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Perception of Safety and Robot Intelligence in Physical Human-Robot Interaction

by

Inara Tusseyeva

Submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Robotics Engineering

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Department of Robotics and Mechatronics
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Declaration

I, Inara Tusseyeva, declare that the research contained in this thesis, unless otherwise formally indicated within the text, is the author's original work. The thesis has not been previously submitted to this or any other university for a degree and does not incorporate any material already submitted for a degree.

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Date:

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Abstract

This thesis focuses on the study of two important aspects of physical human-robot interaction (pHRI): perceived safety – the subjective feeling of safety of a human operator in the physical presence of a robot – and perceived robot intelligence.

The first part of the thesis focuses on reviewing published papers with the goal of understanding what factors influence these two aspects. It was found that, in general, factors influencing the perception of safety are human-robot distance, robot speed, direction of approach, robot size and appearance, motion fluency and predictability, communication and smooth contacts. On the other hand, factors influencing the perceived intelligence of a robot are transparency, animacy, trust, human-like appearance and gestures; other aspects such as adaptability are also influencing perceived intelligence not only for robots, but for intelligent agents in general. Habituation also seems to influence perceived intelligence in some cases, causing it to increase.

The second part of the thesis is related to experiments to study the influence of the above-mentioned factors. Experiments were run in which a human subject shared the workspace with a collaborative manipulator while carrying out independent tasks. Different algorithms were used to plan the motion of the robot, all of which applied the safety standard known as *speed and separation monitoring* (SSM), i.e., the robot speed was decreased proportionally to the distance with the human to guarantee that the robot could stop before a collision occurred. One algorithm generated a fixed path (FP) of the robot with SSM-based modulated speed. A second algorithm (based on *model predictive control*, or MPC in short), kept updating the robot motion based on the current human location, aimed at increasing productivity compared to the FP case. Two variants of these algorithms (namely, FP-HR and MPC-HR) were specifically developed in this thesis, to further decrease the robot speed based on heart rate measurements.

The analysis of the experimental results obtained for 48 subjects showed that MPC was perceived as less safe than FP, which in turn was perceived as safer than FP-HR. The first result was expected, as the MPC-generated motion is in general less predictable, while the second was unexpected, and probably due to frequent pauses of the robot in the FP-HR case. In general, it was observed that further reducing robot speed based on heart-rate measurements did not improve perceived safety; this can be explained by the presence of a lightweight collaborative robot and by the application of SSM, factors that made the non-HR variants of the algorithms already perceived as sufficiently safe, so that no improvement was noticed when introducing the HR-based variants of the same algorithms. Also, participants did not find the robot more intelligent when its motion was governed by more complex algorithms; this can be explained by a relative lack of transparency. In other words, participants had no actual insight in the motion planning algorithms, and did not manage to fully understand their differences during experiments; this caused all algorithms to be perceived as equally intelligent.

Apart from differences between single algorithms, it was found that habituation improved both perceived safety and perceived intelligence – indeed, each participant interacted with the robot in four subsequent sub-sessions – and that the previous experience of the participants in interacting with robots played no role in their perception of safety and robot intelligence.

Acknowledgments

I would like to express my deepest appreciation to my lead supervisor Prof. Matteo Rubagotti, whose guidance and encouragement have been invaluable at every stage of the research process, from the initial concept to the final manuscript. This thesis has been finished by the tremendous instructions, knowledge, and support of Prof. Matteo Rubagotti. The effectiveness of this work was greatly influenced by the supervisor's capacity for identifying research gaps, sharing novel concepts, and providing valuable feedback. His mentorship was characterized by dedication, patience, and an unwavering pursuit of excellence. I'm feeling honored that I've had the opportunity to work under his supervision.

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Chapter 1

Introduction

1.1 Background

1.1.1 Physical human-robot interaction

Physical Human-Robot Interaction (pHRI) has become an increasingly important area in robotics research. It consists of scenarios in which a human shares his or her physical space with a robot. pHRI can take many forms, ranging from workspace sharing while carrying out separate tasks, to collaborative tasks where humans and robots work together to accomplish a shared goal. pHRI often involves the use of sensors, actuators, and control algorithms to ensure safe and effective interaction between humans and robots. The goal of pHRI is to create a seamless interaction between the human and the robot, where the robot can understand and respond to the human's intentions and physical movements, and the human can feel safe and confident in the presence of the robot. A desirable characteristic of pHRI is the human-centered design of robot control and mechanics to enable the implementation of human-friendly behavior and actions [4]. This type of interaction is different from cognitive human-robot interaction, as pHRI is based on how a user can interact physically with a robotic device, whereas cognitive human-robot interaction refers to perception, awareness, and mental conditions [5].

Examples of pHRI scenarios include industrial robotics with robots working in collaboration with human operators in factories [6,7], performing tasks such as assembly and material handling [8–10]; medical robotics in which robots are performing surgeries, rehabilitation exercises, or assisting with physical therapy [11, 12]; service robotics where robots are performing tasks such as cleaning, security, or customer service in public spaces [13]; domestic robotics, i.e., robots performing tasks such as cleaning, cooking [14, 15], or assisting with elderly care in homes [16].

1.1.2 Safety in pHRI

When physically interacting with humans, robotic systems must meet certain constraints. In particular, collisions between humans and robots at relatively high speeds can cause severe human harm [17]. One of the most important criteria is to ensure safety for both human operator and robot while they collaborate in the same space and interact physically [5, 18].

Safety in pHRI was widely studied and observed in a number of survey papers, such as [4, 5, 19–22]. Safety in pHRI is defined as the ability of the robot to avoid any collision that can cause serious injuries to humans [4]. It involves the design of robots and their behavior to minimize the possibility of physical injury, as well as ensuring that the robots operate within their intended limitations. Additionally, safety protocols such as emergency stop buttons or safety zones can be implemented for quick and effective intervention in case of an unexpected interaction.

A number of standards were created in order to guarantee safety in pHRI and ensure that any injuries suffered by human operators would be minor in the worst-case situations [4]. ISO 10218 [23] and ISO/TS 15066 [24] are international standards for safety in collaborative human-robot interaction. ISO 10218 specifies the requirements for the design, integration, and use of industrial robots, with a focus on the safety of human operators and other people in the vicinity of the robot. It covers topics such as mechanical, electrical, and software safety, as well as safety-related control systems. ISO/TS 15066 provides guidelines for the design and integration of collaborative robots (cobots), which are designed to work alongside humans. These robots are typically built using lightweight materials, do not present any sharp edges, have built-in limitations of speed and force and/or sensor-based safety systems, for example to stop the robot as quickly as possible after a contact is detected. ISO/TS 15066 covers the safety requirements for cobots in terms of safety functions, performance, and risk assessment. It also provides recommendations for the design of user interfaces, including tactile and visual feedback. It takes into account cooperative operating methods and specifications, including safety-rated monitored stops, speed and separation monitoring, and power and force limiting [4]. In particular, speed and separation monitoring (SSM) requires that the maximum allowed robot speed be proportional to the measured distance with the human, so that the robot can come to a controlled stop before a collision occurs.

1.1.3 Perceived safety in pHRI

The ability of robots to guarantee the physical safety of users is not sufficient to make the interaction stress-free and comfortable for humans [25], unless the robot is also perceived as safe. From a psychological perspective, the theory of perceived safety may be applied to a wide range of aspects of human life, including the present state of health, background exposure to crime, financial circumstances, and socialization [26]. Perceived safety in pHRI is an important aspect to consider when developing robots intended to interact closely with humans, such as in healthcare, industrial, or domestic settings.

Factors that affect perceived safety include the robot's physical design, its behavior, and the level of transparency and control that the user has over its actions. The aim is to design and deploy robots that are not only safe from a technical standpoint but also feel safe for the people interacting with them.

The perceived safety of a robot in pHRI is assessed through various methods, including user surveys, behavioral observations, physiological measurements, and other methods of measuring attitudes and behaviors. These methods allow researchers to gather data on how users perceive the robot behavior and movements and determine whether they feel safe and comfortable in its presence. The results of these studies can be used to inform the design of robots and their interactions with humans, ensuring that they are perceived as safe and trustworthy. Both physical and perceived safety are essential for creating the best possible engagement in a pHRI scenario [21].

1.1.4 Perceived intelligence in pHRI

In addition to perceived safety, perceived intelligence is important to guarantee a seamless interaction between humans and robots during physical interaction. A robot that is perceived as more intelligent is also trusted more, and this fact also contributes to reducing stress [27]. The perceived intelligence of a robot in pHRI depends on various factors, such as the robot design, behavior, and task in progress. In general, robots that are able to perform complex tasks in an intuitive and human-like manner tend to be perceived as more intelligent by humans. However, cultural and individual biases and expectations also affect the perception of intelligence.

Perceived intelligence is typically assessed through various methods, such as subjective ratings, behavioral observation, physiological measures, and surveys. The employed methods depend on research questions and goals, but all of them aim to gauge the human's perception of the robot's intelligence and abilities. Some common metrics used to measure perceived intelligence include task performance, social skills, and human-like qualities such as natural language processing, emotions, and empathy. Ultimately, the assessment of perceived intelligence in human-robot interaction aims to understand how humans perceive and interact with robots and to suggest the design of more effective and socially acceptable robots.

1.2 Motivation and research questions

Based on the above-mentioned background concepts, perceived safety and perceived intelligence are key metrics in pHRI because they determine how people might interact with robots and perceive them. Humans will be more likely to approach robots and interact with them if they are perceived as safe. If a robot is perceived as intelligent, people will be more likely to believe that it can execute tasks effectively and will trust it during interactions. By evaluating and optimizing these metrics, researchers can create robots that are more useful to humans.

As collaborative robots are being increasingly used in today's industrial practice, this thesis focuses on their use under the ISO/TS 15066 standard, specifically via SSM. The following research questions are considered:

Q1. How do perceived safety and perceived intelligence change if the robot path is either fixed or modified in real time based on the current human position?

Q2. How do perceived safety and perceived intelligence change if the robot speed is decreased in real time when the human operator feels unsafe?

Q3. How do perceived safety and perceived intelligence change due to habituation?

Q4. How do perceived safety and perceived intelligence change based on the participants' previous experience with the robot?

1.3 Thesis outline

Chapters 2 and 3 of the thesis provide a comprehensive survey of perceived safety and perceived intelligence in pHRI. Chapters 4-6 focus on the experimental investigation of the research questions. More precisely, we ran different motion planning algorithms for determining the trajectory of a collaborative robot sharing its workspace with a human operator. All these algorithms guaranteed safety via SSM. Either a fixed robot path or a variable path determined online via optimal control (specifically, model predictive control, or MPC in short), was used. For each of these two cases, a further speed reduction of the robot could be imposed based on the measurement of the heart rate of the participants, as a higher heart rate is typically associated to lower perceived safety. This resulted in four algorithms: fixed-path (FP), fixed-path with HR-based speed modulation (FP-HR), MPC, and MPC with HR-based speed modulation (MPC-HR). A total of 48 subjects took part in the trials reported in this research, in which an Optitrack optical motion capture system was used to detect the positions of different parts of the participants' bodies and deliver them in real time to the cobot control algorithm. Similarly to Pollak et al.'s study [28] on physiological stress, in the experimental work of this thesis perceived safety was assessed by questionnaires and by physiological stress appraisal via HR detected by an Empatica E4 wristband.

The remainder of this thesis is structured as follows:

- In Chapter 2, an overview of the state-of-the-art research on perceived safety in pHRI is provided, starting from the psychological framework of the terms and concepts related to perceived safety. The reviewed articles are categorised by the robot type used in the experiments into industrial manipulators, indoor mobile robots, mobile manipulators, and humanoid robots, highlighting the main research themes of each category. The assessment methods that were applied to measure the level of perceived safety are also considered; specifically, they consist of physiological signals (such as heart rate, Galvanic skin response, and eye gaze), different types of questionnaires, direct input devices, and behavioral assessment (through video, photo, or audio recordings). Finally, the main factors influencing perceived safety are identified.

- Chapter 3 presents a survey on perceived intelligence in human-robot interaction. Similarly to the perceived safety overview, the assessment methods and robot types used in experiments are introduced. After listing the main factors that influence perceived intelligence, the focus is mainly on how the perception of robot intelligence can change as participants gather more experience interacting with the robot during the experiments (habituation).
- Chapter 4 shifts the focus to the experimental research conducted in our laboratory. The four above-mentioned motion planning algorithms are described. The differences between the FP and MPC algorithms, how the boundaries on the cobot speed are established using SSM, and how the cobot velocity is adjusted for the FP-HR and MPC-HR algorithms are all covered in detail.
- Chapter 5 describes research hypotheses, experimental design, experimental procedure, participants, methods and measures used to test the hypotheses.
- Chapter 6 presents and discusses the results of the statistical analysis performed on the collected data, including evaluations of robot productivity, perception of robot safety and intelligence, habituation effects, and the influence of subjects' prior experience with robots.
- Finally, Chapter 7 draws conclusions by discussing the main results of the described research, summarizing the answers to the given research questions, and making suggestions for further research and experiments.

1.4 Contributions

The main contributions of this thesis are the following:

C1. From the point of view of the motion planning algorithms, FP-HR and MPC-HR were defined and implemented for the first time, building on the already existing FP and MPC algorithms.

C2. The variation of perceived safety and intelligence of a manipulator was never studied before in the following cases: (a) if the robot path is either fixed or modified in real time based on the current human position, and (b) if the robot speed is decreased in real time when the human operator feels unsafe. This is true not only for cobots, but for robot manipulators in general.

C3. The variation of perceived safety and intelligence of a manipulator depending on habituation or on previous experience were already studied in several contexts, and this thesis provides further results, specifically for cobots and SSM-based motion planning.

1.5 Related publications

Three publications are related to this thesis:

[1] M. Rubagotti, I. Tusseyeva, S. Baltabayeva, D. Summers, and A. Sandygulova, "Perceived safety in physical human–robot interaction—A survey," Robotics and Autonomous Systems, vol. 151, pp. 1–22, 2022.

[2] I. Tusseyeva, A. Oleinikov, A. Sandygulova, and M. Rubagotti, "Perceived safety in human–cobot interaction for fixed-path and real-time motion planning algorithms," Scientific Reports, vol. 12, no. 1, article no. 20438, 2022.

[3] I. Tusseyeva, A. Oleinikov, A. Sandygulova, and M. Rubagotti, "Evaluation of perceived intelligence for a collaborative manipulator sharing its workspace with a human operator," in Proc. IEEE International Conference on Robot and Human Interactive Communication, pp. 1–6, 2023

The survey paper [1] provides the background material for Chapter 2, while the research papers [2, 3] contribute most of the results related to productivity, perceived safety [2] and perceived intelligence [3] as explained in Chapters 4 to 7.

Chapter 2

Perceived safety: literature review

This chapter provides an overview on perceived safety in pHRI. We will start with Sections 2.1 and 2.2, which will provide, respectively, a comparison of the content of this chapter with previously published surveys covering perceived safety in pHRI, and a summary of the contribution of this chapter. Then, in order to introduce the terminology for understanding perceived safety, Section 2.3 will provide an explanation of terms such as psychological/mental/subjective safety, stress, trust, fear, comfort, anxiety, and surprise. In Section 2.4, we will review the evaluation tools used to measure people's reactions, attitudes, and feelings towards physical interaction with a robot. These methods are based on the guidelines in [29, 30], but also include further considerations. Sections 2.5-2.8 will analyze articles regarding the type of robot used in experiments and precisely industrial manipulators [7, 28, 31–61], indoor mobile robots [62–74], mobile manipulators [75–81], and humanoid robots [82–115]. As seen in Fig. 2.1, we can observe the development of research over time on different types of robots. Robot manipulators were the first to be researched, followed by humanoids. There seems to have been a peak of interest in indoor mobile robots between 2005-2008, while the number of papers on industrial manipulators and humanoid robots has drastically risen in recent years.

2.1 Related survey papers

Perceived safety in pHRI was explored by researchers in various papers. Among them is the paper by Bethel et al. [29] in which the authors describe how to measure different psycho-physiological variables in pHRI. This type of assessment can be applied to perceived safety appraisals. Task performance, behavioral, and self-report measures were also described in combination with psycho-physiological measures. It was concluded that, in order to gain a well-grounded estimate of the interaction between robot and human, it would be more effective to use more than one of these evaluation criteria.

The authors [30] analyzed the aspects of human perception of the robot in pHRI. They formulated a standardized assessment method that contained the perceived safety evaluation through questionnaire items. The whole questionnaire was named *Godspeed questionnaire* and, besides the safety perception, included anthropomorphism, animacy, likeability, and perceived intelligence rates.

The focus of the survey [21] (specifically, of one of its chapters) was on safety methods in pHRI. The authors stated that the assessment of perceived safety during pHRI depended on robot characteristics such as robot appearance, distance to the human, velocity, and acceleration. The second factor that affected the perceived safety rating was the social considerations obtained from the observation of the communication of humans and the social rules that were followed.

The main topic covered in the survey [116] was pHRI in industry, together with its physical and psychological aspects. Collaborative robots, or cobots, should have the capacity to move automatically using a combination of algorithms while at the same time being able to react flexibly using cognitive capabilities (similarly to human workers). The authors stated that these two factors would decrease the human cognitive load by adjusting robot behavior during interaction.

The review paper [117] provided a comprehensive review of safety in pHRI, including perceived safety. The authors focused on the basic robot functions, such as perception, cognition, and action. The following safety measures used in pHRI systems were described: physical, behavioral, and cognitive. In the section on psychological and social factors, the authors referred to the categorization criteria described in [21].

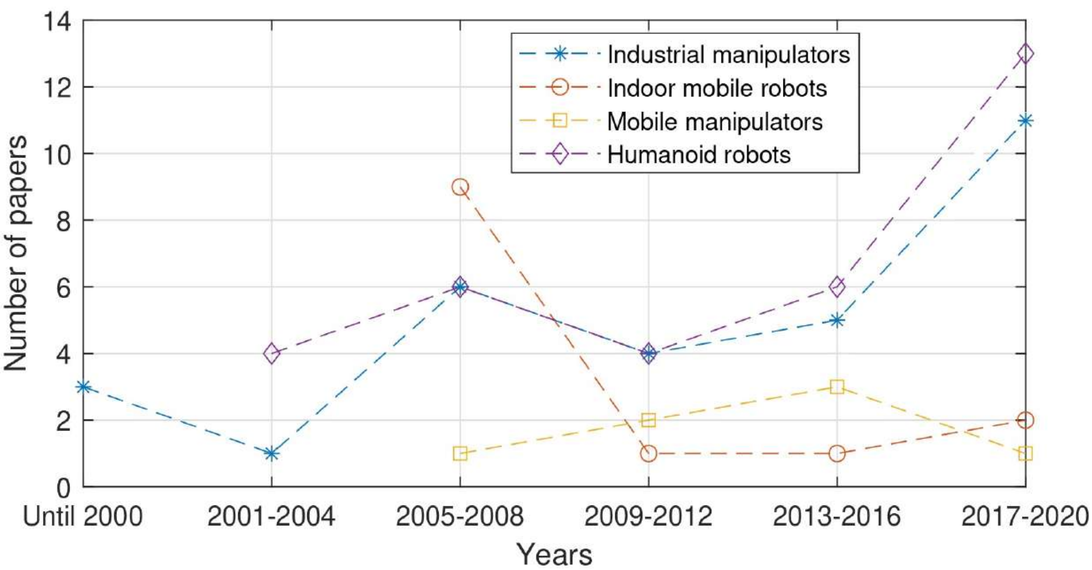

Figure 2.1: Time evolution of the quantity of published articles for each robot type (adapted from [1]).

2.2 Contribution of the present review

We examined journal articles, conference proceedings, and book chapters published in English in international venues up until the year 2020 to obtain the list of works to be reviewed. These works all shared the following characteristics:

1. The paper describes real-world experiments where a moving robot and one or more human participants share a workspace with the possibility of physical contact (either using a real robot or a virtual reality setup);

2. The robot's movement is either autonomously determined by a motion planning algorithm or controlled via the Wizard-of-Oz method [118];

3. Either the measurement of physiological variables, questionnaires, direct input devices, or observation of participant behavior are used to determine perceived safety;

4. Considerations are made regarding the relationship between participant perception of safety and robot behavior.

The review provided in this chapter presents a new overview of the topic as compared to the above-mentioned survey papers. In particular, it reviews more than 80 papers, whereas the previous surveys only focused on specific aspects (for example, [29, 30] only analyzed assessment methods, and [21, 116, 117] focused on safety in pHRI in general) and never analyzed the terminology related to perceived safety in pHRI.

2.3 Defining perceived safety

Different works describe the concept of perceived safety using various terms, which can be synonyms, represent the same concept from different perspectives, or relate to a lack of safety from various points of view. In this section, we provide definitions for these terms from a broad psychological viewpoint and then narrow them down further in the context of pHRI.

The terms listed in Section 2.3.1 express very similar ideas. The terms from Sections 2.3.2 and 2.3.3, however, refer to distinct aspects of perceived safety. For that reason, Table 2.1 presents which of these terms are used in studies relating to each robot type. In particular, in each row, the table lists the considered focus of the paper, which can be trust, comfort, stress, fear, anxiety, and/or surprise. In each column, a different robot type is considered. Almost all terms appear frequently for each kind of robot, with "comfort" being the most popular one.

	Industrial manipulators	Indoor mobile robots	Mobile manipulators	Humanoid robots
Trust	[48] [49] [50] [52] [53] [54] [56] [57] [59] [61]	-	[79] [81]	[102] [103] [106] [108] [111] [112] [113] [114]
Comfort	[41] [43] [44] [45] [46] [47] [48] [49] [53] [54] [55] [56] [57] [59] [61]	[62] [63] [66] [67] [68] [69] [70] [71] [72] [74]	[75] [76] [77] [78] [79] [80]	[82] [84] [87] [88] [89] [92] [93] [94] [97] [99] [102] [103] [104] [107] [108] [110] [111] [112] [113] [114] [115]
Stress	[33] [43] [46] [48] [58] [28]	[67]	[76]	[86] [100] [106] [115]
Fear	[32] [37] [43] [54] [56]	[69] [70] [71]	[77] [81]	[84] [85] [95] [100] [105] [104] [111] [112] [114]
Anxiety	[34] [35] [37] [51] [59] [60]	[71]	[75]	[84] [85] [86]
Surprise	[35] [43]	[74]	[75] [77] [79]	[84] [100] [104]

Table 2.1: Focus on different aspects of perceived safety by robot type (adapted from [1]).

2.3.1 Synonyms of perceived safety

The terms that have the same meaning as "perceived safety" are listed and described below.

Psychological safety. In general, psychological safety was described by Edmondson et al. as “people’s perceptions of the consequences of taking interpersonal risks in a particular context, such as a workplace” [119]. Specifically, when interacting with robots, Lasota et al. stated that “maintaining psychological safety involves ensuring that the human perceives interaction with the robot as safe and that interaction does not lead to any psychological discomfort or stress as a result of the robot’s motion, appearance, embodiment, gaze, speech, posture, social conduct, or any other attribute” [21].

Mental safety. In psychology, psychological safety is typically used as a synonym for mental safety. Villani et al. viewed this concept from the perspective of mental stress and anxiety caused by close cooperation with robots [116]. Alternatively, Sakata et al. defined mental safety as the feeling of not being afraid or surprised when interacting with robots [84].

Subjective safety. From a psychological perspective, Patwardhan et al. [120] suggested that this term reflects someone's feeling of safety in a certain place. However, there is no exact definition of it in pHRI papers. Sorensen and Mosslemi [121] defined it as "the feeling or perception of safety". In pHRI research, this term should not be mistaken with the feature of personalized safety systems that modify their actions based on human characteristics – such as those proposed by Traver et al [122], which are sometimes called "subjective safety".

2.3.2 Concepts related to perceived safety

There are two terms that are associated with perceived safety and may be used in a broader context.

Trust. Trust in a social context is a psychological element that reduces complexity and fosters confidence in a system's safety, according to Mukherjee and Nath [123]. Ferrin et al. further suggest that trust as an attitude helps people rely on each other when faced with social dilemmas [124]. There is no unique specification of the term "trust" in pHRI; however, Kok and Soh [125] defined trust as the multidimensional influence of past events on the decisions one makes in an uncertain environment. In this thesis, we look at papers that address how much humans trust the fact that robots will not harm them. This is connected to the idea of safety, although it is not exactly synonymous. Someone might trust, for example, that a robot will be successful in completing the given task.

Comfort. Pineau [126] stated that comfort is everything that supports the prosperity and convenience of life in the context of perceived safety. Specifically for pHRI, comfort was defined by Koay et al. as the fact that a robot can "perform and provide assistance for certain useful tasks in a socially acceptable manner" [62]. Similar to trust, the concept of comfort is linked to perceived safety, where 'socially acceptable manner' implies that the robot's motion does not appear potentially dangerous for the operator. For instance, Norouzzadeh et al. claimed that "colliding with a robot would definitely imply the risk of injury, which is depicted in the high discomfort rating (negative comfort)" [127].

2.3.3 Expressing lack of perceived safety

The absence of perceived safety is often expressed by terms such as stress, fear, anxiety, and surprise. In our study, we will focus on these emotions as they relate to a lack of perceived safety in a pHRI scenario.

Stress (or strain). According to Folkman and Lazarus [128], stress is a specific relationship between a person and their environment that the individual perceives as challenging or exceeding their capabilities, thus endangering their well-being. In the context of pHRI, stress can be induced by factors such as the robot's proximity to the human operator, its movements, or the potential loss of control resulting from the automation of robotic agents. Pollak et al. [28] have specifically defined these factors in their research.

