Human-Robot Interaction Challenges in the Workplace

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Introduction

In this chapter, we discuss challenges for robots interacting with humans in the workplace. We do so from the perspective of the research field called human-robot interaction (HRI), which studies the engineering methods, design aspects, social issues, and psychological outcomes arising from interacting with robots. The "workplace" in this chapter is defined broadly, and can include any of a number of contexts in which robots are imagined to work alongside humans, such as factories, supermarkets, offices, care facilities, and construction sites. We do, however, exclude some specialized work environments, which already have humans interacting closely with robots, specifically military, space exploration, and surgery contexts. These settings have been covered at length in the literature. Instead we discuss workplace settings in which robots are currently rare, but which are considered by the research community as likely future contexts for HRI.

While there is no commonly agreed upon definition of "robot", we accept a vague boundary delineation, and consider a robot to be a programmable machine that does mechanical work that is not contained fully in an enclosure. Most commonly, a robot would be in the shape of a robotic arm akin to those found on factory floors, a mobile robot in the form of a computer-controlled vehicle, or a human- or animal-like robot designed for interaction.

We present human-robot interaction in the workplace against the background of two better-studied application contexts in which robots are envisioned to operate around humans: at home and in public spaces. Commercially available robots in the home today include mostly cleaning or lawn-mowing robots, but researchers and commercial companies have proposed home robots for companionship, elder care, childcare, teaching, therapy, and entertainment purposes. In public spaces, we see spurious experimental deployments of robots, mainly in transit centers, such as airports and train stations, and also in museums and shopping malls. Still, robots in public spaces are not yet widespread and are an active area of HRI research. Both the home and public spaces have received the majority of attention in the HRI literature.

This chapter's main focus is a third deployment context: everyday workplaces, where robots interacting with humans are virtually nonexistent. We particularly consider non-specialized workplaces, such as offices, retail stores, warehouses, workshops, care facilities, and factories. Some of these workplaces have already started to introduce robots. For example, in many manufacturing areas, preprogrammed robots are in operation, but their interaction with humans is usually minimal. That said, some large and small factories are experimenting with collaborative robots, which interact more closely with humans. While this is not yet widespread, researchers expect this type of deployment to grow further, along with other, currently non-existent, uses of robots in everyday workplaces, such as offices, retail stores, and care facilities.

Each of the three application categories described above (home, public spaces, and work) poses both *physical* and *psychological* challenges for developers of human-interactive robots (see: Figures 1 and 2). Some challenges cut across application contexts, while others are unique to the setting in which the robot is placed. For example, two physical HRI challenges, common to all contexts, are the perception of human activity (Martínez-Villaseñor & Ponce, 2019) and safe navigation around humans (Kruse, Pandey, Alami, & Kirsch, 2013). Some psychological challenges are also common to all three contexts. These include conveying relevant, accurate, and timely information (Robinette, Wagner, & Howard, 2014), understanding and using nonverbal behaviors (Cha, Kim, Fong, & Mataric, 2018; Saunderson & Nejat, 2019), and predicting human actions (Kong & Fu, 2018). That said, each context also comes with its unique set of psychological challenges. A therapy robot in the home may have to take into account compliance and the emotional well-being of a patient (Cabibihan, Javed, Ang, & Aljunied, 2013). An entertainment robot might be concerned with narrative and engagement (Ligthart, Neerincx, & Hindriks, 2020). In contrast, a collaborative robot in a repair workshop would be more focused on skill adaptation and understanding workplace hierarchies (Parker & Draper, 1998).

Figure 1 about here.

Figure 2 about here.

On the following pages, we briefly survey the physical and psychological challenges posed by home and public deployment of robots, to provide a sense of what questions the HRI literature has been concerned with over the past decade and a half. Where available, we will refer the reader to other excellent surveys on the topic for more detail. This chapter will then move to discuss interaction with robots in the workplace. The discussion begins with an overview of workplace deployment contexts and a review of some of the associated challenges currently studied in the HRI literature, which are mostly physical in nature. We will then turn to the less-discussed psychological challenges of working with robots, detailing three studies conducted in our laboratory, which are relevant to the use of robots in the future workplace. The first study relates to the effects of competing with a robot for monetary reward and the resulting demotivation and loss of self-esteem that we found. The second study tackles challenges that occur when a robot attempts to help a worker make complex decisions. The third study also concerns human decision-making, and explores whether an AI agent can infer a human's intentions by tracking the outcomes of the human's decision-making.

Robots in the Home

A large segment of research in HRI studies robots in the home context. Some of the envisioned applications include companionship, education, elder care, entertainment, domestic chores and personal health. One of the most studied application areas of home robots is in support of elder care (Broekens, Heerink, & Rosendal, 2009; Kachouie, Sedighadeli, Khosla, & Chu, 2014). Other therapeutic applications include physical therapy (Fasola & Mataric, 2013, 2012), cognitive therapy (Schroeter et al., 2013), feeding (Gallenberger, Bhattacharjee, Kim, & Srinivasa, 2019) and companionship (Heerink, Kröse, Evers, & Wielinga, 2008; Robinson, MacDonald, Kerse, & Broadbent, 2013; Wada & Shibata, 2007). Robot companions have also been studied as devices to help mitigate feelings of loneliness in populations beyond elder care (K. M. Lee, Jung, Kim, & Kim, 2006; Odekerken-Schröder, Mele, Russo-Spena, Mahr, & Ruggiero, 2020), a global issue accentuated by the COVID-19 pandemic.

Outside of the therapy context, researchers have proposed to use robots for entertainment and more casual uses. Robots have been studied in the role of music listening companions (Hoffman & Vanunu, 2013), game playing companions (Marti & Giusti, 2010; Volkhardt, Mueller, Schroeter, & Gross, 2011) and exercise companions (Graether & Mueller, 2012; Schneider & Kummert, 2016). In contrast to this vision of home robotic companions, research has shown that not all accept this role (Deutsch, Erel, Paz, Hoffman, & Zuckerman, 2019), and that preferred roles may be those of a butler or an assistant instead of a friend (Dautenhahn et al., 2005). An additional major application area of robots in the home is domestic chores (Cakmak & Takayama, 2013) such as floor cleaning (Fiorini & Prassler, 2000; Prassler, Ritter, Schaeffer, & Fiorini, 2000), organizing (Pantofaru, Takayama, Foote, & Soto, 2012), laundry (Estevez, Victores, Fernandez-Fernandez, & Balaguer, 2020) and kitchen assistance (Pham, Hayashi, Becker-Asano, Lacher, & Mizuuchi, 2017).

