MODELING HUMAN-ROBOT TEAMS TO OPTIMIZE THEIR SAFETY, SUSTAINABILITY AND EFFICIENCY

IDENTIFYING VARIABLES AND MODELS

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1 Introduction

Since the start of the first industrial revolution in the late 18th century, machines have been used to support people in difficult tasks. To keep people safe when using these machines, people and machines are usually kept separate in accordance with current health and safety requirements (European Directive 2006/42/EG machinery, Appendix 1). Recent developments have introduced so called cobots or cooperative robots (in the remainder of this report we will refer to these machines as robots), which place the machines on the work floor next to employees. These robots have the potential to fully utilize both the strong points of machine (e.g., accuracy and speed) and of human workers (e.g., flexibility and creativity) in cooperative tasks. The great advantage of this new form of interaction is that the scalability of the production increases, however, it also poses new challenges to secure the safety of workers as separation is no longer a viable option. The necessity to address this challenge Is highlighted by recent incidents that occurred with robots:

> *‘’In December 2015, a 45-year-old warehouse dock coordinator at a water bottling company died after he was crushed when the elevated forks of an automatic laser guided vehicle (LGV) came down on him’’.*
>
> *The incident was the result of an emergency stop button that wasn’t pressed by the worker and that the worker was not detected by the lgv when removing plastic tie raps from the sensors (NIOSH, 2018).*

Another example of an incident with a robot occurred at Amazon, where an automated guided vehicle (AGV) perforated a barrel exposing employees to the hazardous substance capsaicin, a product that (in hindsight) should not have been in the vicinity of the machine, given the risk that the employee was exposed to. The official investigation revealed:

"An automated machine accidentally punctured a 9-ounce bear repellent can, releasing concentrated Capsaican". Capsaicin is the major ingredient in pepper spray (ABC News, Dec 6: 2018).

The primary goal for human-robot interaction should be that a specific task can be performed in a sustainable way, meaning task performance should be good, quick, durable, safe and healthy. However, since human and machine will no longer be separated, keeping these robots inherently safe, requires new solutions. TNO has therefore set itself the goal of contributing to models, methods and criteria for optimizing human-robot interaction. Primarily to determine what variables must be examined to optimise human-robot interaction in a sustainable manner. The central research question we want to answer is:

Which variables can be identified to optimize sustainable human-robot interaction?

Here we specifically focus on human-robot interactions (HRIs) which take place between humans and robots working on the same task and within close physical proximity.

This means that we excluded, for example, teleoperated robots. Furthermore, we limit ourselves to teams that consist of one human and one robot having one-on-one interaction. The resulting model does, however, not exclude more complex teams.

Ultimately, our goal is to examine the exact impact of various characteristics on relevant HRI outcomes (discussed in more detail in Chapter 5). The first step, however, is to create an overview of relevant characteristics that affect the outcomes of HRI. This will be our primary goal in this report: to explore the literature and create a structured overview of characteristics that have been identified in previous studies to be relevant for HRI.

To address the primary goal for this report an exploration of the literature has been carried out. In this report, we will first provide some additional theoretical background to provide context for the remainder of this report. Then, in Chapter 2 we describe the methodology of our literature exploration and we introduce the input-mediator-output-input (IMOI) model that was used to structure the results. Chapter 3 provides an overview of our findings from our literature exploration and the resulting model and in chapter 4 we give a short conclusion regarding this model. Finally, in Chapter 5, we discuss our intended next steps to examine the relative impact of the identified characteristics on sustainable HRI.

1.1 Theoretical Background

In this chapter we provide some theoretical background to help clarify certain context in our discussion of human, technical and environmental factors that influence sustainable human-robot interaction. We will briefly discuss safety and sustainability in the context of HRI, a system approach to HRI, interfaces, and human-robot teaming.

1.1.1 Safety and Sustainability

Safety in human-robot interaction is a versatile concept. In this report it means to cause no physical harm or damage in any way. This includes the mechanical and software means to prevent physical harm to the human.

Sustainability covers all aspects for effective, safe and healthy human robot interaction. Concerning HRI, sustainability can take several meanings. First of all, sustainability means that human-robot interaction should not make the human ill or disabled, neither physically nor mentally. This holds for both the short term as well as the long term. In this report we will refer to this outcome as sustainability. Sustainability can also means that the robot should be able to perform its task while maintaining asset integrity. In other words, the robot (or its environment) should not be damaged by the interaction directly or over time (i.e., wear). In this report we refer to this outcome as asset integrity. Finally, sustainability also means that the interaction should be economically viable for an organization to maintain operations in the long term. In this report we will refer to this outcome as the efficiency of the interaction.

1.1.2 System approach

According to Reason (2000) humans and machines (including robots) operate together in a system. The system can be defined as the conditions under which humans work. In poorly designed systems risks lay dormant waiting to be exposed. Exposure to potential risks can result from the combination of (unexpected) human behaviour and missing or failing system barriers, like the design of the robot. The causes of these errors can also be traced back to the organizational processes that give rise to them. According to Reason countermeasures should be based on the assumption that although we cannot change the human condition, we can change the conditions (the system) in which humans work.

