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MANiBOT

Advancing the physical intelligence and performance of roBOTs towards human-like bi-manual objects MANipulation

D2.3. Trustworthiness and dependability analysis - v1

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Definitions, Acronyms and Abbreviations

Acronyms and Abbreviations	Description
AI	Artificial Intelligence
AR	Augmented Reality
CAD	Computer-Aided Design
COPSOQ II	Copenhagen Psychosocial Questionnaire
DS-MOS	Differential MOS
ETA	Event Tree Analysis
FMEA	Failure Modes and Effects Analysis
FTA	Fault Tree Analysis
HAZOP	Hazard and Operability Study
HEART	Human Error Assessment and Reduction Technique
HRC	Human-Robot Collaboration
HRI	Human-Robot Interaction
HRITS	Human-Robot Interaction Trust Scale
MOS	Mean Opinion Score
PCA	Principal Component Analysis
PHA	Preliminary Hazard Analysis
pHRI	physical human-robot interaction
PLCs	Safety Programmable Logic Controllers
RAM-care	Robot Acceptance Model for Care
ROS	Robot Operating System
TAM	Technology Acceptance Model
TiA	Trust in Automation
UI	User Interface
UX	User Experience
VE	Virtual Environment
VR	Virtual Reality
XAI	eXplainable Artificial Intelligence

Executive Summary

A mobile robot with arms that operates in an environment where people are present needs to be safe, reliable, and accepted by the employees. Without these qualities, its implementation may be ineffective or counterproductive. To address this, dedicated methods for assessing the MANiBOT robot should be developed.

To achieve this, a comprehensive review of the literature on Human-Robot Interaction (HRI) relevant to the MANiBOT project was conducted. This document presents the results of this study, including descriptions of various methods for ensuring safety. The literature review is focused on factors such as trustworthiness and dependability. This deliverable also includes an overview of different methods for measuring worker satisfaction with examples of commonly used questionnaires often used to measure trust, dependability and perceived safety, like Human-Robot Interaction Trust Scale or Godspeed Questionnaire. Finally, it includes the initial version of the questionnaire structure developed in Task 2.3 on the basis of results of the performed literature review.

It should be noted that the final version of the results, including the final version of the questionnaire, will be provided in D2.6. The planned activities in T2.3 include the development of interactive virtual reality-based simulation facilitating safety analysis and developing the research methodology, mainly focusing on the verification of the questionnaire.

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1 Introduction

1.1 Scope of the deliverable

The main purpose of the first version of the deliverable (D2.3 Trustworthiness and dependability analysis - v1) is to provide the results of the extensive literature study concerning aspects of Human-Robot Interaction (HRI) relevant to the MANiBOT project. In particular, the deliverable is focused on methods for safety, trustworthiness and dependability as well as the presentation of methods commonly used to measure the subjective assessment of worker satisfaction with the working conditions present in the robotised working environment. In the deliverable the indicators that cover factors as trust in technology safety; trust in the robotic technology worker support, organisational trust; feeling of predictability in the work environment; support from co-workers and supervisors; job satisfaction; job control; feeling of self-efficacy are described. Considering the results of the literature review, a preliminary version of the questionnaire structure on worker satisfaction was prepared.

1.2 Relation to other Activities and Deliverables

The present deliverable is directly related to the work that is performed in task T2.3 “Safety, trustworthiness and dependability factors analysis for the MANiBOT robots” (M1-M40). Since this is the first version of the deliverable, the results presented here will be mainly used in the second version: D2.6 “Trustworthiness and dependability analysis” (M36). The deliverable D2.6 is a product of the same task as D2.3.

This deliverable focuses on the literature review and presentation of different methods which could be used for safety, trustworthiness and dependability analysis as well as analyse the subjective assessment of worker satisfaction. The final version of the results will be provided in D2.6, including for example, the following contents:

- interactive virtual reality-based simulation to facilitate safety analysis (using information stemming from T7.2 and D7.2 that refer to the pilot sites specifications),
- final version of the method for safety, trustworthiness and dependability analysis,
- final version of the questionnaire on worker satisfaction (taking into account data from T2.2 and D2.2 on user requirements and use cases analysis),
- results of the analysis performed at the pilot test of the real robot (during the pilot tests which are planned and organized by WP7).

1.3 Structure of the deliverable

The deliverable is structured as reported below:

Chapter 1 – Introduction – Provides information on the scope and purpose of the deliverable, the relation to other tasks and deliverables and the structure of the deliverable.

Chapter 2 – Literature review of HRI issues – Provides results of extensive review literature focused on issues of Human-Robot Interactions related to trustworthiness and dependability.

Chapter 3 – Methods of safety, trustworthiness and dependability analysis – Provides extensive review of different methods and tools dedicated to analysis of factors like safety, trustworthiness and dependability in the context of regulations and standards compliance for safety.

Chapter 4 – Methods for analysis of worker’s subjective assessment – Provides extensive review of different methods used for analysis of worker’s subjective assessment including following factor: trust in technology safety; trust in the robotic technology worker support, organisational trust; feeling of predictability in the work environment; support from co-workers and supervisors; job satisfaction; job control; feeling of self-efficacy. The examples of commonly used questionnaires are described as well as the preliminary version of the questionnaire structure is presented.

Chapter 5 – Future work – This chapter is focused on the utilization of Virtual Reality Tools in Cobot simulation for methodology development.

Chapter 6 – Summary and conclusions – Provides short summary of the deliverable.

2 Literature review of HRI issues

2.1 Introduction

Human-robot interaction (HRI) is an interdisciplinary field that encompasses various domains, such as artificial intelligence (AI), robotics, psychology, and design. This field has gained significant attention due to the increasing integration of robots into everyday life, necessitating a deeper understanding of how humans interact with these machines. The study of HRI focuses on the design, implementation, and evaluation of robotic systems that can effectively and safely interact with humans. As robots become more sophisticated, the need for intuitive and user-friendly interfaces becomes paramount, particularly in applications such as healthcare, education, and service industries [1], [2].

One of the critical aspects of HRI is the concept of physical human-robot interaction (pHRI), which emphasizes on the physical aspects of interaction between humans and robots. This subfield addresses the challenges of ensuring safety and comfort during physical interactions, particularly in environments where robots and humans share space. The design of robotic systems must consider human factors, including ergonomics and cognitive load, to facilitate seamless interactions. For instance, the development of soft robotics and flexible sensors has been instrumental in creating robots that can safely engage with humans without causing harm [3], [4]. These advancements allow for more natural interactions, as robots can adapt their movements and responses based on real-time feedback from human users.

Moreover, the integration of AI into robotic systems enhances their ability to understand and respond to human behaviour. AI-driven robots can learn from interactions, improving their performance and adaptability over time. This capability is particularly important in dynamic environments, such as factories or hospitals, where robots must navigate complex tasks while collaborating with human workers [5],[6]. The use of machine learning algorithms enables robots to recognize patterns in human behaviour, allowing for more intuitive interactions that align with user expectations and preferences [7],[8]. As a result, the development of explainable AI (XAI) is crucial, as it provides transparency in robotic decision-making processes, fostering trust and acceptance among users [7].

The psychological aspects of HRI also warrant significant attention. Understanding how humans perceive and interact with robots can inform design choices that enhance user experience. Research has shown that the embodiment of robots—how human-like they appear and behave—can influence social perception and emotional responses [1],[2]. For example, robots designed to exhibit empathy and emotional intelligence can improve user engagement, particularly in healthcare settings where emotional support is vital [9]. The incorporation of social cues, such as facial expressions and gestures, can further enhance the effectiveness of these interactions, making robots more relatable and acceptable to users [10],[11].

Ethical considerations are also paramount in the field of HRI. As robots become more integrated into society, questions regarding their moral status and the implications of their actions arise. The development of social robots that can perform caregiving tasks or provide companionship raises ethical dilemmas about autonomy, responsibility, and the potential for emotional manipulation [9],[11]. It is essential to establish guidelines and frameworks that address these ethical concerns, ensuring that the deployment of robots aligns with societal values and norms [12],[13]. Furthermore, the legal implications of HRI, particularly concerning liability and accountability for robotic actions, must be carefully considered as robots take on more autonomous roles in various sectors [14].

In the context of education, HRI has the potential to revolutionize learning experiences. Robots equipped with AI can serve as personalized tutors, adapting their teaching methods to suit individual learning styles and needs [15],[16]. This capability not only enhances educational outcomes but also fosters engagement among students, particularly in Science, Technology, Engineering, and Mathematics fields where robotics can provide hands-on learning opportunities [15]. The integration of voice recognition and natural language processing allows for more interactive and responsive educational robots, making learning more accessible and enjoyable for children [17].

The future of HRI is poised for significant advancements, driven by ongoing research and technological innovations. As robots become more capable of understanding and responding to human emotions, the potential for their application in various domains expands. For instance, in healthcare, robots could assist in patient monitoring, rehabilitation, and even companionship for the elderly [9],[18]. In industrial settings, collaborative robots (cobots) can enhance productivity by working alongside human operators, performing repetitive tasks while allowing humans to focus on more complex activities [5],[6]. The convergence of AI and robotics will continue to shape the landscape of HRI, leading to more intelligent and adaptable systems that can seamlessly integrate into human environments.

Table 1. A table with short summary of results related to introduction to HRI

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[1]	Neurocognitive Insights in HRI	How can neurocognitive insights improve human-robot interaction?	Understanding human social cognition can inform robot design to enhance social interactions and user experience.
[2]	Social Human-Robot Interaction in Service Robots	What are the key aspects of social interaction in human-care service robots?	Emphasizes the importance of social elements in designing effective human-care service robots in healthcare settings.
[3]	Development of Flexible Sensors in Robotics	How can flexible sensors enhance safety in physical human-robot interactions?	Development of flexible e-skin pressure sensors allows robots to safely engage with humans, reducing the risk of harm during interactions.
[4]	Advanced Sensor Technology in Robotics	How do engineered nanostructures improve the sensitivity and reliability of pressure sensors?	Enhanced sensor technology contributes to safer and more reliable physical interactions between humans and robots through improved sensitivity.
[5]	AI-Driven HRI in Industry 4.0	How can AI enhance human-robot collaboration in industrial settings?	AI-driven robots improve performance and adaptability, enhancing productivity in industrial environments through better human-robot collaboration.
[6]	Human-Robot Collaboration in Cyber-Physical Systems	How can user-awareness be integrated into human-robot collaboration for future systems?	Highlights the need for robots to effectively collaborate with humans in dynamic environments, enhancing safety and efficiency.
[7]	Explainable AI (XAI) in HRI	What are the effects of providing explanations in human-robot interaction?	Implementing explainable AI provides transparency in robot decision-making, fostering user trust and acceptance.

[8]	Emotion Detection in Conversational AI	How can multi-source information fusion improve conversational emotion detection in robots?	Machine learning algorithms enable robots to recognize human emotions, allowing for more intuitive and responsive interactions.
[9]	Social Robots in Mental Health Services	Can robots exhibit empathy to be effectively used in mental health services?	Robots designed with empathy and emotional intelligence can improve user engagement, especially in healthcare settings requiring emotional support.
[10]	Perception of Nonverbal Human Behaviour by Robots	How can robots perceive and interpret nonverbal human behaviour for proactive interaction?	Incorporation of social cues like facial expressions and gestures enhances the effectiveness of human-robot interactions.
[11]	Ethical Considerations and Moral Status of Robots	Should robots be granted moral consideration and rights within a social-relational context?	Raises ethical dilemmas about robot autonomy and responsibility, suggesting the need for ethical frameworks in HRI.
[12]	Ethical Principles and Guidelines in Social Robotics	Why are ethical principles and guidelines necessary for social robots?	Emphasizes establishing ethical guidelines to address concerns in robot deployment, ensuring alignment with societal values and norms.
[13]	Ethical Implications of AI Robot Accountability	What are the ethical considerations of AI robot accountability in an Islamic context?	Discusses ethical concerns and the need for guidelines in robot deployment aligning with specific cultural and religious values.
[14]	Legal Liability of AI and Robotics	What are the legal implications concerning liability and accountability for robotic actions in Balkan states?	Evaluates legal frameworks regarding AI and robotics, highlighting the need for clear laws on liability and accountability.
[15]	Robotics in Early Education	How can voice-controlled robotics be implemented and validated in early education?	Robots can serve as personalized tutors, adapting to individual learning styles, enhancing educational outcomes and student engagement.
[16]	Responsibility Attribution in Nursing with Robots	Can nurses ascribe responsibility to intelligent robots in clinical practice?	Explores ethical considerations of attributing responsibility to robots in healthcare, impacting trust and professional acceptance.

[17]	Speech Recognition and NLP in Educational Robots	How can speech recognition and NLP enhance personal assistant robots for education?	Integration of voice recognition and NLP allows for more interactive and responsive robots, improving user experience in educational settings.
[18]	Robotics and AI in Pandemic Prevention	How can robotics and AI contribute to preventing pandemics like COVID-19?	Robots can assist in healthcare settings with patient monitoring, rehabilitation, and reducing infection risks, especially during health crises.