Finally, a large portion of HRI research addresses the educational use of social robots at home. This includes robot assisted learning of languages (Gordon et al., 2016), mathematics (Kennedy, Baxter, Senft, & Belpaeme, 2016) and improvement of reading skills (Gordon & Breazeal, 2015) among others. Despite the interest in learning from robots, the effectiveness of robot tutors as compared to human tutors has been questioned (Kennedy et al., 2016) and the robot's social behavior has been shown to negatively affect the learning in some cases (Kennedy, Baxter, & Belpaeme, 2015).

The physical human-robot interaction challenges are minimal for most home robots. This is because robots for assisted learning, entertainment and companionship are most often designed as stationary, desktop devices which do not manipulate any objects. However, if robots are to perform domestic chores and physical care tasks for humans such as feeding, they need to physically interact with humans and objects (Bhattacharjee, Lee, Song, & Srinivasa, 2019). These applications pose challenges related to accurate sensing and perception (Yan, Ang, & Poo, 2014), dexterous manipulation (Ozawa & Tahara, 2017), home navigation (Bacciu, Gallicchio, Micheli, Rocco, & Saffiotti, 2014), fault handling (Khalastchi & Kalech, 2018) and human-safe controllers (Duchaine & Gosselin, 2009).

Beyond these physical challenges, there are a host of psychological challenges that developers of home robots have to address. One of them is the understanding and generation of nonverbal behavior. Much work has been done towards recognizing different modes of human nonverbal behavior and generating robot nonverbal behavior in human-robot interaction, and there are several excellent surveys. Some of these surveys focus on individual modes of nonverbal behavior such as arm gestures (Nehaniv et al., 2005), body movements (Bethel & Murphy, 2008), eye gaze (Admoni & Scassellati, 2017), and proxemics, the use of physical space to communicate (Rios-Martinez, Spalanzani, & Laugier, 2014). Others take a broader perspective with multiple modes and interactions between them (Cha et al., 2018; Mandal, 2014; Saunderson & Nejat, 2019). Although researchers have long tried to categorize nonverbal behavior (Ekman & Friesen, 1969), the complexity and variety of its components makes it difficult to devise predictive and generative models.

Emotional appropriateness is another psychological challenge for the developers of home robots. Generating appropriate emotional robot expressions in human-robot interactions requires detection of human emotions and modeling of emotional interaction. Furthermore, the coupling between nonverbal behavior and emotional expression aggravates the challenge. A large body of work has investigated recognition of human emotion through speech (Ayadi, Kamel, & Karray, 2011), body gesture (Noroozi et al., 2019) and facial expressions (Ko, 2018). Several researchers have proposed emotional models (Savery & Weinberg, 2020), with some of the most prominent models being the PAD emotional model (Mehrabian, 1980), Ekman's categorizations (Ekman, 1999), Plutchik's wheel of emotions (Plutchik, 2001) and the Circumplex model of valence and arousal (Posner, Russell, & Peterson, 2005).

While research in HRI has made some strides in the nonverbal and affective aspects of interaction, one of the most significant outstanding challenges in home robotics is maintaining long-term engagement with users. There is not enough research to understand the influence of novelty effects on many of the phenomena studied in HRI (Baxter, Kennedy, Senft, Lemaignan, & Belpaeme, 2016; Smedegaard, 2019). The majority of the existing work studies human-robot interaction in a laboratory setting for a short duration. In contrast, there is a paucity of literature investigating long-term human-robot interaction in the real-world home environment (Aylett, Castellano, Raducanu, Paiva, & Hanheide, 2011; Leite, Martinho, & Paiva, 2013). Some of the impediments to long-term engagement are repetitiveness in interaction, ill-defined use cases, and ethical concerns. Researchers have explored solutions such as personalization (Clabaugh & Matarić, 2018), making robots "imperfect" through human-like cognitive biases (Biswas & Murray, 2015), using narratives (Goodrich, Crandall, Oudah, & Mathema, 2018), adaptive behavior coordination (Bajones, 2016) and social media integration (Mavridis et al., 2009), among others. Still, this area of research presents a large opportunity for new knowledge generation.

Another open area of research is evaluating and building trust between humans and home robots. If long-term interaction is the goal, a robot would have to develop some model of the human's trust in the robot, to help it mitigate breakdowns. Such a model would have to also take into account that people might have a baseline lack of trust in robots resulting from fear of technology (Hancock, Billings, & Schaefer, 2011; Liang & Lee, 2017; Szollosy, 2016). Mistakes committed by the robot also affect its trustworthiness and reliability (Salem, Lakatos, Amirabdollahian, & Dautenhahn, 2015). Trust could be measured in the context of trust-in-technology (Heerink, Krose, Evers, & Wielinga, 2009), but also using methods of interpersonal trust (J. J. Lee, Knox, Wormwood, Breazeal, & DeSteno, 2013). Quantitatively measuring trust is challenging, and many of the measures of trust used in HRI research have been qualitative and descriptive (Hancock, Billings, Schaefer, Chen, et al., 2011).

Finally, developers of home robots have to navigate design challenges resulting from preconceived notions and metaphors that people have about robots, people, animals and objects. Robot design can span from completely functional (such as floor cleaning robots), through animal shaped (like the robot seal Paro or the robotic dog

AIBO), to extremely human-like (such as the android robot Geminoid). The design of the robot could by itself have such a strong effect on people's interaction with it, that it may overshadow any behavioral or cognitive aspect of the robot's software.

In summary, non-cleaning robots in the home are still rare outside of the research laboratory, but many HRI researchers envision desktop robotic companions for therapy, tutelage, and entertainment. Such robots will have to address a number of psychological challenges, many of which are studied in the HRI research community, including reading and producing nonverbal behaviors and emotions, evoking trust, and maintaining long-term engagement.

Robots in Public Spaces

A second context which has attracted the attention of researchers in HRI is that of public spaces. Unlike home robots, which tend to be personal, long-term, and focused on a few users, robots in public spaces engage in short-term customer service interactions with many people. The majority of robots considered for this context are designed to provide information or guide people through the space, leading research to center on communication and navigation in crowds. There is also an emphasis on field research and long-term deployments, examining expectations and acceptance in these public spaces, as well as challenges around robustness over time.

One such public context where robots have been studied is in transit stations, including airports and train terminals. Mobile robots can be used to guide customers through a busy airport (Triebel et al., 2016), answer questions (Shiomi et al., 2008), communicate with large groups (Sakamoto et al., 2009), and help travelers check-in (Tonkin et al., 2018). Other projects have studied robots as a way to provide round-the-clock security in transit stations (Capezio, Mastrogiovanni, Sgorbissa, & Zaccaria, 2007).