To prevent errors companies and system developers incorporate system defences in their technologies as barriers and safeguards. Three system levels can be distinguished in which system barriers and safeguards should be taken to prevent accidents to occur: human, technology and organisation (HTO). For the current study we reshaped the original model a little. Instead of using the term technology we use the term robot. Instead of organization, we use environment which includes certain organizational factors but places more emphasis on the context in which the HRI takes place (e.g., housekeeping or the properties around the task such as temperature, light and movement space). So the actual model used here is a human, robot and environment (HRE)-model.

1.1.3 Robot and interface

The term robots has a wide variety of definitions. According to the International Organization for Standardization (ISO, 8373:2012) a robot is an 'actuated mechanism programmable in two or more axes (4.3) with a degree of autonomy (2.2), moving within its environment, to perform intended tasks". Another definition is the "sense-think-act-communicate" paradigm (Siegel, 2003). For this work we consider a robot as a reprogrammable mechanical system that can interact with the physical world via sensors and actuators in an (semi-)autonomous way.

Within this definition a robot can have AI to interpret sensor data and adjust actuators to, for example, act on changes in the environment. AI by itself is, however, not a robot as AI itself cannot act on the physical world. The interface is the key component that facilitates communication between the human and the robot. Good communication is essential for sustainable robot teams. From industrial automation it is known that the interface quality affects production, output quality and likelihood of life-threatening situations (Budnick & Michael, 2001). Moreover, interfaces quality is linked to disease, like stress or musculoskeletal disorders (Ballav & Ghosh, 2017).

A robot interface communicates to the a human by triggering one or more of the five senses. According to a study by Goodrich and Schultz (2007), the most common interfaces relate to the vision, hearing, and touch. The other two of the five senses, taste and smell, remain largely underexploited (Obrist et al., 2016).

The human body can act as an interface for robots as well. In this case, the robot can 'read' the human body (e.g., through sensors) by relying on several action modalities: sound, hand or body movement, facial expressions and gaze (Sharma, Pavlovic & Huang, 2002). These actions can be captured explicitly (e.g. by designing a GUI that asks the user for specific input) or implicitly by interpreting the human behaviour (e.g. by analysing facial expressions).

1.1.4 Human Robot Teaming

With new advancements, human and robot may become interdependent to complete a task instead of humans solely interacting with or instructing the machine. In other words, the interaction might become a more substantial form of cooperation. Consequently, nowadays researchers are referring to ‘human-machine teaming (HMT)’ instead of the more traditional ‘human-machine interaction’ (HMI) definition (Chen & Barnes, 2014).

This change in terminology represents a change in the underlying HRI framework, in such a way that machines might over time evolve from ‘tools’ (i.e. automation) to ‘teammates’ (i.e. autonomy). However, we believe that it should be desirable to keep in mind that the primary purpose of robots, when working in the same environment and on the same task as a human, should be to act as a tool facilitating the human. Traditionally, a team is defined as “two or more people who interact dynamically, interdependently, and adaptively toward a common and valued goal/objective/mission, who have each been assigned specific roles or functions to perform, and who have a limited life-span membership” (Salas, Dickinson, Converse, & Tannenbaum, 1992, p. 4). Robots still have a long way to go to adhere to this definition of team members. Therefore, we will keep referring to human and robots working together as human-robot interaction. Yet, we do acknowledge that with the continuing technological developments HRI will be substantially different from traditional human-machine interaction.

2 Method

2.1 Literature exploration

For our exploration of the literature we made use of the following primary search terms: *Safe(ty)*; *Risks*; *(Human) robot/computer/machine/automation interaction*, *Human centred design* in various combinations. This provided us with an initial set of relevant papers. In order to extend our search, we took ten review papers, from the initial search result, as starting point to find additional relevant papers in their citations (also known as snowballing). Based on the additional found literature, more specific and aimed searches were conducted on themes and topics that emerged. Finally, numerous papers were also collected in the course of our exploration through contacts and networks of the involved researchers.
Peer reviewed journals, conference papers, and books (chapters) written in the English language were included when they described a qualitative or quantitative study concerning HRI in general. The abstract and title were examined to determine relevance. No time period was defined as exclusion criteria. The exploration was done independently by three researchers, whose findings (i.e. relevant characteristics mentioned in the document) were collected in a central document.

2.2 The IMOI-model

To categorize the information found during the literature exploration we made use of the input-mediation-output (IMOI) model (this model is often used in teamwork studies: e.g., Ilgen, Hollenbeck, Johnson & Jundt, 2005; Rosen, Dietz, Yang, Priebe & Pronovost, 2014). The input part (I) concerns the characteristics of team members, the task, and the environment. The mediator part (M) concerns the conditions or states that emerge from the interaction as a result of the input and which affect the output. The output part (O) concerns the results of the team effort (Rosen et al., 2014), that may serve as input again for a next cycle.
This model seemed fit for our purpose as the overlap between HRI and traditional human teamwork is easy to see. The IMOI-model is not just a linear model (input leads to mediator, leads to output), but also allows direct relations between input and output, or between mediators (Ilgen et al., 2005). Furthermore, the output of an initial interaction could serve as new input for the continuation of the interaction (Ilgen et al., 2005). When an interaction with a machine results in a stressful experience for the human operator, this will likely affect how the operator behaves in the next interaction with that machine.

