceted concept and is often measured along several constructs such as performance-based, integrity-based,

[6] A high-resolution image version can be found in the supplementary material.

or deceit-based trust behavior (Cameron et al., 2021) or functionality, helpfulness, and reliability (Delgosha & Hajiheydari, 2021). Reviewed literature treated trust as an *independent variable* only once. Building on an IS acceptance theory, Guggemos et al. (2020) showed that a robot's trustworthiness positively affects effort expectation, which in turn positively influences intention to use. Trust was also successfully tested as a *mediator variable*. For example, Lu et al. (2021) found that trust mediates the relationship between robot appearance and service encounter evaluations. Cameron et al. (2021) found that when a robot states its competence or offers an apology for an error, humans have more trust in its performance. This, in turn, leads to higher intentions to use the robot in the future. Delgosha & Hajiheydari (2021) showed among others that a more socially present robot leads to higher levels of trustworthiness, which in turn increases its intention to use. Most often, reviewed literature treated trust as a *dependent variable* (e.g., McColl et al., 2017; Y. Song et al., 2021). For example, Tay et al. (2014) – using non-verbal robot cues (speech tempo, pitch, movements) – manipulated the robot's personality (introvert vs. extrovert) and found that more extrovert robots fostered more trust. Akalin et al. (2022) investigated among others the effects of a faulty robot (e.g., failed speech recognition, wrong answer, delayed response) on trust. They found that trust decreases significantly when the robot is faulty.

Human emotions describe a form of an affective sentiment. The reviewed literature investigated valence in terms of positive and negative emotions (e.g., Rosenthal-Von Der Pütten et al., 2014) or describing the strength of emotions (Thimmesch-Gill et al., 2017; Weis & Herbert, 2022). Most reviewed studies treated human emotions as a *dependent variable*. For example, Chuah & Yu (2021) showed, that the viewing of a surprised facial expression by the android Sophia triggered the strongest emotional reactions of Instagram users. Thimmesch-Gill et al. (2017) showed that the presence of a humanoid robot encouraging participants in a stressful situation – induced by submerging the hand in ice-cold water and performing mathematical tasks – reduces their perceived valence. Human emotion was also tested as an *independent variable* by Kim et al. (2020). They discovered that when humans develop positive affect toward a security guarding robot, they also perceive it as more intelligent and increase their expectations.

Anthropomorphism is understood as the attribution of human-like features to non-human agents, e.g., animals, religious figures, or machines (Lesher, 1992). Anthropomorphism has been successfully investigated as *independent* (Qin et al., 2022; C. S. Song & Kim, 2022; Zhao & Malle, 2022), *mediating* (W. Kim et al., 2020; Mara & Appel, 2015b) *and dependent variable* (Appel et al., 2021; Mara & Appel, 2015a; Nicolas & Agnieszka, 2021; Spatola & Wudarczyk, 2021; Szczepanowski et al., 2020; Wiese & Weis, 2020). For instance, Song et al. (2022) showed that perceived anthropomorphism increases the attitude towards HRI. Kim et al. (2020) showed that anthropomorphism positively mediates the relationship between initial expectations towards the robot and perception of intelligence. Appel et al. (2021) revealed that the correctness of a display of emotions by a robot impacts its perceived anthropomorphism.

Repeatedly tested hypotheses. According to our review, 9 out of 297 stated hypotheses in the reviewed HRI literature were tested more than once. It should be noted that this result is highly dependent on how constructs were coded for analysis, which was described in Section 3. For this study, we made a conscious decision to remain on a fine-granular level of construct identification to facilitate hypothesis testing in the future. The two most repeatedly tested hypotheses (3 times each) are summarized in the following.

Robot appearance & trust. Mathur & Reichling (2016) found a nonlinear relationship between machine/human-like appearance and trust so that a more machine-like photo was associated with the highest trustworthiness, followed by the high human-like robot photo and finally the low human-like photo. Lu et al. (2021) demonstrated that perceived trust towards a robot positively mediates the relationship between robot appearance and service ratings in a restaurant context. Song et al. (2021) found that robot appearance characteristics, such as eye size, eye height, eye width, and mouth height have a positive effect on trust. Taken together, the reviewed studies provide empirical evidence that the appearance of a robot fosters trust, but potentially in a non-linear way. Machine-like robots, robots that have a machine-like appearance with human-like features (e.g., eyes, mouth) and very human-like robots can stimulate trust.

Robot appearance & likability. Mathur et al. (2020) found a non-linear relationship between robots with a more machine/human-like facial appearance and their likability. Humans gave the highest likability scores when robots were either very human-like – having a truly human face – or rather machine-like – with a truly robotic face. In a similar vein, Rosenthal-von der Pütten & Krämer (2014) investigated 40 images of robots (e.g., Asimo, ICat, Riba, Nao, Geminoid HI-1) according to human-likeness and mechanicalness on likability. They found that both appearance characteristics – a robot's human-likeness and mechanicalness – foster more likability. Szczepanowski et al. (2020) tested three types of robots, mechanical (i.e. Fanuc LR Mate 200 iD), zoomorphic (i.e. Sputnik), and humanoid (i.e. Nao). The authors found that the most human-like and sociable robots (i.e. Nao, Sputnik) were significantly more liked than the robotic arm – the machine-like and non-sociable robot. In summary, these studies support the conclusion that a more human-like appearance fosters the likability of robots, but in a non-linear relationship so that also more machine-like robots with human-like features can trigger higher ratings of likability.