Another public application context is in malls and commercial spaces, where robots can be used to serve, entertain, or attract customers. Kanda et al. deployed an affective robot in a shopping mall to give shoppers verbal directions and shopping recommendations (Kanda, Shiomi, Miyashita, Ishiguro, & Hagita, 2009). However, the robot was also designed to build rapport with customers over time, through self-disclosure, remembering details about customers, and increasing friendliness. In this field study, the researchers connected the relationships that customers perceived with the robot to the effectiveness of its word of mouth advertising. Both Foster et al. (2016) and Aaltonen, Arvola, Heikkilä, and Lammi (2017) studied how to create engaging interactions with humans and robots in commercial settings, under the premise that entertaining robots will invoke greater acceptance and better customer experiences. Aaltonen et al. in particular found a need for a robot in a mall to balance entertainment and practical behavior, with potential overlap between the two.

Studies in commercial spaces have also explored expectations and acceptance from stakeholders who more permanently inhabit the space. Niemelä, Heikkilä, and Lammi (2017) find that, while consumers expected a robot to play practical roles (e.g. guidance, information), retailers and management hoped a robot could contribute to a warm and entertaining atmosphere. Shi et al. found that managers were interested in using robots to attract visitors to stop, a responsibility they considered stressful for a human to perform (Shi, Satake, Kanda, & Ishiguro, 2016). Along these lines, Foster et al. (2016) designed a robot with socially acceptable verbal, non-verbal, and navigation behaviors in a large shopping center with both consumer and business stakeholders.

A third popular public space in which robots have been studied is in museums or expositions. Thrun et al. (1999) deployed a mobile robot in the Smithsonian Museum for two weeks as a tour guide designed to educate and entertain. The primary challenges this project tackled included safe navigation in packed and dynamic environments and short-term interactions with humans using familiar human-like behaviors. Kuno et al. (2007) modeled a robot museum tour guide off of human tour guide behavior, finding that imitating human guides' head movements while talking could increase engagement with museum visitors.

In terms of physical challenges, robots in public contexts perform roles that require them to navigate through a busy space and communicate information to humans in that space. As a result, “social navigation” is a major focus of HRI research. Social navigation includes not only how to navigate a crowded space in a way that respects social norms and makes humans feel safe (Bera, Randhavane, Prinja, & Manocha, 2017; Chen, Everett, Liu, & How, 2017), but also how to plan shared trajectories alongside a human (Campos, Pacheck, Hoffman, & Kress-Gazit, 2019; Ferrer, Zulueta, Cotarelo, & Sanfeliu, 2017; Murakami, Morales Saiki, Satake, Kanda, & Ishiguro, 2014). For a recent survey of robots in public spaces through the lens of human-aware navigation, see Kruse et al. (2013), who identify comfort, naturalness, and sociability as key challenges in the field.

In addition to navigation, there is also a research emphasis on social communication, including nonverbal behavior and conversational fillers (Kanda et al., 2009), head movements (Kuno et al., 2007), or bowing (Hayashi et al., 2007). This work can go beyond direct communication with humans: Sakamoto et al. (2009) draw on human “passive social” communication (eavesdropping) to design robot-robot interactions that broadcast information in public spaces. Blending these two areas of research is the work on proxemics, which studies how to use physical space and trajectories to communicate with humans (Mead & Matarić, 2017).

The demands of operating in a public space and interacting with groups and individuals accentuates the blurring of the boundary between the social and the functional for robot design. Taking a broader perspective, Mussakhojayeva and Sandygulova (2017) study how robots should adapt their behavior to the social and cultural contexts of the space. For example, should a robot focus on the needs of a child or their parent in a shopping mall? Such directions may be complicated by cross-cultural studies that have found different perceptions and norms around interaction with robots in public spaces (Fraune, Kawakami, Sabanovic, De Silva, & Okada, 2015).

Robots in the Workplace

We now shift our focus to the third application context: the human-robot shared workplace. While there has been much research on psychological challenges in the context of the home and public spaces, and there are several excellent surveys on human-robot interaction in general (Breazeal, Dautenhahn, & Kanda, 2016; Fong, Nourbakhsh, & Dautenhahn, 2003; Goodrich & Schultz, 2007; Thomaz, Hoffman, & Cakmak, 2016), the specific psychological issues arising from humans sharing their workplace with robots have not received as much focused attention. The workplace environment poses unique research perspectives related to psychological outcomes, such as challenges associated with self-determination, inspiration, and role-related social factors (Froman, 2009). The workplace also imposes different behavioral structures, work processes, societal rules, and expectations than the home or public places (*e.g.,* Mann, 2007). This merits a separate discussion from the perspective of human-robot interaction. Clearly, some of the contexts discussed above, especially those in public spaces, function as workplaces for the people employed in them. Airports, train stations, and malls have employees who may be interacting with robots as part of their workday. However, most of the research in public-space HRI, as evident above, focuses on customers and members of the public and not on workers. In a similar vein, therapy and elder care and healthcare robots, including in the home, also interact with care workers and some of these work relationships have been studied occasionally in the past (Gombolay et al., 2018; Mutlu & Forlizzi, 2008; Turja, Rantanen, & Oksanen, 2017). Still, the bulk of HRI research in these domains investigates end-user-robot interaction.

This chapter highlights questions that arise around human-worker interaction in common workplaces, such as offices, workshops, factories, retail, healthcare facilities and points of service. The workplace should be of particular interest to HRI research, as much of the concern, both economic and societal, is surrounding the relationship between humans and robots at work (Moniz & Krings, 2016). Yet most of the research published in the HRI community does not specifically address the psychological challenges that arise specifically from working with robots. The exception to this would be research on HRI in the realm of military, surgery, and outer space deployment, where scholars have looked at relationships between robots and military personnel, surgeons, and astronauts (Ambrose et al., 2000; Barnes & Evans, 2010; Wasen, 2010). These workspaces are extremely specialized, and robots in them interact with highly trained individuals. In addition, these workplaces are unique in that they already see a significant use of robots and can be considered *current* human-robot workplaces.

The remainder of this chapter instead tackles HRI in everyday workplaces, inspired by potential *future* application contexts for interactive robots, which are under development or merely imagined. We begin with an overview of where robots are considered to enter the workplace, and some of the challenges currently studied in these contexts. These challenges are mostly physical in nature, and where they touch on psychological challenges, they deal with rudimentary problems, such as nonverbal behavior and action prediction. We then follow up with research we conducted, which touches on some more complex psychological challenges, such as motivation and creative intention recognition.