2.3 Hardware, Software and Mindware

Aside from distinguishing input, mediator and output characteristics, we made a further distinction between hardware, software and mindware. These refer to the main safety categories these variables belong to. Hardware refers to physical and technical characteristics, software is about knowledge and (underlying) processes or procedures, and mindware is about the attitude and experience. The resulting model (see table 1)

3 Results

Here, we will discuss our findings from the literature by means of the IMOI-model. We already identified the output of interest: The Human robot teaming should occur in a safe, sustainable and efficient manner. Therefore, our literature review mainly focused on relevant input and related mediators. Here we will briefly discuss the relevant output factors for our model. Next, we will provide an overview of the found input factors from the literature. We structured these factors in the hardware, software, and mindware[1] characteristics of the human, robot, and environment, as discussed in the last section. Lastly, we will discuss the relevant mediators that were derived from our analysis of the literature that help connect the input factors with our output factors. Table 1 provides an overview of the factors in the IMOI-model.

Table 1. Input, Mediator and Output factors categorized by hardware, software and mindware

	Input			Mediator	Output
	Human	Robot	Environment		
Hardware	• Physical limitations • Physical characteristics • Supportive tools or PPE • Demographical characteristics • Fatigue	• Safe by design • Ergonomics • Work speed • Force/energy exertion • Accuracy • Consistency • Robustness • Post-collision measures	• Available space • Ergonomics • Housekeeping	• Process • Physical workload	• Safe • Efficient • Asset integrity
Software	• Cognitive capacity (memory) • Understanding (of the system) • Experience • Training • Resilience • Flexibility • Vigilance • Fatigue • Motivation	• Adaptiveness • Predictive software • Controllability / Directability • Transparency • Communicative capabilities • Explainability	• Time pressure • Task complexity • Illumination • Temperature • Noise • Air quality • Weather	• Situational awareness • Cognitive workload	
Mindware	• Attitude • Trust • Self-Efficacy • Stress • Automation bias • Complacency Satisfaction	• Appearance • Consistency • Conformity • Social behaviour • Roll distribution • Human in control • Transparency	• Illumination • Temperature • Noise • Air quality • Weather	• Job quality • Complacency • Perceived workload	• Sustainable

[1] Hardware refers to physical and technical characteristics, software is about knowledge and (underlying) processes or procedures, and mindware is about the attitude and experience.

3.1 Output

As discussed earlier, the desired output of HRI is that it takes place in an efficient, safe and sustainable manner for human and machine. We specifically add the term asset integrity to our list of desirable outcomes to indicate a safe and sustainable outcome of the machine. We have listed these output factors in the last column of table 1. We have linked a sustainable outcome to mindware, whereas we decided that a safe, efficient, and asset integer outcome are linked to both software and hardware (will be further discussed in the section mediation).

Next, we give several examples that could be linked to each outcome to make them measurable constructs (see Table 2).

Table 2. Outcomes of HRI and associated measurable constructs.

Outcome	Construct
Efficient	(Production) target Quality check
Safe[2]	Disruptions of the normal process Loss of control Errors (of omission or commission)
Sustainable	Stress Quality of Life Self esteem
Asset integrity	Wear (damage) Status

3.2 Input variables

3.2.1 Hardware Human

The category Hardware Human contains all characteristics reflecting physical factors and capabilities of the human to perform during the interaction with the robot. Examples of physical factors are characteristics such as body size and posture or demographical characteristics such as age and long-term health problems (musculoskeletal disorders or chronic diseases; Boenzi, Digiesi, Mossa, Mummolo & Romano, 2015). The human body also has certain physical limitations on the areas of speed, force, duration, accuracy and endurance which need to be taken into account. Fatigue, present before the task or as a result of the work, will also affect the interaction. Some of these limitations can be improved through supportive tools or gear, and Personal Protection Equipment (PPE). Note that, to avoid overloading the human, some limitations implicate hard restrictions to robot parameters. This is especially relevant given the finding that humans are also more likely to assign more work to themselves when working with a robot, compared to when working with a human teammate (Gombolay, Gutierrez, Clarke, Sturla, & Shah, 2015).

[2] Accident frequency is low, making empirical data collection surrounding them unfeasible. In addition, simulating accidents (even minor collisions) is not an ethical consideration in the field of science. Therefore, we propose several proxy parameters of occurrences that are likely to precede an actual incident. These proxy parameters show significant overlap with the mediators we will discuss in section 5.3

The importance of these factors has been highlighted in a previous report of TNO discussing robots in relation to workload (Douwes, Huysmans, Kraan & de Looze, 2017). These factors in combination with task characteristics determine the actual workload (see for other studies concerning workload: Funke, Knott, Salas, Pavlas, & Strang, 2012; Wickens, 2000).