Fear. Fear is an emotional response that can prompt changes in one's attitude or intentions, as is a part of the evolutionary mechanism aimed at survival of individuals, as noted in Perkins et al.'s work [129]. In the context of pHRI, we did not find a readily available, specific definition of fear, as it is commonly used without explicit elaboration. For instance, Yamada et al. [32] emphasized that detecting fear was crucial in ensuring the emotional security of humans along with their physical safety.

Anxiety. In psychology, anxiety has three main meanings: anxiety as a state, anxiety as a personality trait, and anxiety as an adaptive emotion or dysfunction. Anxiety is an emotional condition that arises in anticipation of an event. According to Spielberger [130], it involves sensations of nervousness, apprehension, tension, and worry that are accompanied by physiological arousal. In other words, anxiety is a reaction that helps people prepare to confront environmental changes or potential threats [131]. When interacting with robots, Nomura and Kanda [132] defined the term "robot anxiety" as the feelings of fear or anxiety that impede people from interacting with robots that possess communication capabilities, particularly those designed for dyadic communication.

Surprise. Surprise can be described as the astonishment and wonder that a person feels towards the unexpected. Celle et al. [133] defined "surprise" in psychology as an emotion that arises when there is a disparity between what one expects and reality. Although not directly specified, in the context of pHRI, the term is closely associated with the perception of a lack of security. For example, Arai et al. [43] observed that a robot's sizable and bulky appearance, combined with its rapid and unpredictable movements capable of causing collisions, can evoke feelings of fear and surprise. Similarly, Norouzzadeh et al. [127] stated that being caught off guard by the reactions of a robot could contribute to a lower perceived sense of safety.

2.3.4 The concepts of valence and arousal

To move beyond the use of distinct emotions like happiness, fear, and anxiety, researchers in emotion detection often rely on a two-dimensional representation that measures valence and arousal. Kulic and Croft [35] explain that valence indicates whether an emotion is positive or negative, while arousal measures the intensity of the emotion. While the valence/arousal approach provides less detailed information than discrete emotion categories, it appears sufficient for robotic control and can be easily converted into a measure of user approval.

2.4 Assessment methods

To determine the level of perceived safety in pHRI experiments, various methods have been employed in different categories, as indicated in the taxonomy of Fig. 2.2. These methods can be broadly classified into four categories: questionnaires, physiological measurements, behavioral assessment, and direct input devices. Table 2.2 shows how these methods have been used with different robot types. In each row, the table lists the type of assessment, namely questionnaires (Q), physiological assessment (PA), behavioral assessment (BA), direct input devices (D), and their combinations. In each column, a different robot type is considered, and precisely industrial manipulators, indoor mobile robots, mobile manipulators, and humanoid robots. Although a combination of different assessment methods is recommended for a reliable assessment in [29], some studies have solely relied on questionnaires due to their low cost compared to physiological measurements. Questionnaires were also commonly used in conjunction with behavioral assessments. Physiological measurements were always used in conjunction with questionnaires, probably due to the low cost of questionnaires. The use of direct input devices was less common and only found in a few papers.

Physiological assessment is not commonly used in experiments involving indoor mobile robots. The reason might be that this type of measurement is hard to use outdoors or when humans are not stationary. The other point is that physiological feedback is widely used when interacting with industrial manipulators. This may be because many of the experiments involving industrial manipulators were conducted with human subjects in a sitting position, which makes it easier to obtain and reliably measure physiological data. Another probable reason is that industrial manipulators usually perform tasks at a very close distance from humans compared to other robot types.

2.4.1 Questionnaires

In the field of pHRI, the use of questionnaires or surveys is widespread. These research tools rely on self-reported data to gather information from human participants about various aspects of their interaction with robots. In the field of psychology, questionnaires are described as a mean of gathering information from or about individuals in order to describe, compare, or explain their experience, attitudes, and actions [134].

In a typical pHRI experiment, researchers often administer pre-interaction questionnaires to participants. These questionnaires typically include demographic questions such as age, gender, and height, as well as questions related to participants' previous experience with robots, personality assessments (e.g., the Big Five Domain Personality Traits Scale [135] used in previous studies [67, 87, 100, 105]), and any necessary

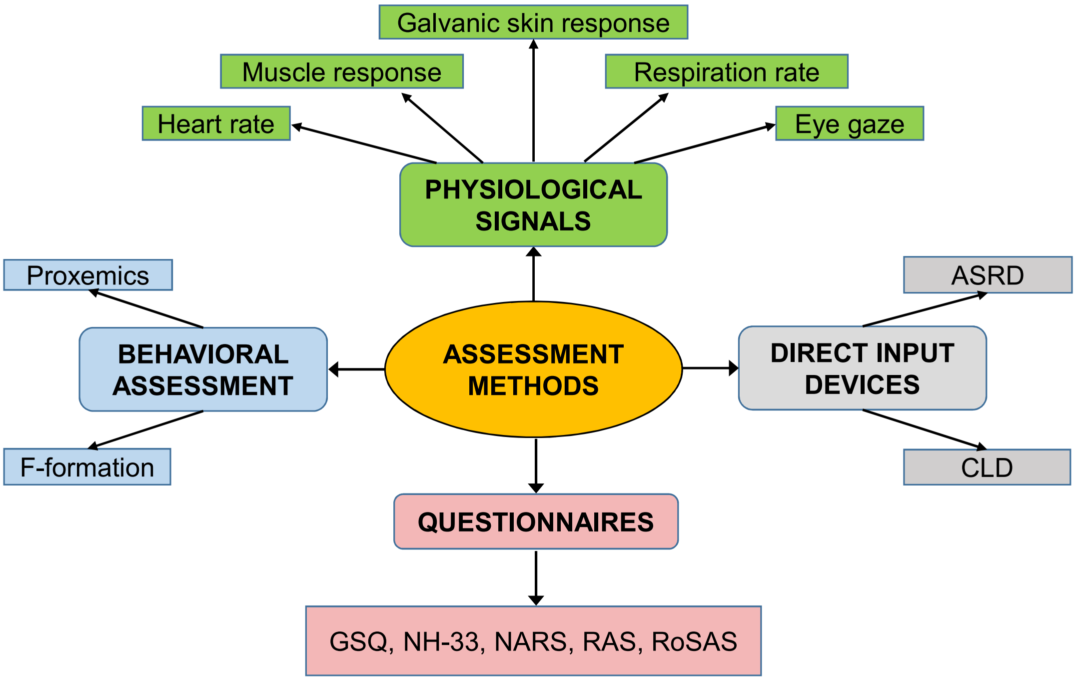

Figure 2.2: Taxonomy of assessment methods for perceived safety in pHRI (from [1]).

	Industrial manipulators	Indoor mobile robots	Mobile manipulators	Humanoid robots
Q	[44] [45] [48] [49] [50] [53] [54] [55] [56] [57]	[67] [70] [71] [72]	[75] [78] [79] [81]	[83] [84] [85] [87] [92] [93] [95] [96] [97] [98] [100] [102] [104] [105] [107] [108] [112] [114] [115]
PA	-	-	-	[86] [106]
BA	[31] [7]	-	-	[88] [99]
Q+PA	[32] [33] [34] [35] [36] [37] [39] [40] [43] [51] [59] [28] [60]	-	[76]	[106]
Q+BA	[52]	[64] [66] [69] [74]	[80]	[82] [91] [94] [101] [103] [111] [110]
Q+PA+BA	[47] [61]	-	[77]	[109] [113]
Q+PA+D	[41]	-	-	-
Q+BA+D	-	[62] [63] [65]	-	-

Table 2.2: Assessment methods by robot type (adapted from [1]).

pre-tests (e.g., typing speed or gaming experience). These questions help researchers analyze the relationship between independent variables (such as age and gender) and dependent variables (such as distance from the robot). After the interaction, participants fill out a post-trial questionnaire to capture their reflections on the pHRI experience and their perception of the robot, and/or a post-test to assess any learning gains or changes in perception [136].

Questionnaires can take different forms, including those with closed questions using scaling methods (such as Semantic Differential (SD) [137] and Likert scale [30]), or those with open questions [137]). Scaling was defined by Taherdoost [137] as “the process of generating the continuum, a continuous sequence of values, upon which the measured objects are placed”. One type of scaling is the SD scale, where “the respondent is asked to indicate his or her position on a scale between two bipolar words, the anchors" [30]. It was invented by Osgood, Suci, and Tannenbaum [138]. In pHRI, it typically includes the phrase: “Please rate your impression of the robot”. Another questionnaire type is the Likert scale, where “subjects are asked to respond to a stem, often in the form of a statement, such as “I like ice cream”. The scale is frequently anchored with choices of “agree”– “disagree” or “like”–“dislike” [30].

An open question is defined by Taherdoost [137] as a question “in which the respondent does not have to indicate a specific response”. This question usually requests a long, detailed answer. On the other hand, a closed question is one “in which a respondent has to choose from a limited number of potential answers” [139]. Closed questions include Yes/No options, multiple choices, Likert, and SD scales.

While analyzing the papers, the following questionnaires were usually found:

- *Godspeed Series Questionnaire (GSQ)*. Bartneck et al. [30] proposed GSQ to evaluate the human perception of robotic setups [140]. The questionnaire comprises five SD [137] scales that measure anthropomorphism, perceived intelligence, likeability, animacy, and perceived safety. The perceived safety scale consists of 5-point SD items such as anxious-relaxed, calm-agitated, and quiescent-surprised. The following works used the GSQ in their experiments: [73, 74, 103].

- *NH-33*. The NH-33 was introduced for the first time in [141] with a focus on the psychological safety of humans by assessing the level of security of specific humanoids. The questionnaire has 33 7-point Likert scale items covering performance, acceptance, harmlessness, humanness, toughness, and agency. This type of questionnaire was used in the work [61].

- *Negative Attitude towards Robots Scale (NARS)*. The Negative Attitude towards Robots Scale (NARS) was developed by Nomura et al. [142]. It assesses the negative attitude of humans, with 14 5-point Likert scale items classified into negative attitudes toward: a) situations and interactions with robots (6 items), b) social influence of robots (5 items), and c) emotions in interaction with robots (3 items). NARS was used in multiple studies [71, 85, 94, 96, 105, 106, 110].

- *Robot Anxiety Scale (RAS)*. RAS was designed by Nomura et al. [85]. It assesses anxiety toward robots. There was a pilot study in which the participants wrote open answers about their anxious feelings when communicating with the robot. Commonly used phrases were detected, such as “anxiety toward motions or approaches of robots", “anxiety toward the unpredictability of robots’ actions”, and “anxiety toward interaction with robots”, and were then included in the questionnaire. RAS was used in different studies, and precisely [96, 105, 106, 110].

- *Robotic Social Attribute Scale (RoSAS)*. RoSAS assesses the perceived social characteristics of robots and how they influence the quality of cooperation with people. This 18-item scale was developed by Carpinella et al. [143]. The scale has three main factors: warmth, competence, and discomfort. Specifically, the “discomfort” factor, which is of interest for perceived safety, contains the following terms: aggressive, dangerous, awful, awkward, scary, and strange. RoSAS was used in [55, 74, 109].

2.4.2 Physiological signals

The second category of methods involves physiological signal measurement, which is a part of the research field known as *psychophysiology*, described in detail in [29]. According to Stern [144], psychophysiology refers to any research in which a physiological measure is the dependent variable in the form of the subject’s reaction, and the experimenter manipulates a behavioral independent variable. Physiological signals are crucial as they provide insight into subconscious and psycho-biological phenomena that subjective measures like questionnaires cannot capture. Also, participants cannot consciously control their autonomic nervous system activities [29], which are related to physiological signals. The dependent variables in the analyzed papers included heart rate, galvanic skin response, eye gaze, muscle response, and respiration rate.

Heart rate measures the cardiac response and serves as a significant biomarker connected to the activation of the autonomic nervous system. Variations in heart rate measurement are typically related to variations in stress and fear (see, e.g., [28, 60]).

Galvanic skin response (sometimes called “electrodermal activity”) provides information on sweat gland production levels related to skin activity and is directly associated with the state of stimulation of the sympathetic nerve. Increased levels of galvanic skin response are related to the subject’s arousal. This emotional state can arise from stress, fear, anxiety, or surprise. Galvanic skin response is composed of two elements: “tonic skin conductance, the baseline value recorded when no emotional stimulus is applied, and phasic skin conductance, the response acquired when environmental and behavioral changes occur” [145]. Galvanic skin response is quicker than heart rate but is affected by muscle contraction, making it difficult to use when performing collaborative tasks [32].

Eye gaze is “an indicator of situation awareness” [146]. In pHRI, the source of danger might be the robot; if people feel secure near the robot, then they may not look at it very often because they do not perceive it as harmful. In some works, such as that of Yamada and Umetani [32], humans’ eye gaze was used in conjunction with pupillary dilation. The latent time from the point when the participants started visually accepting the change in the motion of the robot (i.e., the moment when the robot motion was reason of a sudden acceleration) until the period when their pupils dilated was measured: this time strongly depended on whether the subject predicted the abrupt change in the robot motion.

Muscle response, particularly the corrugator muscle, is associated with negative emotions such as fear and anxiety [40]. This muscle is placed above each eyebrow, near the nose bridge, and makes the brows lower and contract. Other muscles were also considered in some cases. The biceps’ activity was used to monitor physiological arousal in [59]. As an alternative, the researchers in [76] gave a handover task for the subjects and the robot and measured the activity of the deltoid muscle. In all the mentioned papers, muscle activity was detected using electromyography (EMG).

The respiration rate increases with arousal, prepares the body for a fight-or-flight scenario, and decreases when humans feel relaxed [144]. The same hormones that cause an increase in heart rate when a human subject feels stressed are responsible for faster respiration.

Table 2.3 lists all the analyzed papers in which physiological signals were used. In each row, the table lists the evaluated variables, such as heart rate (HR), galvanic skin response (GSR), eye gaze (EG), muscle response (MR), respiration rate (RR), and their combinations. In each column, a different robot type is considered: industrial manipulators (IM), mobile manipulators (MM), and humanoid robots (HR). No physiological assessment was conducted for indoor mobile robots.

2.4.3 Behavioral assessment

The behavioral assessment approach is based on photo and video recordings of the experiments and was applied in [7, 31, 52, 61–66, 68, 69, 74, 80, 88, 91, 99, 101, 103, 110, 111, 113]

Behavioral assessment often involves analyzing how far or how close human participants perform their tasks relative to the robot. This measure is usually inversely

	IM	MM	HR
HR	[51] [28] [60]	-	[109]
GSR	[33] [34] [37] [43]	[77]	-
EG	-	-	[113]
MR	[59]	-	-
GSR+EG	[32]	-	-
HR+RR	-	-	[86]
HR+GSR	[47]	-	-
HR+GSR+EG	[61]	-	-
HR+GSR+MR	[35] [36] [39] [40] [41]	-	-
HR+GSR+RR	-	-	[106]
GSR+EG+MR	-	[76]	-

Table 2.3: Physiological assessment by robot type (adapted from [1]).

related to the perceived level of safety and is based on the concept of proxemics, introduced by Hall [147] to describe how humans use space in cultural contexts during human-to-human interaction. Hall identified four zones applied in interpersonal relations that range from intimate to public in order of closeness: intimate, personal, social, and public. Proxemics in pHRI examines human attitudes and emotions as robots enter any of these zones, with the resulting distance that humans maintain from robots serving as an indicator of their perceived safety. This approach was utilized in several studies, specifically [62–64, 70, 91, 93, 99, 100, 110].

Proxemics in pHRI is also concerned with human-robot spatial arrangements. One relevant concept from psychology is the *F-formation*, which refers to the way people position themselves in a circle during conversations and maintain this arrangement as others join the group by adjusting their spatial orientation and position [148]. The idea of F-formations and similar approaches to human-robot spatial arrangements were applied in studies such as [62–66, 69, 87, 89, 93, 107, 110].

2.4.4 Direct input devices

The final group of behavioral assessment types includes devices designed to provide immediate feedback during an experiment. Like questionnaires, these instruments offer a subjective measure of perceived safety, which can be obtained in real time rather than at the end of the session. Two examples of such devices are the Affective-State Reporting Device (ASRD) and the Comfort Level Device (CLD). The ASRD, as utilized by Zoghbi et al. in [41], was a modified joystick created in-house that was capable of recording affective states expressed by each user. The CLD, on the other hand, was a handheld monitoring device that enabled participants to show their comfort level during the experiment and was employed by Koay et al. in studies such as [62,63,65,89,93].

2.5 Industrial manipulators

Industrial manipulators are the type of robots that have been the subject of the majority of papers in pHRI concerning perceived safety. Standard industrial manipulators and collaborative robots, or "cobots", can be used to classify them. The former are often bigger and move faster than the latter, and they are not designed to share a workplace with people during routine task execution.

Earlier works employed the MH33 (Volkswagen) [7, 31, 38, 42], A460 (CRS) [35, 36, 39–41], P50 (General Electric) [7, 31, 38], Movemaster RM-501 (Mitsubishi) [33, 34, 37], IRB-120 (ABB) [46, 48], SMART SiX (Comau) [44], Motoman-K10S (Yaskawa) and SRX-410 (SONY) [45] standard industrial manipulators (SONY). With the exception of polar and SCARA robots, all of the mentioned manipulators include rotating joints and are serial or quasi-serial (i.e., serial with a kinematic parallelogram). With the exception of MH33, which is a very large robot with a reach of 2400 mm, the described robots are tiny or medium-sized and have a maximum reach between 445 and 1549 mm.

Although perceived safety is taken into account by all papers considered in this chapter, it was viewed from numerous perspectives, as can be seen in the corresponding column in Table 2.1. Furthermore, in [36, 39, 40], the terms "valence" and "arousal" were used to describe the participants' emotional experiences as a general framework. Additionally, the researchers in [44] explicitly focused on motion prediction, while papers [32, 35, 36, 39–41, 43, 45, 46, 48, 49] concentrated on establishing a relationship between perceived safety, robot velocity, and proximity between human and robot. In [33, 41], the perception of the robot's location and approach trajectory by people was investigated. In [33, 37], the impact of the robot's visibility and audibility on human subjects was examined.

More current studies have used the following cobots for their experiments: MICO 6-DOF (Kinova) [50], LBR iiwa 7 R800 (KUKA) [28, 52, 55], Sawyer (Rethink Robotics) [61], UR3 (Universal Robots) [60], UR5 (Universal Robots) [49, 56], UR10 (Universal Robots) [47], and Panda (Franka Emika) [59]. These cobots are small or medium-sized serial manipulators with rotary joints, with a coverage variation between 500 and 1300 mm.

2.5.1 Description of selected papers on industrial manipulators

Karwowski and Rahimi in their pioneering research papers [7, 31] examined how people perceive safe velocity for two industrial manipulators of varying proportions, a P50 (smaller robot) and an MH33 (larger robot). The primary distinction between the two articles is that while [31] featured students as subjects, [7] examined industrial employees' responses. In both works, the size of the robot was noted as a key element that influences the impression of the robot's safe motion. The gender of the subjects was found to have no significant impact on these findings. In fact, the participants found that the smaller robot's maximum speed – 66.6 cm/s in [31] and 63 cm/s in [7] – was associated with better safety ratings, whereas the bigger robot's maximum speed – 39.7 cm/s in [31] and 51 cm/s in [7] – was associated with a lower safety evaluation.

The above-mentioned works by Karwowski and Rahimi were subsequently modified and repeated in a virtual environment in [38]. The authors demonstrated that the two results of [7, 31] (i.e., the subjects' gender does not affect the sense of safety, while the robot size does influence the safe perception of maximum robot velocity) were confirmed. This demonstrated that virtual settings create an effective teaching context. In [42, 45], additional findings were presented regarding how well simulated settings can simulate the perceived safety of real industrial robot manipulators. Notably, in [45] it was shown that the robot type also influences the perception of safety: in fact, participants perceived the maximum range of the robot as larger and waited longer (after the robot had stopped) to enter the manipulator working area for a SCARA robot (SRX-410) than for a 6R-quasi-serial robot (MOTOMAN-K10S), even though there was no distinction in perception between the two robot sizes.

Kulic and Croft [35, 40] measured the anxiety and fear of human participants during experiments with a CRS 460 manipulator. The researchers used a questionnaire and physiological assessments such as galvanic skin response, heart rate, and corrugator muscle activity. There were two motion planning algorithms applied to control the robot motion: a potential field planner with obstacle avoidance and a safe motion planner with an additional danger criterion (i.e., the minimization of the potential force during a collision along the path). The results indicated that participants exhibited higher levels of measured arousal during instances of fast robot motion. Additionally, the potential field planner obtained higher rates of surprise and anxiety compared to the safe planner, specifically when the robot was moving at high velocity. A fuzzy inference engine was employed for valence/arousal detection: according to the authors, this method was reliable for medium/high arousal levels but not for valence. They obtained such a result because the corrugator muscle activity used for detecting valence was inappropriate if the stimulus was the moving robot.

The next works of Kulic and Croft [36, 39] were aimed at detecting the human affective state. They employed a user-oriented approach based on Hidden Markov Models (HMMs [149]) to enhance the valence estimation introduced in their previous works [35, 40]. Similar planners as in [35, 40] were applied for robot control. Three HMMs (low, medium, and high levels) were used for representing valence and arousal.

Contrary to the fuzzy inference engine proposed in [35, 40], the user-specific HMMs evaluated valence rate using the collected complex data from physiological signals. In addition to valence estimation, the authors showed the significance of human attention, as the detected physiological data was different when the stimulus consisted of robot motion or other environmental conditions.

Arai et al. [43] used an SD questionnaire (evaluating surprise, fear, discomfort, and tiredness) as well as a galvanic skin reaction measurement to assess the participants' psychological strain while working alongside a moving industrial manipulator. The participants' responses were assessed regarding the robot's speed, relative proximity, and whether or not they had received prior notice about the robot's motion. The results of the experiments led to the conclusion that, in order to prevent mental fatigue, a minimum distance of 2 m between a person and a robot and a maximum speed of the robot of 0.5 m/s, had to be maintained. Additionally, it was found that having prior notice of the robot's motion greatly diminished mental stress.

By conducting two-phase research, Charalambous et al. [49] determined the key variables affecting trust in pHRI and created an associated trust measurement scale. In order to identify a collection of trust-related topics and create a questionnaire, they performed an exploratory study to get participants' previous views. The questionnaire was then used to collect data from trials using three distinct industrial manipulators. It was found that the perceived threat caused by the size of the robot, the lack of real collisions with the operator, and the existence of a smooth and predictable robot motion were the key drivers of safety-related trust growth when working with industrial manipulators (particularly when the robot was picking up objects and moving slowly). And finally, the majority of participants stated that having more experience working with the robot would enhance their trust rate in the robot.

Koert et al. [57] proposed two approaches (based on spatial deformation and temporal scaling) for real-time human-aware motion adaptation with a focus on generating the robot motion via imitation learning with probabilistic movement primitives. Using a goal-based intention prediction model that was derived from human movements, the work's primary objective was to ensure perceived safety and comfort. By analyzing motion data and questionnaires on perceived safety and subjective comfort level, 25 non-expert human subjects participated in a pick-and-place task to assess the effectiveness of both approaches. It was determined that more communication (such as visual feedback) would likely improve the perception of safety because the regularity of motion as well as the awareness of why the robot was reacting in a certain manner were always linked with higher levels of perceived safety. The findings, however, indicated that it was difficult to make inferences from the subjects' answers. For instance, one group of participants perceived the temporal scaling technique as secure, while another group perceived it as dangerous.

The work of Pollak et al. [28] focused on stress experienced during pHRI tasks involving industrial manipulators. The experiments consisted of a collaborative task executed in both autonomous mode (in which the robot controlled all operations) and in manual mode (in which each operation was initiated by the participant). The results on stress appraisal were collected both via questionnaires and via heart rate measurements. It was concluded that in manual mode, the participants had higher levels of secondary stress appraisal (i.e., "the complex evaluative process of what might and can be done about the demanding situation" [28]) and lower heart rates: this means that the participants felt less confident (and thus more stressed) when not being in control of the interaction (i.e., with the robot working in autonomous mode).

Rather than using industrial robots as in [7, 31, 43], Bergman and van Zandbeek [56] investigated the influence of the manipulator's motion and distance on perceived safety using a cobot (UR5). Using questionnaires, it was determined that perceived safety was directly correlated with human-robot distance and that perceived safety was inversely correlated with robot speed. The employed speeds of 25 cm/s and 40 cm/s were both generally within the range of speeds that were perceived as safe in previous works (the smallest threshold was 39.7 cm/s for large robots in [7]); in both scenarios, the subjects assessed the robot activity as comparatively safe, evaluating it roughly at 5.63 and 4.76, respectively, on a scale from 1 (unsafe) to 7 (safe). This can be attributed to the fact that cobots operate at lower speeds than industrial manipulators. The subjects evaluated, on average, at 5.97 and 4.40 movements with the robot halting at distances of 50 cm and in the 7.5–15 cm range, respectively, using the same scale for perceived safety as described above. The movements were judged to be reasonably safe because the obtained values were in the upper half of the range. This result may appear to be in contradiction with the findings of the [43], which found that a distance of 2 m was required to obtain perceived safety. However, it is reasonable to assume that the smaller operating speeds of cobots and the fact that most participants were aware of the implemented state-of-the-art safety features significantly reduced the threshold set in [43] for industrial robots.

2.5.2 Achieving perceived safety for industrial manipulators

Overall, a higher relative human-robot distance, as seen in works like [43, 47, 53, 54, 56] (potentially exceeding a defined threshold, e.g., 2 m in [43]), and a lower robot speed, as observed in [7, 31, 35, 38, 40, 41, 43, 45, 56, 60] (potentially below a specified threshold, e.g., 0.5 m/s in [43]), contributed to an enhanced sense of perceived safety. Moreover, findings from [56] suggest that deploying a cobot, in particular, lowers the speed threshold at which the manipulator behavior is regarded as safe.