Application Areas and Challenges

Robots are imagined to interact with people in many lines of work, which we broadly divide into five categories: manufacturing and assembly, warehouse logistics and materials handling, service and retail, social work and therapy, and creative work, including research and development.

- **Manufacturing and Assembly** — Production factories are one of the most commonly imagined application area for robots. Traditional industrial robots are large and dangerous machines that operate at a safe distance or physical separation from humans, and are programmed to do a single operation (Sanneman, Fourie, & Shah, 2020). Recently, a new type of lightweight, re-programmable collaborative robots (cobots) are being introduced to the factory floor (Djuric, Urbanic, & Rickli, 2016). These robots, due to their smaller size and lower cost, can also be used in smaller fabrication and craft workshops. The main research questions studied in this context relate to the manipulation of objects, factory processes, task flexibility, and safety (*e.g.,* Billard & Kragic, 2019; Tsarouchi, Makris, & Chryssolouris, 2016; Zanchettin, Ceriani, Rocco, Ding, & Matthias, 2015). There are also a number of studies concerned with the timing and coordination of operations between a human and a factory robot (*e.g.,* Wilcox, Nikolaidis, & Shah, 2013).

- **Warehouse Logistics and Materials Handling** — A second, somewhat related, application of robots is in the context of logistics and materials handling. Improvements in mobile robot navigation and swarm-inspired control of distributed robot systems allowed for commercial deployment of robotic systems in warehouses (D'Andrea, 2012). While robotic warehouse systems include interaction challenges with humans, these are primarily in the form of scheduling, and there is little one-on-one interaction between the human worker and the robot. In most cases, the robots in question are mobile bases for shelving units and are nearly invisible to the workers in the warehouse, who experience the robot's activity more as "moving shelves". There is a strong research thrust to also develop robotic arms for sorting and packing operations (Eppner et al., 2016). In this case, the level of interaction is likely to rise and raise similar challenges as those in the manufacturing and assembly context presented above.
- **Services and Retail** — While much of the robotics literature has traditionally focused on manufacturing and logistics, by far the largest sector in the US economy (both in terms of domestic product and in terms of the percentage of the labor force) is the service sector (source: Bureau of Economic Analysis). Within this sector, the largest industries, by labor force, are retail, business services, health care, leisure, and government. Despite its relative importance in the economy of the US and other industrial nations, the service industry has not seen much robotics in real-world deployment. In recent years, there have been forays in retail and healthcare robotics, mainly in the context of stock monitoring (Bogue,

2019). Two examples include the Moxi robot for hospital wards, and the Badger robot for grocery stores. In contrast, service context research has captured the interest of HRI researchers for years, including robots for hospitality applications (Gockley et al., 2005) and retail (Kamei et al., 2010; Paolanti et al., 2019) Many research problems studied in this context are similar to those in transit centers and museums, tackling primarily navigation and information display (Lichtenthäler, Peters, Griffiths, & Kirsch, 2013). Moreover, research in service and retail HRI focuses mainly on the customer and not the robot's co-workers.

- **Social Work and Therapy** — At the intersection between the personal space and the workplace, robots could be a promising technology for social work and therapy (Wada, Shibata, Musha, & Kimura, 2005). Robots have shown to be successful in improving people's sense of perceived responsiveness in a personal disclosure scenario (Birnbaum et al., 2016). An advantage of using robots in this context is that they can be programmed to preserve a speaker's privacy, and that they are perceived as less judgmental than people. This could make robots a promising technology for counseling or taking testimony after traumatic events, such as natural disasters, expulsion or violence. A robot can provide responsive behavior, a promise of privacy, and some psychological support. In terms of HRI research, the focus has once more been mostly on the relationship between the robot and the patient, and less on that between the healthcare or service worker and the robotic assistant (with some exceptions, as listed in the above section on robots in the home).

- **Creative Work, Design, and R&D** — Finally, a large part of the service economy, and a large percentage of the product development workforce in the US and other countries, is in the design, research, and development sector (National Science Board, 2020). While there has been a large body of research around AI-based assistance to design and other creative labor (*e.g.,* Kim & Cho, 2000), there has been little work exploring the potential use of robotics in this sector.

> Given the relative significance of this work, we present the results from a study focusing on robot assistance in creative work in a subsequent section of this chapter.

Examining the literature that studies robotics in the workplace context, we identify several trends. Research on robots in manufacturing and logistics focuses on the physical challenges of the system. These challenges include navigating in space, sensing object and environments, and manipulating objects. In some cases these physical challenges involve a human worker in the robot's environment (Huang, Cakmak, & Mutlu, 2015; Kemp, Edsinger, & Torres-Jara, 2007; Sisbot, Marin-Urias, Alami, & Simeon, 2007). However, the psychological aspects of these studies are restricted to sensing and predicting human actions; the goal of this research is to use these physical-psychological cues to better solve the physical challenge.

The second group of studies, concerning robots in the service, retail, and healthcare industries mostly focuses on the end-user, not the worker in these spaces. Lastly, the area of research, design, and creative work has seen almost no research in human-robot interaction.

In those cases where psychological challenges are raised in human-robot collaborative work, these challenges are often related to rudimentary nonverbal behaviors, such as gestures and gaze behavior. Gaze, for instance, has been taken into account in robot navigation and handover tasks (Kshirsagar, Lim, Christian, & Hoffman, 2020; Wiltshire et al., 2013). However, the literature has not sufficiently addressed some of the more subtle psychological issues that come with introducing robots into the workplace, which are separate from the physical, sensory, and body language issues.

The following two sections focus on two such issues that we have recently studied in our laboratory: robots as competitors to humans and robots that aid in decision-making. We present three studies in these contexts. In the first study, we examine whether competing with a robot on a mundane task can affect a person's motivation to perform well on the task. We draw upon Economics theory to predict that a faster robot competing with a human worker will cause reduced motivation in the human worker.

In the second and third studies, we turn to human-robot collaborative decision-making. We developed a robot that assists a human designer in a complex design task. First, we present qualitative evidence from video and interview analysis that uncovers considerations for robots in creative contexts, including the negotiation of the physical workspace, roles in the decision-making process, and the alignment of goals. Then, we present a study that aims to infer a human's intentions and preferences from their decision-making actions. Our results show that we can use "simulated human decisions" to help infer what a real human is trying to achieve when searching for solutions for complex cognitive problems.