3.2.2 Hardware Robot

The category Hardware Robot contains all characteristics reflecting physical factors and capabilities of the robot that affect the physical capacity of the human to perform during the interaction with the robot. When possible, safe interaction through design (Pervez & Ryu, 2008) should be followed meaning the robot is preferably light weight and without sharp edges. Also, the focus should ideally be in collision avoidance. There are various methods to accomplish this such as quantitative limits on the robot concerning various parameters (e.g., velocity, energy or force) or speed and separation monitoring with sensors (Lasota, Rossano & Shah, 2014). Since collision may not always be completely avoidable (Pervez & Ryu, 2008), other, post-collision, measures should be taken as well, such as force control without sensors (Stolt, Linderoth, Robertsson, Johansson, 2012), or programming a trade-off between stiffness and speed (e.g., low stiffness at high speed and vice versa; Santis, 2007).

The robot should have a certain degree of accuracy and consistency while performing its task. Furthermore, task (and safety) relevant elements, such as the sensors and interface, should be robust and ergonomically designed. Environmental conditions like lighting or dust, should not lead to malfunction (Santis, 2007).

3.2.3 Hardware Environment

The category Hardware Environment contains all environmental characteristics that affect the physical capacity of the human to perform during the interaction with the robot. A report from 1987 showed that 20 out of 32 analysed robot incidents were due to poor workplace design (Jiang & Gainer, 1987). A human-centred design of the environment (or work cell) in which the human-robot interaction takes place is necessary (Ogorodnikova, 2008). Concerning the physical characteristics this concerns ergonomics (such as the height of the workstation). Other elements are housekeeping, and the presence (or absence) of other robots or workstations in the surroundings (or more specifically the free space available for the moving components of the robot (Ogorodnikova, 2008; Murashov, Hearl & Howard, 2016).

3.2.4 Software Human

The category Software Human contains all characteristics reflecting the knowledge and cognitive capabilities of the human to oversee the interaction with the robot. Interaction with robots, or robot systems have the potential to introduce cognitive workload on employees. This becomes relevant when humans need to monitor multiple robots at the same time (Douwes, Huysmans, Kraan & de Looze, 2017). Additionally, various characteristics of the operator may improve the available cognitive resources or reduce the demanded cognitive resources while performing a certain task.

Examples of such characteristics are; the knowledge of the operator about the robot they are interacting with (Bortot, Born & Bengler, 2013; Dohi Okada, Maeda, Fujitani & Fujita, 2018), previous experience with the robot (or with automation in general; Takayama et al., 2016; Sanders et al., 2017), training (NIOSH, 1981), (team) resilience (Matthews, et al., 2016;

Patriarca, Bergström, Di Gravio & Costantino, 2018), and his or her adaptability to various situations (Michalos, Makris, Papkostas, Mourtzis & Chryssolouris, 2010).

Reduced vigilance or awareness should be avoided during human robot interaction (Ogorodnikova, 2008). According to Ogorodnikova vigilance means to have sustained attention, alertness and maintained performance over time (2008). A decrement of vigilance could decrease productivity, reliability, efficiency or the increase of hazardous situations or human errors due to inadequate workplace or interface design may be avoided. Ogorodnikova states that vigilance can decrease due to, for example, lack of sleep, circadian rhythms, lighting, noise, temperature and high task load (2008).

A lot of researchers acknowledge the value of the human operator in HRI due to their superior flexibility, their ability to rapidly adjust to unexpected situations, and to deviate from set instructions if needed (Gombolay et al., 2015; Lotter & Wiendahl, 2009; Michalos et al., 2010). Yet humans are limited in their cognitive capacities (e.g., working memory), the rate at which they learn, and they can lack motivation (Boenzi et al., 2015). Consequently, human operators might be prone to making errors during human robot interactions (e.g., Ogorodnikova, 2008) causing the human operator to lose control over situations.

The literature refers to this loss of control in several ways. Some literature describes the shared mental model (Cooke, Salas, Cannon-Bowers, & Stout, 2000; Schuster et al., 2011; Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000) or shared vision on the objective (Mathieu et al., 2000) set beforehand between the human and the machine. In other words, does the action of the machine match with the expectation of the human operator about the actions the robot is going to perform. A so called ‘cognitive mismatch’ (for example by misinterpreting the display or other signals) could lead to poor decision making (e.g. erroneous behaviour) and loss of control over the situation (Mohrmann, Lemmers & Stoop, 2015). This increases the likelihood of accidents to occur.

Other literature refers to the (loss of) situational awareness (Stanton, Salmon, Walker, Salas & Hancock, 2017; Onnasch, Wickens, Li & Manzey, 2014; Mohrmann et al., 2015; Shu & Furuta, 2005) by human (or machine). Endsley (1995) distinguished three levels of situational awareness: (1) Knowing what is happening right now, (2) understanding what is happening right now, and (3) knowing what is going to happen next. Loss of situational awareness at any of these three levels could result in an incident.