2.2 Safety

The safety of Human-Robot Interaction (HRI), particularly in the context of collaborative robotics (cobots), has emerged as a pivotal area of research due to the potential hazards associated with robots working alongside humans. The literature reveals a multifaceted approach to safety, encompassing risk assessment, safety architecture, and the development of tools and strategies designed to mitigate risks.

One of the primary concerns in HRI is the physical safety of human operators during interactions with robots. The literature emphasizes the necessity of collision detection and the implementation of responsive control mechanisms to prevent accidents. For instance, Li et al. [8] discuss the importance of robots being equipped with electronic skins that enable them to detect obstacles and assess collision risks, thereby facilitating safer interactions. Similarly, Kovincic et al. [19] propose a model-based strategy for safety assessment that incorporates contact detection and robot reaction mechanisms, underscoring the need for robust safety frameworks in collaborative settings. The integration of these technologies is essential for ensuring that robots can operate safely in close proximity to humans without compromising their safety.

In addition to physical safety, psychological safety is also a critical aspect of HRI. The perception of safety by human operators significantly influences their willingness to engage with robots. Research by Stoll et al. [20] indicates that spontaneous and continuous human-robot collaborations can be achieved in industrial settings, provided that the robots are perceived as safe by their human counterparts. This perception is further supported by findings from Akalın et al. [21], who highlight the various factors influencing perceived safety in HRI, including the design of the robot and the nature of its interactions with humans. The psychological dimension of safety is crucial, as it affects user acceptance and trust, which are vital for the successful integration of cobots into work environments.

The development of safety architectures for cobots has also garnered significant attention in the literature. Beetz et al. [22] present a framework that allows robots to consider both task execution and the safety of human co-workers in their control decisions. This dual focus is essential for creating robots that can operate autonomously while prioritizing human safety. Furthermore, the implementation of safety standards, such as ISO/TS 15066, provides guidelines for the design and operation of collaborative robots, ensuring that safety measures are systematically integrated into their architecture [23]. These standards are instrumental in fostering a culture of safety within industries that utilize collaborative robots.

The use of advanced sensing technologies plays a crucial role in enhancing safety during HRI. For example, Samarathunga [24] discusses the dynamics of biofidelic sensors, which can improve the assessment of human-robot impacts and contribute to safer interactions. Additionally, the work of Luo et al. [25] emphasizes the importance of analysing the dynamics of both the robot and the human hand to ensure safe interactions. The development of compliant actuators and soft robotics technologies has also been highlighted as a means to enhance safety by reducing the risk of injury during physical interactions [26]. These advancements in sensing and actuation technologies are paving the way for more intuitive and safer collaborative robots.

Moreover, the literature underscores the significance of adaptive control strategies in ensuring safety during HRI. Salehi et al. [27] explore safe adaptive trajectory tracking control methods that utilize barrier function transformations to enhance safety in human-robot interactions. This approach allows robots to adjust their movements in real-time based on the presence and behaviour of human operators, thereby minimizing the risk of accidents. Similarly, the work of Khan [28] highlights the importance of fault-tolerant control schemes that can maintain safety even in the event of actuator failures. Such adaptive strategies are essential for ensuring that robots can respond appropriately to dynamic environments and human behaviours.

The integration of augmented reality (AR) technologies into HRI has also been proposed as a means to enhance safety. Michalos et al. [29] discuss the visualization of safety zones around robot arms, providing users with real-time feedback on their proximity to the robot. This proactive approach to safety can help prevent accidents by alerting users when they are at risk of entering a hazardous area. The use of AR in conjunction with traditional safety measures represents a promising avenue for improving safety in collaborative environments.

In addition to technological advancements, the literature emphasizes the importance of user training and education in promoting safety in HRI. Training programs that educate users about the capabilities and limitations of collaborative robots can significantly enhance their confidence and perceived safety [30]. Furthermore, the incorporation of user feedback into the design process of robots can lead to more user-friendly interfaces and safer interactions [7]. By fostering a deeper understanding of HRI, organizations can create safer work environments that encourage collaboration between humans and robots.

The role of regulatory frameworks and standards in ensuring safety in HRI cannot be overstated. As the field of robotics continues to evolve, it is imperative that regulatory bodies establish clear guidelines and standards that address the unique challenges posed by collaborative robots. The work of Valori et al. [31] highlights the need for updated safety standards that reflect the advancements in robot technology and the changing nature of human-robot collaboration. By establishing comprehensive safety regulations, policymakers can help mitigate risks and promote the safe adoption of collaborative robots across various industries.

Furthermore, the literature reveals a growing interest in the ethical implications of HRI and the need for responsible innovation in robotics. As robots become more integrated into daily life, it is essential to consider the ethical dimensions of their design and deployment. Research by Martinetti et al. [32] advocates for a redefinition of safety that encompasses not only physical risks but also ethical considerations related to human-robot interactions. This holistic approach to safety can help ensure that the development of collaborative robots aligns with societal values and expectations.

Table 2. A table with short summary of results related to safety

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[8]	Electronic Skins for Safe HRI	How can multifunctional electronic skins enhance safety and dexterity in human-robot interactions?	Developed electronic skins that enable robots to detect obstacles and assess collision risks, facilitating safer and more dexterous interactions with humans.
[19]	Safety Assessment in HRI	How can a model-based strategy improve safety assessment of robot arms interacting with humans?	Proposed a model-based safety assessment incorporating contact detection and robot reaction mechanisms, emphasizing the need for robust safety frameworks in collaborative settings.
[20]	Perception of Safety in HRI	How does perceived safety impact acceptance of human-robot collaboration?	Found that the perception of safety significantly influences user acceptance and willingness to engage in spontaneous and continuous human-

			robot collaborations in industrial settings.
[21]	Factors Influencing Perceived Safety	What factors influence perceived safety in human-robot interaction?	Identified various factors, including robot design and interaction nature, that affect humans' perceived safety during interactions with robots.
[22]	Safety Architecture for Cobots	How can robots consider both task execution and human safety in control decisions?	Presented a framework allowing robots to autonomously make control decisions that prioritize both task performance and the safety of human co-workers.
[23]	Safety Standards in Industrial HRI	What are the current safety measures, interfaces, and applications in industrial human-robot collaboration?	Reviewed safety standards like ISO/TS 15066 and emphasized systematic integration of safety measures in collaborative robot design and operation.
[24]	Biofidelic Sensors in HRI	How do biofidelic sensors impact the assessment of human-robot impacts?	Discussed the use of biofidelic sensors to improve the assessment of impacts, contributing to safer human-robot interactions by accurately measuring collision effects.
[25]	Dynamics Analysis in Safe HRI	How does analysing robot and human hand dynamics enhance safety in HRI?	Highlighted the importance of understanding both robot and human hand dynamics to ensure safe physical interactions between humans and robots.
[26]	Compliant Actuators for Safe HRI	How can compliant actuators improve inherent safety in human-robot interaction?	Proposed using actuators with high torque-to-inertia and low torque-to-stiffness ratios to enhance safety, reducing injury risks during physical interactions.
[27]	Adaptive Control Strategies for Safety	How can barrier function transformations enhance safe adaptive control in HRI?	Explored safe adaptive trajectory tracking control methods that adjust robot movements in real-time to enhance safety during human-robot interactions.
[28]	Fault-Tolerant Control in HRI	How does adaptive chaos control contribute to safety in humanoid robot arms?	Emphasized the importance of fault-tolerant schemes to maintain safety even during actuator failures, ensuring continuous safe operation.
[29]	Augmented Reality in Enhancing Safety	How can AR applications support human-robot interactive cooperation and safety?	Demonstrated that AR can visualize safety zones around robots, providing real-time feedback to users and enhancing safety by preventing accidental intrusions.

[30]	User Training and Safety Perception	How do safety perception and behaviours change during HRI in virtual environments?	Found that training and virtual simulations can improve users' safety perception and behaviours, leading to safer interactions with robots.
[7]	Explanations in HRI for Safety	What are the effects of providing explanations in human-robot interaction?	Suggested that robots offering explanations can enhance user understanding and perceived safety, contributing to more effective and safer interactions.
[67]	Safety Validation in HRC	How should safety standards evolve to validate safety in human-robot collaboration?	Highlighted the need for updated safety standards and new perspectives to reflect technological advancements and ensure safety in collaborative robotics.
[32]	Redefining Safety in HRI	How should safety be redefined considering current HRI standards and regulations?	Advocated for a holistic approach to safety that includes ethical considerations, ensuring that robot development aligns with societal values and expectations.

2.2.1 Regulations and standards compliance for safety

The robot developed under the project is a typical example of a collaborative robot (cobot). According to the definition from ISO 10218-1:2011, a collaborative robot is a robot designed for direct interaction with a human within a defined collaborative workspace where the robot and a human can perform tasks simultaneously during production operation. The primary regulation in the European community concerning robot safety is the Machinery Directive 2006/42/EC. This directive has been translated into all national languages and incorporated into the legislation of each member state. A robot falls under the scope of the Machinery Directive as it consists of "linked parts or components, at least one of which moves" and is actuated by a drive system. According to the Machinery Directive, a programmable robot provided by a robot manufacturer is classified as "partly completed machinery". Consequently, the robot itself is not CE-marked under the Machinery Directive however, the robot manufacturer provides all necessary information to integrators to ensure safety. For a robot to be considered "completed" machinery, it must be designed or integrated for a specific application and generic robot without his specific application cannot be certified.

Depending on the cobot's features, other directives like the Low Voltage Directive (2006/95/EC), (2014/35/EU), Electromagnetic Compatibility Directive (2014/30/EU), Radio Equipment Directive (2014/53/EU) or General Product Safety Directive (2001/95/EC) when a robotic device is made available on the consumer market, may apply.

Table 3 European Union Directives for Product Safety

Directive	Purpose	Scope	Applicable to
Machinery Directive (2006/42/EC) (Repealed)	Facilitates free circulation of machinery while ensuring worker and consumer safety.	Establishes essential health and safety requirements for machinery.	All machinery, except where hazards are addressed by other directives.

Low Voltage Directive (2006/95/EC)	Facilitates free circulation of electrical equipment while ensuring user protection.	Establishes essential safety requirements for electrical equipment operating within specified voltage limits.	Electrical equipment operating between 50 and 1000 volts AC or 75 and 1500 volts DC.
Electromagnetic Compatibility Directive (2014/30/EU)	Ensures electrical and electronic equipment does not generate or is not affected by unacceptable levels of electromagnetic interference.	Protects health and safety of people and animals, and the proper functioning of other equipment.	All electrical and electronic equipment.
Radio Equipment Directive (2014/53/EU)	Ensures free movement of radio equipment while guaranteeing protection for health and safety, electromagnetic compatibility, and efficient use of the radio spectrum.	Outlines essential requirements for radio equipment to ensure it does not harm health or safety, provides adequate electromagnetic compatibility, and effectively uses radio spectrum resources.	All radio equipment, including devices that transmit and receive radio waves.
General Product Safety Directive (2001/95/EC)	Ensures the safety of all products placed on the EU market.	Applies to a wide range of products, from food and toys to furniture and electrical appliances.	All products placed on the EU market.

In order to place robots on the market or put them into service, it is necessary to follow the conformity assessment process specified in Article 12 of the Machinery Directive 2006/42/EC. This process concludes with the issuance of an EC declaration of conformity and the affixation of the CE marking. The most straightforward method to demonstrate compliance with the directive is by satisfying the requirements of standards harmonized with it. A product is presumed to conform to the specific requirements of a directive if it complies with the relevant provisions of the standards harmonised with it. In the case of workstations equipped with collaborative robots, these are listed in table below.

Table 4 Safety Standards for Robotics and Machinery

Standard	Purpose	Scope	Requirements
EN ISO 12100:2011	Provides general principles for risk assessment and risk reduction in machinery design.	Applies to all machinery, regardless of type or purpose.	Specifies basic terminology, principles, and methodology for achieving safety in machinery design, including hazard identification, risk assessment, and risk reduction strategies through protective measures and user information.
EN ISO 10218-1	Specifies safety requirements for industrial robots.	Applies to industrial robots as standalone units.	Describes basic hazards associated with robots and provides requirements for eliminating or reducing risks through design, technical safeguards, protective measures, and providing information to users.