Humans and Robots Competing in Mundane Tasks

The first study is a controlled experiment studying the effort of people competing for a monetary prize with a robot on a mundane and repetitive task, and how the robot's performance affects people's effort and their attitude toward the robot (Kshirsagar, Dreyfuss, Ishai, Heffetz, & Hoffman, 2019). We manipulated the robot's performance and the monetary incentive level and measured people's effort level and attitudes toward the robot and toward themselves. These attitudes included people's liking of the robot, and their perception of the ability of the robot and of themselves on the task.

It is worth noting here that much of the existing HRI literature is concerned with collaboration between a human and a robot, where both agents share the same goal (Bauer, Wollherr, & Buss, 2008). In contrast, the public perception and also the economic reality is that robots and AI may compete for work with humans. These scenarios are almost never studied in HRI. The small number of studies that have investigated competition between humans and robots (Fraune, Sherrin, Šabanović, & Smith, 2019; Mutlu, Osman, Forlizzi, Hodgins, & Kiesler, 2006; Short, Hart, Vu, & Scassellati, 2010) only looked at game-playing scenarios. Game playing is often a reasonable model for competition, but it is also inherently enjoyable, whereas most of the real-world application contexts for robots will have mundane and repetitive jobs. Also, in most of the HRI research, participants are paid a fixed show-up fee for participating in the study. This method assumes that people are motivated to do well in the experimental task and as a result these studies do not measure the effect of incentives on people's effort. Such monetary incentives are a key feature of real world behavior. Our study, thus, makes two contributions: studying human-robot competition on mundane tasks, and introducing monetary reward as a factor in human-robot interaction.

When people make decisions on whether and how much to work on a task, they are motivated by a number of factors. These include the direct value of the reward for the work, but also other psychological and cognitive biases, which result in a deviation from rational behavior. For example, behavioral economics researchers have shown that people perceive the disappointment resulting from loss of a reward more strongly than the satisfaction resulting from gaining an equivalent reward (Kahneman & Tversky, 2013). In competitive scenarios, the gains/losses perceived by people are relative to a reference point based on the expected outcome of the competition, which depends on their own performance and the performance of the competitor. These factors suggest that the competency of a competitor could affect a person's motivation to do well on the task.

Economists almost always think of human competitors in the above analysis. But, as robots become ubiquitous in the workforce, we can expect situations to arise where this competitor is a robotic co-worker. People might compete, or feel like they are competing for winning resources or for demonstrating capabilities. Therefore, we are interested to investigate the effect of a competitor robot's performance and monetary rewards on people's effort on a mundane and repetitive task. We are also interested to study the effect of a competitor robot's performance on people's attitudes towards the robot and towards themselves.

We designed an experimental scenario to study human-robot competition in the workplace. Participants were rewarded cash prizes with some uncertainty depending on the difference between their performance and the robot's performance. The task consisted of counting a specific letter in strings of random characters and placing a block in a bin corresponding to the count. The participants were allowed to do as many such tasks as they want in a time limit of 2 minutes. For each correct block placement, they received one point. The robot counted characters in a different set of strings and moved a block to the corresponding bins in its workspace which was adjacent to the human's workspace. The robot also received one point for each correct placement. Each 2-minute competition round had a cash prize associated with it, and the participant's chances of winning the cash prize were proportional to the difference between their score and the robot's score. For example, if the participant's and the robot's scores were equal, the participant had a 50% chance of winning the cash prize. For every point scored by the participant, their chance of winning the prize increased by 1%, and for every point scored by the robot, the participant's chance decreased by 1%. Our experiment setup consisted of a robot arm with an overhead camera, a screen with the user interface, and the robot's and the human's workspaces. The screen displayed the current and the predicted scores of the robot and the human, remaining time in the round, prize amount of the round and the human's chances of winning the prize.

Each participant competed against the robot in 10 competition rounds, but they were not told about the number of rounds ahead of time. In each round, we manipulated the robot's speed and the cash prize. The robot's speed was kept constant throughout a round and was randomly chosen such that the robot's score was in the range [5,...,45]. The prize for each round was also randomly drawn, from [$0.10, $0.20,...$3.80]. Our experimental design was inspired by a previous study conducted by (Gill & Prowse, 2012), in which they studied a competitive scenario between two humans. Their experimental task was sequential i.e. the second participant would perform the task after the first one completed their task, as opposed to our experiment, in which both the competitors performed their tasks simultaneously.

We used the theoretical model of expectations-based reference dependent (EBRD) loss aversion (Kőszegi & Rabin, 2006, 2007, 2009) to base our hypotheses about the effect of the robot's performance and the prize value on the human's performance. This model predicts a discouragement effect of the robot's score on the human's performance, and the discouragement effect increases with increase in the prize value. For more details about the theoretical predictions and our hypotheses, please refer to our paper (Kshirsagar et al., 2019).

We analyzed the data obtained from 60 participants. A fixed-effects multivariate regression controlling for round number and participant number revealed a small discouragement effect of the robot's performance on the participants' performance ($p = 0.002$) i.e. the participant's performance decreased if the robot performed better. Increasing the robot's score from 5 to 45 decreased the human's score by an average of 1.72 which was 8.4% of the human's average score (20.42). In contrast to Gill and Prowse, we did not find an interaction effect of the prize on this discouragement effect. Even more surprisingly, the effect of the prize value on the human's performance was negligible.

We also elicited participants' attitudes towards the robot and towards themselves after each competition round. Specifically, we asked participants to rate the robot's competence and the robot's likability. We also asked participants to report their perceived ability of doing this task. We found that participants liked a low-performing robot competitor more than a high-performing one ($p < 0.0001$), even though they found a low-performing robot to be less competent ($p < 0.0001$). Also, they perceived themselves to be more competent at performing the task when the robot did not perform well ($p < 0.0001$). This suggests that people might assess their ability to perform a task relative to that of their robotic competitor.

In summary, the better the robot performed, the less effort the participants exerted. Moreover, a highly performing robot competitor was rated as less likable and led to lower self-assessment by the human competitors.

Our findings could have significant implications to the incentive schemes in workplaces where robots are being introduced to work alongside human workers. While it may be tempting to design such robots for optimal productivity, engineers and managers need to take into consideration how the robots' effort may affect the human workers' effort and attitudes toward the robot and even toward themselves.

Human-Robot Collaborative Decision-Making

Whereas the first study was concerned with the understudied challenge of humans and robots competing, the second and third studies return to human-robot collaboration in the workplace. However, in contrast to most research in HRI, we explore here how a robot might assist a human in a creative task including complex decision-making, rather than in a mundane and repetitive task. We also are interested in a robot as a *cognitive* assistant, rather than as a tool for physical labor.