Furthermore, participants exhibited greater acceptance of higher robot acceleration and speed as their distance from it increased [32, 34, 48]. Smaller robots were considered to be less dangerous [49] and enabled greater velocities to be viewed as being safe [7,31]. The specific type of robot employed in the experiments can also affect how safe individuals feel [45], but there is no comprehensive research on how structural robot characteristics affect people's perceptions of safety.

Additionally, in [49,53,56,57,59,60] and [43,57], perceived safety is achieved when the robot behavior is generally smooth and predictable. Because of this, the human subjects tended to feel more comfortable when they had some control over the robot motion, such as when exactly the motion would begin [28]; this is obviously linked to the predictability problem mentioned in [49, 53, 56, 57, 59, 60]. The handling forces and the prevention of sudden robot movements during handovers also improved perceived safety [44, 50, 55].

When the subjects were well-experienced with robots [37, 39, 49, 54, 55] or had prior knowledge of the robot safety features [49, 52], their sense of safety increased. Gender does not appear to be a relevant factor, based on the findings of [7,31,61], while extrovert participants tend to get closer to the manipulator, based on [61].

2.6 Indoor mobile robots

In this thesis, we consider a moving base without robot arms or other moving components that operates in indoor spaces as an indoor mobile robot. PeopleBot (ActivMedia Robotics) was the most widely used robot in the articles [62–71], followed by Cozmo [73], Giraff [72], and Sphero [74]. Both Giraff and PeopleBot are telepresence robots that consist of a movable base and a vertical extension where a screen is placed that allows the robot to communicate with the human operator. The total height of PeopleBot is 112 cm and Giraff is 170 cm. Instead, Cozmo and Sphero are toy robots, and their heights are 6.35 cm and 7.28 cm, respectively.

The majority of the mentioned works do not explicitly concentrate on the perceived risk of injuries that existed when working with industrial manipulators; rather, they seek to assess participants' comfort as the robot approaches them or maneuvers around them. It could be explained by the comparatively slow speed of motion of the studied mobile robots (the highest speed of PeopleBot is 0.8 m/s, for example), which makes them less dangerous for potential physical injury.

Mobile robots were used for entertainment, service, guidance, and duties like fetching and carrying in [62, 63, 66, 68, 69, 71], reaching or being reached by humans in [68, 70, 72, 73], and following people in [64, 65]. In order to analyze how close the robot could get to the human and from what side, standard proxemics [64, 70, 73, 74] and F-formation concepts [64, 72] were used when the participants selected their most and least favored approach routes for the robot motion in [62–64, 66–69, 71, 72]. Robot distance and velocity were taken into account in [66–71, 74]. The Wizard-of-Oz method was the model that was most frequently used to determine the robot movements in [62–65, 67].

2.6.1 Description of selected papers on indoor mobile robots

In the research conducted by Koay et al. [62], the connection between subjects' comfort and how far they were from the robot as it moved around them was examined. The CLD that was previously presented in Section 2.4.4 was used to gather responses from participants. The subjects would usually act uncomfortable whenever the robot would either follow them, appear on a collision route with their direction of motion, or block the way they were going. Similar findings were reached by Koay et al. [63], who captured their experiments on video and subsequently examined them to judge how comfortable people were feeling based on their body language, facial expressions, and speaking. In addition to the results in [62], it was found that the human subjects felt discomfort when the robot rotated in place or was crashing objects. The subjects preferred the robot following them at a closer distance when it was on the left side (such that it was visible) rather than when it was directly behind them in [65].

In the experiments conducted by Hüttenrauch et al. [64], the participants accompanied the robot on a tour around a room while the latter followed behind them. The human then requested that the robot look for a particular piece of furniture or close or open it. A hidden human operator would receive the information from the subject's speech and would directly control the robot using a Wizard of Oz style. Following the trials, the researchers used questionnaires from users, videos, and audio recordings of the subjects' instructions to perform a spatial interaction analysis. The F-formation system was also used in [72] to evaluate the participant's comfort with the robot moving around them while they were playing Mikado in groups sitting at a table. The assessment was made using the Likert scale [150] and confirmed the result in [64], i.e., the participants preferred the robot approaching them from the front.

Woods et al. [66] took into consideration the various starting locations of the participants while the robot was bringing a snack to the subjects. After each experimental set, the users responded to a questionnaire asking about their opinions on the robot's movements. Another subject was present in the experiments who was viewing a live video broadcast of the scenario (video trial), in addition to the subject who would directly engage with the robot in the live trial. This second person also had to give feedback on the robot's movements. Live subjects preferred the robot approaching them from the front-left or front-right orientation in the first scenario (subject sitting at a table), whereas the subjects in the video trials preferred the robot arriving from the front. Subjects in both live and video trials reported feeling uncomfortable when the robot approached them from the front in the second scenario (humans leaning against a wall with the wall behind them). Finally, in live and video trials, both subjects preferred the robot approaching from the front-left and front-right directions (as in the first scenario), while the robot approaching from the back was the least comfortable case in scenarios with the subject standing or sitting (in both cases, in an open space).

The study by Syrdal et al. [67] intended to determine a relationship between the participants' comfort level as the robot approached them from various sides and their psychological characteristics (personality traits). These were characterized using the Big Five Domain Scale that is discussed in Section 2.4. According to the experiment findings, the front-right and front-left motions of the robot were the most pleasant for the participants. However, more extroverted people demonstrated higher rates of tolerance for robot behavior when the robot approached them from uncomfortable directions, such as from behind.

The outcomes of two research studies that examined the optimal approach path to a sitting human subject by the robot were discussed in the work by Dautenhahn et al. [68]. Most participants were more comfortable when the robot came at them from the right or left side rather than the front.

In the article by Walters et al. [70], subjects were communicating with PeopleBot. It was found that 56% of the subjects permitted the robot to approach their personal zone, in accordance with Hall's proxemics theory. Additionally, the human participants who had previously used PeopleBot came closer to it (on average, 51 centimeters) than those who had never used it before (73 cm). The distances in both instances were between 40 and 80 centimeters, which is the usual range for human-human contact between friends and relatives (see, for example, [151]). The influence of the voice with which the robot communicated with the subjects (synthesized/female/male voice) was also considered, concluding that, when the robot was speaking with a synthesized (neutral) voice, the human subject, on average, would allow it to keep a distance (of 80 cm) greater than that used when the robot spoke with a male/female voice ($41/60$ cm, respectively).

Two sessions of interaction with PeopleBot were part of the studies reported by Syrdal et al. [71]. The robot showed more socially engaged behavior in one session, adapting its behavior to the participants, rather than treating them as any other obstacle in the environment. The findings demonstrated that because the robot's movement was less predictable, its more socially engaged behavior was uncomfortable for the user.

2.6.2 Achieving perceived safety for indoor mobile robots

The front-right and front-left directions of the mobile robot's approach towards the subjects appeared to be the most comfortable, whereas the approach from behind appeared to be the most uncomfortable [62, 66, 67, 72]. Participants who were more extroverted demonstrated a higher tolerance for uncomfortable directions of approach [67]. When participants were siting or leaning against a wall, the straight frontal approach was viewed as uncomfortable, but in open areas, these approach directions were accepted as comfortable [66, 68, 69]. The subjects preferred that the robot followed them from the side rather than directly behind them in [65, 69], most likely to keep it in their field of vision. The subjects evaluated the comfort level of interaction as low when the robot was either in their way or was moving in their direction with probable collision [62, 63].

According to Hall's proxemics, the favored distance when performing a job in collaboration with someone was in the personal zone; based on the intersection of the findings in [64, 70], we estimated that this distance for pHRI tasks was between 46 and 80 cm. However, when participants were working independently, they may have felt uneasy if the robot was placed closer than 3 meters away from them or in the social zone set aside for face-to-face interactions. A greater proximity to the robot was also found to make participants from particular ethnic backgrounds feel more comfortable [73]. When completing a job in collaboration, the face-to-face arrangement in terms of F-formation was demonstrated to be the best one [64].

In contrast to participants without prior experience, those who had participated in pHRI experiments in the past permitted the robot to approach them closer [70]. Finally, when the robot motion was unpredictable, the human respondents felt uneasy [71].

Due to the fact that all of the studied indoor mobile robots are comparatively small in size, it is unclear whether the findings can be applied to larger robots. For example, would a person feel secure when interacting with a large mobile robot in Hall's personal zone, such as the Waypoint Robotics MAV3K, which has a surface area of almost 2 meters and can carry up to 1360 kg of payload? Even though we anticipate that human participants would choose a larger distance for a larger robot based on the findings described for industrial manipulators, this is still a question that remains unresolved.

2.7 Mobile manipulators

When a robot has one or more robotic arms installed on a moving base, we refer to it as a mobile manipulator in this thesis. The articles where the robot has two arms and a face (even if implemented, for example, by using a computer monitor) are instead excluded from this category and included in the humanoid robots category described in the next section. The list of the included mobile manipulators are: Jido [76], which consists of an MP-L655 platform with a Mitsubishi PA-10 (a mid-size 6-DOF serial industrial manipulator with a load capacity of 10 kg) on top; HERB [78], which consists of a Segway mobile platform with two Barrett 7-DOF WAM arms (1000 mm of stretch and 3 kg of load capacity); Care-O-bot3 [80], which consists of a Neobotix MOR omnidirectional platform with a KUKA LBR manipulator (800 mm of stretch and 7 kg of load capacity) and a Schunk SDH gripper.

For mobile manipulators, perceived safety was evaluated in terms of: comfort

[75, 76, 78–80], trust [79, 81], fear [81], stress [76], surprise [75, 79], and anxiety [75]. The most common application for mobile manipulators in research articles and experiments was the execution of handover tasks [76, 78]. As was the case for industrial manipulators, the impact of mobile manipulators' velocity and distance from human subjects was examined in a number of papers (see, for example, [76, 78, 80, 81]). Virtual reality tools rather than real experiments were used in [75].

2.7.1 Description of selected papers on mobile manipulators

Dehais et al. [76] implemented a previously created human-aware motion planning algorithm to give the robot secure and ergonomic motions when performing a bottle handover task with a human partner. Three distinct motions were performed, each with a different velocity, grasp recognition method, and implementation of the planner. The questionnaires and the galvanic skin reaction, deltoid muscle activity, and eye gaze were used to measure the levels of stress and comfort (defined, in this situation, as the physical demand needed to grasp the bottle). Looking specifically at the findings for robot velocity, it was determined that a motion with a medium velocity (up to 0.25 m/s) was the safest and most comfortable. Motions with a low speed (four times slower than with the medium-velocity profile) still had low levels of comfort because the participants would become anxious and try to grasp the bottle before the robot motion was complete. Motions at a high velocity (no limits were enforced on the robot's velocity) were perceived as the most unsafe.

Understanding how people respond to the touch initiated by robots was the goal of Chen et al. [77]. 56 people participated in trials where the Cody robot would touch and wipe their forearms. The subject could be verbally informed by the robot about the touch or not. Even though the robot action would be identical, it could audibly indicate whether the contact was intended to comfort the subject or clean their skin (instrumental touch) by using the terms "affective touch" or "instrumental touch", respectively. The subjects felt more at ease when they thought that an instrumental touch, rather than an affective touch, was being applied. This proved how a person's subjective reaction to robot-initiated contact can be greatly influenced by their perception of the robot's purpose. When there was no verbal notification, participants displayed a greater degree of comfort. Even though there was no obvious inference to be drawn from this, it demonstrated that verbal warnings were not always better for participants' experiences and should be carefully planned.

Strabala et al. [78] first examined works about the process of how people perform handover tasks with an emphasis on their coordination process, particularly in terms of shared signs and cues. Based on this information, the authors proposed a coordination paradigm for human-robot handovers that separately considered the social-cognitive and physical elements of the interaction. They conducted experiments to assess human-robot handover behaviors. The researchers came to the conclusion that the human subjects did not feel comfortable when the robot used high force when handing an object to them, managed to keep a fast velocity when it was near their hands, or was performing an action that was commonly considered unpredictable.

The study by Dragan et al. [79] concentrated on various robot motion features and how they affected physical cooperation with human participants. A robot's behavior can be functional (achieving the goal without colliding), predictable (meeting the human's expectations), or legible (enabling the human collaborator to understand the robot's goal). In experiments where a mobile manipulator helped a human person make a cup of tea, it was crucial to understand how the human subject perceived the robot's behavior as it moved to grasp the cup. All three motion types – functional, predictable, and legible – were performed, and after each trial, a questionnaire was completed. The results showed that legible and predictable movements were perceived as being safer than motions that were only functional.

2.7.2 Achieving perceived safety for mobile manipulators

The perception of robot safety increases as the human-robot distance increases [81] and is relatively high if the robot's motion is not fast, particularly when the robot is near the human body [76, 78, 81]. The participants permitted the robot to approach them closer (precisely, at a distance equal to 57 centimeters) if the robot was moving at a slow velocity and/or if they had prior experience with the same activity, based on the results in [80]. Furthermore, the motion's predictability raised people's perception of safety, as noted in [76, 78, 79]. In particular, during handover tasks, the perception of safety was reduced if the robot moved the item slowly and did not hand it over for a considerable amount of time [76], or if it pushed the participant's hand back during the transfer [78].

For a different type of contact than handover, the authors of [77] found out that different verbal warnings given before contact can affect the comfort level (even when the actual motion performed by the robot was the same) and that in some cases, verbal warnings could decrease comfort. In case the robot's arm velocity decreased as it was getting closer to the human hand, the participants felt safer [78].

The importance of robot size was not specifically investigated by comparing two or more robots, as was done in the case of indoor mobile robots, but we anticipate that mobile manipulators would be subject to the same factors stated in Section 2.6.2.

2.8 Humanoid robots

The works in this subsection are concerned with humanoid robots, or robots with two arms along with legs or a base, which can be either movable or motionless. As a result, the Baxter [102–104, 109, 112, 114, 115], Willow Garage PR2 [94, 97, 98, 111], Robovie [83, 85, 91], HRP-2 [84, 95], Nao [96, 106], Pepper [107, 108], WE-4RII [86], PeopleBot with head [87], iCat with arms [90, 92], Domo [88], Meka [100], Robi [101], iCub [105], and ARMAR-6 [113] robot systems were all included in this part. Moreover, these works included PeopleBot with four appearance versions [89, 93], Robovie with ASIMO [91], Sacarino with or without a human-like upper part [99], Nao with PR2 of two height setups [110], and Nomadic Scout II with and without a mock-up body [82].

The research papers that used humanoid robots in the experiments frequently examined perceptions of humanlikeness or anthropomorphism of these robots in addition to perceived safety [84, 91, 95, 97, 101, 106, 110, 113]. They also studied the differences and the common features of robot and human conditions during interaction [90–92]. Some papers were inspired by results of human-human communication from the psychological point of view [94, 97, 98, 105, 108, 110, 111].

The robots performed the following tasks in close proximity to the human subjects: handover [88,90,92,97,98,109]; approaching the human subject [82,89,93,94,107,110]; playing games [89, 93, 95, 108]; pick and place [84]; talk and touch [96, 106]; handshake [95].

2.8.1 Description of selected papers on humanoid robots

Several of the early research investigations into psychological safety employed Robovie [83, 85, 91]. The Robovie's construction details and one of its first assessments by human beings were provided by Kanda et al. [83]. The experiment evaluated three robot behaviors as a consequence of a human-initiated interactive action: passive (after touching, the robot completed one action and returned into the waiting phase), active (after touching, the same action was performed by the robot and the participant viewed it), and complex (after touching, the robot went to daily work and idling tasks, in which it was moving in the surrounding space). The participants chose passive behavior as their preferred one and kept a 41-centimeter distance from the robot, which is in the intimate zone.

PeopleBot in [87, 89, 93] was another robot that was used for similar studies. The findings of a long-running study (5 weeks, 8 sessions) involving 12 participants were given by Koay et al. in [89] and [93]. Two men and one woman from each set of participants interacted with one of four PeopleBot variations: small/tall mobile robots without heads or small/tall humanoids. There were three distinct approaching scenarios (no-interaction, physical, and verbal). The participants' degree of comfort was assessed through CLD, a questionnaire, and a semi-structured interview based on the Big Five domain scale [135]. In the final analysis, it was determined that the robot approaching from either the front or the side was the most acceptable situation. Additionally, participants were more inclined to give permission to the robot to come closer towards the end of the 5-week period than at the beginning. Furthermore, individuals eventually began to choose verbal communication over physical contact, which was not the case at the start of the trial. According to [93], when the robot blocked their way or moved following a collision trajectory with them, people did not feel at ease. The participants were comfortable when the robot warned them before approaching. Additionally, it was determined that the participants' level of comfort would significantly rise due to the robot's consistency.

The handover task performed by an iCat robot with arms was evaluated in an experiment by Huber et al. [90], testing two velocity profiles for the robot: a conventional trapezoidal velocity profile in joint coordinates and a minimum-jerk profile of the end-effector in Cartesian coordinates. Participants rated the level of how human-like the robot's motion was and how safe they perceived it to be. The results suggest that participants' level of trust was similar in both cases, and both velocity profiles were similarly perceived as human-like. However, the minimum-jerk profile had higher safety ratings, and the robot was perceived as safe if its maximum speed did not exceed 1 m/s.

The perception of safety was also examined using Willow Garage PR2 in the following papers: [94, 97, 98, 111]. Takayama et al. [94] focused on the features that might affect proxemic behaviors and the perception of safety. Three scenarios were used in the experiment: a person approaching the robot, the robot moving independently, or being controlled remotely while approaching a participant. The results of monitoring people's behavior and their questionnaire responses indicated that individuals who owned pets or had experience with robots were more likely to let the robot approach them. Participants of both genders moved closer to the robot when it was looking down at their legs, but when it was looking up at their faces, women tended to distance themselves from the robot more compared to men.

Butler and Agah [82] focused on the psychological impact of robot behavior patterns on humans in daily life, such as approaching or avoiding a human and executing tasks in crowded surroundings. Two types of robots were used in the experiments: mobile robot and humanoid. Participants rated the fast-moving humanoid with a maximum speed of 40 inches per second as the most uncomfortable and a motion with a slow speed (10 inches per second) for both robot types as the most pleasant. Overall, when the body was added to the mobile base and the robot became a humanoid, the human subjects rated the behavior of such a robot as less comfortable.

Rajamohan et al. [110] investigated the effects of multiple factors on people's preferential communication distances with robots. There were three robot types: a humanoid Nao robot (58 cm), a short PR2 (133 cm), and a tall PR2 (164.5 cm). When one of the robots approached participants, they were instructed to say "stop" whenever they felt uncomfortable. Additionally, subjects were told to approach the robots and to stop if they felt uncomfortable. The findings indicated that humans preferred when the robot approached them, rather than when they did it themselves. Men let the robot come closer than women did. The maintained distance was also impacted by the robots' height, since the Nao robot was permitted to approach people more closely than either the PR2 short or tall robot.

Fitter et al.'s [112] used perceived safety and trust as their primary measures. During the experiments, a human and a Baxter robot performed a hand-clapping exercise for an hour to assess the robot's physical reactivity, facial reactivity, arm stiffness, and clapping rhythm. Facial reactivity increased the participants' perception of Baxter's pleasantness and energy, but physical reactivity decreased their perception of Baxter's pleasantness, energy, and dominance. While a greater clapping speed made Baxter appear more enthusiastic and more dominating, higher arm stiffness enhanced perceived safety and lowered dominance.

2.8.2 Achieving perceived safety for humanoid robots

A great part of research using humanoid robots studied how people's proximity to the robot and preferred approach direction affected their behavior. As a result, data indicated that participants desired Robovie to remain at a distance of 41 centimeters [83].The front approach was preferred for the PeopleBot [93]. Along with these findings, PR2 [94] and PeopleBot [89] both showed that past exposure to pets and robots had an impact on people's proximity.

Comparison of perceived safety between two or more robots was also made. As a result, the short and tall PR2 robots in [110] were allowed to move closer to humans than the small Nao humanoid. Another example is the comparison of ASIMO, ROBOVIE, and humans in the proxemics experiment [91]: human participants were at a shorter distance from ASIMO in contrast to Robovie or another human.

Non-verbal social cues were also investigated, and the following outlines were drawn: Baxter's facial reaction was seen as more pleasant [110], whereas PR2's eye contact was critical for handover duties [98]. Men were observed to allow the robot to approach them closer than women did [110], particularly when the robot was looking straight into the participants' faces [94].

Other works in this section also focused on the robot motion: for instance, the comfort level grew with predictable robot behavior [93], Baxter's higher arm stiffness raised perceived safety [112], and the minimum-jerk profile of the iCat arms obtained higher safety scores [90].

In addition to the obvious physical and behavioral distinctions between robots, such as size, height, and vocal and non-verbal indications, there are a number of additional visual and design features that are significant. The uncanny valley effect [152] and anthropomorphism, for instance, might affect how safe humans believe the robot to be.

	Industrial manipulators	**Indoor mobile robots**	**Mobile manipulators**	**Humanoid robots**
Distance	[43] [47] [53] [54] [56]	[63] [64] [70]	[81]	[83]
Robot speed	[31] [7] [35] [40] [41] [43] [45] [60]	-	[76] [78]	-
Robot speed $\propto$ distance	[32] [34] [48]	-	[80] [81]	-
Direction of approach	-	[62] [66] [67] [68] [69] [72]	-	[93]
Robot size & appearance	[31] [7] [49]	-	-	[89] [91] [110]
Motion fluency & predictability	[49] [53] [56] [57] [59] [60]	[71]	[76] [78] [79]	[90] [93]
Communication	[43] [57]	-	-	[98] [110]
Smooth contacts	[44] [50] [55]	-	[76] [78]	-

Table 2.4: Factors that influence perceived safety (adapted from [1]).

2.9 Discussion

2.9.1 Factors determining perceived safety

Table 2.4 lists the key elements of robot behavior and features that affect perceived safety for all robot types examined in Sections 2.5-2.8. In particular, distance, robot speed, proportionality between robot speed and distance, direction of approach, robot size and appearance, motion fluency and predictability, communication, and smooth contacts are the factors that are given in each row. The different types of robots are taken into account in each column.

The results for each factor are listed in the following:

- Distance: The perception of a robot's safety increases with the increasing distance between humans and robots. For industrial manipulators and cobots [43, 56] the distance needs to be greater than values of about 2 m and 0.5 m, respectively. For indoor mobile robots [64, 70] this space must be 46-80 cm. For small humanoid robots [83], it is better for the robot to be 41 cm further from the human. In a few situations, distances were correlated with the various proxemics zones of Hall.

- Robot velocity: Slower moving robots are considered safer. For industrial manipulators, for example, a comfortable speed threshold of 0.5 m/s was determined in [43].

- Robot speed proportional to distance: as the robot gets further away from humans, greater and faster speeds are perceived as safe.
- Direction of approach: Some directions of approach are considered safer than others (e.g., coming from the side rather than the front, or from the back side).
- Robot size and appearance: Despite how the robot moves, bigger robots and those with certain characteristics (related to shape and color) are considered less safe.
- Motion fluency and predictability: People's perceived safety is higher when a robot moves fluently and predictably.
- Communication: By adding notifications that give a heads-up about the specific robot action (by making a sound before it moves, for example), perceived safety is increased.
- Smooth contacts: When interactions occur (such as during a handover), the absence of sudden robot movements positively affects how safe people perceive the situation to be.

There are some characteristics that are universal (such as motion fluency and predictability), while others are limited to specific types of robots (e.g., an industrial manipulator handover task might involve transferring smooth contact forces). Certain aspects are ignored for some kinds of robots simply due to the settings of the experiments. For example, in papers on indoor mobile robots, the robot velocity and size were never taken into account as factors related to perceived safety because they were always too small to affect the participants. Finally, people who have previously dealt with a comparable system typically consider the robot safer.

There were only five articles that used the Wizard-of-Oz approach in the experiments, compared to the other 78 observed papers that applied other controlling techniques for robot motion. This was expected, as stated in [30] – the use of Wizard-of-Oz was applicable only to the research environment and laboratory conditions, and had limitations to be used in the "complex world of everyday users". What is common for these researches was that all of them worked with the indoor mobile robot PeopleBot, the most commonly used robot type. Additional similarity is that proxemics was studied in [62–64]. The articles [62,63,65] used the questionnaire, behavior assessment together with the device to rate the human perception of comfort about the robot. There are some already mentioned results of the articles that utilized this approach: the robot motion toward the human was rated as the most comfortable from the front (right and left directions), and less comfortable from behind [62, 67]. Humans preferred the robot to follow them from the side, compared to behind direction [65]. When the robot blocked the path of the human, this kind of behavior was uncomfortable for them [62, 63].

2.9.2 Perceived safety and safety standards

A number of safety standards have been developed to protect human operators. For instance, the European Union regulates the use of machinery by the 2006/42/EC standard, which guarantees a uniform regulation of safety. According to the ANSI/RIA R15.06 and R15.08 standards of the United States, industrial manipulators, autonomous mobile robots, and mobile manipulators must meet certain specifications and safety precautions. The International Standard Organization (ISO) has also established safety requirements for personal care robots used in non-medical applications (ISO 13482) and industrial robots (ISO 10218-2 and ISO/TS 15066).