EN ISO 10218-2	Specifies safety requirements for industrial robot systems and integration.	Applies to industrial robot systems and robot cells.	Addresses hazards and hazardous situations associated with integrating robots into systems and cells, providing requirements for installation, programming, operation, maintenance, and decommissioning to ensure safety.
ISO/TS 15066	Provides guidelines for collaborative robot system safety.	Applies to collaborative robot systems, where robots and humans share workspace.	Specifies guidelines for designing and implementing collaborative workspaces, including limits on force and pressure during human-robot contact to ensure safe interaction between humans and robots in industrial environments.
EN ISO 13849-1	Specifies a methodology for the design and integration of safety-related parts of control systems.	Applies to safety-related parts of control systems of machinery.	Specifies requirements for the design of hardware and software components, including safety categories, performance levels (PL), and system architecture to ensure the required reliability of safety functions.
EN ISO 13849-2	Specifies procedures for the validation of safety-related parts of control systems.	Applies to safety-related parts of control systems of machinery.	Provides procedures for validation by analysis and testing to confirm that safety-related parts meet specified safety requirements and achieve the required performance level (PL).
EN IEC 60204-1	Provides requirements for the electrical equipment of machines.	Applies to the electrical equipment of industrial machines.	Specifies requirements for electrical safety, including protection against electric shock, electrical control systems, wiring, grounding, operator interfaces, and technical documentation to ensure safe installation and operation of machinery.
EN ISO 13850	Specifies requirements for the emergency stop function on machinery.	Applies to emergency stop functions on machinery.	Defines functional requirements and design principles for emergency stop systems, including the placement and construction of control devices, their visibility, accessibility, and reliable operation in emergency situations.
EN ISO 3691-4	Specifies safety requirements for driverless industrial trucks.	Applies to driverless industrial trucks and their systems.	Specifies safety requirements and verification methods for driverless trucks, including control systems, obstacle detection, emergency stop, pedestrian interaction, and maintenance procedures to ensure safe operation in industrial environments.

2.2.2 Hazards posed by autonomous or collaborative robots

The integration of autonomous and collaborative robots into various sectors has raised significant concerns regarding the potential hazards they pose to human operators. As robots increasingly operate in close proximity to humans, particularly in unstructured environments, the hazard associated with physical human-robot interaction (pHRI) become more pronounced. This interaction can lead to injuries due to unexpected robot behaviour, inadequate safety measures, or the inherent unpredictability of human actions. For instance, Miyata and Ahmadi [33] emphasize the need for compliant sensing and force control to mitigate risks during pHRI, highlighting that traditional collision avoidance methods may not suffice in dynamic environments where human actions are unpredictable. Similarly, Zagirov et al. [34] note that unexpected robot failures and poorly designed security systems can lead to injuries during collaborative tasks, underscoring the necessity for robust safety protocols.

Moreover, the design and implementation of collaborative robots, or cobots, must prioritize human safety to prevent accidents. Kaonain et al. [35] discuss the critical challenges in human-robot interaction, particularly the hazard of human injury when robots operate in shared spaces with humans. Vasic & Billard [36] further elaborate on the potential hazards posed by robots in industrial settings, where the introduction of robotic systems can disrupt established workflows and create new safety concerns for human workers. The need for comprehensive risk assessments in domestic environments, as highlighted by Badia et al. [37], is essential for ensuring that collaborative robots can operate safely alongside humans without compromising their well-being.

The psychological aspects of human-robot interaction also contribute to the perceived risks associated with collaborative robots. Hanoch et al. [38] explore how the presence of robots can influence human risk-taking behaviour, suggesting that individuals may engage in riskier actions when interacting with robots, potentially leading to hazardous situations. This phenomenon is compounded by the fact that humans often anthropomorphize robots, attributing them with human-like qualities that can distort perceptions of risk and safety [39]. As robots become more integrated into daily life, understanding these psychological dynamics is crucial for designing safer interaction protocols.

In addition to physical risks, the ethical implications of human-robot interaction must also be considered. The potential for robots to manipulate human behaviour, as discussed by Franklin and Ashton [40], raises concerns about the ethical ramifications of persuasive robotics, where robots may exert undue influence over users. This manipulation can lead to unintended consequences, particularly in vulnerable populations, necessitating a careful examination of the ethical frameworks governing robot design and deployment.

Furthermore, the development of safety standards for collaborative robots is imperative to ensure their safe operation in human environments. Navarro et al. [41] emphasize the importance of adhering to established safety standards, such as ISO 10218, which outlines the requirements for safe human-robot interaction. These standards are designed to minimize risks associated with physical contact between humans and robots, ensuring that safety measures are integrated into the design and operation of robotic systems.

The role of technology in enhancing safety during human-robot interactions cannot be overlooked. Advances in sensor technology and artificial intelligence have the potential to improve the safety of collaborative robots significantly. For instance, Li et al. [8] discuss the development of multifunctional electronic skins that enable robots to interact safely and dexterously with humans, enhancing their ability to perceive and respond to human presence. Such innovations could mitigate risks associated with physical interactions, allowing for safer collaboration in various settings.

Moreover, the use of virtual reality (VR) and augmented reality (AR) technologies for testing and training in human-robot interaction scenarios presents a promising avenue for enhancing safety. Badia et al. [37] highlight the potential of VR to create safe testing environments where robots can be evaluated in simulated interactions with humans, thereby identifying and addressing potential hazards before real-world deployment. This proactive approach to safety can help mitigate hazard associated with human-robot collaboration.

The challenges of ensuring safety in human-robot interactions extend beyond technical solutions. The social dynamics of human-robot collaboration also play a crucial role in determining safety outcomes. Olawoyin [42] emphasizes that the cognitive skills and flexibility of human workers must be considered in the design of collaborative robotic systems to optimize safety and performance. Understanding the interplay between human capabilities and robotic functionalities is essential for creating effective and safe collaborative environments.

Another significant hazard arises from the interaction between autonomous robots and human operators. As robots increasingly collaborate with humans, the potential hazards escalates. Vasić and Billard [36] emphasize the safety issues in industrial settings where robots operate with high speed and force, which can pose significant risks to human workers. Furthermore, the design of robots must consider the potential for unintended consequences during human-robot interactions, as noted by Guiochet [43], who discusses the importance of hazard analysis in these contexts. The lack of clear communication and understanding between humans and robots can lead to misjudgments and accidents.

The reliability and safety of the software that governs autonomous robots is another critical concern. Many autonomous systems rely on complex algorithms for navigation and decision-making, which can introduce vulnerabilities. Ingibergsson et al. [44] argue that the software components of autonomous robots are safety-critical and must undergo rigorous testing and certification to ensure their reliability. Additionally, the verification and validation of these systems are essential to prevent failures that could result in hazardous situations, as highlighted by Fisher et al. [45] in their overview of challenges faced by inspection robots. The complexity of these systems makes it difficult to predict their behaviour in all scenarios, which can lead to unforeseen hazards.

Moreover, the physical design and operational capabilities of autonomous robots can also pose hazards. For instance, heavy and fast-moving robots can cause severe injuries if they collide with humans or objects. Weng et al. [46] discuss the safety testing of legged robots, which are expected to operate in environments shared with humans, emphasizing the need for effective collision avoidance mechanisms. Similarly, the design of mobile robots for hazardous environments must account for their ability to traverse difficult terrains without losing stability or control, as noted by Guiochet [43]. The potential for mechanical failures or malfunctions further exacerbates these risks.

The deployment of autonomous robots in public spaces introduces additional safety concerns. As these robots operate in environments populated by humans, the potential for accidents increases. Brandao [47] discusses the implications of using less accurate models for certain demographic groups, which can lead to safety disparities when robots interact with diverse populations. The lack of standardized safety protocols for robots operating in public spaces can lead to inadequate protection for pedestrians and bystanders, as highlighted by Salvini et al. [48]. This necessitates the development of comprehensive safety regulations to govern the operation of autonomous robots in such settings.

Furthermore, the integration of artificial intelligence (AI) in autonomous robots introduces additional complexities. AI systems can make decisions based on data inputs, but they may also misinterpret information or fail to account for unexpected variables. This can lead to hazardous situations, particularly in environments where rapid decision-making is crucial. Ertle [49] emphasizes the need for safety knowledge to be learned from human demonstrations to improve the reliability of autonomous systems. The potential for AI systems to make erroneous decisions underscores the importance of incorporating robust safety measures and fail-safes in their design.

The challenges of maintaining operational safety in collaborative environments are also significant. As robots work alongside humans, the potential for accidents increases due to the unpredictability of human behaviour. Parsa et al. [50] highlight the importance of understanding operator workload and performance in teleoperation scenarios, which can impact the safety of collaborative tasks. The design of collaborative robots must prioritize safety features that account for the dynamic interactions between humans and machines.

Table 5. A table with short summary of results related to hazards posed by autonomous or collaborative robots

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[33]	Compliant Sensing and Force Control in pHRI	How can compliant sensing and force control mitigate risks during physical human-robot interaction in dynamic environments?	Emphasizes the need for compliant sensing and force control to mitigate risks during pHRI, as traditional collision avoidance methods may not suffice in unpredictable and dynamic environments where human actions are unpredictable.
[34]	Safety Protocols in Human-Robot Collaboration	How do unexpected robot failures and poorly designed security systems lead to injuries during collaborative tasks?	Highlights the necessity for robust safety protocols, as unexpected robot failures and inadequate security systems can result in injuries during collaborative tasks, underscoring the importance of safety measures.
[35]	Hazard Assessment in Human-Robot Interaction	What are the critical challenges in HRI regarding human injury when robots operate in shared spaces?	Discusses critical challenges and emphasizes the potential hazard of human injury when robots and humans share operational spaces, stressing the need for effective safety measures.
[37]	Risk Assessment in Domestic Robot Environments	Why is comprehensive risk assessment essential for collaborative robots operating in domestic environments?	Highlights the necessity of comprehensive risk assessments to ensure collaborative robots can safely operate alongside humans in domestic settings without compromising well-being.
[38]	Psychological Aspects and Risk-Taking in HRI	How does the presence of robots influence human risk-taking behaviour?	Suggests that individuals may engage in riskier actions when interacting with robots, potentially leading to hazardous situations, indicating a need for awareness in design and protocols.
[39]	Anthropomorphism and Risk Perception in HRI	How does anthropomorphizing robots affect perceptions of risk and safety?	Finds that humans often attribute human-like qualities to robots, which can distort perceptions of risk and safety, potentially leading to underestimation of hazards.
[40]	Ethical Implications of Persuasive Robotics	What are the ethical ramifications of robots manipulating human behaviour?	Raises concerns about robots exerting undue influence over users, leading to unintended consequences, especially in vulnerable populations, necessitating ethical frameworks in design and deployment.
[41]	Safety Standards for Collaborative Robots	What is the importance of adhering to safety standards like ISO 10218 for safe HRI?	Emphasizes that adhering to established safety standards minimizes risks associated with physical contact between humans and robots, ensuring safety measures are integrated into design and operation.

[8]	Sensor Technology for Safe HRI	How can multifunctional electronic skins enhance safe and dexterous human-robot interactions?	Developed electronic skins that enable robots to interact safely and dexterously with humans, enhancing their ability to perceive and respond to human presence, thereby mitigating physical interaction risks.
[37]	VR for Safety Testing in HRI	How can virtual reality create safe testing environments for evaluating robots?	Highlights that VR can simulate interactions to identify and address potential hazards before real-world deployment, helping to mitigate risks associated with human-robot collaboration.
[42]	Human Cognitive Skills in Collaborative Robotics	Why must cognitive skills and flexibility of human workers be considered in collaborative robot design?	Emphasizes that considering human cognitive skills and flexibility is essential for optimizing safety and performance in collaborative robotic systems, leading to more effective and safer collaboration.
[36]	Safety Issues in Industrial HRI	What are the safety issues when robots operate at high speed and force in industrial settings?	Highlights significant risks posed to human workers when robots operate at high speed and force, emphasizing the need for safety measures to prevent accidents in industrial human-robot interactions.
[43]	Hazard Analysis in Human-Robot Interactions	Why is hazard analysis important in human-robot interactions?	Stresses the importance of hazard analysis in robot design to prevent unintended consequences during HRI, ensuring that potential risks are identified and mitigated proactively.
[44]	Safety Certification Practices in Autonomous Robots	Why must software components of autonomous robots undergo rigorous testing and certification?	Argues that software in autonomous robots is safety-critical and requires rigorous testing and certification to ensure reliability, preventing failures that could lead to hazardous situations.
[45]	Verification and Validation Challenges in Inspection Robots	What are the challenges in verifying and validating inspection robots to prevent hazardous situations?	Highlights the need for thorough verification and validation to prevent failures in autonomous systems that could result in hazardous situations, particularly in inspection tasks.
[46]	Safety Testing of Legged Robots	How can safety testing ensure legged robots operate safely in human-shared environments?	Emphasizes the need for effective collision avoidance mechanisms and safety testing in legged robots to prevent injuries when operating alongside humans.
[47]	Safety Disparities Due to Model Inaccuracies in HRI	What are the implications of using less accurate models for certain demographic groups in HRI?	Using less accurate models can lead to safety disparities when robots interact with diverse populations, indicating a need for inclusive design and accurate modelling across demographics.