Most research on collaborative robotics in the product development process focuses almost exclusively on the late stages of the process such as fabrication (Gleeson, MacLean, Croft, & Alcazar, 2013), assembly (Hayes & Scassellati, 2013), and warehouse operation (Rosenfeld, Noa, Maksimov, & Kraus, 2016). However, as mentioned above, much of the US product development economy is in research and development, and it has been shown that a large portion of the value added stems from this portion of the process (Gemser & Leenders, 2001; National Science Board, 2020; Roy & Potter, 1993). We would therefore like to investigate whether robots can help in workplace contexts where the main task is related to creative work, design, and decision-making. We first discuss a qualitative study examining how humans interact with a decision-making-assistance robot, and how they negotiate the physical and creative space that occurs between the human and the robot (Law, Jeong, Kwatra, Jung, & Hoffman, 2019). Our study reveals psychological challenges that could be applicable to a large number of creative tasks in the workplace. We then discuss a study that tests whether an AI assistant can infer a human designer's intentions in a complex decision-making task (Law et al., 2020).

Robots are well-suited for collaboration with humans on complex unstructured tasks like complex decision-making. Humans are excellent at contextualizing and prioritizing problems, generalizing ideas across contexts, and reasoning abductively (Dorst, 2011; Egan & Cagan, 2016; Gonzalez & Haselager, 2005; Kolko, 2010). Machines are able to generate and evaluate potential solutions with super-human scale and precision. The potential in blending these capacities has inspired many AI decision-making support tools (Babbar-Sebens & Minsker, 2012; Banerjee, Quiroz, & Louis, 2008; Cho, 2002; Karimi, Grace, Davis, & Maher, 2018; Smith, Whitehead, & Mateas, 2010). Furthermore, based on research that draws on embodied and enactive cognition (Davis, Hsiao, Popova, & Magerko, 2015) we argue that creative work can benefit from physical and social interaction between a human and an embodied AI partner, i.e. a robot.

We illustrate this premise with two studies that examine human-robot collaborative design and decision-making work. In both studies, we built an interface that enables a human to work on a real-world design problem by arranging a set of markers representing design components. In the first study, we built a physical interface in the form of a sand table. A robotic arm sat directly across from the human, constantly searching for improvements to the human's design, and occasionally rearranging the shared set of blocks to realize an improvement that meets a set of criteria. In the second study, we designed a screen interface to test whether the AI agent can infer the human designers' intentions from the trail of solutions that the human explored.

In the study with our physical interface and the robot, we observed a series of negotiations that arose between human and robot, around the physical, creative, and social aspects of working together. We had twelve participants work with the robot to design an earth-observing satellite system. Participants were presented with twelve different types of sensors and five different orbits in which they could deploy any of the sensors. The sensors interacted in complex ways with the orbits and one another. For example, an active sensor that required more power might be more effective in an orbit with more exposure to the sun, and two sensors might share underlying subsystems that make deploying them together more efficient. Solutions were constructed by arranging blocks representing sensors into different regions of the sand table, representing different orbits. For each solution, a life-cycle cost was predicted, as well as a score indicating how well the system satisfied 371 data collection criteria from the World Meteorological Society. Participants were asked to work with the robot to construct a solution that maximized this score while minimizing the life-cycle cost.

Through a thematic analysis of think-aloud video data and post-study semi-structured interviews, we observed participants negotiating turns and use of space with the robot in the shared physical interface, as well as roles, goals, and strategies in approaching the shared creative task. Concurrently, we observed participants engaging with the robot in social ways, addressing it directly or ascribing social meaning to its actions, even though the robot was not designed to behave in a deliberately social way.

On the surface level, the human participants felt the need to negotiate with the robot over the shared physical workspace and design representation. This could be as simple as working out turns to access the workspace or where to place object blocks. Sharing a workspace affords shared reference objects, visibility, and so forth, but also creates constraints on simultaneous work, as each collaborator's actions affect the other's. For some, negotiating the physical space resulted in issues around creative control. Issues around turn-taking also manifested themselves in terms of pacing and compatibility with different cognitive styles. Some of our participants adopted a rapid pace, trying as many solutions as possible to see what insights fell out about the design space. Others were much more deliberate, reflecting a "comprehensive" style of top-down idea organization. For participants on either end of this spectrum, the robot's interventions were disturbing, as it either moved too slow for them and subsequently suggested stale ideas, or moved too quickly, upsetting the participant's deliberate train of thought. We also noticed that some of our participants used the physical space to spatially represent ideas. For example, one participant adopted a pattern of moving all the components he liked to the right side of the table. This reflects studies of human-human design collaboration, where designers use objects, gesture, and space to externalize and organize ideas together (Cash & Maier, 2016; Tuikka & Kuutti, 2000).

This tendency presents an opportunity for a robot to understand more about what a human is thinking. At the same time, it creates a challenge in terms of recognizing what spatial structures are significant and not disturbing them unintentionally.

We also recognized tendencies among our participants to gravitate towards different collaborative roles with respect to the shared design task. Some participants sought control, verbally telling the robot what to do or granting it permission to change the configuration on the table. One participant expressed a belief that a robot's use should be limited to "hard labor". Other participants viewed themselves as subordinates to the robot, perceiving its expertise at the task to be superior. These participants tried to follow the robot's lead, even if they felt that some changes it made were suboptimal. One participant told us that she felt like the robot was her colleague, listening and responding to her. This seemed to have a lot to do with timing, with the robot sometimes incidentally reaching for components that she was considering or dropping blocks when it made a change she didn't like. She described its role as more than assistance, rather "a colleague...discussing through this process". Finally, some participants perceived an adversarial relationship with the robot, which they variously saw as annoying, "trying to confuse me", or "playing with me".

Whether these perceived roles led to collaboration or conflict, we found the participant's ability to establish shared intentions with the robot to play a key factor. In decision-making or other open-ended tasks, framing the problem through a set of intentions is prerequisite to seeking a solution. In our study, conflicts arose over both longer term goals and intermediate strategies. Participants struggled to understand the robot's intentions. This created conflicts with participants who favored one objective or adopted different search strategies. Failure to do so could result in annoyance or breakdown in trust. As one participant put it, "I wouldn't say it was stupid for wanting its own agenda but it was annoying to me" . This is complicated by the fact that, in unstructured tasks, intentions can evolve as the actor learns more about the problem. While it is not necessary for human and robot goals to exactly align at all times, understanding a robot's goals makes it easier for a human to collaborate with it, and the converse should apply as well. This motivates further work toward both explainable AI for robots and models that infer the intentions of human decision-makers.