The other seven hypotheses were tested twice, respectively. Robot appearance was tested on eeriness (Mara & Appel, 2015a; Yam et al., 2021), human emotions (Lu et al., 2021; Thimmesch-Gill et al., 2017), and anthropomorphism (Mara & Appel, 2015a; Szczepanowski et al., 2020). Anthropomorphism was found to affect eeriness (Mara & Appel, 2015b; Yam et al., 2021) and is predicted by attitude towards robots (Nicolas & Agnieszka, 2021; Szczepanowski et al., 2020). Finally, agent type as a predictor of social presence (Edwards et al., 2019; J. Li et al., 2016) and trust as a predictor of intention to use received multiple attention (Cameron et al., 2021; Delgosha & Hajiheydari, 2021).

5. Contributions and Implications

This study set out to analyze the literature on HRI on social robots from the last 10 years to identify (a) the shifts in HRI research and (b) key theoretical constructs as well as relationships to provide more nuanced insights into HRI literature. This research has several contributions with theoretical implications to offer.

First, our HRI mapping review suggests two shifts in focus: on the one hand, there seems to be renewed interest in investigating physically-present robots and images of robots in empirical research. However, the findings of image-based research on the effects of social robots need to be treated carefully (Fernández-Llamas et al., 2018). On the other hand, while general social robot research without a specialized application field is still dominant, more and more research investigated collaborative robots or service robots. With an increasing number of robots becoming part of the workforce, in reality, it seems necessary that research with physically-present robots in specific application areas will be conducted. Thus, we call for more application-specific research with physically-present robots, for instance, social robots as teammates in knowledge work settings, service robots, or robots in hospitality services.

Second, this literature analysis offers novel insights into the most prominent theoretical constructs and relationships confirmed in HRI literature that differentiate this study from other reviews (e.g., Diederich et al., 2022; T. Fong et al., 2003; Malinowska, 2021). For example, while Diederich et al. (2022) also extracted key concepts relevant to conversational agent research, their analysis lacks an analysis of the complex relationships between these concepts. Earlier reviews, such as Fong et al. (2003) identified the same or similar key concepts. Similar to Diederich et al., they investigated the key determinants for robot acceptance. In contrast, this review quantitatively assessed each study's theoretical constructs and tested hypotheses to offer a complete overview of the complex, interwoven dynamics of these constructs and their relationships. With this review, we offer researchers a publicly available resource[7] as a starting point to navigate the abundant HRI knowledge accumulated over almost 10 years and contribute to their research efforts threefold. First, researchers can use the network to uncover missing edges and edge directions between nodes (e.g., between perceived robot gender and acceptance). Second, the tool can help researchers with empirical design choices concerning which other constructs were studied in past research in relation to the constructs of interest in a planned study. Finally, the tool can facilitate controlling for alternative explanations with respect to hypothesized effects in the design of experimental studies.

This research additionally offers contributions for practitioners. The provided review can function as a helpful knowledge source for robot designers. Several robot design characteristics (e.g., robot appearance) were identified, and their consequences were made visible. Additionally, organizations deploying robots can use this review as a guide for their robot purchasing, deployment, evaluation, and employee training initiatives. The identified key constructs can offer insights into factors that influence human perception and which can hinder (e.g., eeriness) or foster (e.g., trust, anthropomorphism) the acceptance and adoption of robots in the workplace.

6. Limitations and Future Research

The following limitations should be considered, which offer opportunities for future research. First, constructs from all reviewed articles had to be coded manually with the challenge to rename constructs when they were measuring the same 'thing' (e.g., perceived human-likeness and anthropomorphism) or aggregating constructs to higher-order concepts (e.g., valence and arousal were re-coded into the general concept of emotions). To mitigate any inconsistencies in coding, the authors met repeatedly during the coding phase.

[7] Available at: https://osf.io/d9nz8/

Nonetheless, the network analysis does not consider alternative naming or hierarchies of higher-order or lower-order concepts. The network analysis also does not include hypothesized relationships that were rejected. Future research could also apply text analysis tools to further increase the scope of articles analyzed and the quality of the extracted information. Research could expand the network analysis to also show alternative construct names, offer effect directionality, visualize hierarchies, and differentiate significantly from insignificant relationships. Reviews considering moderating effects and time-series/within-subject effects could not be modeled with the network analysis and hence were excluded. Future research could expand our analysis by including the moderating effects in a different systematic review.

Second, the kernel theories which the reviewed literature built on have not yet been considered in this review due to space restrictions. Future research could synthesize the underlying theories to further guide researchers in theory-driven HRI research.

Finally, the review also revealed that the main focus of past research was on the socio-emotional consequences of robot implementations. Future research could investigate additional outcomes for organizations and individuals, applying robots in value-adding functions. Additionally, the research could focus more on the dark side and ethical implications of HRI, for example, focusing on mediating perceptions, which can hinder their adoption. An exemplary study found that the support of a robot in task fulfillment led to frustration and increased workload (Syrdal et al., 2015), which can lead to the rejection of the robot.

7. Conclusion

HRI is a complex field spanning many disciplines. With the increasing relevance of social robots in the real work context, it becomes increasingly important to provide an overarching review of the existent theoretical concepts, to guide further theory development and research. This cross-disciplinary literature review with network analysis has contributed a collected overview of the shifts in foci of the HRI studies since 2012 as well as the key predictors and outcome variables that influence human perception, which can hinder or foster the adoption of social robots in the workplace.

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