[48]	Safety in Mobile Robots Serving in Public Spaces	What are the safety concerns for robots operating in public spaces?	Highlights the lack of standardized safety protocols, leading to inadequate protection for pedestrians and bystanders, necessitating the development of comprehensive safety regulations for public spaces.
[49]	Learning Safety Knowledge from Human Demonstrations	How can safety knowledge learned from human demonstrations improve autonomous systems?	Emphasizes the need for autonomous systems to learn safety knowledge from human demonstrations to improve reliability and safety, reducing the likelihood of erroneous decisions.
[50]	Operator Workload and Safety in Teleoperation	How does operator workload impact safety in teleoperation scenarios?	Highlights that understanding operator workload and performance is essential for safety in collaborative tasks involving teleoperation, as high workload can compromise safety.

2.3 Trustworthiness

The trustworthiness of Human-Robot Interaction (HRI) in collaborative robots (cobots) is a multifaceted issue that encompasses various dimensions, including cognitive, emotional, and social factors. As cobots become increasingly integrated into workplaces and daily life, understanding the dynamics of trust in these interactions is crucial for their successful adoption and effective collaboration. This response synthesizes current research on trust in HRI, focusing on the factors that influence trustworthiness, the implications of trust in collaborative settings, and strategies for enhancing trust in cobot interactions.

Trust in HRI is often conceptualized through two main dimensions: cognitive trust and affective trust. Cognitive trust is based on the robot's reliability and performance, while affective trust is influenced by emotional responses and social perceptions of the robot [51],[52]. For instance, Pinto et al. [52] emphasize the importance of measuring trust in HRI, noting that understanding the factors influencing trust perception is vital for designing trustworthy robots. This aligns with findings by Ahmad et al. [51], who argue that cognitive trust arises from a robot's performance, while affective trust is shaped by users' perceptions of the robot's motives.

The complexity of collaborative robotics introduces unique challenges in establishing trust. Unlike traditional robots with limited action spaces, cobots operate in dynamic environments where the state, action, and potential failure modes are more complex [53]. This complexity necessitates a deeper understanding of the teaming dynamics between human and robot agents, as highlighted by Hopko and Mehta [53], who explore how cognitive processes in humans affect their trust in shared-space collaborative robots. The interplay between cognitive load and trust is also significant; as cognitive load increases, the ability to assess a robot's reliability may diminish, leading to reduced trust [51]. Trust is not static; it evolves based on experiences and interactions between humans and robots. This dynamic aspect of trust is further illustrated by the work of Esterwood and Robert [54], who discuss trust repair strategies in HRI, emphasizing the need for robots to effectively restore trust after mistakes. The ability to adapt and respond to human feedback is essential for maintaining trust over time, as highlighted by the findings of Guo et al. [55], who propose a trust inference and propagation model that captures the dynamics of trust in multi-robot teams.

Moreover, the emotional aspects of HRI play a crucial role in shaping trust. Eyam et al. [56] discuss how emotion-driven analysis can enhance HRI by considering users' emotional states during interactions. This perspective is echoed by Valori et al. [57], who suggests that familiarity and comfort with robots can foster trust, particularly in contexts where robots are designed to provide companionship. The design of robots that can effectively communicate their intentions and emotional states is essential for building trust, as users are more likely to trust robots that exhibit human-like emotional responses [56],[57].

The design of cobots must also consider the social context in which they operate. For example, the work of Olatunji [58] emphasizes the importance of participatory design approaches to create robots that are perceived as trustworthy by older adults in home environments. This participatory approach ensures that the design process incorporates the needs and expectations of users, thereby enhancing the perceived trustworthiness of the robots. Similarly, Chen and Jia's [59] research on facial anthropomorphism highlights how the design of a robot's face can influence trustworthiness perceptions, indicating that aesthetic factors are critical in HRI.

In collaborative tasks, mutual adaptation between humans and robots is vital for establishing trust. Nikolaidis et al. [60] demonstrate that trust can be elicited through mutual adaptation during collaborative tasks, where both agents adjust their behaviours to enhance cooperation. This adaptability is crucial in maintaining trust, especially when unexpected situations arise. The ability of robots to explain their actions and decisions can further bolster trust, as users are more likely to trust robots that provide transparent reasoning for their behaviours [61],[62].

The implications of trust in HRI extend beyond individual interactions; they influence the overall acceptance of robots in society. Research indicates that trust in robots is a significant predictor of their acceptance in various domains, including healthcare and manufacturing [63]. As robots become more prevalent, understanding the factors that foster trust will be essential for their successful integration into human environments. For instance, studies have shown that robots that can effectively communicate their intentions and exhibit socially competent behaviours are more likely to be trusted by users [64].

Furthermore, the role of cultural factors in shaping trust perceptions cannot be overlooked. Research by Korn et al. [65] highlights how cultural differences affect the acceptance and design preferences of social robots, suggesting that trust is influenced by cultural norms and expectations. This underscores the need for culturally aware design practices in HRI to ensure that robots are perceived as trustworthy across diverse user groups.

One of the foundational aspects of trust in HRI is the reliability of the robot's performance. Research has shown that users' trust is significantly influenced by their perceptions of a robot's reliability and competence in performing tasks. For instance, a study by Nikolaidis et al. [60] emphasizes that participants' ratings of trust were closely linked to the robot's performance during collaborative tasks, indicating that consistent and reliable performance is crucial for building trust. Similarly, Faccio et al. [66] argue that safety features in cobots enhance trust by ensuring that human operators feel secure while interacting with robots. This connection between reliability and trust is further supported by findings from Babamiri et al. [67], who discuss how usability and trust are interrelated, suggesting that higher usability leads to increased trust in robotic systems.

Communication also plays a vital role in establishing trust in HRI. Effective communication between humans and robots can mitigate misunderstandings and enhance collaborative efforts. Xu and Dudek [68] propose that integrating personality-based factors into trust models can improve the predictive power of these models, thereby facilitating better communication and understanding between human and robot agents. Furthermore, the ability of robots to convey their intentions clearly is essential for fostering trust. Lee et al. [69] emphasize that calibrating intent and capabilities is crucial for effective collaboration, as it helps humans understand the robot's actions and decisions. This is echoed by the work of Chen et al. [70], who introduce a trust-aware decision-making model that incorporates human trust as a latent variable, highlighting the importance of transparent communication in HRI.

Moreover, the design and embodiment of robots significantly impact human perceptions of trust. Research by Maris et al. [71] indicates that the physical appearance and behaviour of robots can influence trust levels, with more human-like robots often eliciting higher trust. This anthropomorphic design approach is supported by findings from Onnasch and Laudine [72], who argue that anthropomorphic features can enhance attention and trust in industrial HRI settings. However, it is essential to balance anthropomorphism with functionality, as overly human-like designs may lead to unrealistic expectations and potential trust violations [73].

The context in which HRI occurs also affects trust dynamics. For instance, the complexity of tasks and the environment can influence how trust is established and maintained. Research by Wagner-Hartl et al. [74]

suggests that task complexity can lead to variations in trust levels, with simpler tasks often fostering higher trust due to reduced uncertainty. Additionally, the social context of HRI, including factors such as social conformity and communication styles, can shape trust perceptions. Studies have shown that social dynamics play a crucial role in how humans interact with robots, with conformity influencing trust levels in collaborative settings [75].

Furthermore, the role of emotions in HRI cannot be overlooked. Emotional responses to robots can significantly impact trust, as demonstrated by the work of Savery et al., which explores the use of emotional musical prosody to enhance trust in robotic communication [76]. Understanding the emotional landscape of HRI is essential for designing robots that can effectively engage with humans and foster trust.

The performance of robots is a critical determinant of trustworthiness in HRI. Brule et al. [77] demonstrated that a robot's task performance significantly influences human trust, suggesting that higher performance leads to greater perceived trustworthiness. This finding is corroborated by Zhu [78], who noted that trust is not static but varies with the complexity of tasks, indicating that straightforward or highly complex tasks tend to elicit more trust compared to those of intermediate complexity. This dynamic nature of trust underscores the importance of designing robots that can adapt their performance to varying task complexities, thereby fostering a reliable partnership with human collaborators.

Moreover, the behavioural style of robots plays a pivotal role in shaping human trust. Brule et al. [77] also highlighted that the behavioural style of a robot, alongside its performance, affects human trust perceptions. This aligns with the findings of Lyons et al. [79], who emphasized that the stated social intent of robots can serve as a predictor of trust, suggesting that transparency in a robot's intentions enhances trustworthiness. The integration of these behavioural cues into robot design can significantly improve the quality of interactions, making robots more relatable and trustworthy to human users.

Facial expressions and physical appearance of robots also contribute to trust perceptions. Calvo-Barajas et al. [80] found that children's evaluations of trustworthiness were not significantly influenced by robotic facial expressions, indicating that trust judgments may not be as straightforward as in human interactions. However, Chen and Jia's [59] research on the baby schema effect suggests that certain facial features can enhance perceived trustworthiness, particularly in social robots designed for family or elderly care. This highlights the need for careful consideration of aesthetic design in robots to foster trust, especially in sensitive environments.

The role of explanations in HRI cannot be overlooked. Research by Javaid and Estivill-Castro [81] indicates that providing explanations for a robot's actions significantly enhances trust in collaborative settings. This finding is supported by the work of He et al. [82], who identified key properties of trustworthy robots, including the necessity for transparency and explainability in their operations. By ensuring that robots can articulate their decision-making processes, developers can enhance user trust and facilitate smoother interactions.

The implications of trust extend beyond individual interactions to encompass broader societal perceptions of robots. Kok and Soh [83] highlighted the challenges and opportunities in developing trustworthy robots, emphasizing the need for robust trust measurement frameworks and guarantees on robot behaviour in real-world settings. This is particularly relevant as robots are increasingly integrated into public and private sectors, where trust is paramount for user acceptance and collaboration.

Trust in HRI can be conceptualized as a multifaceted construct that encompasses cognitive, emotional, and social dimensions. Cognitive trust relates to the reliability and performance of the robot, while emotional trust is influenced by the perceived intentions and social behaviours of the robot [60],[73]. The interplay between these dimensions is crucial for effective collaboration, as trust can significantly affect human willingness to engage with robots in various tasks [84],[85],[69]. For instance, Pinto et al. emphasize the importance of understanding the factors influencing trust perception in HRI, suggesting that a robust trust assessment framework must account for both cognitive and emotional dimensions.

The role of anthropomorphism in trust assessment is another critical area of exploration. Research indicates that the design features of robots, such as their appearance and behaviour, can significantly influence human trust perceptions. Roesler et al. [86] found that anthropomorphic features can enhance initial trust levels, although the effects may vary depending on the context and the nature of the task [87],[86]. This suggests that trust assessment methods should consider the impact of robot design on human perceptions, as these factors can shape the overall trust dynamics in collaborative scenarios.

Furthermore, the impact of robot errors on trust is an essential consideration in trust assessment methodologies. Studies have shown that human trust can be adversely affected by robot failures, particularly when those failures are perceived as unpredictable or unexplainable [88]. Trust repair strategies, as explored by Esterwood and Robert [89], are vital for restoring trust after such failures, highlighting the need for assessment methods that evaluate not only initial trust but also the potential for trust recovery. This underscores the importance of developing comprehensive trust assessment frameworks that account for the entire lifecycle of human-robot interactions.

One of the foundational aspects of trust in HRI is the multidimensional nature of trust itself. Research indicates that trust is not a singular construct but rather encompasses various dimensions, such as cognitive trust (based on the robot's performance and reliability) and affective trust (based on emotional responses and interpersonal relationships) [90],[91]. This multidimensionality suggests that different factors can influence trust in distinct ways. For instance, the robot's anthropomorphism—its human-like features—can enhance affective trust by fostering a sense of familiarity and emotional connection [92],[93]. Furthermore, the robot's ability to communicate effectively and transparently can significantly impact cognitive trust, as users are more likely to trust robots that provide clear explanations of their actions and intentions [81],[70].

The context in which human-robot interactions occur also plays a crucial role in shaping trust. For example, in high-stakes environments such as healthcare, the consequences of trust misalignment can be severe, leading to potential harm to patients [94,[95]. In these settings, trust is often influenced by the robot's perceived competence and the user's prior experiences with similar technologies [96],[97]. Studies have shown that users who have had positive prior experiences with robots are more likely to trust them in future interactions [99]. Conversely, negative experiences, such as errors or failures during interactions, can lead to a rapid decline in trust, necessitating effective trust repair strategies [89],[98].

Trust dynamics in human-robot collaboration are further complicated by the need for robots to adapt their behaviours based on the user's trust level. Research has explored various models for predicting and managing trust, including Bayesian inference approaches that allow robots to update their trust assessments based on user interactions and feedback [100],[101]. These models can help mitigate issues of over-trust or under-trust, which can lead to either complacency or excessive caution in human operators [102],[103]. For instance, if a robot consistently performs well, users may become overly reliant on it, potentially overlooking critical monitoring of its actions [102]. Conversely, if a robot makes mistakes, it must employ trust repair tactics, such as apologies or corrective actions, to regain the user's confidence [89],[104].