Even if these safety standards are not concerned with perceived safety, they can help raise perceived safety. A first demonstration of this concept is the speed and separation monitoring (in short, SSM) mode of operation outlined in ISO/TS 15066 [153, clause 5.5.4] (which will play an important role in the experimental part of this thesis), requiring that an industrial manipulator reduces its velocity proportionally to the distance from human operators in order to prevent a potential collision. As shown in Section 2.9.1, higher speeds are only considered safe when the robot is further away from humans, which means that speed-and-separation monitoring enhances perceived safety. A second demonstration of the same idea is the power and force limiting mode of operation, which is described in ISO/TS 15066 [153, clause 5.5.5]: as long as the exchanged kinetic energy is lower than a certain threshold, the robot is permitted to collide with the human operator at a nonzero speed. As a consequence, lighter robots are permitted to go at higher speeds since the robot's kinetic energy is proportional to both its speed and mass. This factor relates to perceived safety as well, since human participants often feel nervous around a fast-moving robot when it has a larger size (see Section 2.9.1).

2.9.3 Experiment duration and location

In general, the majority of the described works deal with short-term studies that lasted from a few minutes to a few hours and were often conducted on the same day for each participant. The explanation for this is that the length of the experiment allowed researchers to evaluate participants' responses and test out new assessment techniques. The exceptions were [37, 89, 93], which carried out longer experiments over a period of up to two months to evaluate the impact of the human subjects' long-term habituation on the interaction with the robot.

Experiments were conducted in (i) research laboratories, (ii) surroundings close to the living environments of the subjects, (iii) factories, (iv) symposia and fairs, and (v) virtual environments. Due to the obvious advantages in terms of trials set up, the majority of investigations were carried out in laboratory conditions. In order to improve the amount of natural human-robot interaction, the studies that were carried out in settings that were closer to actual living conditions were conducted in homes, apartments, and rooms. The participants remarked that, because of these circumstances, they could act naturally and did not feel like they were being examined. Therefore, based on these articles, we may draw the conclusion that this type of location can raise the degree of truthfulness of subjects' reactions. The purpose of the factory studies was to evaluate how safely humans and robots could interact in settings more akin to manufacturing operations. In order to easily reach people with various degrees of familiarity with robotics technology, experiments were carried out during trade exhibitions [52] and a symposium reception event [70]. In some articles, virtual reality was employed, so as to reduce safety hazards while still giving the participants an immersive experience. According to Weistoffer et al. [47], physical experiments are still required for complete research, particularly when it comes to measuring human physiological parameters, even though virtual reality may be a useful tool to gauge the acceptability of interaction between humans and robots and draw preliminary conclusions through questionnaires.

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Chapter 3

Perceived intelligence: literature review

This chapter provides an overview on the concept of robot perceived intelligence and on how it has been studied in the literature, concentrating on the relationship between perceived intelligence and habituation. The chapter is structured as follows: Section 3.1 mainly focuses on a summary of the factors that influence perceived intelligence. Section 3.2 describes general aspects of the surveyed papers on the connection between perceived safety and habituation, such as the assessment methods (questionnaires) used for perceived intelligence assessment and a description of the robots used in the experiments. Section 3.3 reports a brief survey of existing papers, with the objective of assessing how the effect of habituation was studied in relation to perceived intelligence, and what results were obtained. Section 3.4 provides a discussion of the different results obtained in the surveyed papers, with the aim of detecting general trends in the variation of perceived intelligence.

3.1 Factors that influence perceived intelligence

High levels of perceived intelligence, which usually correspond to high levels of trust, are important to make robots accepted by potential users. Perceived intelligence has been studied not only for robots, but for a wider category of intelligent agents, such as chatbots and smartphones. In [154] it is mentioned that, if an agent is perceived as more intelligent, its perceived usefulness increases [155], together with the trust towards it [156].

If perceived intelligence influences perceived usefulness and trust, it is in turn influenced by different factors, as studied in [157–160]. According to the categorization in [154], the perceived intelligence of an agent increases with the following characteristics:

- *autonomy:* the extent to which an agent can operate in an independent and goal-directed way without human intervention;
- *adaptability:* the ability to improve the match between its functioning and the environment;

- *reactivity:* the capacity to react to changes in the environment;
- *multifunctionality:* the ability of a single agent to execute multiple functions;
- *cooperativeness:* the capability to cooperate with other agents to achieve a common goal;
- *human-like interaction:* the degree to which an agent communicates and interacts with humans in a natural, human-like fashion;
- *personality:* the ability to show the properties of a credible character.

In addition to the above-mentioned general results, the factors that influence perceived intelligence were also studied specifically for robots. To the best of our awareness of the literature, perceived intelligence is positively influenced by the following factors:

- *Transparency:* the previous knowledge by the human participant of the task that the robot will perform [161].
- *Animacy:* how much the robot is perceived as behaving as a living being [27, 162, 163].
- *Trust:* how much a user can be confident that the robot will successfully complete an assigned task [164, 165].
- *Human-like appearance:* as we are used to expect other human beings to be more intelligent than, for example, animals or machines, a higher level of intelligence is typically assigned to robots that appear as more human-like [162, 163, 166]. Indeed, anthropomorphism and perceived intelligence are known to be positively correlated [167], even though the relationship between these two characteristics can be influenced by the so-called *uncanny valley*, i.e., the fact that "more human-looking characters will be perceived as more agreeable up to a point at which they become so human people find their nonhuman imperfections unsettling" [167].
- *Human-like gestures:* they play a similar role as human-like appearance [168,169], but they are not influenced by the uncanny valley.

In case a robot can speak, voice tone and speed of talking also influence perceived intelligence [169–172].

Thousands of papers were written in recent years in which the perceived intelligence of robots was assessed, but, to the best of the author's knowledge, no review papers were written to summarize these results. After having surveyed the main characteristics related to perceived intelligence in the previous part of this section, in this chapter we focus on understanding how perceived intelligence changes as a result of multiple interactions with a robot. In this case we can use the term *habituation*, which has already been studied in HRI to understand the effects of human participants becoming accustomed to interacting with robots (see, e.g., [89, 173]). Regardless of its specific contextualization in robotics, habituation was first defined in the field of neurobiology as “a behavioral response decrement that results from repeated stimulation and that does not involve sensory adaptation/sensory fatigue or motor fatigue” [174].

3.2 Overview of the surveyed papers

The publications studying the variation of perceived intelligence analyzed in this survey correspond to references [55, 93, 101, 175–184]. In order to assess the effect of habituation, perceived intelligence was rated after each of multiple experimental sessions, possibly assessing the effect of habituation. In the remainder of this section, we provide information on (A) how perceived intelligence was assessed, (B) what robots were used for the experiments, and (C) how the chosen papers were selected.

3.2.1 Assessment methods for perceived intelligence

Since its introduction in 2009 by Bartneck et al., The Godspeed questionnaire [30] has been the most commonly used assessment method to measure perceived intelligence (and other characteristics) of robots. The ideas at the basis of this questionnaire were derived from Warner and Sugarman’s *intellectual evaluation scale* [185]. Specifically, the *perceived intelligence* scale consists of the evaluation of the following robot capabilities in the form of five-point semantic differential scales with Likert type scaling: *incompetent-competent*, *ignorant-knowledgeable*, *irresponsible-responsible*, *unintelligent-intelligent*, *foolish-sensible*. It is worth reporting that Bartneck and co-authors had already mentioned the use of a robot intellectual evaluation scale, excluding the *incompetent–competent* item, prior to [30], and precisely in [162, 163, 186–188]. The Godspeed questionnaire was used in [101, 177, 179–181, 183].

A concept that can be considered as practically equivalent to perceived intelligence is that of *competence* of a robot, as perceived by human subjects. Indeed, *incompetent-competent* was one of the Godspeed questionnaire items, and the term *perceived intelligence* will be used in the remainder of the chapter to refer to the concept of *competence* as well. Competence is used as a general category in the Robotic Social Attributes Scale (RoSAS) [143] and is further split into the evaluation, via a Likert scale, of how well the following adjectives (items) describe the robot: *reliable, competent, knowledgeable, interactive, responsive* and *capable*. Specifically, competence according to the RoSAS questionnaire was studied in [55, 176, 178, 182].

Ad-hoc questionnaires were also employed. A questionnaire that, similarly to RoSAS, evaluated competence, was used in [175], by assessing (again via a Likert scale) the perception of the following robot qualities: *intelligent, organized, expert* and *thorough*. In [93], participants were asked the following questions: ”How intelligently did the robot respond to your directions in each trial?” and ”In which trial did the robot behave the most intelligently?”. These two questions were rated on a Likert scale from 1 (“very intelligent”) to 5 (“not at all intelligent”).

3.2.2 Robots used in the experiments

The most commonly used types of robots in the analyzed works were humanoid robots: Nao in [180], Pepper in [181], the 3D blended embodiment Furhat in [176, 178, 182], the humanoid robot Rapiro in [183], and Robi in [101]. The combination of humanoid and mobile robots was studied in [177] with Nao and Roomba, in [93] with four appearance configurations of PeopleBot, and in [184] with QTrobot and Mistry robot. The collaborative manipulators KUKA LBR iiwa 7 R800, Universal Robots UR5 was used in [55, 179], respectively. Finally, the two virtual agents IVA Vince (robot-like) and IVA Billie (human-like) were compared in [175].

3.2.3 Research method

In order to select the papers object of this survey, we first used different search engines (Google Scholar, IEEEXplore, ScienceDirect, Scopus) for the keywords “robot” AND (“perceived intelligence” OR (“competence” AND “RoSAS”)) AND (“habituation” OR “longitudinal” OR “novelty effect” OR “ordering effect”). Indeed, the term *competence* is often used with different meanings outside the RoSAS questionnaire, and terms such as *longitudinal study, novelty effect* and *ordering effect* were often used to indicate a study of habituation, even when the term “habituation” was not explicitly mentioned. In addition to the publications found with this method, we also considered works cited in them that were potentially relevant. The articles were further screened by eliminating those entries which did not satisfy the following requirements:

- The work is published in English language either as an international journal papers, in the proceedings of an international conference or as a book chapter.
- Experiments are run in which human participants interact with a robot (either real or, in few cases, virtual), and perceived intelligence is evaluated using a suitable questionnaire.
- The change in perceived intelligence over multiple sessions is assessed and presented in the results.

After this screening, the above-mentioned 13 works [55, 93, 101, 175–184] were obtained.

3.3 Analysis of the surveyed papers

In this section we provide a description of the surveyed papers in chronological order, by focusing either on the connection between habituation and perceived intelligence, both in the description of the experiments and in the interpretation of the questionnaire results by the authors. Additional experimental tasks and/or questionnaires not related to perceived intelligence are mostly not reported, to focus on the survey topic. It is worth noticing that in [93, 178, 179, 181–183] the so-called *Wizard of Oz* approach [118] was used, meaning that these robots were partially controlled by a human operator without participants being aware of it.

Perceived robot intelligence was rated in [93] by having participants play the so-called “hot and cold game” with a robot. In this game, the robot searched for an object randomly chosen by the participant in a room, while the participant guided the robot by saying “hot” or “cold”, respectively, if it was either close or far from the object. The experiment consisted of three rounds, in which the robot would always avoid obstacles in the room: during the first and third rounds the robot reacted to human words by changing its motion direction on the word “cold”; in the second round, instead, it moved randomly across the room without reacting to human words. The results of the questionnaire showed that the robot was rated as more intelligent during the third round of the trial, whereas the lowest marks were given in the second round. This work did not assess habituation by studying the variation of perceived intelligence while the same robot behavior was observed; therefore, it is not possible to conclude if habituation had a positive or negative effect on the perception of intelligence. However, the different evaluation of the same robot behavior in rounds one and three seems to indicate that perceived intelligence is influenced by what participants experienced immediately before the round. More specifically, an improvement of the actual robot intelligence led to a positive bias in its perception.

In [175], each participant interacted with one of two virtual agents: a human-like agent with child voice named Billie and a robot-like one with machine voice named Vince; each of them, throughout the whole experiment for a single participant, would either make gestures when speaking, or not (the type of agent and the presence/absence of gestures was randomly assigned). The virtual agent performed a self-introduction and asked the participant to answer a questionnaire about perceived level of competence. After filling the questionnaire, the participant watched a presentation given by the virtual agent, before evaluating competence once more. For both agents it was observed that, on average, competence rates improved in the second questionnaire when the use of co-speech gestures was present, and worsened when it was absent. Although the robot behavior between first session (introduction) and second session (presentation) was different, to the best of our understanding this behavior did not display a varying level of intelligence. Therefore, the variation of perceived intelligence can be attributed to habituation, differently from [93], in which the robot behavior was purposefully changed to be less intelligent in the second session.

In [101], human subjects engaged – either actively or passively – in conversations with a small humanoid robot in pairs over two sessions. Perceived intelligence was assessed after the first session and after the second session (in which its rating increased, though not significantly, with respect to the first session).

When evaluating human-to-robot handovers, the authors of [55] varied three factors – initial position, retraction speed, and grasp type – in people's interactions with the robot for a total of 8 conditions per user. Regardless of the obtained results relating competence to the listed factors, the authors examined whether the participants' perception changed over the course of repeated handover interactions with the robot, concluding that there was no significant trend in competence.

In [176], participants were gradually exposed to the motionless 3D blended embodiment Furhat (consisting of a robotic head) with different variation in terms of human-likeness. There were three stages of interaction: first participants only observed the robot when this was motionless, just blinking the eyes; then, the robot introduced itself by speaking without reacting to the participant's actions; finally, the robot interacted with the participant by playing a game involving a conversation. While there was no significant difference in robot competence ratings between the first and second stages, there was a significant difference in perceived competence between the last stage compared to the first and second stages, with this difference being more pronounced when the more human-like variants of the face were used. This confirms the foreseeable expectation that "the more participants are exposed to the robot's capabilities, the more competent they perceive it" [176].

With the aim to evaluate perceived intelligence of a vacuum cleaner Roomba robot during its interaction with a humanoid Nao robot, [177] conducted a within-subject design study with two conditions: "interactive" and "no interactive". In the "interacting" condition, the Roomba robot consistently achieved a higher rating of perceived intelligence by the participants as compared to the "no-interactive" condition. However, there was no ordering effect for perceived intelligence.

In [178,182] participants played a geography-themed cooperative game with a Furhat robot three times (3-10 days apart) with a different robot embodiment (human-like, machine-like and morphed, cf. [176]) and had a social face-to-face chat before and after the game. Data from study [178] showed that the human-like robot face was perceived as significantly more competent compared to the morphed face, while the findings from study [182] additionally suggest significant differences in competence ratings between human-like and machine-like embodiment. In both works, no significant changes in perceived intelligence due to habituation were reported.

In [179] it was investigated how animal-like character animation principles (appearance, smooth motion, breathing, gaze and posture) can enhance perceived intelligence of the Universal Robots UR5 cobot in a collaborative task. Results from two user studies suggested that while appearance, smooth motion and posture did not have an effect on cobot's perceived intelligence, manipulating animal-like breathing motions as well as gazing behaviour significantly improved cobot's perceived intelligence. However, no correlation was found between these factors and any ordering effects.

In [180], a Nao robot interacted with participants by means of spoken sentences and gestures. The interaction during each of two sessions consisted of ten sentences pronounced by the robot with their accompanying gestures. For half of the participants, in the first session the first five sentences were determined using a pre-programmed method, while the next five sentences were selected using an ad-hoc machine-learning-based method developed in the paper; the reverse order was followed in the second session. For the other half of the participants, the opposite sequence of methods was followed through the sessions. While no significant differences on perceived intelligence were found regarding the use of different methods, it was determined that, regardless of the used order of methods, perceived intelligence significantly increased from the first session to the second.

The goal of the research [181] was to evaluate a 5-week mindfulness sessions administered by either a teleoperated Pepper robot controlled by an experienced human coach via teleoperation, or by the same human coach directly. In both cases, no significant differences were observed in perceived intelligence over time.

The focus of the research work [183] was to study the perception of the fact that a Rapiro robot would take (or not) the initiative to initiate an interaction with human participants. Participants interacted in sequence with both robot conditions: active (the robot was first to greet participants) and passive (the robot waited for participants to greet the robot first), with the order being counterbalanced. Neither the specific condition (active or passive) nor the order of execution of the conditions led to any significant variations in terms of perceived intelligence.

The work described in [184] explored how the employees of a tech company perceived a QTrobot and a Misty robot as well-being coaches programmed to deliver positive psychology exercises four times over four weeks. No significant differences in competence ratings were obtained neither between the two robots, nor between subsequent sessions.

3.4 Discussion

The results on perceived intelligence for each of the analyzed papers are reported in Fig. 3.1. Paper numbers are reported on the horizontal axis, whereas the vertical axis indicates if there were any significant perceived intelligence variations detected, or

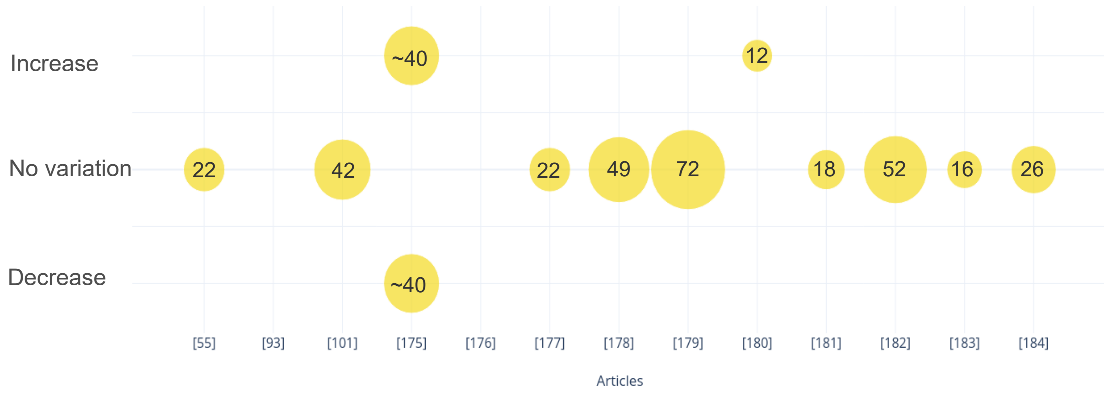

Figure 3.1: Summary of the variation of perceived intelligence, in different papers, due to habituation. The size of each circle is proportional to the number of participants, which is indicated inside the sphere.

not. The number of participants is proportional to the size of each circle, and indicated inside the circle. Out of the 80 participants of [175], some of them were randomly assigned to an agent making gestures (for which an increase was detected) and some to an agent not making gestures (for which a decrease was detected); this is the reason for the presence of two circles, for each of which we assume a size of approximately 40. No correlation was found between the obtained results and the number of participants.

Habituation seems to cause, regarding perceived intelligence,

- a significant increase in [175, 180];
- no significant change in [55, 101, 177–179, 181–184];
- a significant decrease in [175].

It is worth highlighting that papers [93, 176] could not be used to assess the effect of habituation as, despite running multiple experimental sessions each followed by a questionnaire, the robot behavior changed quite dramatically in subsequent sessions, and the order in which these behaviors were presented to the users was always the same. In particular, [93] presented a result on how the variation of perceived intelligence in subsequent sessions can be influenced by the previously-observed robot behavior. Specifically, after observing a non-intelligent robot behavior, participants tend to evaluate the robot as more intelligent when it behaves normally, compared to the same evaluation of this normal behavior without any previous experience; this observation should be accounted for in future research.

The great majority of surveyed papers showed no significant changes in perceived intelligence due to habituation. An increase was observed for a robot or virtual agent speaking with participants while making gestures in [175]. However, again in [175] the perceived intelligence of the same virtual agent decreased when the latter was not making gestures. This can be related to the fact that, as already mentioned in the introduction, the presence of human-like gestures in general improves perceived intelligence ratings. In [180], instead, an increase of perceived intelligence was observed for all conditions. Overall, we can conclude that habituation seems to have a positive effect on perceived intelligence, although no significant variations were observed in the majority of the analyzed papers.

A possible explanation of the general trend is that, as the robot behavior is complex, it is not easy to immediately infer the rules that determine its actions. Thus, as a better understanding of the robot behavior is achieved in subsequent sessions, the perceived intelligence rates also increases.

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Chapter 4

Safe motion planning algorithms

As mentioned in the introductory chapter, the experiments described in this thesis were aimed at evaluating perceived safety and robot perceived intelligence during pHRI. The human participants executed a task consisting of moving objects on a table while sitting on a chair placed in front of it (a more detailed explanation of the task will be provided in Chapter 5). In the meantime, a collaborative robot, placed behind the same table and in front of the participant, executed an independent sequence of pick-and-place tasks. The goal configuration to be reached by the robot, which assumed different values in time – for instance, based on the cube that had to be picked up – was formulated in the robot's configuration space. The latter was defined by the vector of joint angles $\boldsymbol{\theta}$, whose size n_θ was equal to the number of joints (specifically equal to 7 for the considered Kinova Gen3 robot). During the robot motion, safety had to be guaranteed for the human participant. This was accomplished via the SSM safety criterion, already mentioned in Section 2.9.2, which is further detailed in the following section.

4.1 Speed and separation monitoring

The SSM strategy presented in this section is based on the ISO/TS 15066 SSM criterion that Marvel et al. [189] described in their paper in detail. The aim of SSM is to provide safe and comfortable interaction between people and robots by continuously controlling the robot speed (typically measured by optical encoders) based on the distance to the human (obtained via encoders to assess the robot configuration and using an optical motion capture system to determine the location of several points of the human body). The underlying concept is the following: the robot always needs to be able to come to a halt before humans can touch it. As the time after which the human can reach physical contact with the robot is proportional to the distance between the two, the upper bound on the robot speed decreases with the human-robot distance. In the following, we explain how this is achieved in mathematical terms.

The SSM framework works under the hypothesis that a person's velocity would never exceed a certain limit $\bar{v}_h$ (specifically set by safety regulations), which in our trials equals 2 m/s. A number of virtual spheres, each centered at a different time-varying position (for example, coinciding with the second robot joint or with the left shoulder of the human), are used to provide a conservative estimate of the volume occupied by both robot and human. In the proposed case study, we implemented $n_r = 7$ spheres for the robot and $n_h = 14$ spheres for the human.

The spheres radii on the human operator and the center coordinates in a determined fixed reference frame are defined as $R_{h,j}$ and $\boldsymbol{p}_{h,j}$, respectively, with $j = 1, \ldots, n_h$. It is assumed that the speeds of these sphere centers can never be higher than $\bar{v}_h$. For the robot spheres, the following variables are used: the center coordinates of the robot spheres, located in the same reference frame as for the human participant, are referred to as $\boldsymbol{p}_{r,i}$, with $i = 1, \ldots, n_r$. The radii of the same robot spheres are identified as $R_{r,i}$, with $i = 1, \ldots, n_r$. The scalar velocity of each robot sphere center is indicated by v_i.

The distance d_{ih} between the i^{th} robot sphere and the union of all human spheres can be obtained as

$$d_{ih} = \min_{j=1,\ldots,n_h} \{d_{ij} - (R_{r,i} + R_{h,j})\}\,, \tag{4.1}$$

where $d_{ij} \triangleq \|\boldsymbol{p}_{r,i} - \boldsymbol{p}_{h,j}\|$ is the distance between the centers of the corresponding spheres. In case the value $d_{ij} - (R_{r,i} + R_{h,j})$ (and consequently d_{ih}) becomes negative, then it means that a collision between the robot and human spheres has happened. We also introduce the distance d_{rh} between the unions of all robot spheres and all human spheres, which is equal to

$$d_{rh} = \min_{i=1,\ldots,n_r} d_{ih}. \tag{4.2}$$

The objective of the SSM implementation is to enforce the following condition:

$$\bar{v}_h \left(T_{dr} + \frac{v_i}{\bar{a}_r}\right) + v_i T_{dr} + \frac{v_i^2}{2\bar{a}_r} + \epsilon_s \le d_{ih},\ i = 1, \ldots, n_r, \tag{4.3}$$

where $\bar{a}_r$ indicates the maximum deceleration that the motors may apply to the robot sphere centers, which in our study was set equal to 5 m/s^2; T_{dr} is the so-called “detection and reaction time”, accounting for the time interval needed for the robot to get access to the human operator’s position and to accordingly modify its speed (this time interval was set equal to 100 ms, i.e., twice the sampling period of the motion planning algorithm); ϵ_s indicates the accuracy of human location tracking achieved with the available motion capture system, which is equal to 4 mm.

Now we will explain how the above condition (4.3) is related to the explanation of the SSM principle provided above. The value $\bar{v}_h\,(T_{dr} + v_i/\bar{a}_r)$ represents how far the human operator is able to go during the detection and reaction time of the robot (in total, a distance equal to $\bar{v}_h T_{dr}$), and while the robot speed decelerates until it stops (a distance equal to $\bar{v}_h v_i/\bar{a}_r$). The expression $v_i T_{dr} + v_i^2/(2\bar{a}_r)$, instead, returns the distance reached within the same time period by the i^{th} robot sphere center. The sum of these distances, plus the measurement precision ϵ_s, cannot be greater than the current distance d_{ih} between the human and the center of the i^{th} robot sphere. This guarantees that the robot can always stop before a possible collision happens, under the conservative assumption that human and robot are on a collision course, pointing at each other (as there is no a-priori information on the direction of the velocity vectors associated with robot and human speeds). At each sampling time, the motion planning algorithm has to determine the maximum permitted speed of each robot sphere center, which we refer to as $\bar{v}_i$, by solving (4.3) as a second-order algebraic equation.