3.2.5 Software Robot

The category Software Robots contains all characteristics reflecting the communicative capabilities and underlying algorithms that affect the cognitive capacity of the human to stay in control of the interaction with the robot. Communication is considered a vital aspect of teamwork (Salas, Sims & Burke, 2005) and human-machine interaction also benefits from proper communication (Klein et al., 2004).

Machines can communicate with humans through various mediums from speech (Stedmon, Sharples, Littlewood, Cox, Patel & Wilson, 2007), gestures (Tang, Charalambous, Webb & Fletcher, 2016), light signals, (holographic) projections, and interfaces.
More importantly, the communication needs to be effective in providing the human operator with the knowledge he or she requires to stay in control of the interaction (Green, Billinghurst,

Chen & Chase, 2008; Goodrich & Yi, 2013; Leonard, Graham & Bonacum, 2004; Scheutz, DeLoach, & Adams, 2017). Interfaces are an important aspect through which machines and robots share information with the human operator. Ballav and Gosh (2017) found in their study that commonly reported problems during HMI were navigation (difficult flow or procedures) and information overload. Proper interface design can help avoid such usability problems and their design should therefore be in line with ergonomic principles such as easy to learn, efficient to use and safe to use (e.g., Flaspöler et al., 2009; Nielsen, 1994) and kept intuitive (Moniz & Krings, 2016).

The transparency of the robot (system) is a closely related topic to interfaces that receives a lot of attention in relation to HRI (Ososky, Jentsch, Hancock, & Chen, 2014b; Chen, Campbell, Gonzalez & Coppin, 2015; Chen, Barnes, Wright, Stowers, & Lakhmani, 2017; Steijn, Janssens, Kwantes, van der Beek & Jansen, 2018). Transparency of the robot (system), for example through user-friendly interfaces, help keep the robot observable, predictable and directable for the human operator (Johnson, Bradshaw, Feltovich, Jonker, van Riemsdijk & Sierhuis, 2014; Werkhoven, Kester & Neerincx, 2018). Transparent and appropriate communication decreases the workload and increases performance, safety and the control of the human operator (Chen et al., 2015;). Especially robots with AI (or machine learning) will require transparency of their algorithms to keep them explainable (to avoid the 'black box'), avoid bias and keep accountability of events (Gunning, 2017; Steijn et al., 2018; Werkhoven, Kester & Neerincx, 2018). Regarding transparency it would be interesting to determine the exact amount of information that needs to be shared with the human operator while avoiding information overload.

Automation complacency is another challenge concerning the cognitive capacity of the human when interacting with the robot (Wickens, Sebok, Li, Sarter & Gacy; 2015). In other words, human operators might over rely on the robot and might therefore be more susceptible to errors. Adaptive automation (Kaber, Perry, Segall, McClernon & Prinzel, 2006; Onnasch et al., 2014), through which the robot adjusts the level of assistance based on the requirements of the operator, can avoid this.

There is also a field of literature that examines the capabilities of the robot to adapt to its environment and to 'read' the human operator while collaborating (Dohi et al., 2018; Lasota et al., 2014; Murashov, Hearl & Howard, 2016; Tsarouchi et al., 2016; Vasic & Billard, 2013). Through sensors and complex algorithms, the robot can perceive its environment and react to it. Through motion prediction models, robots might be able to avoid collision (pre-collision methods; Lasota et al., 2014) even when the human operator has lost control.

3.2.6 Software Environment

The category Software Environment contains all environmental characteristics that affect the human's cognitive capacity to oversee the interaction with the robot. Both time pressure and the complexity of the task (e.g., having to handle multiple tasks at once) increase the cognitive workload of the human operator (Mattsson et al., 2016; Moniz & Krings, 2016; Xie & Salvendy, 2000).

Environmental characteristics such as temperature, lighting and noise (or the weather when outside) are potentially distractors (e.g., Vasic & Billard, 2013; Niemalä, Rautio, Hannula, &

Reijula, 2002). For example, office noise can affect concentration (and other things) and air quality can affect productivity (Haynes et al., 2017).

3.2.7 Mindware Human

The category 'Mindware Human' contains all human characteristics reflecting how people experience or perceive the interaction with the robot. This concerns factors such as the attitude of the individual, but also psychosocial factors such as trust (Douwes et al., 2017). Overall, the quality of the job (and work environment) is determined by available work place resources (e.g., work autonomy and opportunities to learn): insufficient resources can turn them into stressors (Cazes, Hijzen, & Saint-Martin, 2015).

One human mindware factor is the attitude of the employee towards robots or automation, which can influence trust development (Schaefer, Chen, Szalma, & Hancock, 2016). Emotional responses, including trust, towards a robot can contribute to acceptance, safety and performance (Lee & See, 2004). Trust development also depends on the physical appearance, functional capabilities and performance of the robot (Schaefer et al., 2016, Hancock, Billings & Schaefer, 2011). Furthermore, attitude toward automation is related to complacency, commission errors, omission errors, and trust (Mohrmann, Lemmers & Stoop, 2015).