Moreover, the design and functionality of robots significantly influence trustworthiness. Factors such as the robot's appearance, its ability to exhibit social behaviours, and the clarity of its communication can all impact how users perceive its reliability and intentions [105],[72]. For example, robots designed with more anthropomorphic features tend to elicit higher levels of trust, as they are perceived as more relatable and approachable [93],[92]. Additionally, the interface through which users interact with robots can also affect trust levels; studies have shown that different feedback mechanisms and interface designs can lead to varying degrees of trust in collaborative tasks [106],[105].

The implications of trust in human-robot collaboration extend beyond individual interactions to encompass broader societal and ethical considerations. As robots become more autonomous and integrated into daily life, understanding the factors that foster or hinder trust will be essential for ensuring their acceptance and effective use [107].

Demographic factors also play a significant role in trust assessment. Kühne's research indicates that variables such as age and gender can influence how individuals evaluate a robot's trustworthiness and competence [108]. This finding is supported by Sarkar et al., who discusses how personal characteristics and experiences shape trust in robotic coworkers, suggesting that tailored approaches to user interaction may enhance trustworthiness [109]. Furthermore, the design of robots, including their physical appearance and functionality, can impact user trust. For instance, Gervasi's [110] work on cobot size reveals that user experience varies significantly with the robot's dimensions, indicating that design considerations are critical for fostering trust in collaborative settings.

In addition to psychological and operational factors, the communication strategies employed by cobots significantly influence trustworthiness. Effective communication, including the use of gestures and verbal cues, can enhance user understanding of the robot's intentions and actions. Sauer's [111] exploration of zoomorphic gestures for conveying robot states illustrates how non-verbal communication can improve trust by making robots more relatable and understandable to users. Similarly, Casalino et al. [112] emphasize the importance of operator awareness in collaborative environments, suggesting that feedback mechanisms can enhance mutual understanding and trust.

The role of context in trust evaluation cannot be overlooked. Trust is often context-dependent, influenced by the specific tasks being performed and the environment in which the collaboration occurs. For instance, the complexity of tasks, as highlighted by Wagner-Hartl [74], can affect trust levels, with more complex tasks potentially leading to increased uncertainty and decreased trust. This underscores the need for context-sensitive trust assessment methodologies that consider the dynamic nature of human-robot interactions.

Table 6. A table with short summary of results related to trustworthiness

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[51]	Trust and Cognitive Load in HRI	How does cognitive load affect trust in human-robot interaction?	Increased cognitive load diminishes the ability to assess a robot's reliability, leading to reduced trust.
[52]	Measurement of Trust in HRI	How can trust in human-robot interaction be measured effectively?	Emphasizes the importance of understanding factors influencing trust perception to design trustworthy robots.
[53]	Cognitive Processes Affecting Trust	How do human cognitive processes affect trust in shared-space collaborative robots?	Highlights the need for understanding teaming dynamics due to the complexity of cobots in dynamic environments.
[54]	Trust Repair Strategies in HRI	How can robots effectively restore trust after making mistakes?	Discusses the necessity for robots to employ trust repair strategies to regain human trust after errors.
[55]	Trust Dynamics in Multi-Robot Teams	How can trust dynamics be captured in multi-human multi-robot teams?	Proposes a trust inference and propagation model capturing trust dynamics in complex team settings.
[56]	Emotion-Driven Analysis in HRI	How can users' emotional states enhance human-robot interaction?	Suggests that considering users' emotional states can improve HRI by making interactions more responsive.
[31]	Familiarity and Comfort in HRI	How does familiarity and comfort with robots foster trust?	Indicates that familiarity and comfort with robots can enhance trust, especially in companionship roles.
[58]	Participatory Design for Trustworthy Robots	How can participatory design enhance perceived trustworthiness by older adults?	Emphasizes involving users in the design process to create robots perceived as trustworthy by specific demographics.

[59]	Design Aesthetics and Trust	How does the design of a robot's face influence trust perceptions?	Shows that aesthetic factors, like facial design, are critical in influencing trustworthiness perceptions.
[60]	Mutual Adaptation in Collaboration	How can mutual adaptation between humans and robots elicit trust?	Demonstrates that mutual behavioural adjustments enhance cooperation and trust in collaborative tasks.
[61]	Trust After Automation Failure	How does automation failure affect human trustworthiness in teamwork?	Highlights the importance of robots explaining actions to bolster trust post-failure.
[62]	Explanations in HRI	How can robot explanations enhance trust in collaboration?	Emphasizes that robots explaining their actions can bolster user trust during collaboration.
[63]	Trust and Acceptance in Industry	What factors influence robot acceptance in industrial settings?	Identifies trust as a significant predictor of robot acceptance in manufacturing domains.
[65]	Cultural Factors in Trust	How do cultural differences affect social robot acceptance?	Highlights that cultural norms influence trust, necessitating culturally aware robot design.
[66]	Safety Features Enhancing Trust	How do safety features in cobots enhance trust?	Argues that safety features increase operator trust by ensuring secure interactions.
[67]	Usability and Trust in Robotics	How does usability influence trust and willingness to use robots?	Indicates that higher usability leads to increased trust and willingness to adopt robots.
[68]	Trust Modelling in HRI	How can personality factors improve trust models in HRI?	Proposes integrating personality traits into trust models to enhance predictive accuracy.
[69]	Calibration of Intent and Capabilities	How does calibrating intent and capabilities affect collaboration?	Suggests that aligning robot intent with capabilities aids understanding and trust.
[70]	Trust-Aware Decision Making	How can human trust be incorporated into robot decision-making?	Introduces a model incorporating human trust as a latent variable to improve transparency.
[71]	Robot Embodiment and Trust	How does robot appearance influence trust levels?	Finds that human-like appearance and behaviour in robots often elicit higher trust.
[72]	Anthropomorphic Design in HRI	How do anthropomorphic features affect trust in industrial settings?	Argues that such features enhance attention and trust in industrial human-robot interactions.

[74]	Task Complexity and Trust	How does task complexity affect trust, considering gender and age?	Suggests simpler tasks foster higher trust; complexity can reduce trust due to uncertainty.
[75]	Social Dynamics in Trust	How do social conformity effects influence trust in HRI?	Demonstrates that social dynamics, like conformity, significantly impact trust levels.
[76]	Emotions and Trust in HRI	How can emotional musical prosody enhance trust in robots?	Explores how emotional cues in communication can improve trust in robotic interactions.
[77]	Performance and Behavioural Style	How do robot performance and behaviour affect human trust?	Shows that both high performance and appropriate behaviour styles increase human trust.
[78]	Task Complexity and Trust Dynamics	How does task complexity influence trust in HRI?	Finds that very simple or highly complex tasks elicit more trust than those of intermediate complexity.
[79]	Decision Authority and Trust	How do decision authority and social intent predict trust in robots?	Indicates that transparent social intent enhances trustworthiness in autonomous robots.
[80]	Facial Expressions and Trust	How do robot facial expressions affect children's trust?	Finds that facial expressions did not significantly influence children's trust evaluations.
[81]	Explanations Enhancing Trust	How do robot explanations affect trust in collaboration?	Concludes that providing explanations significantly enhances trust in collaborative tasks.
[82]	Human-Centered AI for Trust	What are key properties of trustworthy robots?	Identifies transparency and explainability as crucial for trustworthy robot operations.
[83]	Challenges in Developing Trustworthy Robots	What are the challenges and opportunities in robot trust development?	Emphasizes the need for robust trust measurement and behaviour guarantees in robots.
[84]	Theory of Mind in HRI	How does theory of mind influence trust in collaboration?	Suggests that understanding human mental states enhances trust and willingness to engage with robots.
[85]	Modelling Trust in HRI	How can trust in HRI be effectively modelled?	Surveys various predictive models for managing trust in human-robot interactions.
[87]	Trust Models in Multi-Robot Systems	How can trust be modelled in multi-robot architectures?	Proposes trust models that account for anthropomorphic features impacting initial trust levels.

[86]	Anthropomorphism and Trust	How do anthropomorphism and failure comprehension affect trust?	Finds that anthropomorphic features can enhance initial trust, depending on context and tasks.
[89]	Trust Repair in HRI	How can robots regain user trust after failures?	Highlights the importance of trust repair strategies for restoring trust post-failure.
[90]	Measurement of Trust	How reliable are current trust measures in HRI?	Points out that trust is multidimensional, requiring comprehensive measurement approaches.
[91]	Trust Modelling and Measurement	How can trust in HRI be modelled and measured effectively?	Emphasizes the need for assessment methods accounting for trust's multidimensional nature.
[92]	Inner Speech and Trust	How does a robot's inner speech affect trust and anthropomorphism?	Shows that inner speech can enhance affective trust by fostering emotional connections.
[101]	Trust Dynamics Modelling	How can Bayesian inference model trust dynamics in teaming?	Explores predictive models allowing robots to update trust assessments based on interactions.
[100]	Trust Dynamics in HRI	How can trust dynamics be predicted in human-robot teams?	Provides a Bayesian approach to mitigate over-trust and under-trust in collaborations.
[102]	Trust Repair Tactics	How can robots repair human trust after mistakes?	Suggests that apologies and corrective actions are effective in regaining user confidence.
[103]	Trust Transfer in HRI	How can trust be transferred across tasks in HRI?	Proposes models to manage trust dynamics, preventing over-reliance or excessive caution.
[105]	Context and Design in Trust	How do context and design influence trust and attributions in HRI?	Finds that design and functionality significantly impact user trust perceptions.
[106]	Interfaces and Trust	How do interface designs affect trust in collaborative tasks?	Demonstrates that different interfaces can lead to varying trust levels in collaboration.
[95]	Trust in Healthcare Robots	What influences trust in robots within healthcare?	Notes that perceived competence and prior experiences affect trust in healthcare robots.
[108]	Demographics and Trust	How do age and gender influence robot trust evaluations?	Indicates that demographic factors like age and gender affect trust and competence perceptions.
[109]	Personal Characteristics and Trust	How do personal traits and experiences shape trust in robotic coworkers?	Suggests tailored interaction approaches enhance trust based on individual characteristics.

[110]	Cobot Design and Trust	How does cobot size affect user experience and trust?	Finds that robot dimensions significantly impact user experience and trust in collaboration.
[111]	Communication Strategies in HRI	How can zoomorphic gestures enhance trust in cobot interactions?	Shows that non-verbal cues make robots more relatable, improving communication and trust.
[112]	Feedback Mechanisms and Trust	How do feedback mechanisms enhance trust in collaborative environments?	Emphasizes that feedback enhances mutual understanding and trust in human-robot collaboration.

2.4 Dependability

In the realm of Human-Robot Interaction (HRI), ensuring system dependability is paramount for effective and safe collaboration between humans and robots. Dependability is defined as a system's ability to provide a service that can justifiably be trusted, minimizing the frequency and severity of failures and avoiding outages longer than acceptable to users [252]. The concept of dependability encompasses attributes such as reliability, availability, safety, adaptability, maintainability, and security [252]. These attributes are essential for building trust and acceptance of robotic systems within human environments.

Safety is a paramount concern in HRI, particularly in environments where robots and humans share physical spaces. It refers to the robot's ability to operate without causing harm to human users or itself. Research indicates that physical human-robot interaction (pHRI) must prioritize safety mechanisms to prevent accidents and ensure compliance with safety standards [113],[32]. For instance, the implementation of admittance control in industrial robots allows for compliant behaviour, reducing the risk of injury during collaborative tasks [113]. Furthermore, the design of robots must consider ergonomic factors that influence human cognition and interaction dynamics, thereby enhancing safety [114].

Reliability pertains to the robot's consistent performance over time, ensuring that it can complete tasks as expected without failure. This dimension is critical as it directly impacts user trust; if a robot frequently malfunctions or fails to perform its intended functions, users may become hesitant to rely on it [115]. Studies have shown that users' perceptions of a robot's reliability can be influenced by its design and the transparency of its operational processes [116]. For example, robots that exhibit predictable behaviours are often perceived as more reliable, which can enhance user confidence in their capabilities [116].

Availability refers to the robot's readiness for use when required. This dimension is particularly relevant in service-oriented applications where robots must be accessible to assist users promptly. Research highlights that the perceived availability of robots can significantly affect user satisfaction and their willingness to engage with robotic systems [117]. In environments such as hospitality or healthcare, where timely assistance is crucial, ensuring high availability can lead to improved user experiences and outcomes [118].

Maintainability involves the ease with which a robot can be repaired or updated to ensure continued performance. This dimension is essential for long-term deployment, as robots may require regular maintenance to function optimally [32]. The design of robots should facilitate straightforward maintenance procedures, which can enhance user trust by demonstrating a commitment to reliability and performance sustainability [119]. Moreover, the integration of self-diagnostic capabilities can further support maintainability by allowing robots to identify and report issues autonomously [32].