4.2 Motion planning with fixed and variable path

The standard way of implementing the SSM criterion is to modulate a robot motion that has already been defined in the absence of the human operator. For the considered pick-and-place tasks, this motion in its basic formulation would not account for the distance with the human: to adapt it, the robot path (i.e., the sequence of configuration values without any reference to robot speed) is maintained constant, and the speed is modulated so as to guarantee SSM. Let us refer to the velocity of the i^{th} robot sphere center for the basic robot motion without human presence as $\hat{v}_i$. In order to maintain the same path as in basic robot motion, all robot joint velocities have to be scaled to the same quantity. It can be easily shown that, in order to guarantee SSM, all robot's joint speeds have to be multiplied by the following coefficient:

$$c = \min\left(\min_{i=1,\ldots,n_r} \frac{\bar{v}_i}{\hat{v}_i}, 1\right). \tag{4.4}$$

Actually, the scaling has to be achieved for the linear velocities of the sphere centers rather than for the angular velocities of the robot joints; however, the latter implies the former, as a result of the linear relationship between the robot's sphere center velocities and joint speed (see, e.g., [190]). Modulating the robot speed on a fixed path as described above will be referred to in the remainder of the thesis as a fixed-path (FP) algorithm. A continuous regulation of the robot velocity will be used in this work by recalculating c at each sampling instant; this is a more advanced version of the standard SSM algorithm used in industrial practice, where the robot speed threshold only changes based on specific thresholds that identify the human location (the reason for this is that a motion capture system would be too expensive to use in industrial practice, and therefore simpler sensors such as laser scanners are routinely employed).

If humans often block the robot's path, productivity (in our case, depending on how many cubes can be placed in a given time interval) may be low, as the robot has to keep stopping and waiting for the human to move away again. Oleinikov et al. [191] suggested a real-time motion planning algorithm as a potential solution, which defines the robot joint velocities based on a prediction of the robot movement given the human operator position measured at the current time instant. This motion planning algorithm is implemented using model predictive control (MPC), which solves a nonlinear constrained optimal control problem in real time (i.e., at each sampling time). This problem consists of minimizing a suitable cost function that accounts for quantities such as the distance of the robot configuration from its reference (to be eventually steered to zero) and the joint velocities (which should not be kept high if not necessary). As for the constraints, they include avoidance of fixed obstacles (i.e., the table surface) and a slightly more conservative version of the SSM constraint defined in (4.3), together with limits on joint angles and velocities. In the following, we will refer to this motion planning strategy with a variable path simply as MPC. MPC is a more "intelligent" version of SSM, which adds the ability to change the robot path to that of modulating the robot speed; in the following, we will be testing if participants would actually perceive this different level of intelligence or not. As this thesis is using the MPC algorithm to study perceived safety and robot perceived intelligence, and the definition itself of the MPC algorithm does not constitute an original contribution, we omit the mathematical details of how the optimal control problem is formulated and numerically solved; the interested reader will find all necessary details in [191]. On the contrary, the variations of the FP and MPC algorithms described in the following section were defined in [2] and are a contribution of this thesis.

It is worth mentioning that the robot path for the FP algorithm is established by running MPC without a human operator present, so that the comparison between the two algorithms can be fair, based on the same baseline motion. In this way, when the human participant is absent, FP and MPC roughly determine the same robot motion and thus have the same productivity.

In order to provide a visual representation of the robot's motions for these two algorithms, one can see in Fig. 4.1 how the robot performs a pick-and-place task by moving a cube from the left to the right of the human operator, with the latter being motionless in the shown position. This figure presents the behavior of the two algorithms and displays the task completion time (for the pick-and-place motion) for each scenario. Specifically, in Fig. 4.1a and Fig. 4.1b, the human was close enough to have an impact on the robot's motion: MPC chose to move the robot slightly away from the human so that it could move faster in accordance with the SSM principle and achieve a lower task completion time, while FP only decreased the robot velocity along its predetermined path. In Fig. 4.1c and Fig. 4.1d, where the human was closer to the robot, FP had to halt its motion after 5 s in order to meet the requirements of SSM. In Fig. 4.1c and Fig. 4.1d, where the human was closer to the robot, FP had to halt its motion after 5 s in order to meet the requirements of SSM; in contrast, MPC built a completely different path, raising the end-effector height during its movement in order to maintain a distance from the human that enabled the robot to finalize its task. Since a human operator must generally move continually to finish a task, when FP is used, the robot motion never

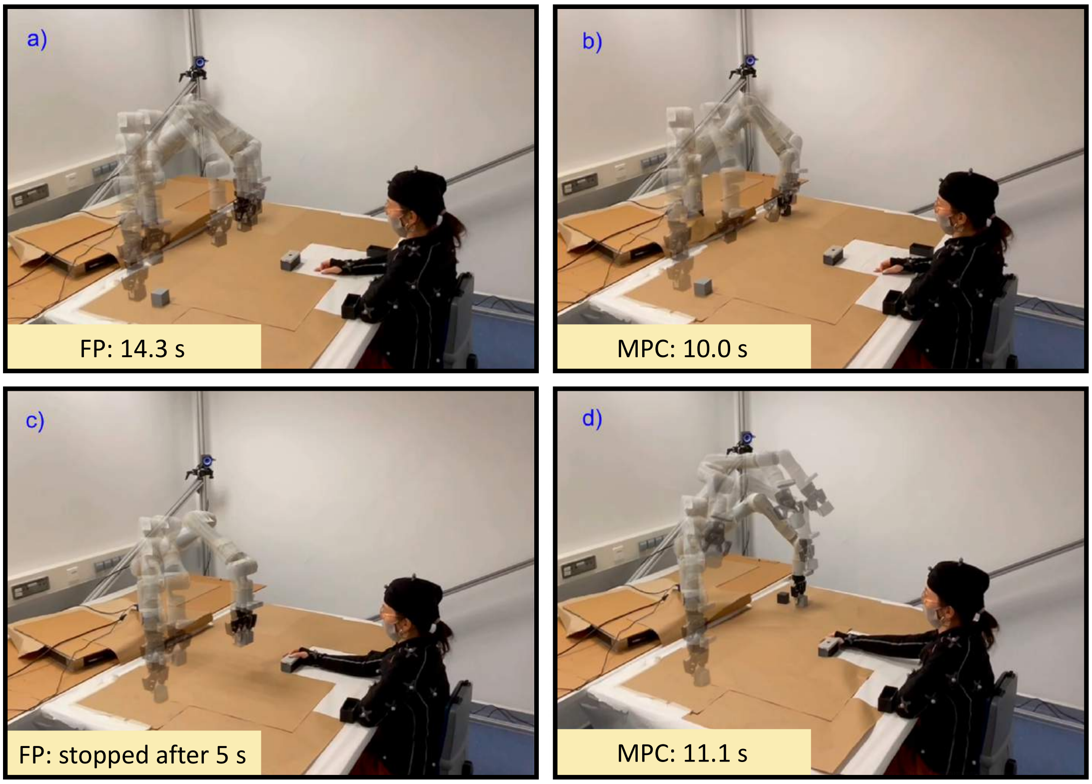

Figure 4.1: Robot trajectory for the human operator's shown in static poses, with the presented numerical value showing the task completion time for the specified pick-and-place operation (from [2]).

totally stops but instead restarts as soon as the space between the person and robot grows once again; however, this may significantly lower robot productivity.

4.3 Heart-rate based motion planning

As already mentioned in Section 2.9.2, decreasing robot speed proportionally to human distance, as done with SSM, can also improve perceived safety because people typically feel safer if the robot velocity reduces with distance, as already discussed in Chapter 2. However, in Chapter 2 it was also noticed that perceived safety can depend on robot speed without considering how far the robot is from the human. Reducing the robot speed at all times to improve perceived safety might not be a good idea, as that would always reduce productivity; however, it might be effective to further slow down the robot if the operator feels nervous, which we did by measuring heart rate (HR). Monitoring the physiological characteristics of the human operator is a real possibility in modern industrial settings because of the accessibility of low-cost sensors built into user-friendly equipment like wristbands.

The Empatica E4 wristband used in our studies provides HR and Galvanic skin response (GSR) measurements with a 1 s sampling period. Preliminary tests with our setup (with GSR measurements) demonstrated that the GSR value steadily grew as the user executed the given task, and the GSR value could not be related to the perception of the robot by the human. The reason for the increasing GSR value depends on a well-known fact: GSR can be significantly affected by muscle contraction, making it challenging to effectively utilize it during scenarios that require a long-term motion of the human [32]. As a result, we made the decision to simply rely on HR, which was also the solution adopted by Pollak et al. in [28].

Since each subject's resting HR value varies between 60 and 100 beats per minute, we decided not to determine the robot speed only based on the HR value; otherwise, the robot would move slower for subjects who have a higher resting HR value. Instead, we chose to base the definition of our *perceived safety index* σ on the HR growth above a baseline level HR_0. The baseline level HR_0 is an average HR value that must be determined for each subject when he/she executes the same task without a moving robot. Thus, ideally, the increase of the HR value measured during the experiments beyond HR_0 should be due to the presence and motion of the robot.

For properly scaling the σ value such that it would usually take values between 0 and 1, we also tried to obtain the value of the difference $\mathrm{HR}-\mathrm{HR}_0$ for which the subject would be reasonably scared or stressed to justify a significant reduction in the robot velocity; this value is referred to in the following as HR_Δ. In order to find this value, we explored the literature on how the HR value changes due to lack of comfort, having human participants watch scary movies [192], watch threatening images [193], perform cognitive tasks [194] and interact with robots [47, 51, 106]. The research by Weistroffer et al. [47], which examined whether human subjects found the presence of robots in assembly lines acceptable, is the one that comes closest to our own. It came up with a value of HR_Δ equal to 20 beats per minute (bpm), and we will use this value for normalization.

Overall, the value of σ will be defined as follows at each sampling instant:

$$\sigma = \max\left\{\frac{\mathrm{HR}-\mathrm{HR}_0}{\mathrm{HR}_\Delta}, 0\right\}. \tag{4.5}$$

The HR value is not supposed to take values below HR_0, but if it did, we would get $\sigma = 0$ in accordance with (4.5). Typically, the value of σ ranges between 0 and 1, with the possibility of times when it exceeds 1, if the HR value takes values higher than $\mathrm{HR}_0+\mathrm{HR}_\Delta$. We chose to use this terminology (i.e., naming σ "perceived safety index") despite the fact that the value of σ is actually inversely related to perceived safety, as inferred by the HR value. The reason for this is that the notion of perceived safety is already well-established in the literature, and a name such as "discomfort index" might not have been immediately understandable.

The value of σ was used to generate two variants of the FP and MPC algorithms, called FP-HR and MPC-HR. In these new motion planning algorithms, after defining a tuning parameter $\gamma \in [0, 1]$, the value of $\bar{v}_i$ for each robot sphere center (defined for FP or MPC) would be instantly replaced with a new value $\bar{v}'_i$, corresponding to

$$\bar{v}'_i = \max \{1 - \gamma\sigma, 0\} \cdot \bar{v}_i. \tag{4.6}$$

A sudden change in the participant's HR value would result in a similarly rapid change in the value of $\bar{v}'_i$; in fact, the resulting modification in the robot real speed would normally occur in less than a second.

There would be minimal variation between the FP and MPC algorithms and their modified variants if the constant coefficient γ had a value that was too small. On the other hand, an excessively high value of γ would significantly lower the robot speed even for a slight increase in HR above HR_0, which might diminish productivity too much. By following a trial-and-error procedure, we choose to select $\gamma = 0.5$ in order to find a middle ground between these two extreme scenarios.

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Chapter 5

Methodology

This chapter provides an explanation of the methodology followed to run the experiments that are at the core of the thesis. It introduces the experimental setup, the experimental procedure, the formulated hypotheses, and the measures defined to confirm or reject them.

5.1 Experimental setup

Figure 5.1 provides an overview of the experimental setup. As a robot manipulator, a Kinova Gen3 was used, which is an ultra-lightweight robotic arm specifically designed for pHRI. The motion planning algorithms were developed for this specific robot on a Linux computer running the Robot Operating System (ROS) that was connected to the robot. This computer was equipped with 16 GB of RAM and an Intel Core i9-7900X

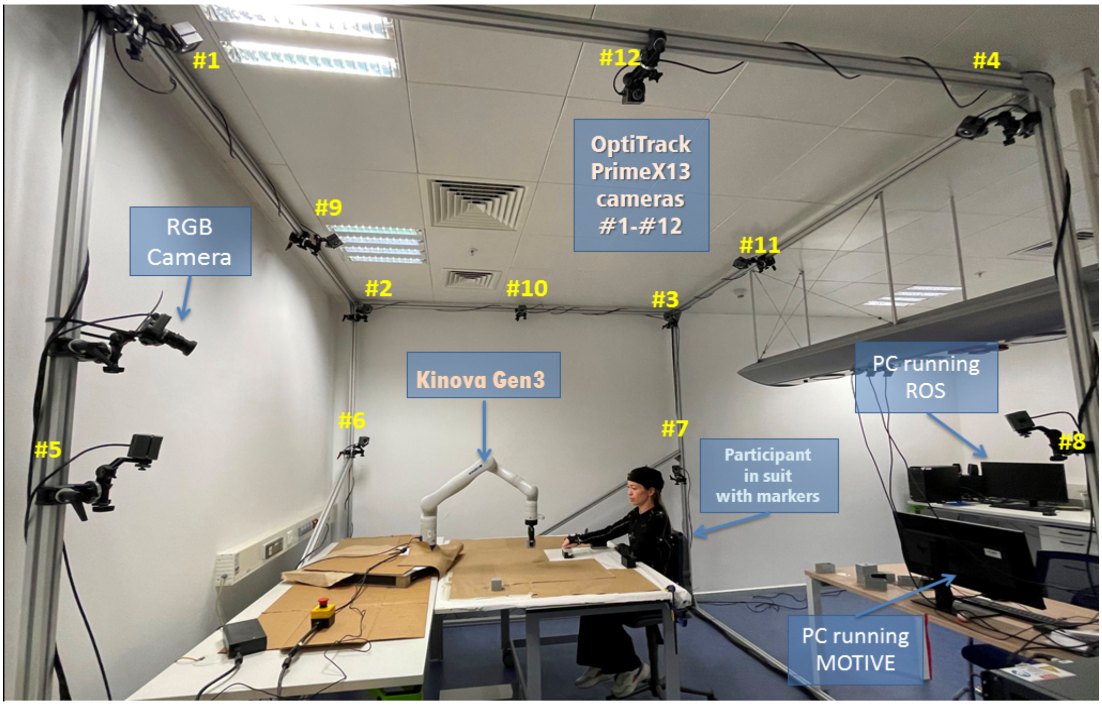


Figure 5.1: Experimental setup. The 12 PrimeX13 cameras, the RGB camera, and the supporting cube frame that make up the OptiTrack motion capture system are shown in this figure. One can see the table inside the cube where the Kinova Gen3 robot is set up and where the human participants, wearing the marker-equipped suit, complete the task given to them.

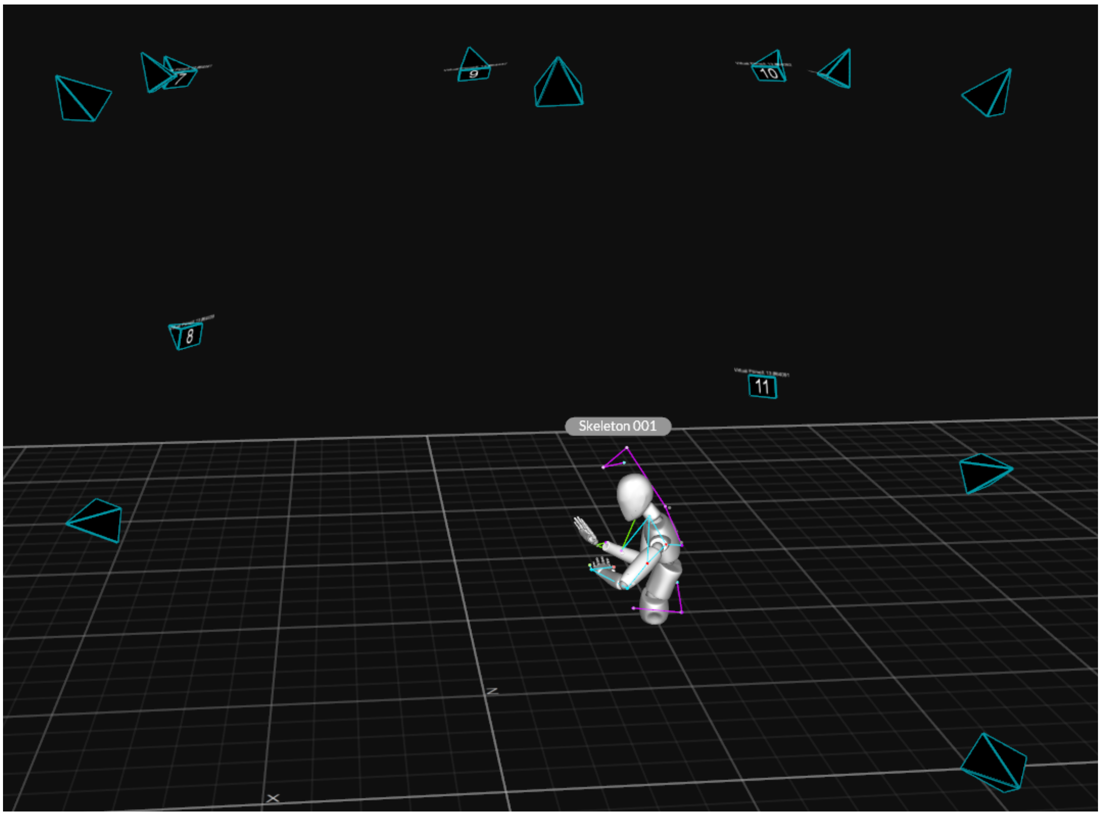


Figure 5.2: Motive software connected to the OptiTrack and analyzed camera input in order to provide global 3D locations, markers, rotational information with respect to the human local reference, and skeletal tracking.

CPU. The operational details in terms of the applied optimization algorithms along with their associated details are unchanged compared to the MPC algorithm described by Oleinikov et al. [191] and are therefore not reported in detail here. The software toolbox ACADO [195] was used to generate a C code to solve the optimal control problems associated with the MPC and MPC-HR algorithms in real time.

An OptiTrack system consisting of 12 OptiTrack PrimeX13 cameras and one RGB camera was used for tracking human movements. The cameras were fixed to a support frame made of aluminum extrusions that were joined to form a robust cube frame. The first step for employing the OptiTrack system in the experimental setup is the calibration process, which is necessary to achieve precise spatial relationships between multiple cameras. The purpose of calibration is to guarantee that the system recognizes the relative locations and orientations of all cameras. Calibration and the tracking processes were executed by the Motive software prior to the experiments. The calibration of the motion capture system was executed with respect to the robot coordinate system with a maximum error (equivalent to the specified measurement precision ϵ_s) of 4 mm and a maximum time delay of 11 ms (consisting of acquisition period and software delays). The Motive software was connected to the OptiTrack device using a specialized Windows PC (also with an Intel Core i9-7900X CPU and 16GB RAM) and acquired

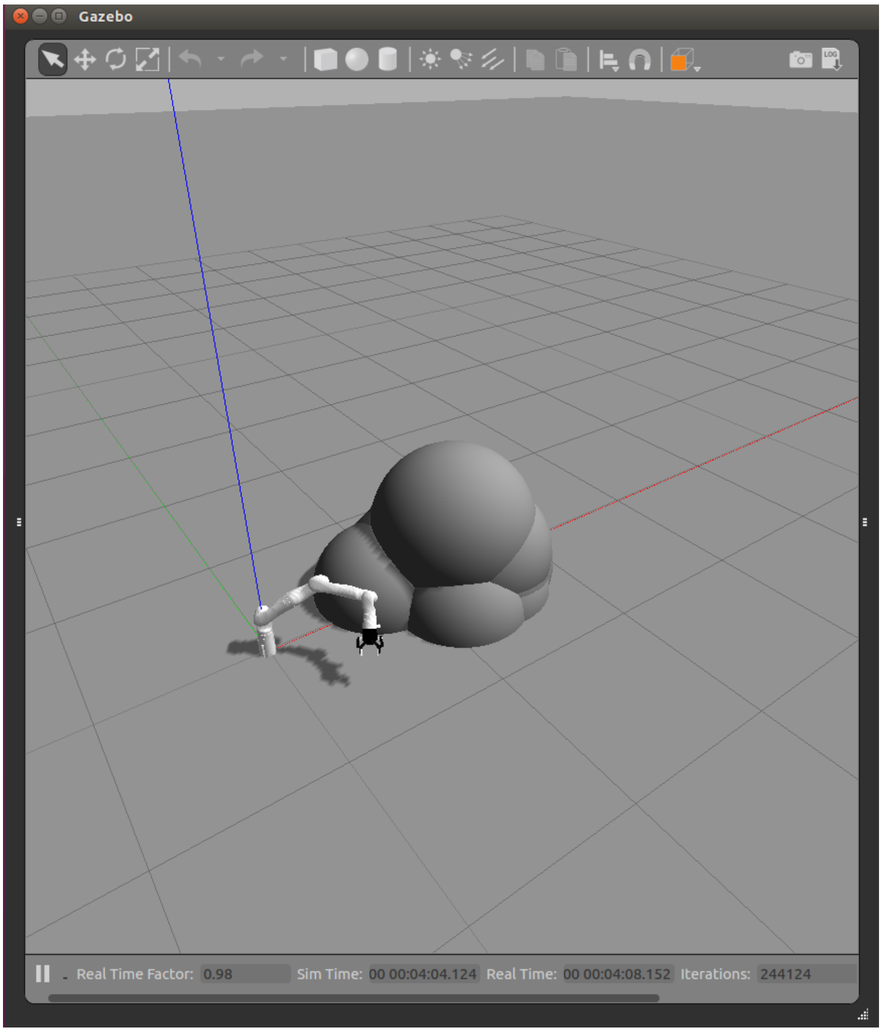


Figure 5.3: 3D simulation in Gazebo of the Kinova Gen3 manipulator and of the human (represented using the virtual spheres mentioned in Chapter 4).

the current human upper-body position in space (Fig.5.2). Each human subject was required to wear a set of markers connected to a special suit (since the OptiTrack system was of the marker-based type), and their positions were identified by the cameras in real time, as shown in Fig.5.4. Motive analyzes the image projections of markers from multiple camera angles, and then uses an advanced algorithm to triangulate their locations. Using this information, it creates a complete 3D reconstruction of the human skeleton. The Windows PC streamed the motion capture data that was received by the ROS machine through the NatNet Client. A 3D simulation in Gazebo of the Kinova Gen3 manipulator exactly replicating the movement from the experimental setup and of the human is shown in Fig.5.3.

The aforementioned Empatica E4 bracelet (shown in Fig.5.5, Bluetooth-enabled with an app called "E4 realtime") was used to collect HR data. The ROS machine was linked to the E4 real-time software through a TCP/IP interface, and it continuously updated the HR value. A photoplethysmography sensor inside the wristband monitored the blood

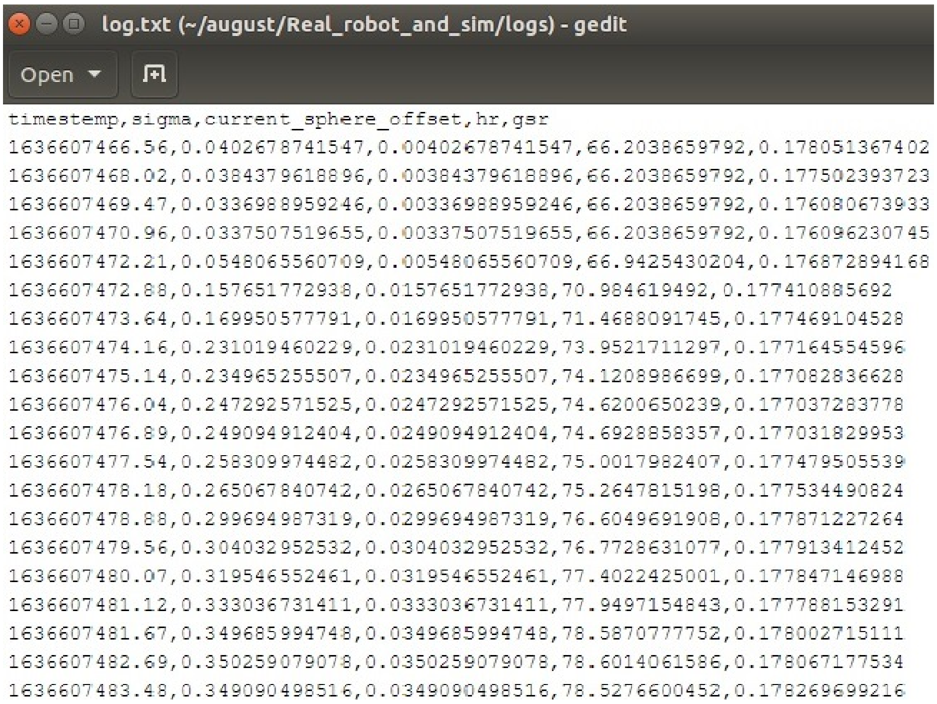
Figure 5.4: The scheme for attaching markers to the costume of the participant in the experiment in the Motive application.

volume pulse, from which it determined the interbeat interval (IBI). The wristband built-in algorithm immediately eliminated invalid IBIs [196]. To lessen the potential impact of measurement noise in our trials, the resultant HR value was low-pass filtered through a three-sample moving average filter. The example of the resulting log file is shown in Fig.5.6.

5.2 Experimental procedure

There were 48 individuals who participated in a within-subject experiment, including 18 men and 30 females, between the ages of 18 and 38 (24.98 ± 5.289, where 24.98 is the mean age and 5.289 is the standard deviation). They were all either Nazarbayev University employees (managers, laboratory technicians, and administrative staff) or students (either undergraduate or graduate students in robotics, psychology, education,

Figure 5.5: E4 wristband.