Another factor is self-efficacy, or the degree in which the individual believes to be able to accomplish certain tasks. Having a low self-efficacy (i.e., little trust in own capabilities) increases the chance to become complacent rely too much on the automation (Prinzel 2002). High self-efficacy, however, could lead to confidence and underuse of the automation, increasing the cognitive workload in turn (Prinzel, 2002). Another study found that elderly people liked fully autonomous support less than a more adaptive system (Yu, Spenko & Dubowsky, 2003).

Closely related to self-efficacy is self-esteem. Social rejection by a robot can lead to reduced self-esteem, although it does not result in a negative view concerning the use of robots in everyday life (Nash, Lea, Davies, & Yogeeswaran, 2018). Technology errors tend to go unacknowledged, resulting in people being blamed or blaming themselves for errors instead (Norman 1988; as cited in de Visser, Pak & Shah, 2018). This could consequently lead to a reduced sense of self-efficacy and self-esteem. Malle, Scheutz, Arnold, Voiklis and Cusimano (2015) did find that humans are capable to attribute moral blame (in terms of permissibility and wrongness) to robots.

Stress is another important factor in the model. Stress (i.e., a higher workload) can have negative long-term health effects (e.g., McEwen & Stellar, 1993) and lead to a reduction in trust (Wang, Jamieson, & Hollands, 2011). Proper interface design can help reduce not only the cognitive but also emotional workload of a task (Ogorodnikova, 2008; Nachreiner, Nickel, & Meyer, 2006). Also, robot motion can affect human wellbeing and performance (Bortot et al., 2013). Arai, Kato and Fujita (2010) found an increased mental strain when the robot moved closely towards the operator, with sustained approaching speed and without advance notice of their motion. Another study reported that participants exhibited discomfort when the robot blocked their path or was on a collision course with them and within 3 meters (Koay, Dautenhahn, Woods, & Walter, 2006). De Visser, Pak and Shah (2018) argue that a robot should be able to detect stress and discomfort and aim to ease this human state and, if necessary, repair trust.

A lack of trust between the human and robot can lead to disuse. Take for example the operators who decided to manually control a tele-manipulated search and rescue robot when they lost trust in in the automation system (Gao, Clare, Macbeth, & Cummings, 2013). Notably, a reliable robot system can still be perceived untrustworthy and thus not fully utilised (i.e., under reliance; Parasuraman & Riley, 1997). Alternatively, overtrust, in the forms of automation bias and complacency, can also lead to system misuse and errors of commission and omission. With automation bias, the human tends to over-rely on automation and its output. Automation bias can occur independent of the experience or training of the operator and can affect decision making in both individuals and teams (Parasuraman & Manzey, 2010). With complacency, the human non-vigilance is based on an unjustified assumption of reliance and satisfactory system state as of which insufficient attention is payed to output monitoring. Complacency can arise where, for multiple tasks, a manual task competes with an automated task for the operator’s attention. Complacency occurs independent of the experience or training of the operator (Parasuraman & Manzey, 2010).

Job quality is generally considered a multidimensional concept affected by various elements (Warhurst, Wright, & Lyonette, 2017). A study that measured job quality or satisfaction in human robot teaming reported that humans felt safer, more comfortable and were more satisfied with an adaptive robot (i.e., human-aware motion planning) as a teammate than a standard robot (Lasota & Shah, 2015). In other words, both performance and satisfaction are influenced by the (perceived) capabilities of the robot.

3.2.8 Mindware Robot

The category Mindware Robot contains all characteristics of the robot that affect how the human experiences or perceives the interaction with the robot. This could be seen as the non-verbal communication of the robot to the human.

The appearance of the robot can affect its perception by the human. Appearance, specifically a larger over a smaller robot, leads to lower comfort ratings in nearly all cases, suggesting that the robot’s size and form factor can influence psychological safety (Butler & Agah, 2001). Humans perceive robots with humanoid features differently than other computer technology and tend to think such robots have human-like qualities and intelligence than they actually have (Hegel, Krach, Kircher, Wrede, & Sagerer, 2008; Murashov, Hearl &Howard, 2016, Reeves & Nass, 1996). This suggests that machine like robots may be more appropriate when they are expected to be less reliable and less well equipped for the task (Murashov, Hearl &Howard, 2016). Hinds, Roberts and Jones (2004) also found that respondents retained more responsibility for the task when working with a machine-like robot. They conclude that machine like robots are more appropriate for tasks in which the human is expected to maintain responsibility, whereas more human like robots should be used for tasks that are too demanding for humans and where complacency is not a concern during the task. The mode of communication (verbal, written, tactile, auditory, etc.) also affects how the robot is perceived and how intelligent it is. For example, human-like speech and the level of trust (Schaefer et al., 2016).

Literature shows that the “perceived ease of use” and “perceived usefulness” have a strong effect on user’s attitude towards a technology (Legris, Ingham, & Collerette, 2003; Adams, Nelson, & Todd, 1992). This also relates to consistency and conformity to user expectations.