Security encompasses the protection of both the robot and the data it processes from unauthorized access or malicious attacks. In an era where cyber threats are prevalent, ensuring the security of robotic systems is vital for maintaining user trust. Research indicates that users are more likely to engage with robots that exhibit robust security measures, as this can mitigate concerns about data privacy and system integrity. The development of security protocols and the implementation of secure communication channels are crucial for fostering a trustworthy environment in HRI [32].

Table 7. A table with short summary of results related to dependability

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[113]	Safety Mechanisms in pHRI	How can admittance control enhance safety in physical human-robot interaction?	Implementation of admittance control allows for compliant robot behaviour, reducing the risk of injury during collaborative tasks.
[32]	Safety, Security, and Maintainability in HRI	What are the current standards and regulations for safety and security in HRI? How can maintainability be improved?	Emphasizes the need for robust safety mechanisms, security measures, and self-diagnostic capabilities to maintain user trust and ensure reliable, maintainable robot operation.
[114]	Ergonomic Design and Safety in HRI	How do ergonomic factors influence human cognition and safety in human-robot interaction?	Designing robots with ergonomic considerations enhances safety by positively influencing human cognition and interaction dynamics.
[115]	Reliability and User Trust in Robots	How does a robot's reliability affect user trust and willingness to rely on it?	Frequent malfunctions decrease user trust; consistent and reliable robot performance is critical for fostering user reliance.
[116]	Design Transparency and Perceived Reliability	How do design and operational transparency influence users' perceptions of robot reliability?	Users perceive robots with predictable behaviours and transparent operations as more reliable, enhancing user confidence and trust.
[117]	Robot Availability and User Satisfaction	How does the perceived availability of robots affect user satisfaction and engagement?	High perceived availability significantly improves user satisfaction and willingness to engage with robotic systems in service applications.
[118]	Robot Availability in Hospitality	What is the impact of robot availability on user experiences in hospitality settings?	Ensuring timely assistance by robots in hospitality enhances user experiences and positive outcomes.
[119]	Maintainability in Service Robots	How can robot design facilitate ease of maintenance to ensure continued performance?	Emphasizes the importance of designing robots that allow straightforward maintenance procedures to enhance reliability and performance sustainability.

3 Methods of safety, trustworthiness and dependability analysis

3.1 Introduction

In the evolving landscape of robotic applications, the integration of autonomous and collaborative robots into human-centric environments presents both opportunities and challenges. The MANiBOT project aims to advance the state of robotic technology by developing robots that can efficiently and safely interact within human-populated settings. Critical to the success of such innovations are the safety, trustworthiness, and dependability of the robotic systems. These three pillars form the foundation upon which the acceptance and effectiveness of robotic systems in society rest.

This chapter outlines the methodologies employed in the MANiBOT project to analyse and enhance these crucial aspects. It addresses the inherent risks associated with the deployment of autonomous and collaborative robots, and details specific analytical approaches designed to ensure that the robots not only meet but exceed the necessary safety and reliability standards. Through comprehensive safety, trustworthiness, and dependability analysis, the project seeks to establish robust frameworks that guarantee the robots are capable of operating in complex, dynamic environments without compromising human safety and comfort.

3.2 Methods and tools for safety analysis

3.2.1 Introduction

In the evolving landscape of human-robot interactions (HRI), ensuring the safety of both humans and robotic systems is paramount. As robots become increasingly integrated into diverse environments—from industrial floors to personal spaces—the need for rigorous safety analysis becomes more critical. This introduction outlines a structured approach to safety analysis in HRIs, covering a spectrum of methods and tools designed to identify, evaluate, and mitigate risks effectively. From risk assessment techniques that identify and quantify potential hazards, to compliance with international safety standards, and the deployment of advanced safety analysis tools, this framework seeks to establish robust safety protocols that enhance the dependability and security of robotic systems in their interactions with humans. By systematically addressing these aspects, we aim to foster a safer and more reliable integration of robotic technology into daily operations and interactions, ensuring that safety remains at the forefront of technological progress in the field of robotics. This overview outlines the key methods and tools used to assess and enhance safety in HRIs, contributing to the development of robots that are both effective and secure in their operations.

3.2.2 Methods for Safety Analysis

1. Risk Assessment
    - Hazard Identification: Systematically identifying potential sources of harm in the interaction between humans and robots.
    - Risk Estimation: Quantifying the likelihood and severity of identified hazards to assess the level of risk associated with each.
    - Risk Evaluation: Comparing estimated risks against acceptable risk criteria to determine whether they are tolerable or require mitigation.
    - Risk mitigation and Reduction Measures: Implementing strategies to eliminate, minimize or mitigate risks to acceptable levels, such as engineering controls, administrative controls, or personal protective equipment.
2. Hazard Analysis Techniques. Examples include:

- Fault Tree Analysis (FTA): A top-down approach that models the pathways to system failures, helping to identify and analyse potential causes of hazards.
- Event Tree Analysis (ETA): A bottom-up method that starts with an initiating event and examines possible outcomes, useful for understanding the consequences of failures.
- Failure Modes and Effects Analysis (FMEA): A systematic technique for identifying potential failure modes within a system and assessing their effects on overall safety.
- Hazard and Operability Study (HAZOP): A structured examination of complex systems to identify and evaluate problems that may represent risks to personnel or equipment.

3. Human Factors Analysis. Examples include:

- Task Analysis: Evaluating the tasks performed by humans and robots to identify potential safety issues arising from human error or miscommunication.
- Human Error Analysis: Assessing how human errors can contribute to unsafe situations, using methods like the Human Error Assessment and Reduction Technique (HEART).
- Cognitive Workload Analysis: Ensuring that the human operator's workload is within manageable limits to prevent mistakes that could lead to safety hazards.

4. Compliance with Safety Standards (e.g.)

- ISO 10218: International standards specifying safety requirements for industrial robots and robotic systems.
- ISO/TS 15066: Technical specifications providing guidance on collaborative robot operations, focusing on safety requirements and protective measures.
- IEC 61508: Standards for functional safety of electrical/electronic/programmable electronic safety-related systems.

3.2.3 Tools for Safety Analysis

1. Simulation and Modelling Software

- Computer-Aided Design (CAD) Tools: For designing robots with safety considerations integrated from the outset.
- Robotics Simulation Platforms: Software like ROS (Robot Operating System) with Gazebo or V-REP allows testing robot behaviours and interactions in virtual environments to identify potential safety issues before physical deployment.
- Human Motion Prediction Tools: Software that predicts human movements to optimize robot paths and avoid collisions.

2. Safety Monitoring Systems

- Sensors and Vision Systems: Utilization of cameras, LiDAR, ultrasonic sensors, and proximity sensors to detect human presence and prevent collisions.
- Safety Programmable Logic Controllers (PLCs): Specialized controllers that monitor safety-critical operations and ensure immediate response to unsafe conditions.
- Emergency Stop Devices: Hardware and software mechanisms that allow immediate cessation of robot operations in case of detected hazards.

3. Risk Management Software

- Safety Lifecycle Management Tools: Software that assists in documenting and managing the safety lifecycle of robotic systems, ensuring compliance with safety standards.

- Risk Assessment Applications: Tools that facilitate the systematic recording, analysis, and mitigation planning of identified risks.

4. Testing and Validation Tools

- Physical Testing Facilities: Laboratories equipped to safely test robots in controlled environments that simulate real-world conditions.
- Verification and Validation Software: Tools that help in verifying that safety requirements are correctly implemented and validating that the system meets those requirements in practice.

3.2.4 Literature review

The safety analysis of Human-Robot Interaction (HRI) systems, particularly collaborative robots (cobots), is a critical area of research due to the inherent risks posed by close human-robot collaboration. Various methods have been developed to ensure safety, ranging from uncertainty quantification to advanced monitoring systems. This chapter synthesizes various methodologies and frameworks for safety analysis in human-robot interactions (HRI), specifically focusing on collaborative robots (cobots).

Uncertainty quantification is a method used to evaluate the safety of robot systems by measuring the reliability of critical parameters such as distance and velocity between humans and robots. This approach helps in assessing safety limits online and determining whether a situation is safe or dangerous. The method involves calculating the propagated measurement uncertainty of parameters, which accounts for sensory device errors and environmental disturbances. Validation experiments in both simulations and real-world settings have demonstrated the effectiveness of this approach in maintaining safety in HRI systems [120].

An electronic tool (e-tool) has been developed for safety risk evaluation in robotic applications within the construction industry. This tool, created through a mixed-methods approach, helps identify and mitigate HRI safety risks by incorporating various mitigation strategies and aiding in pre-task planning. It has been tested by industry stakeholders, proving its effectiveness and practicality in enhancing worker safety and productivity [121].

A two-layer approach combining formal methods and simulation models is proposed for hazard analysis in collaborative automation systems. This method synthesizes unsafe behaviours from a formal model using Supervisory Control Theory, which are then analysed in detail through simulation. This approach is particularly beneficial for complex systems where traditional hazard analysis methods are insufficient [122].

A vision-based safety monitoring system has been developed to enhance safety in manufacturing settings. This system creates a 3D reconstruction of the collaborative scene and records human-robot interaction data in real-time. It allows for offline analysis through virtual replicas, providing a user-friendly visualization tool for performance review and failure diagnosis [123].

Machine learning algorithms, specifically Convolutional Neural Networks (CNNs), are employed to recognize and predict collisions in shared workspaces. This method involves isolating objects, filtering them, and tracking cobots and human operators to predict possible collisions. The approach has shown high accuracy in recognizing objects and predicting collisions, highlighting the importance of understanding human behaviour in cobot interactions [124].

A Multi-Agent Safety System (MASS) utilizes wearable technologies and machine learning classifiers to predict safety risks in HRI systems. Principal Component Analysis (PCA) is used for data dimension reduction, and classifiers like Decision Trees are employed to predict human distraction, which could pose safety risks. This system aims to improve the privacy, efficiency, and reliability of safety systems in Industry 5.0 workplaces [125].

The safety of human-robot collaboration is fundamentally tied to the design and operational parameters of the robots themselves. Cobots are designed to work alongside humans, which necessitates a focus on their intrinsic safety features. For instance, lightweight and flexible designs are essential to minimize injury risks during interactions. Antonelli et al. [126] emphasize that collaborative work-cells must be robustly designed to accommodate human presence while ensuring operational safety. Furthermore, the implementation of safety measures such as torque sensors and compliant joints can significantly reduce the risk of injury during physical interactions.

Motion prediction is another critical aspect of ensuring safety in HRI. Mugisha [127] discusses the use of Gaussian processes for motion prediction, which can enhance safety by anticipating human movements and adjusting the robot's actions accordingly. By employing velocity modulation techniques, robots can maintain a safe distance from humans while still performing their tasks efficiently. This predictive capability is crucial in dynamic environments where human behaviour can be unpredictable.

Moreover, the assessment of risks associated with human-robot interactions must consider human factors extensively. Rahman et al. [128] highlight that the proximity of robots to human workers raises significant safety concerns, necessitating a comprehensive understanding of human comfort zones and workspace dynamics. This is echoed by Vicentini et al. [129], who propose a risk analysis methodology that incorporates human behaviour unpredictability into safety assessments. Such methodologies are essential for developing a holistic understanding of safety in collaborative environments.

The integration of virtual reality (VR) and augmented reality (AR) technologies offers innovative approaches to safety analysis in HRI. Badia et al. [37] advocate for the use of VR simulations to test collaborative scenarios safely, allowing for the evaluation of human-robot interactions without the risk of physical harm. This approach enables researchers to explore various interaction dynamics and identify potential safety hazards in a controlled environment. Additionally, the use of digital twins can facilitate real-time monitoring and risk assessment during collaborative tasks, as discussed by Bazzi [130].

Another significant aspect of safety analysis in HRI involves the continuous adaptation of robots to human behaviours and preferences. Kwon et al. [131] emphasize the importance of modelling human behaviour accurately to enhance safety and efficiency in collaborative tasks. By understanding and anticipating human actions, robots can adjust their operations to minimize risks. This adaptability is further supported by the work of Salehi et al. [27], who present methods for safe adaptive trajectory tracking that account for human interactions.

Furthermore, the psychological aspects of HRI cannot be overlooked. The perception of safety by human operators plays a crucial role in the effectiveness of collaborative systems. Lu et al. [132] discuss the impact of mental stress on human-robot collaboration, indicating that high stress levels can lead to decreased performance and increased risk. Therefore, incorporating ergonomic assessments and mental well-being considerations into safety analysis frameworks is essential for fostering effective human-robot collaboration.

In terms of regulatory and standardization frameworks, the ISO/TS 15066 standard provides guidelines for safety in collaborative robotics. This standard outlines common hazards and risk assessment processes, but it lacks detailed guidance for users navigating the complexities of collaborative environments. To address this gap, Murino et al. [133] propose a practical risk assessment approach that combines Failure Mode and Effects Analysis (FMEA) with a risk priority list, offering a structured methodology for evaluating safety in cobot applications.