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1636607483.48,0.349090498516,0.0349090498516,78.5276600452,0.178269699216
```

Figure 5.6: The figure displays a screenshot of the Log.txt file obtained from the E4 wristband with the timestamp, HR, and GSR data.

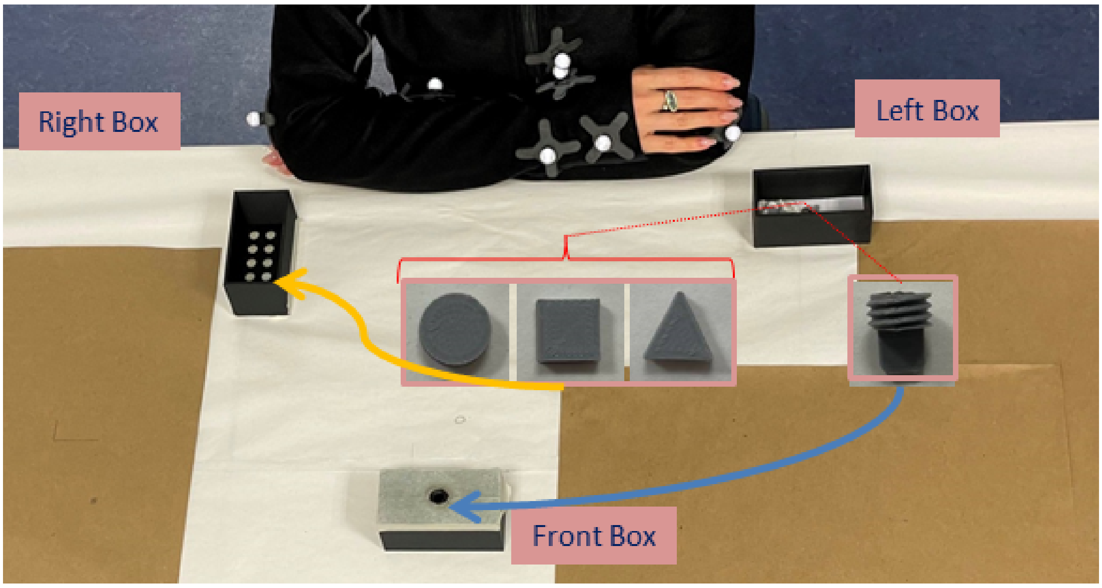

Figure 5.7: The figure displays a detailed view of the task. There is a box on the left where the pieces are stored. The box for the triangle, square, and circle pieces is placed on the right. The box for placing the screw is located in front of the human participant.

or chemistry). Each individual engaged with the robot while interacting in four circumstances (FP, MPC, FP-HR, and MPC-HR algorithms). To prevent an ordering effect, we carefully counterbalanced the conditions; more specifically, each of the 24 possible sequences of the four motion planning algorithms was executed exactly for two participants.

Each participant took part in a single session that lasted for approximately 30-40 minutes. Each participant read and signed the consent form and completed a pre-experiment questionnaire that asked about their age, attitude toward sharing workspace with robots, and prior experience working with robots. Then the subject was shown a video of the task to be completed. After that the experimental session started. The subject would sit in the chair shown in Fig. 5.1 while wearing the OptiTrack suit with markers and the E4 wristband on the left arm.

The task for humans that was previously explained in the video is shown in Fig. 5.7. The task included selecting one of four different types of small elements (a screw, triangle, square, or circle) from a box to the left side of the participant and either inserting it in the box to the right (for triangles, squares, and circles) or screwing it into the box in front of the participant using the right hand while keeping the left arm in a resting, motionless pose. This task explanation is suitable for right-handed respondents. The terms “left” and “right” in the task description must be switched for the left-handed subjects.

The experiment task was designed so as to replicate, in an idealized and simplified way, a manufacturing task involving human-robot workspace sharing. When the human was inserting a small piece into the box in front of him/her, the robot at that time had chance either to avoid the human hand, or to stop, depending on the running algorithm, as was mentioned before. These different robot behaviors were supposed to be rated by the human participants as more or less intelligent and safe, depending on the subjects' perception about the robot.

The considered task can be seen as a simplified version of an assembly scenario within a factory. For example, factory workers might be assembling parts of a car engine while a manipulator works on different parts of the same engine. Alternatively, one can think about a human operator sorting boxes in a warehouse, while the robot executes a similar task in the same shared workspace.

The task was executed for a period of 4 minutes for each motion planning algorithm. Before running the task with the moving robot, the average HR value was recorded during the execution of the task for 4 minutes without the moving robot, and this average value was assigned as HR_0 value to the participant. After a brief pause, the participant would perform the same activity for 4 minutes while the robot carried out its pick-and-place task using one of the four motion planning algorithms mentioned earlier. The robot would move cubes from the participant's left to right sides, and vice-versa. The participant would complete a questionnaire regarding their perception of the robot throughout the experiment at the end of the four minutes; the specific questions will be detailed in Section 5.4. During this activity (lasting about one minute), a new value for HR_0 would be established in order to account for the possibility that performing the task might slightly increase the participant's HR baseline, which cannot be ascribed to stress but only to physical activity. Then, another experiment with a different algorithm would be executed, and a related questionnaire would be completed. As a result, all four algorithms would be performed on one subject. At the end of the last questionnaire, each subject was requested to sort the four algorithms from the safest to the least safe.

Prior to running the experiments, several manipulation checks were performed. During these tests, we found out that the skin conductance was increasing because the human was moving his/her hand while executing the task, not because of feeling unsafe or uncomfortable. That was the reason to eliminate the skin conductance from the biological signals detection measure for our experiments as was stated in Section 2.3. Next, the human felt tired when executing one experimental set for 5 minutes, so we shortened it to 4 minutes, and gave some short break for one minute for the subjects to have a rest. After different trials, the box where the screws had to be inserted was placed on the table in front of the human on a distance that was comfortable, at the same time making the robot deviate from its original trajectory (in case of MPC or MPC-HR) or stop (in case of FP or FP-HR), in order to make the difference between FP and MPC more obvious for the humans.

The Nazarbayev University Institutional Research Ethics Committee (NU-IREC), which follows the guidelines outlined in the report "Ethical Principles and Guidelines for the Protection of Human Subjects of Research" ("Belmont Report"), approved the experimental procedure that was followed for all 48 subjects. An application for NU-IREC's approval titled "Experiments on human-robot workspace sharing" was approved on June 20, 2021. All participants provided a written informed consent form.

5.3 Hypotheses

In the following, we formulate our hypotheses based on the experiment's outcomes. Although the main focus of this work is on perceived safety and robot perceived intelligence, the first hypothesis is related to productivity. Indeed, it is important to assess the productivity of the algorithms used, as, for example, an improvement in perceived safety also has to be assessed against the variation in productivity for the same algorithm. Indeed, an algorithm that improves both productivity and perceived safety is a very good candidate for being implemented in industrial practice; on the other hand, an algorithm that improves perceived safety but worsens productivity has to be carefully considered based on the specific application. Given the provided description of the employed motion planning algorithms, it may be predicted that the robot will achieve higher productivity when it is able to move continuously, redefining its motion in real time (i.e., in the case of MPC or MPC-HR), compared to the case in which it often has to stop due to human presence without being able to modify its path (i.e., in the case of FP or FP-HR). Also, the decline of the robot speed based on HR data is likely to decrease productivity. Based on this reasoning, the following hypothesis was formulated:

H1: a) robot productivity with MPC is higher than with FP;
b) robot productivity with MPC-HR is higher than with FP-HR;
c) robot productivity with FP is higher than with FP-HR;
d) robot productivity with MPC is higher than with MPC-HR.

The next three hypotheses are instead related to perceived safety. The HR-based variants of the algorithms were defined with the aim of improving perceived safety. Indeed, based on the results from the literature reported in Chapter 2, if the robot speed decreases due to an increase in the HR value, we expect the human participants to perceive the robot as safer. Therefore, we formulated the following hypothesis:

H2: a) perceived safety with FP is higher than with MPC;
b) perceived safety with FP-HR is higher than with MPC-HR;
c) perceived safety with FP-HR is higher than with FP;
d) perceived safety with MPC-HR is higher than with MPC.

Furthermore, when participants interact with the robot for a longer time and become aware of the fact that the robot motion is safe (regardless of the algorithm employed), their perception of safety should improve. This leads to formulating the following hypothesis:

H3: perceived safety increases with time within the same experimental session due to habituation.

The third hypothesis on perceived safety is related to the previous experience that participants might have with working with robots. Similarly to what we formulated for H3, we expected that accumulated experience (as long as the participant did not have negative experiences, e.g., getting injured) should increase comfort during pHRI experiments. Therefore, we formulate the following:

H4: perceived safety increases proportionally with previous participants' experience interacting with robots.

The final three hypotheses are related to perceived intelligence. We expected that the MPC algorithm would be perceived as more intelligent by the participants in contrast to the FP algorithm since it can modify the robot path when necessary. The comparison of MPC-HR with FP-HR would also follow the same logic. Additionally, we believed that the HR-based speed modulation would make the robot perceived as more intelligent compared to the regular versions of the same algorithms for both the FP-HR and MPC-HR scenarios; the reason for this is that the participants might understand that the robot slows down when their HR increases. The following was thus formulated:

H5: a) perceived intelligence with MPC is higher than with FP;
b) perceived intelligence with MPC-HR is higher than with FP-HR;
c) perceived intelligence with FP-HR is higher than with FP;
d) perceived intelligence with MPC-HR is higher than with MPC.

As already mentioned, in our experiments, participants were exposed to different motion planning algorithms executed by the robot in sequence, without knowing what algorithm the robot was currently executing. If a single algorithm had to always be used, two outcomes would be possible: (i) if the behavior of the robot can be explained by straightforward principles, over time humans will come to realize these rules and eventually consider the robot as less intelligent; (ii) if the robot shows a complicated behavior, humans will gradually understand it and will judge the robot as more intelligent as time passes. Each trial set in our research utilized a different algorithm, but because their order was counterbalanced and the robot behavior was generally highly complex, we anticipated effect (ii) to be present (also based on the conclusions of Chapter 3), so we made the following hypothesis:

H6: perceived intelligence increases with the number of the experimental set.

Finally, we were interested in determining how participants' prior experience interacting with robots affected their perceptions of robot intelligence. On the one hand, more knowledgeable human subjects may be able to quickly figure out the nuances of the motion planning algorithms and judge the robot to be intelligent. On the other hand, the same respondents may have had lower overall assessments of perceived intelligence if they had higher expectations for the robot's intelligence. Assuming that these two effects counterbalance each other, we may expect that prior experience has no bearing on how intelligent the robot is perceived:

H7: perceived intelligence does not vary with the previous experience of participants interacting with robots.

5.4 Measures

The following independent and dependent variables were considered to test the formulated hypotheses.

Independent variables:

- The *motion planning algorithm* and the *order of execution* of each algorithm within each experiment: both choices were made by the scientist conducting the experiment.
- The *previous experience* of the subject, which came from the pre-experiment questionnaire as a response to the question: "Have you ever worked/interacted with a robot?". Response options were (4) "I work with robots", (3) "often", (2) "once or twice", or (1) "never".

Dependent variables:

- The *robot productivity*, which was indirectly evaluated using the average task completion time (ATCP). This value indicates the mean duration of the time frame – within a period of time equal to 4 minutes – which the robot needed to move a cube from its rest location to its target place. The ATCP value was solely dependent on the applied algorithm and the movements of the subject, since the distance between these positions remained nearly constant. The ATCP is inversely linked to productivity because this indicator suggests that fewer pick-and-place activities will be performed in the same amount of time with a large ATCP.
- Two 5-point Likert scales for response to the pre-experiment questionnaire – "I would feel nervous while interacting with the robot (with answers: 1-strongly

disagree to 5-strongly agree)” and “I would feel nervous while sitting in front of the robot (with answers: 1-strongly disagree to 5-strongly agree)” – which were combined by averaging the scores; the resulting scale was called *pre-experiment nervousness*. The Negative Attitude Towards Robots (NARS) questionnaire [142] was the basis for these questions, with slight modifications. In particular, the first question is an adjusted version of NARS item 8 ("I would feel nervous operating a robot in front of other people"), changed to take into consideration that the human participants did not operate the robot, instead they physically collaborated with it; the second question is an adjusted version of NARS item 10 ("I would feel very nervous just standing in front of a robot"), modified to account for the fact that the subjects in our study would be sitting instead of standing when answering the question.

- The *perceived safety* experienced by the participant. This was measured by five distinct measures (three subjective and two physiological), and precisely:

  1. The *average HR* value within a period of 4-minutes. A higher *average HR* value is an indicator of higher physiological stress [28] for the same subject. This tendency indicates lower perceived safety.
  2. The *average* σ within a period of 4-minutes. There is a relationship between this measure and the previous one, but there is no 1-to-1 correlation between the two.
  3. Two 5-point Likert scales for response to the post-experiment questionnaire – “I felt nervous while interacting with the robot (1-strongly disagree to 5-strongly agree)” and “I felt nervous while sitting in front of the robot (with answers: 1-strongly disagree to 5-strongly agree)” - merged by averaging the rates (Cronbach’s $\alpha = .87$) [197]. It resulted in a single scale named *nervousness*. This is the post-experiment version of the *pre-experiment nervousness* rate shown above.
  4. Two 5-point semantic differential scales to answer the questions “Please rate your emotional state on this scale” from “anxious” to “relaxed” and from “calm” to “stressed” were merged by averaging the rates (Cronbach’s $\alpha = .844$). These questions form a subset of those in the Godspeed questionnaire on perceived safety [30] that substituted the original term "agitated" with the term "stressed". It was done because we considered the participants, who were all non-native English speakers, would understand it better. The resulting differential scale (DS) was called *perceived safety DS* for simplification.
  5. The *ranking* of the experienced robot motions, as a response to the question “Sort the four experiments (1-4) from the one in which you felt the safest to

the one in which you felt the least safe”, that was asked to the subjects at the end of the whole experimental session.

- The robot *perceived intelligence*, obtained in the post-experiment 5-point semantic differential scale questionnaire - “Please rate your impression of the robot on these scales:“ from “non-intelligent” to “intelligent”.

Chapter 6

Results and discussion

This chapter provides the results of the statistical analysis of the results of the experiments whose methodology was described in Chapter 5. A more detailed account of the data related to these results is given in Appendix A. To evaluate the assumption of normality, a set of Kolmogorov-Smirnov (K-S) and Shapiro-Wilk tests [198] overall and within groups were performed on all dependent variables. We primarily focus on presenting significant differences (defined by a p-value satisfying the condition $p < 0.05$). We provide data on the central tendency and dispersion as (mean $\pm$ standard deviation) for each dataset that is discussed. Since the majority of scores were not normally distributed, a series of Friedman tests [199] was used for the statistical data analysis. When data were normally distributed, one-way and two-way repeated measures ANOVA tests [200] were used. Mauchly's Test of Sphericity [201] was conducted, and when the assumption of sphericity was violated, a Greenhouse-Geisser correction [202] was used. The results are then discussed.

6.1 Results on robot productivity (H1)

A Friedman test was run on the ATCP values (inversely proportional to productivity) to verify H1. Between different algorithms, there was a statistically significant difference in *robot productivity*: $\chi^2(3) = 127.575$, $p < 0.001$. The robot was significantly less productive with FP (19.99 ± 2.87) than with MPC (11.76 ± 0.78): $\chi^2(1) = 48.000$, $p < 0.001$, as shown in Fig. 6.1a.In addition, productivity was significantly higher with MPC-HR (13.50 ± 2.10) than with FP-HR(22.64 ± 4.61): $\chi^2(1) = 48.000$, $p < 0.001$. We can thus accept H1a and H1b.

The productivity results with FP (19.99 ± 2.87) was significantly higher than productivity with FP-HR (22.64 ± 4.61): $\chi^2(1) = 16.333$, $p < 0.001$, productivity with MPC (11.76 ± 0.78) obtained significantly higher productivity than with MPC-HR (13.50 ± 2.10): $\chi^2(1)$ =30.083, $p < 0.001$. So, H1c and H1d are accepted.

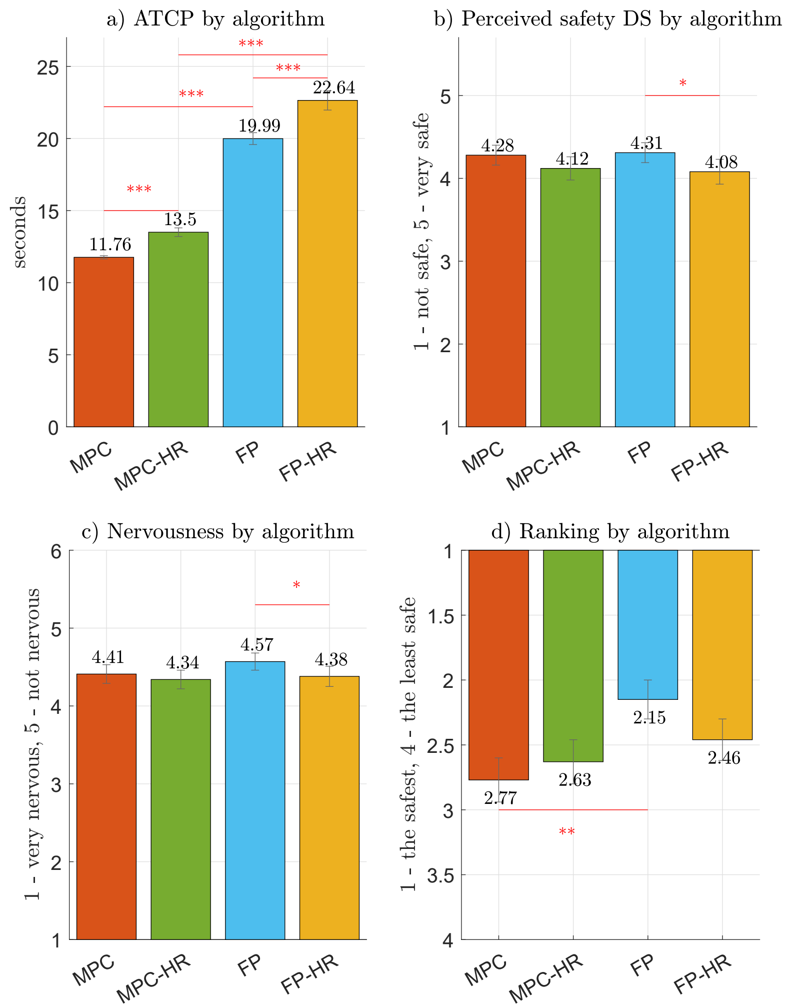

Figure 6.1: Mean values for different motion planning algorithms: a) ATCP (inversely proportional to *robot productivity*); b) *perceived safety DS*; c) *nervousness*; d) *ranking*. Significance levels for pairwise comparisons are indicated as * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$. The error bars display the standard deviation (from [2]).

6.2 Results on perceived safety (H2, H3 and H4)

6.2.1 Perceived safety with different algorithms (H2)

A set of Friedman tests were run on the *perceived safety* measures mentioned in Section 5.4 in order to assess H2. The *average HR* and *average* σ values, corresponding to physiological measures, did not show significant differences amongst algorithms.

Between FP and FP-HR, there was a statistically significant difference in how individuals evaluated *perceived safety DS*: $\chi^2(1) = 4.172$, $p = 0.041$. Participants evaluated their level of *perceived safety DS* for the FP algorithm (4.31 ± 0.83) substantially higher than they did for FP-HR (4.08 ± 1.05), as demonstrated in Fig. 6.1b.

The *nervousness* measure was then analyzed using a number of Friedman tests. Between FP and FP-HR, there was a statistically significant difference in the *nervousness* score: $\chi^2(1) = 3.857$, $p = 0.049$. Similarly to *perceived safety DS*, we discovered a significant difference between the two FP-based algorithms, with or without HR-based speed modulation, since FP (4.57 ± 0.78) was considered to make participants feel less nervous than FP-HR (4.38 ± 0.90), as shown in Fig. 6.1c.

Furthermore, a Friedman test showed significant differences in *ranking* between MPC and FP (Fig. 6.1d): $\chi^2(1) = 8.333$, $p = .004$. MPC (2.77 ± 1.12) was rated as the least safe algorithm, with FP (2.15 ± 1.01) being the one that generated the safest robot motion.

In conclusion, we can reject H2b-d and partially accept H2a as indicated by the *ranking* measure.

6.2.2 Effect of habituation (H3)

We studied the *perceived safety* distribution based on the order in which each of the four subsequent robot motions was executed, regardless of the applied motion planning algorithm. As was mentioned before, each motion was executed for 4 minutes, and all achievable sequences were tested among 48 participants.

A Friedman test showed a statistically significant difference in *perceived safety DS* based on the sequence of execution: $\chi^2(3) = 9.572$, $p = 0.023$. According to Fig. 6.2a, there was a statistically significant difference between the first and second robot motions ($\chi^2(1) = 10.800$, $p = 0.001$), and between the first and third motions ($\chi^2(1) = 4.235$, $p = 0.040$).a. The first robot motion's *perceived safety DS* rating (3.91 ± 0.15) was significantly lower than that of the second (4.27 ± 0.11) and third (4.30 ± 0.12) motions.

The nervousness measure was then subjected to several Friedman tests. The difference between the first and fourth robot movements on the nervousness scale was statistically significant ($\chi^2(1) = 3.846$, $p = 0.049$). The first robot motions caused participants to feel significantly more nervous (4.24 ± 0.14) than the fourth robot motions (4.58 ± 0.11) (Fig. 6.2b).

We can accept H3 as supported by subjective measures such as *perceived safety DS* and *nervousness*.