Our last study therefore focuses on the challenge of inferring human intentions (Law et al., 2020). Here we propose a model of intentions with respect to another multi-objective decision-making task. In our study, participants were asked to draw fair voting districts in a US state. We chose this problem because it represents a decision-making challenge where the very definition of the "fairness" objective is open to interpretation. We enabled participants to choose among three fairness objectives and any combination thereof: (1) the population balance between districts, (2) the voter efficiency of districts, and (3) the compactness of district shapes.

Within this formulation, we explored the question of whether an AI agent could predict which combination of these fairness objectives a human was focused on, based on the trajectory of fairness outcomes as they explored possible solutions. To do so, we used a deep neural network (DNN) to model the mapping between outcomes and intentions. The DNN was a combination of a long-short-term-memory (LSTM) architecture with a fully convolutional network (FCN) from (Karim, Majumdar, Darabi, & Harford, 2019), chosen for its ability to represent complex relationships, including temporal connections between data points (Karim, Majumdar, & Darabi, 2019). The intention-inference problem thus becomes a supervised learning problem. In theory, if we had enough ground truth data of humans exploring voting district solutions with knowledge of the human's design intentions in each case, our DNN could be able to learn this mapping. However, DNNs require large amounts of data, and data generated by humans working on such a task is expensive to collect. Furthermore, in many cases, humans might not be explicitly aware of their exact intentions and preference structure.

In consideration of this challenge, we trained our model on data generated by another AI agent, simulating the human decision-making process via a search optimization algorithm. We set a fixed preference distribution of the three fairness goals, and built a human-simulating agent to find optimal districting solutions given these preferences. This resulted in synthetic training data that mapped preferences to exploration trajectories, consisting of outcomes from 130 episodes of 100 districting steps each, for a total of 73,710 training samples.

This approach, of course, relies on the extent to which simulated explorations can accurately model human behavior for a given complex decision-making task. To test this, we evaluated our model, trained on the above-mentioned synthetic data, on "real" data, collected from four humans who we asked to delineate districts for each of the possible combinations of intentions. The human test data consisted of an average of 689.4 steps per task across the four participants.

The core metric we used to evaluate our trained model was its prediction accuracy on the intentions specified for each task. Our model was able to infer the complete combination of intentions across three objectives 31.3% of the time (versus 14.3% random accuracy). The model inferred the complete intention set in its top two predictions 50.9% of the time, and 67.2% of the time in its top three (versus 42.9% and 57.1% random accuracy). For the three individual intentions, *balancing population*, *improving voter efficiency*, and *maximizing compactness*, the network predictions' average precision was 0.739 and its average recall was 0.700 (F1-score 0.719). In other words, when the network predicted a human was holding any one of the three intentions, it was correct, on average, 73.9% of the time, and it detected when the human was holding an intention, on average, 70.0% of the time. A random prediction would select a particular intention 57.1% of the time.

This study is an early investigation on the ability of AI to infer intentions in complex decision-making tasks. However, in such decision-making tasks, possible intentions can evolve and may not even be clear to the human worker at the start. To support collaboration, this dynamic necessitates the development of more complex models and representations. Future work will seek to improve on this model using more contextual information about the task itself, as well as physical interactions with a shared interface and a robot.

Once the human creative intention is correctly inferred, there remain additional questions: What is the best way to make use of knowledge about a human collaborator's intentions in an unstructured task? Should the robot simply adopt the human's intentions? Should it use information about the human's goals to optimize the likelihood of achieving its own using a game-theoretic approach?

In the two studies described, we identified challenges in human-robot collaborative decision-making and proposed a model to give a robot more information about its partner's intentions. Given the increasing importance of cognitive and decision-making work in the future workplace, continuing to study this problem will remain a central challenge for the HRI research community.

Conclusion

Robots entering the workplace could be thought of as merely another type of machine or tool, a capital investment made by an employer to improve the efficiency of processes and tasks. However, years of laboratory research in human-robot interaction has shown that in many cases, people treat robots as social actors (*e.g.,* Fischer, 2011; Fussell, Kiesler, Setlock, & Yew, 2008; Jung & Lee, 2004; Lombard & Xu, 2021), which might place robots in a category more akin to a team member. The subsequent relationship between robotics and labor puts the workplace robot in a societal and economic context that might be different than other workplace tools. Economists are still divided on how robots might affect labor in the long term, but the evidence shows that they do so at the moment, reducing both workforce participation and wages (Acemoglu & Restrepo, 2017).

Whether robots replace workers or enter human teams as additional labor, robots in the workplace will interact with humans in psychologically intricate ways. The research field of HRI tackles both the engineering and the social aspects of this interaction, but it has predominantly focused on interaction in the home, in public places, and with service customers. This chapter argues that there will be unique and worthwhile research questions that specifically address the psychological needs and outcomes of workers interacting with robots, be it in offices, in warehouses, in factories, or in service locations, such as care facilities or retail centers.

Our own research presented here examined three such challenges. In one study, we evaluated how monetary competition with robots affects people's motivation to do well on a mundane and repetitive task. We found a demotivating effect, as well as a decrease in people's liking of the robot and their self-competency assessment when a robot was doing better at the task. In a second study, we saw that when the task is anything but mundane, complex dynamics need to be negotiated. Questions such as whose turn it is to act, what the goal of the team is, who leads and who follows, and how certain gestures might be perceived, all played a role when a human and a robot tried to solve a complex decision-making problem. A third study asked whether we can develop AI that can correctly infer a human's intentions in such a cognitive work task, and whether simulated data from other AI algorithms can serve as adequate models for human behavior. We found that even training on simulated decision-making, our system was able to infer real human participants' intentions better than chance, suggesting promising ways in which robots could support workers in contexts outside of manufacturing.

These studies address only three of the many workplace-related psychological questions the field of HRI is sure to tackle in the years to come. Other issues may relate to the question *where* robots would be most beneficial, not just economically, but also from a psychological perspective. This requires both an analysis of the labor market and a public discussion on the values and goals we set as a society. Researchers and members of the public have to ask themselves what kinds of work we would want robots to do (Ju & Takayama, 2011; Takayama, Ju, & Nass, 2008). Do we want robot teachers, psychologists, or police investigators? Will future robots work in collaboration or in competition with human workers? As the bulk of the economy is moving from manufacturing and agriculture to services, and more and more workers are doing creative and open-ended work, the field of HRI has to also adapt to solve some of the complex problems in artificial intelligence that the research and development domains carry.