Moreover, the development of proactive safety strategies is crucial for enhancing the safety of human-robot interactions. Sanderud et al. [134] propose a simplified risk analysis strategy that leverages kinematic redundancy to minimize risks during collaborative tasks. This proactive approach allows for the identification and mitigation of potential hazards before they result in accidents.

The role of communication in HRI is also vital for ensuring safety. Effective communication between humans and robots can significantly enhance situational awareness and reduce the likelihood of accidents. Degeorges and Sziebig [135] emphasize the importance of developing communication protocols that facilitate clear interactions between human operators and robots. Such protocols can help in establishing mutual understanding and trust, which are essential for safe collaboration.

Finally, the integration of advanced technologies such as artificial intelligence (AI) and machine learning into safety analysis frameworks can further enhance the safety of HRI. For instance, the use of AI for real-time monitoring and decision-making can help robots adapt to changing conditions and human behaviours dynamically. This capability is crucial for maintaining safety in environments where human actions may be unpredictable.

Table 8. A table with short summary of results related to methods and tools for safety analysis

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[120]	Uncertainty Quantification in HRI Safety Evaluation	How can uncertainty quantification be used to evaluate and maintain safety in HRI systems?	Introduced a method that calculates propagated measurement uncertainties to assess safety limits online, enhancing safety in HRI systems through accurate reliability assessment.
[121]	Safety Risk Evaluation Tools in Construction HRI	How can an electronic tool assist in evaluating and mitigating safety risks in HRI within construction applications?	Developed an e-tool that aids in identifying and mitigating HRI safety risks, enhancing worker safety and productivity as validated by industry stakeholders.
[122]	Hazard Analysis Using Formal Methods and Simulation	How can a two-layer approach combining formal methods and simulation enhance hazard analysis in complex collaborative automation systems?	Proposed a method that synthesizes unsafe behaviours using Supervisory Control Theory and analyses them through simulation, improving hazard analysis in complex systems.
[123]	Vision-Based Safety Monitoring in Manufacturing HRI	How can a vision-based system enhance safety monitoring and analysis in manufacturing human-robot interactions?	Developed a system that creates 3D reconstructions of collaborative scenes for real-time data capture and offline analysis, enhancing safety monitoring and failure diagnosis.
[124]	Collision Prediction Using Machine Learning in HRI	How can CNNs be utilized to recognize and predict collisions in shared human-cobot workspaces?	Employed machine learning to accurately predict collisions by tracking cobots and human operators, emphasizing the importance of understanding human behaviour in improving safety.
[125]	Multi-Agent Safety Systems with Wearable Tech and ML	How can a MASS using wearable technology and machine learning predict safety risks in HRI systems?	Introduced a system that predicts human distraction and safety risks using PCA and classifiers, enhancing safety systems' efficiency and reliability in Industry 5.0 workplaces.
[126]	Design Considerations for Safety in Collaborative Workcells	How should collaborative workcells be designed to ensure safety and accommodate human presence?	Emphasized robust design with intrinsic safety features like lightweight and flexible robots to minimize injury risks in collaborative environments.

[127]	Motion Prediction Using Gaussian Processes in HRI	How can Gaussian processes be utilized for motion prediction to enhance safety in HRI?	Showed that Gaussian processes effectively predict human motion, allowing robots to adjust actions and maintain safe distances, enhancing safety in dynamic environments.
[128]	Human Factors and Risk Assessment in HRI	How do human comfort zones and workspace dynamics impact safety in HRI?	Highlighted the need for comprehensive risk assessments that consider human factors like comfort zones to address safety concerns arising from robot proximity.
[129]	Incorporating Human Unpredictability into Risk Analysis	How can human behaviour unpredictability be integrated into safety risk analysis methodologies?	Proposed a methodology that accounts for human unpredictability, enhancing the thoroughness and effectiveness of safety assessments in HRI.
[37]	Using VR/AR for Safety Analysis in HRI	How can VR simulations enhance safety analysis and testing in human-robot collaboration?	Advocated for VR use to safely test collaborative scenarios, enabling evaluation of interactions and hazard identification without physical risk.
[130]	Digital Twins for Real-Time Monitoring in HRI	How can digital twins be utilized for real-time monitoring and risk assessment in collaborative tasks?	Demonstrated that digital twins enable real-time monitoring and risk assessment, improving safety during human-robot collaboration.
[131]	Modelling Human Behaviour in HRI	How does accurate modelling of human behaviour improve safety and efficiency in collaborative tasks?	Emphasized that accurate human behaviour modelling enhances robots' ability to anticipate actions, improving adaptability and minimizing risks.
[27]	Safe Adaptive Trajectory Tracking in HRI	How can adaptive trajectory tracking methods enhance safety by accounting for human interactions?	Presented methods allowing robots to adjust trajectories in real-time, enhancing safety by adapting to human presence and movements.
[132]	Impact of Mental Stress on HRI Safety	How does mental stress affect performance and safety in human-robot collaboration?	Found that high mental stress reduces performance and increases safety risks, highlighting the need to incorporate ergonomic and well-being considerations into safety analysis.
[133]	Practical Risk Assessment Methods for Cobots	How can combining FMEA with a risk priority list improve safety evaluation in cobot applications?	Proposed a combined approach offering a structured and practical method for evaluating and prioritizing risks, enhancing safety assessment in collaborative robotics.
[134]	Proactive Safety Strategies	How can kinematic redundancy be used in risk analysis to minimize risks in	Introduced a simplified risk analysis leveraging kinematic redundancy to proactively identify and mitigate potential

	Using Kinematic Redundancy	human-robot collaboration?	hazards, enhancing safety during collaboration.
[135]	Communication Protocols for Safety in HRI	How do effective communication protocols between humans and robots enhance safety in HRI?	Emphasized that clear communication protocols improve situational awareness and mutual understanding, reducing accidents and enhancing safety in collaborative tasks.

3.3 Methods and tools for trustworthiness analysis

3.3.1 Introduction

Trustworthiness in human-robot interactions (HRI) is a crucial factor that affects how humans accept and rely on robotic systems. It encompasses aspects like reliability, transparency, ethical behaviour, and safety. Below is an overview of the methods and tools used for trustworthiness analysis in HRI.

3.3.2 Methods for Trustworthiness Analysis

1. Human Trust Assessment
   - Surveys and Questionnaires: Tools like the Trust in Automation Scale or the Human-Robot Trust Scale measure users' perceived trust in robots.
   - Behavioural Observation: Analysing how users interact with robots, such as their willingness to delegate tasks or follow robot instructions.
   - Physiological Measures: Monitoring heart rate, skin conductance, or eye-tracking to infer trust levels during interactions.
2. Reliability and Performance Evaluation
   - Failure Mode and Effects Analysis (FMEA): Identifying potential failure points in the robot's operation and their impact on trust.
   - Statistical Reliability Testing: Assessing the robot's performance over time to ensure consistent behaviour.
3. Transparency and Explainability
   - Explainable AI (XAI): Implementing algorithms that make the robot's decision-making processes understandable to users.
   - Interactive Feedback Mechanisms: Providing real-time explanations or status updates to keep users informed about the robot's actions.
4. Ethical and Social Impact Assessment
   - Ethical Frameworks: Applying guidelines like the IEEE's Ethically Aligned Design to evaluate the robot's adherence to ethical standards.
   - Cultural Sensitivity Analysis: Ensuring the robot's behaviour aligns with the social and cultural norms of the users.
5. Simulation and Modelling

- Human Behaviour Modelling: Creating models that predict how users might react in various interaction scenarios.
- Scenario-Based Testing: Simulating different interaction contexts to identify potential trust issues.

6. User Experience (UX) Research

- Usability Testing: Evaluating how easy and intuitive it is for users to interact with the robot.

Focus Groups and Interviews: Gathering in-depth feedback from users about their trust perceptions.

3.3.3 Tools for Trustworthiness Analysis

1. Simulation Software

- Robot Operating System (ROS) Simulators: Tools like Gazebo allow for testing robot behaviours in virtual environments (VE).
- Virtual Reality (VR) Platforms: Creating immersive scenarios to study HRI without physical risks.

2. Data Analysis Tools

- Statistical Software: Programs like SPSS or R for analysing survey data and behavioural metrics.
- Machine Learning Frameworks: TensorFlow or PyTorch for developing and testing AI models focused on explainability and predictability.

3. Human Monitoring Equipment

- Eye-Tracking Systems: To study where users focus their attention during interactions.
- Physiological Sensors: Devices that measure heart rate variability, skin conductance, etc.

4. Ethical Assessment Tools

- Ethics Checklists: Standardized lists to ensure all ethical considerations are addressed during development.
- Compliance Software: Tools that help verify adherence to regulations like GDPR for data privacy.

5. User Interface (UI) Design Tools

- Prototyping Software: Tools for designing intuitive robot interfaces that enhance user trust.

Interaction Design Frameworks: Guidelines for creating interactions that are predictable and transparent.

3.3.4 Literature review

The assessment and evaluation of trustworthiness in mobile collaborative robots (cobots) are complex and multifaceted challenges that involve understanding the dynamics between human perception, robot performance, and their interaction. Effective methods for assessing trust integrate a variety of approaches, such as multi-valued logic, paired comparison methods, physiological and behavioural measures, and affective computing, all aimed at capturing the nuanced dynamics of human-robot interactions and providing insights into trust levels. Additionally, trust is a crucial element in human-robot collaboration (HRC), influencing the safety and effectiveness of these interactions. This paper synthesizes current methodologies for evaluating cobot trustworthiness by examining psychological, operational, and design factors. The complexity of trust in human-robot interactions (HRI) stems from various elements, including robot design, perceived reliability, and the specific context of the interaction, making this evaluation critical as robots become increasingly integrated into sectors like healthcare, manufacturing, and service industries. Moreover, trust dynamics in HRI are influenced by robot behaviour, human perception, and contextual factors, requiring a comprehensive understanding of these elements to enhance the effectiveness and efficiency of collaborative tasks. This chapter explores diverse studies to provide a thorough overview of trust assessment methods in cobots.

One prominent method for assessing trust in cobots involves the use of trust scales, which quantify human perceptions of robot reliability and intentions. For example, Pinto et al. [52] developed a trust scale specifically tailored for HRI, validating its effectiveness in measuring trust levels in collaborative contexts. This scale can be utilized to gauge trust before, during, and after collaborative tasks, providing insights into how trust evolves over time. Similarly, Jerčić et al. [136] explored the impact of emotions and social behaviour on trust during collaborative tasks, highlighting the significance of emotional engagement in fostering trust. Their findings suggest that trust assessment should not only focus on performance metrics but also consider emotional and social interactions between humans and robots.

"The Trust Perception Scale-HRI" and "The HRI Trust Scale" are two widely recognized tools used to assess human-robot trust in the field of human-robot interaction (HRI). The "Trust Perception Scale-HRI" was developed by Schaefer in her Ph.D. dissertation, where she focused on understanding the intricacies of how humans perceive and measure trust in robots in various contexts [137]. This scale emphasizes the subjective experience of trust from the user's perspective, addressing factors such as reliability, predictability, and overall confidence in robotic systems. On the other hand, "The HRI Trust Scale" created by Yagoda and Gillan [138] is specifically designed to quantitatively measure the level of trust humans place in robots across different tasks and settings. Their work highlights the importance of trust in successful human-robot interactions, offering insights into the dynamics that foster trust in these relationships.

Another effective approach to trust assessment is the use of experimental paradigms that simulate real-world collaborative scenarios. For instance, Nikolaidis et al. [60] conducted experiments that elicited trust ratings from participants after completing collaborative tasks with robots, demonstrating that direct interaction significantly influences trust levels [136],[60] . Such experimental designs allow researchers to manipulate variables related to robot behaviour and task complexity, providing a controlled environment to study trust dynamics. Additionally, the use of immersive environments, as explored by You et al. [139], can enhance the realism of these experiments, thereby improving the ecological validity of trust assessments.

Moreover, the integration of real-time trust monitoring systems has emerged as a promising method for assessing trust during HRI. Xu and Dudek [140] developed a trust model that quantifies human trust states in real-time, enabling adaptive robot behaviour based on the assessed trust levels. This dynamic approach allows robots to adjust their actions to maintain or enhance trust, thereby fostering more effective collaboration. Such models can incorporate various factors, including task performance, user feedback, and contextual cues, to provide a comprehensive understanding of trust dynamics in real-time interactions.

In addition to quantitative measures, qualitative assessments of trust can also provide valuable insights. For example, narrative reviews and interviews can capture the nuances of human perceptions regarding robot trustworthiness, as highlighted by Hannibal [141], who emphasized the importance of understanding human experiences and attitudes towards robots in collaborative settings. This qualitative approach can complement quantitative measures, offering a more holistic view of trust in HRI.