Here we define consistency as a robot or its interface always following the same principles (e.g., in terminology and workflow). With conformity we mean that a robot, application or interface should behave as users expect it. Where consistency is restricted to the (computer) system itself, conformity extends to the interaction with the real world. For example, attitudes in human–robot interaction are positively affected when robot behaviour is human like, although inconsistencies herein (i.e., human and non-human like behaviour mixed) could hinder overall performance (Wiese, Metta, & Wykowska, 2017).

The social behaviour of a robot during HRI also affects how the robot is perceived. For example, people react more strongly to robots who have a high approach speed or invade personal space than to other humans manoeuvring in the same manner (Joosse, Sardar, Lohse, & Evers 2013). The design should ensure that the motions of the robot are predictable to avoid that humans are unpleasantly surprised (Murashov, Hearl & Howard, 2016). In addition, humanlike imperfect fallible behaviour, i.e. cognitive biases, is expected to be effective for increasing the enjoyment human-robot interactions (Biswas & Murray, 2017). The ability “to act like a human worker” can also improve emotional safety, though such capabilities can lead to unintentional attribution of non-existent reasoning or intelligence of the robot (Murashov, Hearl & Howard, 2016).

The distribution of role and responsibilities of the both the human and the robot should be considered in the interaction to ensure a good cooperation. Mattsson, Fasth, and Stahre (2012) define three types of interaction:

- human centred (incorporates factors to study, describe human factors);
- automation centred (the machine performance indicators like performance, error/failure management, cost/economy, changes);
- Interaction centred (human and machine as joint system of human-automation).

An automation-centred approach of the robot implementation has the potential to leave the leftover task for human for which the human is not well suites (Parasuraman, 1997). A human-centred or interaction-centred approach should give the human an active role rather than a monitoring role (Billings, 1996). How the work should be divided and performed should be based on adjustable work agreements (Werkhoven et al., 2018). Having control over the level of autonomy has been found to influence productivity, satisfaction and the desire to work (Gombolay, et al., 2015). Transparency of the robotics system further enhance trust (Ososky et al., 2014; Selkowitz, Lakhmani, Chen & Boyce, 2016).

3.2.9 Mindware environment

For the category Mindware Robot, no literature was found describing characteristics of the environment that affects how the human experiences or perceives the interaction with the robot. However, earlier mentioned environmental characteristics such as temperature, lighting and noise (or the weather when outside) could potentially affect the durability of performance over time.

3.3 Mediators

Mediators in the IMOI-model concern conditions or states that emerge from the interaction. These mediators are influenced by the input characteristics and affect the output. As such, they are essential to understand the connection between the input and output characteristics on an interaction.

In our model we currently identify seven mediators in total: two hardware, two software, and three mindware mediators. These mediators were determined organically while processing the literature and identifying the relevant input characteristics. This list is not meant to be exhaustive or definitive. However, they are sufficient for now to explore the horizontal, vertical and diagonal relationships that are in our model. Next, we will briefly describe all seven mediators by giving several examples on how they relate to input and output of our model. Note that not all relations will be described. The first mediator in the hardware domain is physical workload. This mediator tells how hard the human must physically work, based on the inputs from the human, robot and environment. To exemplify the physical workload mediator, consider that the human has a preferred and limited handling speed (physical properties and limitation). The work speed of the robots and time pressure from the environment should match the human capabilities. Better training or more experience of the human could allow for higher work speed with the same workload. Directability of the robot could allow the human to indicate its preferred work speed. In the end a too low or high workload affects stress and satisfaction in job quality or increase complacency. In the end, this can result in loss of control and thus unsafe situation or less efficient production.

The mediator process is about the handling, structure and workflow of the task. The process could include that the human must reach for supportive tools or dress in protective equipment. This increases safety and sustainability. It could also be that, directed by the robot implementation, the human must be flexible to accept a variety of task, which can affect job quality. The robot safety systems could result in a process where the robot stops working when the human is in close proximity. This is safe but could decrease efficiency. Distractors from the environment could interrupt the process, which could decrease situational awareness, and result in unsafe situations.

Situational awareness, a mediator in the software domain, is a model on itself. It explains how environmental elements and events are perceived, comprehended and projected to future states. The awareness will be negatively affected by fatigued or less alert humans. The ergonomics of the robot interface and the monitoring system of the environment will affect how the human can perceive and comprehend the system's status. A cluttered workspace, due to poor housekeeping, will also reduce situational awareness. Being unaware of the system could jeopardize asset integrity as the robot breaks something or itself, or reduce efficiency as, for example, inadequate work or product quality were not noticed in time.

The cognitive workload mediator describes the effort being used in the working memory. This workload is rather subjective and can be perceived differently by people with other demographical characteristics, such as age and education. Further it greatly depends on the cognitive capacity of a human and the complexity of the task. A high cognitive load can have negative effects on task completion and thus efficiency. A too high or low workload will reduce attention for the other parts of the task and environment and could thus reduce situational awareness and safety.