6.2.3 Effect of previous experience with robots (H4)

To test H4, we divided the participants into two groups based on their prior experience: inexperienced (those who answered "never" or "once or twice" to the question "Have you ever worked/interacted with a robot?") and experienced (those who answered "often" or "I work with robots" to the same question). 34 individuals were classified as being inexperienced, and 14 as being experienced. H4 is rejected because there was no statistically significant difference between the groups for either the algorithms or the order of execution.

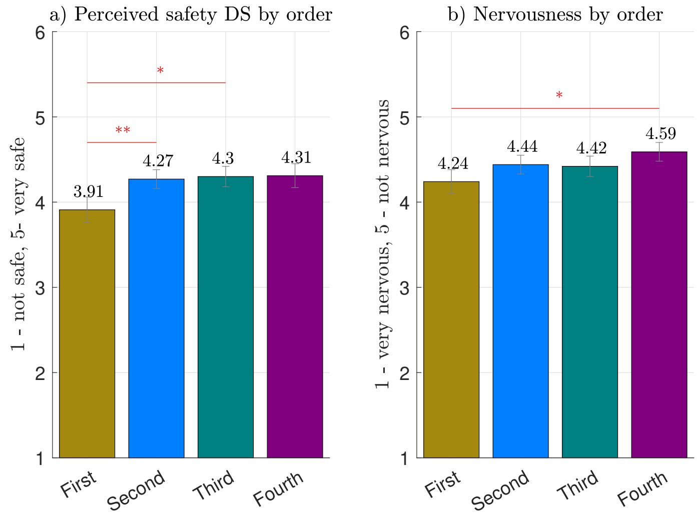

Figure 6.2: Mean values based on the order of execution: a) *perceived safety DS*; b) *nervousness*. Significance levels for pairwise comparisons are indicated as * for $p < 0.05$, ** for $p < 0.01$, and *** for $p < 0.001$. The error bars display the standard deviation (from [2]).

It is worth noticing that the information on *pre-experiment nervousness* obtained in the pre-experiment questionnaire never provided any significant results regarding its relationship with the variables obtained from the questionnaires filled out after the experimental sessions.

6.3 Results on Perceived Intelligence (H5, H6 and H7)

6.3.1 Perceived intelligence with different algorithms (H5)

To evaluate the assumption of normality, a series of Kolmogorov-Smirnov (K-S) and Shapiro-Wilk tests were run on the *perceived intelligence* scale from the post-experiment questionnaire.

The motion planning algorithms MPC (3.92 ± 1.048), MPC-HR (3.75 ± 1.021), FP (3.94 ± 1.080), FP-HR (3.85 ± 1.072) resulted in no significant difference in *perceived intelligence* scores, according to a Friedman test: $\chi^2(3) = 1.090$, $p = 0.780$. In Fig. 6.3a, the resulting mean values and standard errors are displayed. Thus, we concluded that H5 is not supported by our experimental data.

6.3.2 Effect of habituation (H6)

A Friedman test used to assess H6 showed a significant difference in *perceived intelligence* depending on the order in which the algorithms were run: $\chi^2(3) = 8.202$, $p = 0.042$. As can be seen in Fig. 6.3b, there was a minor statistically significant difference between the first and second motion $\chi^2(1) = 3.571$, $p = 0.058$, the first

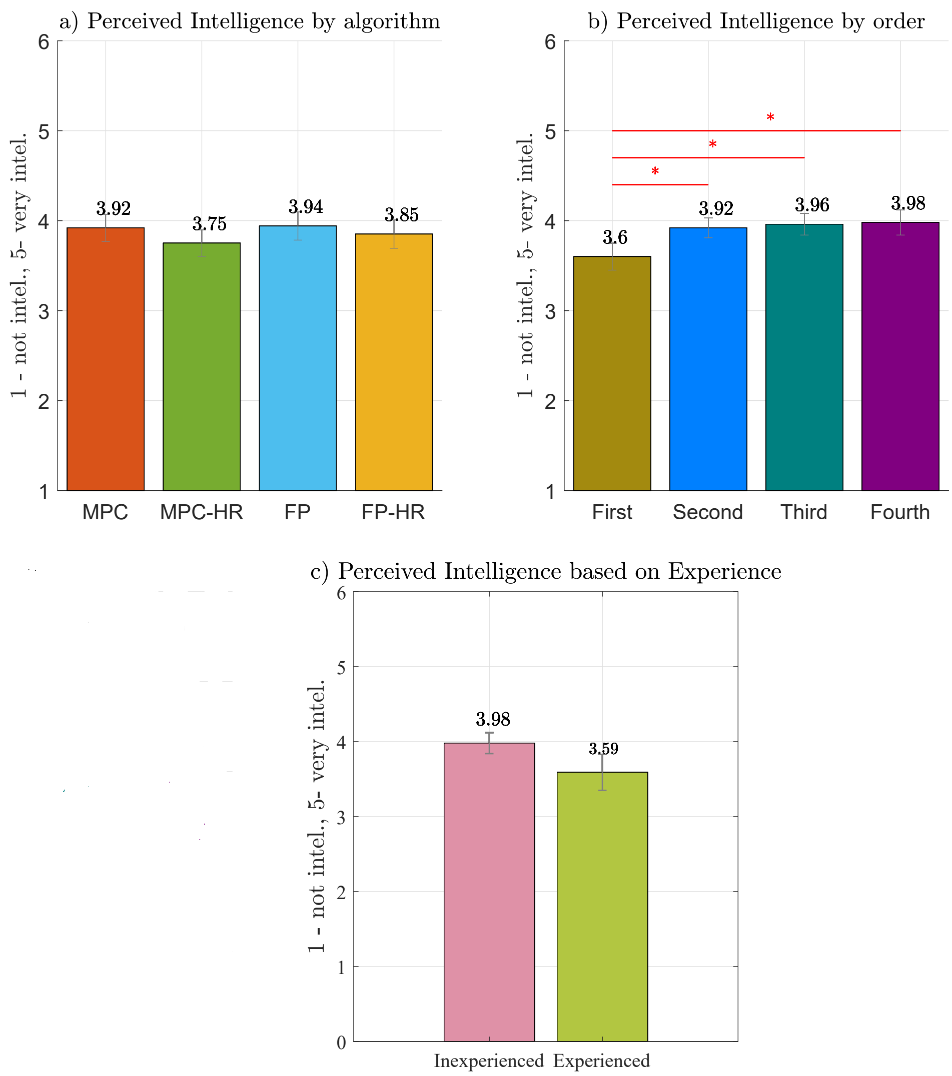

Figure 6.3: Mean values of Perceived Intelligence a) between algorithms irrespective of their execution order, b) between algorithms depending on their execution order and c) based on the participant's previous experience. Significance levels for pairwise comparisons are indicated as * for $p < 0.05$ (from [3]).

and third motions: $\chi^2(1) = 6.000$, $p = 0.014$, and the first and fourth motions: $\chi^2(1) = 5.261$, $p = 0.022$. When compared to the second (3.92 ± 1.028), third (3.96 ± 1.051), and fourth (3.98 ± 1.120) robot motions, the perceived intelligence of the very first (3.60 ± 0.984) motion was much lower. H6 was therefore approved.

6.3.3 Effect of previous experience with robots (H7)

In order to test H7, we divided the participants into the same two groups (experienced and inexperienced) that had already tested H4. According to one-way ANOVA (see Fig. 6.3c), there was no statistically significant difference between the two groups based on *previous experience* with the robot ($F(1, 46) = 2{,}057$, $p = 0.158$).

6.4 Discussion

6.4.1 Productivity

Our findings completely confirm H1. Regarding H1a and H1b, we would like to point out that not every type of human motion would lead to a higher performance of MPC over FP (and of MPC-HR over FP-HR). In fact, changing the robot's path based on the present location of the human is only convenient when the human blocks the robot's movement over a relatively long period (of at least a few seconds). In the case of very fast human motion, for example, with the participant approaching the robot only to quickly pick up an object, the strategy put in place by FP (i.e., just slow down and wait for the human to move away) could achieve a higher level of productivity than defining a new robot motion, as done by MPC. Indeed, the new motion would lead to a longer robot path, which might not be beneficial when the human blocks the shorter path followed by FP only for a very short time interval. Instead, as the robot velocity reduces in MPC-HR with respect to MPC and in FP-HR with respect to FP, we can confidently predict that the productivity of the HR-based algorithms will never be greater than that of the algorithms without an HR-based speed decrease. As a result, we anticipate that H1c and H1d will always be confirmed, regardless of the specific human motion.

6.4.2 Perceived safety with different algorithms

One of our subjective assessments (ranking) led us to accept H2a, indicating that FP had a greater perceived level of safety than MPC. While the robot in the MPC scenario occasionally was generally more unpredictable and moved more rapidly (it could move faster, being able to remain at a larger distance from the human, based on SSM), the robot in the FP case moved along a fixed trajectory by specification and at a slower speed. Both characteristics are generally linked to increased perceived safety in the robotics literature [40, 41, 53, 107, 112], as discussed also in Chapter 2. As a result, this finding correlates with earlier research results. Despite the rejection of H2b-d, we discovered a different pattern in the connection between the *perceived safety* ratings in FP and FP-HR. Indeed, both *perceived safety DS* and *nervousness* indicate that people generally perceive FP to be safer than FP-HR. This could be because the robot's average slower velocity during FP-HR also resulted in more frequent pauses, which increased the participants' anxiety and nervousness.

A notable observation that combines the results of H1 and H2 is that implementing the HR-based speed reduction in both FP or MPC does not result in any positive outcome, at least based on our trials, as it reduces productivity and has no effect on perceived safety (or, for FP, even worsens it). As was already indicated, the decline in productivity was mostly predictable because using HR-based techniques slows down robot speed. The lack of influence of HR-based speed modulation on perceived safety was instead unexpected. In order to better understand this aspect, we explored the literature to see if similar results were obtained in the past.

Unfortunately, there are few published studies where robot behavior is changed in real time in response to physiological feedback from humans [203–206]. Only Kulic and Croft's work [206] examines how a person and a manipulator interact, making it the only one whose findings can be compared to ours. So-called medium-term and short-term planners were used to plan the robot's motion at three separate levels (long, medium, and short term) and were affected by physiological feedback. A danger index was calculated based on the current position and velocity of the robot and the human, as well as the human's head orientation and the physiological assessment of the affective state, reducing the robot speed in proportion to the detected level of anxiety. Kulic and Croft's experiment results [206] analyzed the implications of this additional speed decrease on robot movements, but they did not assess the impact that adding this component to the motion planning algorithms had on the participants' perceived safety. Even so, the robot used by Kulic and Croft was an industrial manipulator, and the motion of the robot was not designed using SSM, which was developed a few years later: its motion without speed reduction would have, as a consequence, resulted in a rather "scary" experience for the participants. Therefore, we would expect that in their approach, if perceived safety had been measured, it would have improved when speed reduction occurred. On the contrary, in our case, the robot was already lightweight (being a cobot) and moved relatively slowly, even without HR-based speed reduction, in order to satisfy the SSM requirements. As a consequence, the further reduction in speed might not have been perceived as improving safety, as the MPC and FP motions were already perceived as safe.

6.4.3 Perceived intelligence with different algorithms

According to the obtained results, there was no significant difference in the perceived intelligence ratings of the four algorithms and the user's previous experience with robots. We were surprised to find that, despite the differences among the various algorithms, there was not a significant difference in perceived intelligence in H4. Indeed, as discussed in Chapter 3 (specifically, in Section 1), adaptability is a major factor that influences the perceived intelligence of an intelligent agent, although this factor was never specifically studied in the past for robots. It is possible that this occurred because even the most basic algorithm (FP) produced a relatively complicated robot motion (for instance, applying the SSM conditions). Additionally, FP made it more obvious to the subjects that the robot would reduce its speed when it came close to the participant's body. This may not have been the case when using MPC, as the robot would always change its path, thus making it more difficult to infer when and why it would change its speed. As a result, the perceived intelligence of MPC and MPC-HR may not have differed significantly from FP and FP-HR due to the difficulty in comprehending the complicated behavior of these algorithms, which may have compensated for their real higher level of complexity. The fact that participants generally did not understand how robot speed varied based on the HR value may have contributed to the lack of variability in perceived intelligence when applying the HR-variant of the algorithms.

6.4.4 The effect of habituation

Based on subjective measurements, our findings show the impact of habituation on perceived safety. This outcome confirms H3, and it is consistent with findings from the robotics literature, including [39, 40, 89, 93], as participants frequently become adapted to the experimental setting and the movements of the robot.

The finding of significance also concerned the impact of habituation on the perceived intelligence rate, which may have been caused by the fact that, at least according to the participants' expectations, the robot behavior was generally non trivial to understand. Participants would therefore rate the robot as more intelligent as they came to understand the rules that controlled its behavior. This result is in line with the general trend in the literature discussed in Chapter 3. In particular, the majority of studies found no significant change in perceived intelligence due to habituation. A few studies were instead pointing towards a significant increase in perceived intelligence due to habituation, and the result in this thesis provides a further element in this direction.

6.4.5 The effect of previous experience with robots

Even though earlier studies [85, 142] suggested that prior robot experience would affect participants' perceptions of safety, this was not supported by our study. This is probably due to the robot's very low velocity, mass, and size, as well as to the fact that all of the developed algorithms are safe according to the ISO/TS 15066 standard. This factor reduced the disparities between experienced and inexperienced people by enabling novice participants to quickly adapt to physically interacting with the system.

As was expected, the perceived intelligence ratings of the robot were not affected by previous experience with the robot, which confirmed H7. Unfortunately, we did not find any previous works where any correlation between experience and perception of robot intelligence was studied to compare with our findings.

Chapter 7

Conclusions

In this final chapter, we summarize the thesis content focusing on the research questions defined in Chapter 1. An overview of possible future work is also provided.

7.1 Addressing the research questions

The first research question focused on how perceived safety and perceived intelligence change if the robot path is either fixed or modified in real time based on the current human position. Participants ranked the fixed-path motion planning algorithm FP as safer than the variable-path MPC algorithm – based on the *ranking* measure – which led to accepting H2a ("perceived safety with FP is higher than with MPC"). This was expected, due to the relatively higher speed and lower predictability of MPC as compared to FP; indeed, these two factors were described in the literature – in [7, 31, 35, 40, 41, 43, 45, 60] and [49, 53, 56, 57, 59, 60], respectively – as influencing perceived safety for robots in general and for manipulators in particular (see also Section 2.9.1). On the other hand, the FP-HR algorithm was not perceived as safer than MPC-HR, and this could be explained by the lower speed of the robot for both algorithms, which might have made their differences less apparent. Regarding perceived intelligence, there was no significant difference between the four algorithms. This might have happened because even the most straightforward algorithm (FP) generated a somewhat complex robot motion following the SSM requirements; as a consequence, the ability of MPC to modify the robot path was not perceived as an additional level of intelligence, also due to lack of transparency, as the participants were not aware of the implemented algorithms.

The second research question directed its attention to the difference in perceived safety and perceived intelligence between the case in which the robot speed is decreased in real time based on the HR measurement value, and the case in which this does not happen. The expected outcome of higher perceived safety and perceived intelligence when the HR variant of the algorithms was used was not confirmed by the experimental results. In particular, no significant result was obtained, apart from one case: specifically, when the FP algorithm was used, the robot was rated as safer than when the FP-HR variant was run, which contradicted our expectations. This might be explained by the frequent robot pauses that happened in the FP-HR case, which increased the participant's nervousness. In terms of perceived safety, this general outcome might be due to the fact that the robot motion was already perceived as safe using either MPC of FP, without their HR-based versions. In terms of perceived intelligence, the same considerations reported for the first research question apply.

The third research question asked how perceived safety and perceived intelligence change due to habituation. Habituation led to a significant increase of both perceived safety and perceived intelligence, leading to the acceptance of both H3 and H6. This result was probably obtained also thanks to the above-mentioned lack of transparency. More in detail, as the participants were not aware of the details of the algorithms governing the robot motion, they might have expected the robot to be neither very safe nor very intelligent at the beginning. However, as participants interacted for a longer period with the robot, they gradually learnt that this was both safe and intelligent.

Finally, the fourth research question focused on how perceived safety and perceived intelligence change based on the participants' previous experience with the robot. According to our obtained results, previous experience with robots affected neither perceived safety nor perceived intelligence in a significant way. These findings are in contrast with the results of previously published research. For instance, in [37, 39, 49, 52, 54, 55] more experienced human participants rated the robot as safer. The reason for our result on perceived safety is probably that the robot motion was safe enough to be perceived as such also by an inexperienced participant. As for perceived intelligence, the result is probably due the fact that a more experienced participant would be able to understand the features of the motion planning algorithm, but at the same time would have higher expectations in terms of robot intelligence.

7.2 Limitations

One of the main limitations of this research study consists of how perceived safety is assessed in real time via physiological feedback to modify the robot motion. Relying only on heart beat is clearly simplistic, and the use of Galvanic skin response did not seem feasible, as this was influenced by the fact that the participant was moving. During the preliminary phase of the experiments, we considered the possibility of analyzing the human subjects' face expressions in real time to assess perceived safety, but all participants wore masks during the experiments because of the Covid-19 pandemics.

A second limitation is the fact that these algorithms, being aimed at manufacturing applications, should be ideally tested on factory workers, who might have a different perception of safety and robot intelligence compared to students and university employees. This was also made difficult by the Covid-19 pandemics, and by the fact that in Kazakhstan there are few high-tech companies in which workers routinely work in contact with collaborative manipulators.

7.3 Open Research Questions

There is a number of open research questions related to the results of this thesis. For example:

1. Would a different strategy for reducing the robot speed based on a real-time estimate of perceived safety (other than FP-HR and MPC-HR) achieve better results in terms of improving perceived safety itself? For example, would the detection of face expression achieve better results?
2. How would the results of the described experiments change when actual factory workers participate in the study, and what modifications should be made to the algorithms to better adapt to factory workers?
3. If applied to industrial (non-collaborative) manipulators, would the HR-based algorithms actually improve perceived safety?

7.4 Future Work

Future work on perceived safety could be directed towards using similar motion planning algorithms on standard industrial manipulators. In this case, the robot would have higher mass and size, and would move in general at higher speeds. This could highlight the differences between the FP and MPC algorithms on the one hand, and their HR versions on the other hand. Furthermore, more sophisticated MPC versions on one side (e.g., MPC based on explicit predictions of the human motion), and simpler algorithms on the other side (e.g., safety-rated monitored stop) could be added to provide a wider spectrum of motion planning algorithms to compare. The consideration of industrial employees in the participant pool is another possible research direction.

A possibility for further research on perceived intelligence would be to conduct experiments with different robots, different a-priori information given to participants and different tasks, to assess how perceived intelligence varies depending on transparency, animacy, human-like appearance and gestures. In particular, the role of information (i.e., transparency) surely deserves further investigation. One can expect that little information provided before the experiment on either robot appearance or task would more likely lead to a change in perceived intelligence as compared to the case in which a very detailed description is provided, or (even more) to the case when a video of the task is shown to the participant before the experiment. Regarding habituation, we can expect that either little initial information or a complex robot behavior that has to be understood would lead to a more significant variation of perceived intelligence, compared to the case in which participants know all details of the task beforehand, or in which the robot behavior is very easy to predict.

As discussed in [79], a motion is *legible* if the robot reaches the goal and avoids collisions, enabling the human participant to quickly and confidently infer the goal. The effect of legibility is as important as that of predictability in the way it influences perceived safety. In the experiments described in this thesis, legibility was not relevant, as the robot goal was clear from the beginning (i.e., the human would always know where the cube was going to be placed). However, the path that the robot would follow to reach that location was changed when using MPC and MPC-HR, which reduced predictability. In future work, the described experiments could be modified to study the effect of legibility on perceived safety. For example, the robot could place a picked cube at one of two different locations: these locations would be known to the participants, who however would not know which one the robot would choose every time. Two MPC algorithms could be defined with different levels of legibility. One algorithms (more legible) would be the same as implemented in this thesis. In the other one (less legible), the goal point in the optimal control problem would be changed during the robot motion, which would make it difficult for the participant to infer where the robot would eventually place the cube.

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Appendices

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Appendix A

Experimental data