Finally, future research will likely be grounded in questions surrounding the workplace social dynamics, organizational structures, and incentives. This will include ethnographic research observing workplace processes and behaviors, and also the adaptation of existing research on the many facets of HRI which were studied in other contexts. Researchers could study psychological issues such as social hierarchies, personality, dialog, trust, cognitive biases, and many others, in the relatively unexplored context of HRI in the workplace.

To summarize, research in human-robot interaction has made great strides in the nearly two decades that it exists as a field. Many of its findings and developments are already relevant to offices, warehouses, factories, and grocery stores. With continued advances in artificial intelligence and robotics, HRI studies could make an increasing impact, as robots are more often used in the spaces in which humans work.

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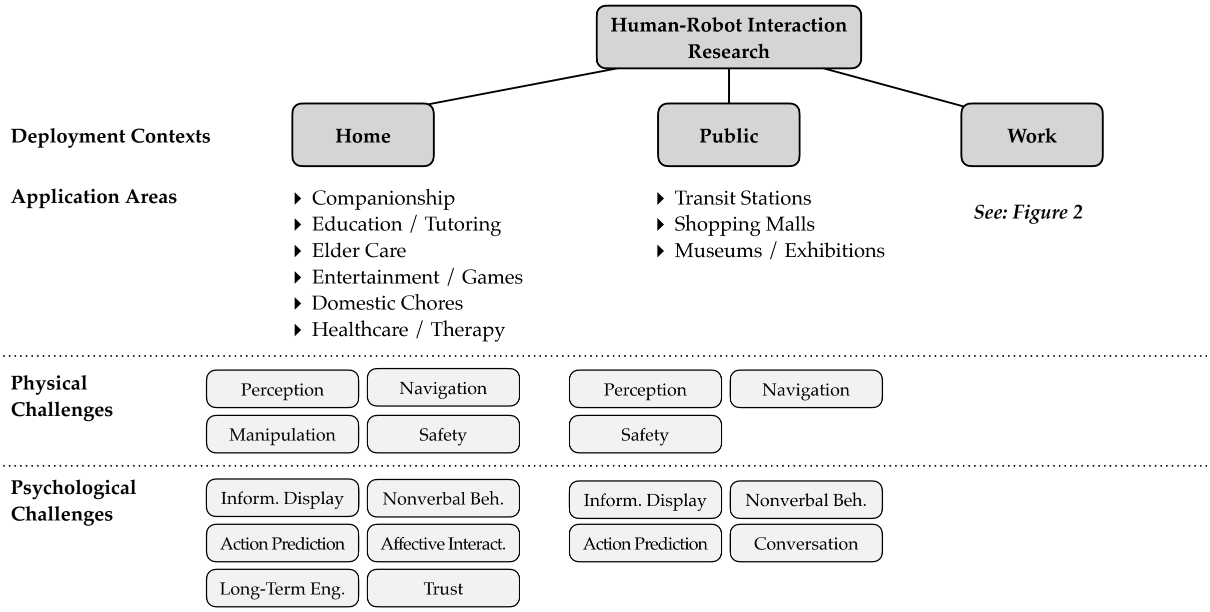

Figure 1. Application areas for human-robot interaction at home and in public spaces, along with research challenges related to physical and psychological aspects of the interaction. Most physical challenges are common to both context, whereas home interaction with robots presents more complex pscyhological challenges, such as affective interaction, long-term engagement, and trust.

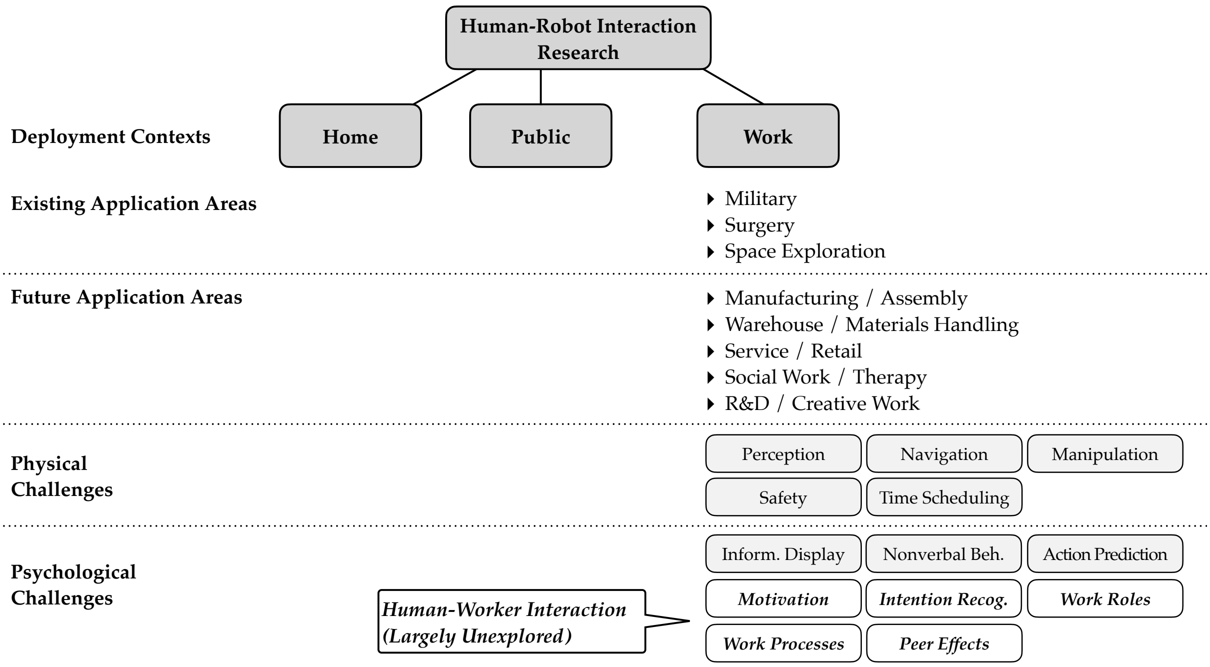

Figure 2. Established and future application areas for human-robot interaction in the workplace, along with research challenges related to physical and psychological aspects of the interaction. Most physical challenges are similar to those of the home and public context. There are important psychological challenges related to robot-worker interaction that are currently unexplored (clear boxes on bottom right). These include: worker motivation, intention recognition in complex creative work, negotiation of roles between humans and robots, understanding work processes, and taking into account peer effects.