Job quality is a multidimensional mediator in the mindware domain. Physical hazards that pose a risk to health and wellbeing negatively affect job quality. Ergonomics of the environment and robot could affect these physical hazards. Also, the work intensity, like the work speed of the robot or time pressure affect job quality. A key factor to improve this is to allow a self-selected work pace via a directable or adaptive robot. The social environment could improve job quality by the presence of other people in the environment. All in all, job quality relates to the quality of individuals' lives and their well-being, and therefore the suitability of the human-robot team.

Next in the mindware domain is complacency which stands for non-vigilance of the human as of which insufficient attention is paid to output monitoring. This immediately shows a link to the mediator situational awareness: a higher complacency could result in reduced situational awareness. Combined this is a recipe for unsafe, unsustainable and inefficient output. Complacency could not be changed by experience or training. To prevent complacency, the workload should not be too high, which could be achieved by a self-selected work pace, adaptive robots or less time pressure.

Finally, there is perceived workload as mindware output. This is a subjective indicator of how hard the human must work. This includes the human interpretation of the mental and physical workload. Also, time pressure and task complexity affect the perceived workload. Reducing this workload could reduce human error and increase safety, productivity and job quality.

4 Conclusion

Given technological advancements human-robot interactions (HRI) will increase between robots working side-by-side with humans on the work floor on a shared task. This poses challenges concerning task performance, safety of the human and sustainability of the interaction. To solve those challenges, this report is part of a larger research project in which we examine what factors influence HRI and promote a more sustainable outcome. In this report we lay the foundation for this project by providing an overview of relevant characteristics of HRI considering performance, safety and sustainability of the interaction collected from the numerous studies and papers on related topics. Doing so we identified the characteristics which can potentially be used to optimize sustainable human-robot interaction.

In our overview we clustered HRI characteristics with common themes using two main constructs. First of all, we distinguished the found characteristics as relevant input, mediator and output according to IMOI approach. We identified four outcome factors that define a durable interaction. Next, based on a literature exploration, we identified 57 characteristics of humans, robots and the environment that can affect the outcome of the interaction. We also identified seven mediators that emerge from the interaction and which are the potential connectors of the input and output factors. As second construct, we distinguished between hardware, software and mindware characteristics to emphasize the fact that HRI is not only physical, but also affected by cognitive and psychological factors.

The resulting model provides a clear overview of relevant characteristics that affect HRI. Furthermore, its structure facilitates the extraction of potential relationships between the characteristics. As such, this model provides a good starting point for the continuation of our research project. In the next chapter we will briefly address the future directions for our project given the results reported here.

5 Directions for the future

The literature exploration described in this report provides the basis for further analyses of human-robot interactions. The described model should not be considered a completed or final product, but provides a solid starting point to derive hypotheses to be studied in order to gain more insight in the exact elements at play during HRI. The collected data from these studies will help with further amending the model by removing characteristics with negligible effects, or by placing emphasis on characteristics that have a strong impact on safe, sustainable and efficient HRI. In turn, the established relationships could provide a basis for the development of minimal design requirements for robot systems intended for HRI. The ultimate goal being to obtain information and tools that can help organizations optimize their working conditions.

The next step in our research project will be to validate the relationships that can be derived from the IMOI model. To this purpose we intend to obtain data by means of investigating several use cases. Examples of relevant use cases are:

- Agriculture: Large to very large-scale operations on agricultural fields with large robotic vehicles.
- Logistics: AGVs or packing robots in one or more company halls and / or warehouses.
- Assembly: Robots next to the human in a work cell, completing products together.

In preparation of a use case, hypotheses will be formulated and tested concerning specific relationship between characteristics in our model. These hypotheses will be based on previous findings from studies collected in the current literature exploration. Characteristics with proven and large effects on relevant outcomes will be tested in the use cases first. Based on the nature of the use case, we will be able to determine exactly how input, mediator or output characteristics can be measured (for example by means of a questionnaire study, a single question, or measuring skin conduction).

Example
A relationship that can be derived from the model is that a negative attitude of the human could lead to a poorer job quality, negatively affecting the sustainability of the HRI for the human as stress could be considered a related construct to job quality (i.e., lower job quality could lead to stress over time). If, the use case allows for measurements of skin conductance to measure the stress level, the specific hypothesis will then be formulated as: Individuals with a negative attitude to robots will show a higher stress level during the interaction than individuals with a positive attitude towards robots.

The intention is to make snapshots of the human-robot interaction during the use cases. In other words, the interaction and its relevant variables will be measured at certain moments in time, where the interval of those moments depends on the duration of the entire interaction. The output at one moment during the interaction can serve as input for a succeeding moment. This can be scaled from sub-elements of a task, to successive tasks, or contact moments during an autonomous machine operation. On the long term, the data collected from various use cases could result in data profiles concerning specific robot systems. These profiles could facilitate future studies or even applications in practice.
Ultimately, the collected data will help us provide developers and users of human-robot systems with the information and tools necessary to optimally organize the intended system with a view to sustainability, safety and efficiency of the deployment of HRI.

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