Tables A.1 - A.12 presented in the following show the data obtained from the participants, reporting either the answers from the questionnaires or the bio-metric measures from the E4-wristband. The following list describes the terms used in the data report and their explanation:

- *Pre-Experiment: Experience* - Answer to the question "Have you ever worked/interacted with a robot?" with the options: 1-"never", 2-"once or twice", 3-"often", 4-"I work with robots".
- *Pre-Experiment: Nervous Interacting* - Answer to the statement "I would feel nervous interacting with a robot" with the options: from 1-"not nervous" to 5-"very nervous".
- *Pre-Experiment: Nervous Sitting* - Answer to the statement "I would feel nervous just sitting in front of a robot" with the options: from 1-"not nervous" to 5-"very nervous".
- *Post-Experiment: (Algorithm Name) Order* - Order of execution of the algorithm during the experiment, from 1-first to 4-fourth.
- *Post-Experiment: (Algorithm Name) Nerv. Interacting* - Answer to the statement "I felt nervous while interacting with the robot" with the answers: from 1-"not nervous" to 5-"very nervous".
- *Post-Experiment: (Algorithm Name) Nerv. sitting* - Answer to the statement "I felt nervous sitting in front of the robot " with the answers: from 1-"not nervous" to 5-"very nervous".
- *Post-Experiment: (Algorithm Name) Anxious-Relaxed* - Answer to the statement "Please rate your emotional state on these scales" with the answers: from 1-"Anxious" to 5-"Relaxed".
- *Post-Experiment: (Algorithm Name) Calm-Stressed* - Answer to the statement "Please rate your emotional state on these scales" with the answers: from 1-"Stressed" to 5-"Calm".

- *Post-Experiment: (Algorithm Name) Rating Place* - Answer to the statement "Sort four experiments (1-4) from the one in which you felt THE SAFEST to the one in which you felt THE LEAST SAFE" with the answers: from 1-"THE SAFEST" to 4-"THE LEAST SAFE".

- *Post-Experiment: (Algorithm Name) Average HR (bpm)* - Average heart rate measnrement from E4 wristband of each participant during one algorithm execution (4 minutes) in bpm.

- *Post-Experiment: (Algorithm Name) Average Safety Index* - Average sigma value - defined as described in the paper in equation (4) - obtained for each participant during one algorithm execution (4 minutes).

- *Post-Experiment: (Algorithm Name) Average ATCP (s)* - ATCP (s) is the average task completion time of the robot, inversely proportional to its productivity.

Afterwards, Tables A.13 - A.15 show the scales obtained by merging two rates:

- *Pre Nervousness* - Obtained by averaging the answers from Pre Nervous Interacting and Pre Nervous sitting.

- *(Algorithm Name) Perceived Safety DS* - Obtained by averaging the answers from (Algorithm Name) Anxious-Relaxed and (Algorithm Name) Calm-Stressed.

- *(Algorithm Name) Nervousness* - Obtained by averaging the answers from (Algorithm Name) Nervous Interacting and (Algorithm Name) Nervous sitting.

	Subject ID	**1**	**2**	**3**	**4**
Pre-Experiment	Experience	3	4	2	2
	Nervous Interacting	2	5	4	5
	Nervous Sitting	5	5	5	5
MPC	Order	2	4	1	3
	Nerv. Interacting	5	4	4	5
	Nerv. Sitting	5	5	4	4
	Anxious-Relaxed	5	5	3	4
	Calm-Stressed	5	5	4	5
	Rating Place	3	3	4	1
	Average HR	7.09E+01	7.29E+01	6.51E+01	8.77E+01
	Average SI	1.16E-01	3.36E-02	2.11E-01	5.65E-01
	Average ATCP	1.16E+01	1.16E+01	1.16E+01	1.09E+01
MPC-HR	Order	4	3	3	1
	Nerv. Interacting	4	4	5	4
	Nerv. Sitting	5	5	5	4
	Anxious-Relaxed	5	5	5	3
	Calm-Stressed	5	5	5	4
	Rating Place	4	4	1	2
	Average HR	6.88E+01	7.22E+01	6.80E+01	9.32E+01
	Average SI	3.69E-02	9.33E-03	3.73E-01	4.08E-01
	Average ATCP	1.61E+01	1.21E+01	1.36E+01	1.42E+01
FP	Order	1	2	2	2
	Nerv. Interacting	5	5	5	4
	Nerv. Sitting	5	5	5	5
	Anxious-Relaxed	5	5	5	4
	Calm-Stressed	5	5	5	4
	Rating Place	1	1	3	3
	Average HR	6.66E+01	7.55E+01	6.56E+01	8.64E+01
	Average SI	6.53E-02	2.27E-01	2.68E-01	1.01E-01
	Average ATCP	2.84E+01	2.03E+01	1.62E+01	1.77E+01
FP-HR	Order	3	1	4	4
	Nerv. Interacting	5	4	5	4
	Nerv. Sitting	5	5	5	4
	Anxious-Relaxed	5	5	5	4
	Calm-Stressed	5	4	5	5
	Rating Place	2	2	2	4
	Average HR	6.96E+01	7.52E+01	6.50E+01	8.45E+01
	Average SI	2.45E-01	1.79E-02	1.57E-01	7.93E-01
	Average ATCP	2.46E+01	2.13E+01	2.41E+01	2.46E+01

Table A.1: Data obtained during the experiments. Part 1

	Subject ID	**5**	**6**	**7**	**8**
Pre-Experiment	Experience	3	4	3	1
	Nervous Interacting	4	5	3	5
	Nervous Sitting	4	5	4	5
MPC	Order	4	2	3	1
	Nerv. Interacting	4	5	3	5
	Nerv. Sitting	5	5	3	5
	Anxious-Relaxed	5	4	3	5
	Calm-Stressed	5	5	3	5
	Rating Place	3	3	4	1
	Average HR	7.59E+01	8.70E+01	8.81E+01	7.47E+01
	Average SI	0.00E+00	1.48E-01	2.86E-01	1.62E-01
	Average ATCP	1.13E+01	1.15E+01	1.11E+01	1.22E+01
MPC-HR	Order	2	1	2	2
	Nerv. Interacting	4	5	3	5
	Nerv. Sitting	5	5	2	5
	Anxious-Relaxed	4	4	2	5
	Calm-Stressed	4	5	3	5
	Rating Place	1	1	2	2
	Average HR	7.49E+01	9.25E+01	8.84E+01	7.01E+01
	Average SI	6.45E-03	2.11E-01	4.41E-01	5.02E-02
	Average ATCP	1.18E+01	1.30E+01	1.33E+01	1.37E+01
FP	Order	1	4	1	3
	Nerv. Interacting	5	5	3	5
	Nerv. Sitting	5	5	3	5
	Anxious-Relaxed	2	4	3	5
	Calm-Stressed	2	5	2	5
	Rating Place	2	4	1	4
	Average HR	7.42E+01	8.81E+01	8.50E+01	7.69E+01
	Average SI	6.03E-02	8.87E-02	3.12E-01	4.23E-01
	Average ATCP	1.66E+01	1.89E+01	1.83E+01	1.93E+01
FP-HR	Order	3	3	4	4
	Nerv. Interacting	5	5	3	5
	Nerv. Sitting	5	5	4	5
	Anxious-Relaxed	5	4	2	4
	Calm-Stressed	5	5	2	5
	Rating Place	4	2	3	3
	Average HR	7.54E+01	8.66E+01	8.77E+01	7.30E+01
	Average SI	2.41E-01	7.77E-02	1.60E-01	1.38E-01
	Average ATCP	1.96E+01	2.21E+01	2.14E+01	2.28E+01

Table A.2: Data obtained during the experiments. Part 2

	Subject ID	**9**	**10**	**11**	**12**
Pre-Experiment	Experience	4	2	3	2
	Nervous Interacting	4	3	5	5
	Nervous Sitting	5	5	5	5
MPC	Order	2	3	1	1
	Nerv. Interacting	5	5	3	5
	Nerv. Sitting	5	5	4	5
	Anxious-Relaxed	5	5	2	5
	Calm-Stressed	5	5	4	5
	Rating Place	2	2	4	4
	Average HR	7.55E+01	6.82E+01	7.13E+01	8.01E+01
	Average SI	4.18E-02	1.79E-01	3.09E-02	4.32E-02
	Average ATCP	1.12E+01	1.11E+01	1.07E+01	1.12E+01
MPC-HR	Order	3	1	4	2
	Nerv. Interacting	5	5	5	5
	Nerv. Sitting	5	5	4	5
	Anxious-Relaxed	5	3	2	5
	Calm-Stressed	5	4	5	5
	Rating Place	3	4	1	3
	Average HR	7.67E+01	7.03E+01	7.23E+01	7.94E+01
	Average SI	6.73E-03	1.93E-01	2.03E-01	1.73E-01
	Average ATCP	1.19E+01	1.28E+01	1.24E+01	1.24E+01
FP	Order	4	4	2	4
	Nerv. Interacting	5	5	4	5
	Nerv. Sitting	5	5	5	5
	Anxious-Relaxed	5	5	4	5
	Calm-Stressed	5	5	3	5
	Rating Place	1	1	2	1
	Average HR	7.67E+01	7.03E+01	7.01E+01	7.37E+01
	Average SI	4.79E-02	9.26E-02	2.27E-01	2.63E-02
	Average ATCP	1.72E+01	1.92E+01	1.85E+01	1.80E+01
FP-HR	Order	1	2	3	3
	Nerv. Interacting	5	5	5	5
	Nerv. Sitting	5	5	4	5
	Anxious-Relaxed	5	5	2	5
	Calm-Stressed	5	4	4	5
	Rating Place	4	3	3	2
	Average HR	7.49E+01	6.88E+01	7.20E+01	7.97E+01
	Average SI	7.59E-02	9.81E-02	3.96E-01	1.49E-01
	Average ATCP	2.18E+01	2.17E+01	2.09E+01	2.07E+01

Table A.3: Data obtained during the experiments. Part 3

	Subject ID	**13**	**14**	**15**	**16**
Pre-Experiment	Experience	1	1	1	2
	Nervous Interacting	5	5	5	4
	Nervous Sitting	5	5	5	5
MPC	Order	1	1	2	4
	Nerv. Interacting	1	4	5	5
	Nerv. Sitting	2	3	5	5
	Anxious-Relaxed	3	2	5	5
	Calm-Stressed	4	3	5	5
	Rating Place	4	4	3	1
	Average HR	7.64E+01	1.01E+02	8.96E+01	8.90E+01
	Average SI	1.63E-02	4.30E-03	5.23E-01	3.09E-01
	Average ATCP	1.29E+01	1.10E+01	1.13E+01	1.15E+01
MPC-HR	Order	4	3	3	3
	Nerv. Interacting	5	2	5	4
	Nerv. Sitting	5	4	5	5
	Anxious-Relaxed	4	4	5	4
	Calm-Stressed	5	4	5	4
	Rating Place	2	3	4	2
	Average HR	7.73E+01	9.57E+01	8.55E+01	9.03E+01
	Average SI	6.05E-02	1.36E-01	8.25E-02	2.30E-01
	Average ATCP	1.24E+01	1.28E+01	1.23E+01	1.25E+01
FP	Order	3	4	1	1
	Nerv. Interacting	5	5	4	5
	Nerv. Sitting	5	5	5	5
	Anxious-Relaxed	5	5	5	4
	Calm-Stressed	5	5	5	5
	Rating Place	1	1	2	4
	Average HR	7.79E+01	9.44E+01	9.04E+01	9.21E+01
	Average SI	2.76E-02	2.18E-02	4.90E-02	4.42E-04
	Average ATCP	1.85E+01	1.87E+01	1.98E+01	1.96E+01
FP-HR	Order	2	2	4	2
	Nerv. Interacting	5	3	4	4
	Nerv. Sitting	5	3	5	5
	Anxious-Relaxed	4	3	5	4
	Calm-Stressed	5	3	4	5
	Rating Place	3	2	1	3
	Average HR	7.71E+01	9.83E+01	8.45E+01	9.24E+01
	Average SI	8.79E-02	1.09E-01	1.70E-01	1.52E-01
	Average ATCP	2.10E+01	2.06E+01	2.14E+01	2.16E+01

Table A.4: Data obtained during the experiments. Part 4

	Subject ID	**17**	**18**	**19**	**20**
Pre-Experiment	Experience	2	1	2	1
	Nervous Interacting	5	4	3	5
	Nervous Sitting	5	5	3	5
MPC	Order	2	4	4	2
	Nerv. Interacting	5	5	3	5
	Nerv. Sitting	5	5	5	5
	Anxious-Relaxed	5	5	4	5
	Calm-Stressed	5	5	4	5
	Rating Place	3	3	3	3
	Average HR	8.51E+01	8.99E+01	8.81E+01	7.39E+01
	Average SI	2.77E-01	4.69E-02	1.09E-02	5.35E-02
	Average ATCP	1.13E+01	1.14E+01	1.15E+01	1.14E+01
MPC-HR	Order	1	1	1	4
	Nerv. Interacting	5	5	2	5
	Nerv. Sitting	5	5	2	5
	Anxious-Relaxed	5	5	2	5
	Calm-Stressed	5	5	2	5
	Rating Place	4	1	4	1
	Average HR	8.19E+01	9.35E+01	8.43E+01	7.26E+01
	Average SI	1.90E-02	7.74E-02	2.79E-02	1.29E-02
	Average ATCP	1.21E+01	1.24E+01	1.24E+01	1.25E+01
FP	Order	3	2	3	3
	Nerv. Interacting	5	5	4	5
	Nerv. Sitting	5	5	4	5
	Anxious-Relaxed	5	5	4	5
	Calm-Stressed	5	5	5	5
	Rating Place	2	2	2	2
	Average HR	7.73E+01	9.18E+01	8.79E+01	7.43E+01
	Average SI	1.38E-02	1.44E-01	1.17E-01	1.02E-01
	Average ATCP	1.87E+01	1.89E+01	2.04E+01	1.91E+01
FP-HR	Order	4	3	2	1
	Nerv. Interacting	5	5	3	5
	Nerv. Sitting	5	5	5	5
	Anxious-Relaxed	5	5	4	5
	Calm-Stressed	5	5	4	5
	Rating Place	1	4	1	4
	Average HR	7.92E+01	9.34E+01	8.40E+01	7.79E+01
	Average SI	3.97E-01	1.52E-01	1.24E-01	1.18E-01
	Average ATCP	2.10E+01	2.19E+01	2.23E+01	2.18E+01

Table A.5: Data obtained during the experiments. Part 5

	Subject ID	**21**	**22**	**23**	**24**
Pre-Experiment	Experience	3	2	1	2
	Nervous Interacting	4	5	3	4
	Nervous Sitting	5	5	4	5
MPC	Order	3	4	3	3
	Nerv. Interacting	5	4	3	5
	Nerv. Sitting	4	5	5	5
	Anxious-Relaxed	5	4	2	5
	Calm-Stressed	5	2	4	5
	Rating Place	3	4	3	2
	Average HR	9.68E+01	7.30E+01	9.54E+01	8.23E+01
	Average SI	8.11E-02	3.27E-01	8.13E-01	2.85E-02
	Average ATCP	1.17E+01	1.15E+01	1.15E+01	1.17E+01
MPC-HR	Order	4	2	4	2
	Nerv. Interacting	5	4	4	4
	Nerv. Sitting	4	5	5	2
	Anxious-Relaxed	5	4	4	2
	Calm-Stressed	5	2	5	2
	Rating Place	4	3	4	4
	Average HR	9.54E+01	6.95E+01	8.54E+01	8.32E+01
	Average SI	1.86E-01	2.14E-02	3.03E-01	1.70E-02
	Average ATCP	1.25E+01	1.24E+01	1.25E+01	1.22E+01
FP	Order	2	3	1	4
	Nerv. Interacting	5	5	4	5
	Nerv. Sitting	5	5	5	5
	Anxious-Relaxed	5	5	4	5
	Calm-Stressed	5	2	5	5
	Rating Place	2	2	1	1
	Average HR	9.72E+01	7.23E+01	9.27E+01	7.86E+01
	Average SI	1.57E-01	1.98E-02	2.71E-01	3.25E-03
	Average ATCP	1.88E+01	1.93E+01	1.88E+01	1.90E+01
FP-HR	Order	1	1	2	1
	Nerv. Interacting	5	4	4	3
	Nerv. Sitting	5	5	5	3
	Anxious-Relaxed	5	4	4	2
	Calm-Stressed	5	2	5	3
	Rating Place	1	1	2	3
	Average HR	9.61E+01	6.84E+01	9.11E+01	8.59E+01
	Average SI	3.16E-01	8.74E-02	2.04E-01	2.50E-02
	Average ATCP	2.15E+01	2.17E+01	2.11E+01	2.11E+01

Table A.6: Data obtained during the experiments. Part 6

	Subject ID	**25**	**26**	**27**	**28**
Pre-Experiment	Experience	1	1	3	2
	Nervous Interacting	5	5	5	2
	Nervous Sitting	5	5	5	2
MPC	Order	4	1	3	2
	Nerv. Interacting	5	5	5	2
	Nerv. Sitting	5	5	5	4
	Anxious-Relaxed	5	4	4	2
	Calm-Stressed	5	5	5	2
	Rating Place	1	4	2	1
	Average HR	7.38E+01	1.08E+02	7.69E+01	1.01E+02
	Average SI	1.44E-02	1.67E-01	1.03E-01	4.26E-02
	Average ATCP	1.18E+01	1.13E+01	1.17E+01	1.46E+01
MPC-HR	Order	3	4	4	1
	Nerv. Interacting	5	5	5	2
	Nerv. Sitting	5	5	5	3
	Anxious-Relaxed	5	4	5	1
	Calm-Stressed	5	4	5	2
	Rating Place	2	1	1	2
	Average HR	7.70E+01	1.07E+02	7.74E+01	1.03E+02
	Average SI	4.80E-01	2.80E-01	2.21E-02	5.54E-02
	Average ATCP	1.44E+01	1.54E+01	1.12E+01	1.21E+01
FP	Order	2	3	1	3
	Nerv. Interacting	5	5	5	1
	Nerv. Sitting	5	5	5	2
	Anxious-Relaxed	5	3	4	5
	Calm-Stressed	5	4	5	1
	Rating Place	3	2	3	3
	Average HR	7.38E+01	9.85E+01	7.95E+01	1.05E+02
	Average SI	1.10E-01	2.40E-01	7.88E-02	1.74E-01
	Average ATCP	1.56E+01	1.99E+01	2.10E+01	1.61E+01
FP-HR	Order	1	2	2	4
	Nerv. Interacting	5	5	5	1
	Nerv. Sitting	5	5	5	1
	Anxious-Relaxed	5	4	4	1
	Calm-Stressed	5	5	5	1
	Rating Place	4	3	4	4
	Average HR	6.74E+01	1.04E+02	7.37E+01	1.03E+02
	Average SI	6.40E-01	0.00E+00	8.37E-03	1.20E-01
	Average ATCP	4.05E+01	3.01E+01	3.47E+01	2.01E+01

Table A.7: Data obtained during the experiments. Part 7

	Subject ID	**29**	**30**	**31**	**32**
Pre-Experiment	Experience	4	3	1	2
	Nervous Interacting	4	4	4	4
	Nervous Sitting	5	5	4	3
MPC	Order	1	1	1	1
	Nerv. Interacting	5	5	3	4
	Nerv. Sitting	5	5	2	4
	Anxious-Relaxed	4	4	3	3
	Calm-Stressed	4	5	4	4
	Rating Place	2	1	4	4
	Average HR	7.90E+01	7.94E+01	8.97E+01	9.04E+01
	Average SI	4.42E-01	7.65E-02	3.65E-01	3.29E-01
	Average ATCP	1.18E+01	1.24E+01	1.10E+01	1.15E+01
MPC-HR	Order	3	4	2	2
	Nerv. Interacting	4	4	3	4
	Nerv. Sitting	5	2	4	4
	Anxious-Relaxed	3	3	4	4
	Calm-Stressed	3	4	4	4
	Rating Place	4	2	3	1
	Average HR	8.36E+01	8.18E+01	8.80E+01	8.50E+01
	Average SI	7.10E-01	2.43E-01	3.28E-01	8.73E-02
	Average ATCP	2.03E+01	1.33E+01	1.29E+01	1.21E+01
FP	Order	2	2	3	4
	Nerv. Interacting	5	3	4	5
	Nerv. Sitting	5	3	5	4
	Anxious-Relaxed	5	3	4	4
	Calm-Stressed	4	4	5	4
	Rating Place	1	3	2	2
	Average HR	8.10E+01	8.06E+01	8.74E+01	8.73E+01
	Average SI	4.36E-01	1.97E-01	4.14E-01	5.09E-01
	Average ATCP	1.97E+01	2.98E+01	1.74E+01	2.36E+01
FP-HR	Order	4	3	4	3
	Nerv. Interacting	4	2	5	5
	Nerv. Sitting	5	3	5	4
	Anxious-Relaxed	2	3	5	4
	Calm-Stressed	3	3	5	4
	Rating Place	3	4	1	3
	Average HR	8.27E+01	8.09E+01	8.65E+01	8.57E+01
	Average SI	4.34E-01	2.45E-01	1.01E-01	3.68E-01
	Average ATCP	2.15E+01	1.89E+01	1.93E+01	2.45E+01

Table A.8: Data obtained during the experiments. Part 8

	Subject ID	**33**	**34**	**35**	**36**
Pre-Experiment	Experience	3	1	1	2
	Nervous Interacting	4	5	4	2
	Nervous Sitting	4	5	5	5
MPC	Order	1	2	2	3
	Nerv. Interacting	5	5	4	4
	Nerv. Sitting	4	5	5	4
	Anxious-Relaxed	5	5	4	5
	Calm-Stressed	4	5	4	5
	Rating Place	1	1	1	3
	Average HR	8.27E+01	7.54E+01	6.77E+01	8.13E+01
	Average SI	3.42E-01	2.54E-01	1.94E-01	3.92E-01
	Average ATCP	1.14E+01	1.29E+01	1.32E+01	1.10E+01
MPC-HR	Order	3	4	3	2
	Nerv. Interacting	5	4	4	5
	Nerv. Sitting	5	5	5	4
	Anxious-Relaxed	5	4	4	4
	Calm-Stressed	5	3	5	5
	Rating Place	2	4	3	4
	Average HR	8.30E+01	7.47E+01	6.66E+01	7.96E+01
	Average SI	1.09E-01	4.49E-01	1.11E-01	4.14E-01
	Average ATCP	1.15E+01	1.59E+01	1.30E+01	1.32E+01
FP	Order	4	1	1	1
	Nerv. Interacting	5	4	3	4
	Nerv. Sitting	5	4	4	5
	Anxious-Relaxed	5	3	4	4
	Calm-Stressed	5	4	3	4
	Rating Place	3	2	4	2
	Average HR	8.29E+01	6.95E+01	8.05E+01	8.05E+01
	Average SI	2.65E-01	5.25E-01	3.21E-01	4.65E-01
	Average ATCP	1.87E+01	2.04E+01	1.88E+01	1.88E+01
FP-HR	Order	2	3	4	4
	Nerv. Interacting	5	3	5	5
	Nerv. Sitting	5	4	5	5
	Anxious-Relaxed	5	4	4	5
	Calm-Stressed	5	3	5	4
	Rating Place	4	3	2	1
	Average HR	8.41E+01	7.50E+01	6.84E+01	8.15E+01
	Average SI	3.66E-01	4.00E-01	2.48E-01	5.65E-01
	Average ATCP	2.33E+01	2.91E+01	1.71E+01	1.77E+01

Table A.9: Data obtained during the experiments. Part 9

	Subject ID	**37**	**38**	**39**	**40**
Pre-Experiment	Experience	2	2	1	1
	Nervous Interacting	5	4	5	5
	Nervous Sitting	5	5	5	5
MPC	Order	4	4	2	3
	Nerv. Interacting	5	4	3	5
	Nerv. Sitting	5	4	4	4
	Anxious-Relaxed	5	4	3	4
	Calm-Stressed	5	4	4	4
	Rating Place	1	4	3	4
	Average HR	8.48E+01	9.42E+01	5.37E+01	8.05E+01
	Average SI	4.00E-01	6.41E-01	2.02E-02	5.01E-01
	Average ATCP	1.11E+01	1.40E+01	1.17E+01	1.21E+01
MPC-HR	Order	2	3	1	1
	Nerv. Interacting	5	3	2	5
	Nerv. Sitting	5	5	3	5
	Anxious-Relaxed	5	3	3	5
	Calm-Stressed	5	3	2	5
	Rating Place	4	3	4	2
	Average HR	9.17E+01	9.52E+01	5.62E+01	7.88E+01
	Average SI	9.75E-01	7.91E-01	6.52E-02	5.84E-01
	Average ATCP	1.50E+01	1.42E+01	1.12E+01	1.43E+01
FP	Order	1	1	4	2
	Nerv. Interacting	4	4	3	5
	Nerv. Sitting	5	5	5	5
	Anxious-Relaxed	3	5	5	5
	Calm-Stressed	4	5	5	4
	Rating Place	3	2	2	3
	Average HR	8.49E+01	9.26E+01	5.36E+01	7.80E+01
	Average SI	3.58E-01	6.28E-01	1.52E-01	4.90E-01
	Average ATCP	2.08E+01	2.42E+01	1.85E+01	1.94E+01
FP-HR	Order	3	2	3	4
	Nerv. Interacting	5	3	1	5
	Nerv. Sitting	5	4	5	5
	Anxious-Relaxed	5	4	2	4
	Calm-Stressed	5	4	2	5
	Rating Place	2	1	1	1
	Average HR	8.57E+01	9.66E+01	5.62E+01	7.99E+01
	Average SI	4.82E-01	4.14E-01	1.95E-01	4.13E-01
	Average ATCP	1.73E+01	2.03E+01	2.40E+01	2.49E+01

Table A.10: Data obtained during the experiments. Part 10

	Subject ID	**41**	**42**	**43**	**44**
Pre-Experiment	Experience	1	2	3	1
	Nervous Interacting	5	5	3	4
	Nervous Sitting	5	5	2	5
MPC	Order	4	3	4	2
	Nerv. Interacting	5	3	4	5
	Nerv. Sitting	5	4	4	5
	Anxious-Relaxed	4	3	3	4
	Calm-Stressed	5	4	4	4
	Rating Place	4	4	4	3
	Average HR	8.76E+01	8.84E+01	9.24E+01	9.15E+01
	Average SI	2.20E-01	1.06E+00	6.11E-01	6.37E-01
	Average ATCP	1.15E+01	1.21E+01	1.25E+01	1.29E+01
MPC-HR	Order	1	1	1	4
	Nerv. Interacting	5	5	4	5
	Nerv. Sitting	5	5	4	5
	Anxious-Relaxed	5	4	4	5
	Calm-Stressed	5	5	4	4
	Rating Place	3	3	3	2
	Average HR	9.46E+01	9.09E+01	8.41E+01	9.39E+01
	Average SI	4.44E-01	5.97E-01	7.60E-01	7.44E-01
	Average ATCP	1.16E+01	1.58E+01	1.51E+01	1.56E+01
FP	Order	2	4	3	3
	Nerv. Interacting	5	5	4	5
	Nerv. Sitting	5	5	4	5
	Anxious-Relaxed	4	5	5	4
	Calm-Stressed	5	4	5	4
	Rating Place	1	1	1	1
	Average HR	9.05E+01	8.82E+01	8.75E+01	9.18E+01
	Average SI	4.97E-01	5.55E-01	3.04E-01	6.08E-01
	Average ATCP	1.91E+01	2.17E+01	2.03E+01	2.33E+01
FP-HR	Order	3	2	2	1
	Nerv. Interacting	5	4	4	3
	Nerv. Sitting	5	3	4	2
	Anxious-Relaxed	4	5	4	2
	Calm-Stressed	5	4	5	2
	Rating Place	2	2	2	4
	Average HR	8.70E+01	8.29E+01	8.80E+01	9.62E+01
	Average SI	1.72E-01	3.01E-01	4.26E-01	4.74E-01
	Average ATCP	1.74E+01	1.84E+01	2.56E+01	2.58E+01

Table A.11: Data obtained during the experiments. Part 11

	Subject ID	**45**	**46**	**47**	**48**
Pre-Experiment	Experience	1	1	2	4
	Nervous Interacting	3	4	3	5
	Nervous Sitting	5	5	5	5
MPC	Order	2	3	4	3
	Nerv. Interacting	3	5	5	5
	Nerv. Sitting	3	5	5	5
	Anxious-Relaxed	4	5	5	5
	Calm-Stressed	4	5	5	5
	Rating Place	3	3	4	1
	Average HR	6.60E+01	1.05E+02	7.22E+01	9.41E+01
	Average SI	4.34E-01	6.14E-01	6.83E-02	8.39E-01
	Average ATCP	1.16E+01	1.15E+01	1.22E+01	1.22E+01
MPC-HR	Order	3	4	2	2
	Nerv. Interacting	3	5	4	5
	Nerv. Sitting	3	5	3	5
	Anxious-Relaxed	3	5	3	4
	Calm-Stressed	4	4	4	5
	Rating Place	2	4	1	2
	Average HR	6.26E+01	1.02E+02	7.65E+01	9.33E+01
	Average SI	2.74E-01	5.64E-01	4.07E-01	7.23E-01
	Average ATCP	1.34E+01	1.31E+01	2.22E+01	1.50E+01
FP	Order	4	2	3	4
	Nerv. Interacting	2	5	5	5
	Nerv. Sitting	3	5	5	5
	Anxious-Relaxed	3	5	4	2
	Calm-Stressed	3	4	5	2
	Rating Place	4	2	3	4
	Average HR	6.42E+01	1.03E+02	7.39E+01	9.64E+01
	Average SI	3.68E-01	5.53E-01	9.75E-02	6.71E-01
	Average ATCP	2.44E+01	2.26E+01	2.59E+01	2.12E+01
FP-HR	Order	1	1	1	1
	Nerv. Interacting	4	5	4	5
	Nerv. Sitting	5	5	3	5
	Anxious-Relaxed	5	4	2	4
	Calm-Stressed	5	4	2	4
	Rating Place	1	1	2	3
	Average HR	6.11E+01	1.00E+02	7.56E+01	9.68E+01
	Average SI	4.30E-01	1.82E-01	9.44E-02	4.47E-01
	Average ATCP	1.75E+01	2.64E+01	3.31E+01	1.65E+01

Table A.12: Data obtained during the experiments. Part 12

Subject ID	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Pre Nervousness	3.5	5.0	4.5	5.0	4.0	5.0	3.5	5.0	4.5	4.0	5.0	5.0	5.0	5.0	5.0	4.5
MPC Perceived Safety DS	5.0	5.0	3.5	4.5	5.0	4.5	3.0	5.0	5.0	5.0	3.0	5.0	3.5	2.5	5.0	5.0
MPC-HR Perceived Safety DS	5.0	5.0	5.0	3.5	4.0	4.5	2.5	5.0	5.0	3.5	3.5	5.0	4.5	4.0	5.0	4.0
FP Perceived Safety DS	5.0	5.0	5.0	4.0	2.0	4.5	2.5	5.0	5.0	5.0	3.5	5.0	5.0	5.0	5.0	4.5
FP-HR Perceived Safety DS	5.0	4.5	5.0	4.5	5.0	4.5	2.0	4.5	5.0	4.5	3.0	5.0	4.5	3.0	4.5	4.5
MPC Nervousness	5.0	4.5	4.0	4.5	4.5	5.0	3.0	5.0	5.0	5.0	3.5	5.0	1.5	3.5	5.0	5.0
MPC-HR Nervousness	4.5	4.5	5.0	4.0	4.5	5.0	2.5	5.0	5.0	5.0	4.5	5.0	5.0	3.0	5.0	4.5
FP Nervousness	5.0	5.0	5.0	4.5	5.0	5.0	3.0	5.0	5.0	5.0	4.5	5.0	5.0	5.0	4.5	5.0
FP-HR Nervousness	5.0	4.5	5.0	4.0	5.0	5.0	3.5	5.0	5.0	5.0	4.5	5.0	5.0	3.0	4.5	4.5

Table A.13: Scales obtained by merging two rates. Part 1

Subject ID	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
Pre Nervousness	5.0	4.5	3.0	5.0	4.5	5.0	3.5	4.5	5.0	5.0	5.0	2.0	4.5	4.5	4.0	3.5
MPC Perceived Safety DS	5.0	5.0	4.0	5.0	5.0	3.0	3.0	5.0	5.0	4.5	4.5	2.0	4.0	4.5	3.5	3.5
MPC-HR Perceived Safety DS	5.0	5.0	2.0	5.0	5.0	3.0	4.5	2.0	5.0	4.0	5.0	1.5	3.0	3.5	4.0	4.0
FP Perceived Safety DS	5.0	5.0	4.5	5.0	5.0	3.5	4.5	5.0	5.0	3.5	4.5	3.0	4.5	3.5	4.5	4.0
FP-HR Perceived Safety DS	5.0	5.0	4.0	5.0	5.0	3.0	4.5	2.5	5.0	4.5	4.5	1.0	2.5	3.0	5.0	4.0
MPC Nervousness	5.0	5.0	4.0	5.0	4.5	4.5	4.0	5.0	5.0	5.0	5.0	3.0	5.0	5.0	2.5	4.0
MPC-HR Nervousness	5.0	5.0	2.0	5.0	4.5	4.5	4.5	3.0	5.0	5.0	5.0	2.5	4.5	3.0	3.5	4.0
FP Nervousness	5.0	5.0	4.0	5.0	5.0	5.0	4.5	5.0	5.0	5.0	5.0	1.5	5.0	3.0	4.5	4.5
FP-HR Nervousness	5.0	5.0	4.0	5.0	5.0	4.5	4.5	3.0	5.0	5.0	5.0	1.0	4.5	2.5	5.0	4.5

Table A.14: Scales obtained by merging two rates. Part 2

Subject ID	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**	**46**	**47**	**48**
Pre Nervousness	4.0	5.0	4.5	3.5	5.0	4.5	5.0	5.0	5.0	5.0	2.5	4.5	4.0	4.5	4.0	5.0
MPC Perceived Safety DS	4.5	5.0	4.0	5.0	5.0	4.0	3.5	4.0	4.5	3.5	3.5	4.0	4.0	5.0	5.0	5.0
MPC-HR Perceived Safety DS	5.0	3.5	4.5	4.5	5.0	3.0	2.5	5.0	5.0	4.5	4.0	4.5	3.5	4.5	3.5	4.5
FP Perceived Safety DS	5.0	3.5	3.5	4.0	3.5	5.0	5.0	4.5	4.5	4.5	5.0	4.0	3.0	4.5	4.5	2.0
FP-HR Perceived Safety DS	5.0	3.5	4.5	4.5	5.0	4.0	2.0	4.5	4.5	4.5	4.5	2.0	5.0	4.0	2.0	4.0
MPC Nervousness	4.5	5.0	4.5	4.0	5.0	4.0	3.5	4.5	5.0	3.5	4.0	5.0	3.0	5.0	5.0	5.0
MPC-HR Nervousness	5.0	4.5	4.5	4.5	5.0	4.0	2.5	5.0	5.0	5.0	4.0	5.0	3.0	5.0	3.5	5.0
FP Nervousness	5.0	4.0	3.5	4.5	4.5	4.5	4.0	5.0	5.0	5.0	4.0	5.0	2.5	5.0	5.0	5.0
FP-HR Nervousness	5.0	3.5	5.0	5.0	5.0	3.5	3.0	5.0	5.0	3.5	4.0	2.5	4.5	5.0	3.5	5.0

Table A.15: Scales obtained by merging two rates. Part 3