One of the primary methods for evaluating trustworthiness in cobots involves assessing user satisfaction and perceived safety. Fraboni et al. [142] highlight that key performance indicators such as worker satisfaction, stress levels, and usability can be measured through surveys and feedback mechanisms to gauge the effectiveness of technology integration in workplace settings. This approach aligns with findings from Eyam et al. [56], who emphasize the importance of emotional responses in human-robot interactions, suggesting that understanding user emotions can enhance the design of trust-enhancing features in robots. Moreover, Olatunji's [58] participatory design approach underscores the necessity of involving users in the design process to ensure that robots are perceived as safe and reliable, thereby fostering trust.

Another important aspect of trustworthiness evaluation is the robot's operational reliability. Trust in robots is often contingent upon their performance in executing tasks accurately and consistently. Studies have shown that users are more likely to trust robots that demonstrate high reliability in functional tasks [87]. Studies such as Chen et al. [70] have proposed trust-aware decision-making models that allow robots to infer human trust levels based on their actions, thereby enhancing collaborative performance. Additionally, the integration of fault management systems, as discussed by [87], can help maintain trust by ensuring that robots can effectively handle operational failures and communicate their status to human partners.

The psychological dimensions of trust are also critical in evaluating cobots. Research by Shafiei et al. [143] indicates that brain activity can serve as an objective measure of trust during robot-assisted tasks, providing insights into the cognitive processes underlying trust in human-robot interactions. This neurophysiological approach complements traditional assessment methods, offering a more nuanced understanding of how trust develops and fluctuates during collaborative tasks. Moreover, the concept of trust repair is essential when trust is compromised; strategies for rebuilding trust after errors or failures are crucial for maintaining long-term collaborative relationships [54].

Furthermore, the design of trustworthiness assessment frameworks is essential for systematically evaluating cobots. Alarcon et al. [144] propose a comprehensive scale for measuring system trustworthiness, which incorporates various dimensions of user experience and interaction quality. This structured approach allows for a more rigorous evaluation of cobot performance and user perceptions, facilitating the identification of areas for improvement. Additionally, the integration of machine learning techniques, as discussed by Liu [145], can enhance the adaptability of trust assessment models, allowing for real-time adjustments based on user feedback and interaction history.

Multi-valued logic techniques are employed to handle imperfect information and control mobile robots under uncertainty. This approach allows for the specification of robot movements and swarming behaviours using artificial neural networks with mobile neurons. Such techniques are particularly useful in processing non-probabilistic uncertainties and making decisions with imperfect information, forming a robust framework for subjective trust assessment in mobile cobots [146].

The Adaptive Paired Comparison method, based on particle filtering, is effective for subjective assessments in environments with weak control. This method reduces test time and improves reliability compared to traditional methods like Mean Opinion Score (MOS) and Differential MOS (DS-MOS). It is particularly beneficial for non-expert users, enhancing the reliability of subjective assessments in mobile cobot interactions [147].

Pairwise Comparison (PC) methods are also highlighted as more precise and robust than traditional rating scales in physical human-robot collaboration. PC methods reduce response bias and enhance data reliability by focusing on direct comparisons between items, thus fostering authentic participant engagement [148].

Integrating physiological, behavioural, and subjective measures provides a comprehensive approach to assessing trustworthiness in cobots. This method involves recording neural and cardiac activity, alongside standard subjective and behavioural measures, to correlate mental stress and fatigue with task complexity and other factors. Such multimodal assessments are crucial for understanding the impact of cobots on human workers in industrial settings [149].

Affective computing, which interprets emotions from human biosignals, is a promising area for subjective trust assessment in human-robot interaction. By using non-invasive biosensors to infer psychological states, this approach can provide valuable insights into human emotions and perceptions during interactions with cobots. The use of devices like the NeuroSky Mindset EEG neuroheadset demonstrates the feasibility of inferring subjective assessments from biosignals, offering a potential tool for future applications in human-robot interaction [150].

Subjective evaluation methods, such as those used in mobile terminal assessments, involve simulating actual use environments to gather user feedback on operability and user experience. These methods can be adapted for mobile cobots to assess user perceptions and trustworthiness effectively [151].

Additionally, subjective evaluation scales, derived from factor analysis of human-friendly robot motion, can be used to construct algorithms for mobile robots. These scales help in understanding user perceptions of familiarity, activity, and reliability, which are critical for developing trust in cobots [152].

While these methods provide comprehensive tools for assessing trustworthiness, it is important to consider the limitations and challenges associated with each approach. For instance, the complexity of integrating physiological and behavioural measures may require sophisticated equipment and expertise, while paired comparison methods may not capture the full range of user experiences. Therefore, a combination of these methods, tailored to specific contexts and user needs, is likely to yield the most effective results in assessing the trustworthiness of mobile cobots. Evaluating trustworthiness in cobots requires a multifaceted approach that encompasses user perceptions, operational reliability, communication strategies, and contextual factors. By integrating insights from various studies, it becomes evident that fostering trust in collaborative robots is not only about ensuring technical reliability but also about understanding and addressing the psychological and emotional dimensions of human-robot interactions.

Table 9. A table with short summary of results related to methods and tools for trustworthiness analysis

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[52]	Trust Scales in HRI	Developed a trust scale tailored for human-robot interaction (HRI). How effective is it in measuring trust levels in collaborative contexts?	Validated the effectiveness of the trust scale in measuring trust levels in collaborative contexts; the scale can be used before, during, and after tasks to gauge how trust evolves over time.
[136]	Emotions and Trust in HRI	Explored the impact of emotions and social behaviour on trust during collaborative tasks. Should trust assessment consider emotional and social interactions?	Found that emotional engagement significantly fosters trust; suggested that trust assessment should not only focus on performance metrics but also include emotional and social interactions between humans and robots.
[137]	Trust Perception Scale-HRI	Developed the "Trust Perception Scale-HRI" to understand how humans perceive and measure trust in robots in various contexts.	Emphasized the subjective experience of trust from the user's perspective, addressing factors such as reliability, predictability, and overall confidence in robotic systems.
[138]	The HRI Trust Scale	Created a scale to quantitatively measure the level of trust humans place in robots across different tasks and settings.	Highlighted the importance of trust in successful human-robot interactions; offered insights into the dynamics that foster trust in these relationships through quantitative measurement.
[60]	Experimental Paradigms for Trust Assessment	Conducted experiments eliciting trust ratings after collaborative tasks with robots. How does direct interaction influence trust levels?	Demonstrated that direct interaction significantly influences trust levels; experimental designs allow manipulation of robot behaviour and task complexity to study trust dynamics in controlled environments.
[139]	Immersive Environments in Trust Assessment	Explored the use of immersive environments to enhance the realism of trust assessment experiments. Does immersion improve ecological validity?	Found that immersive environments improve the ecological validity of trust assessments by enhancing realism, thereby providing more accurate insights into trust dynamics during human-robot interactions.

[140]	Real-time Trust Monitoring in HRI	Developed a trust model quantifying human trust states in real-time for adaptive robot behaviour. How can robots adjust actions based on trust levels?	Enabled robots to adjust their actions to maintain or enhance trust, fostering more effective collaboration through dynamic adaptation based on real-time trust assessments incorporating task performance, user feedback, and contextual cues.
[141]	Qualitative Assessments of Trust	Emphasized understanding human experiences and attitudes towards robots in collaborative settings. How can qualitative assessments complement quantitative measures?	Narrative reviews and interviews capture nuances of human perceptions regarding robot trustworthiness, offering a holistic view of trust in HRI that complements quantitative measures.
[142]	User Satisfaction and Perceived Safety	Measuring worker satisfaction, stress levels, and usability to evaluate technology integration effectiveness in workplaces. How do these factors inform trust evaluation?	Surveys and feedback mechanisms gauge effectiveness; key performance indicators inform trustworthiness evaluation in workplace settings, aligning with user satisfaction and perceived safety to enhance trust in cobots.
[56]	Emotional Responses in HRI	Emphasized the importance of emotional responses in human-robot interactions. How do emotions influence trust in robots?	Understanding user emotions enhances the design of trust-enhancing features in robots; emotional engagement is crucial for fostering trust in human-robot interactions.
[58]	Participatory Design for Trust	Involving users in the design process to ensure robots are perceived as safe and reliable. Does participatory design foster trust?	Participatory design fosters trust by aligning robot design with user expectations and perceptions of safety and reliability, thereby enhancing acceptance and trustworthiness of cobots.
[70]	Trust-Aware Decision-Making Models	Proposed models allowing robots to infer human trust levels based on their actions. How can robots enhance collaboration by adapting to trust levels?	Enhances collaborative performance by enabling robots to adjust their behaviour according to inferred human trust levels, leading to more effective and trust-sensitive interactions.
[87]	Fault Management in Trust Maintenance	Discussed the integration of fault management systems to maintain trust during operational failures. How does fault handling affect trust?	Effective handling of operational failures and communication of status helps maintain human trust in robots, ensuring transparency and reliability even when errors occur.

[143]	Neurophysiological Measures of Trust	Investigated brain activity as an objective measure of trust during robot-assisted tasks. Can brain activity provide insights into trust dynamics?	Brain activity provides insights into the cognitive processes underlying trust; neurophysiological measures complement traditional assessment methods, offering a nuanced understanding of trust development and fluctuation during collaborative tasks.
[54]	Trust Repair in HRI	Explored strategies for rebuilding trust after errors or failures. What are effective trust repair mechanisms in human-robot collaboration?	Trust repair is essential for maintaining long-term collaborative relationships; strategies include apologies, explanations, and corrective actions to rebuild trust after it has been compromised.
[144]	Trustworthiness Assessment Frameworks	Proposed a comprehensive scale for measuring system trustworthiness incorporating user experience and interaction quality. How can systematic evaluation improve cobots?	Provided a structured approach for rigorous evaluation of cobot performance and user perceptions, facilitating identification of areas for improvement and enhancing overall trustworthiness through comprehensive assessment.
[145]	Machine Learning in Trust Assessment	Discussed enhancing the adaptability of trust assessment models using machine learning. How can ML improve real-time trust assessment?	Machine learning techniques allow for real-time adjustments in trust assessment models based on user feedback and interaction history, improving adaptability and responsiveness in human-robot interactions.
[146]	Multi-Valued Logic in Trust Assessment	Employed multi-valued logic techniques to handle imperfect information in mobile robot control. How does this approach aid in trust assessment?	Provided a robust framework for subjective trust assessment under uncertainty; useful in processing non-probabilistic uncertainties and making decisions with imperfect information, enhancing control and trust in mobile cobots.
[147]	Adaptive Paired Comparison Method	Used particle filtering in subjective assessments with weak control. How does this method improve assessment reliability?	Reduces test time and improves reliability over traditional methods like Mean Opinion Score (MOS); beneficial for non-expert users, enhancing the reliability of subjective assessments in mobile cobot interactions.
[148]	Pairwise Comparison in HRI	Highlighted the precision and robustness of Pairwise Comparison methods over traditional rating scales. How do PC methods enhance trust assessment?	PC methods reduce response bias and enhance data reliability by focusing on direct comparisons between items, fostering authentic participant engagement and providing more precise and robust assessment in physical human-robot collaboration.

[149]	Multimodal Assessment of Trustworthiness	Integrated physiological, behavioural, and subjective measures in cobot assessment. How do these measures correlate with trust and performance?	Recording neural and cardiac activity correlates mental stress and fatigue with task complexity and other factors; such multimodal assessments are crucial for understanding the impact of cobots on human workers in industrial settings and for assessing trustworthiness comprehensively.
[150]	Affective Computing in HRI	Used biosignals to interpret emotions in human-robot interaction. Can biosignals provide valuable insights into trust assessment?	Non-invasive biosensors like EEG neuroheadsets can infer psychological states; demonstrated the feasibility of inferring subjective assessments from biosignals, offering a potential tool for future applications in assessing trust through affective computing.
[151]	Subjective Evaluation Methods	Assessed user feedback on operability and experience in simulated environments. How can these methods be adapted for cobot trust assessment?	Methods involving simulating actual use environments to gather user feedback can be adapted for mobile cobots to effectively assess user perceptions and trustworthiness, providing valuable insights into user experience and operability.
[152]	Subjective Evaluation Scales	Derived scales from factor analysis of human-friendly robot motion. How do user perceptions affect trust development in cobots?	Understanding perceptions of familiarity, activity, and reliability aids in developing trust in cobots; subjective evaluation scales help construct algorithms for mobile robots that align with user expectations and enhance trust through motion design.

3.4 Methods for dependability analysis

3.4.1 Introduction

Dependability is a cornerstone in the realm of human-robot interactions (HRI), essential for ensuring that robotic systems perform reliably and safely across various operational contexts. The concept encompasses several critical attributes such as reliability, availability, safety, maintainability, and integrity. This chapter explores the sophisticated methods and tools used to assess and bolster these dependability attributes in HRIs, reflecting their pivotal role in achieving robust and efficient robot performance.

Reliability is a key facet of dependability, assessing how consistently a robot performs its intended functions without failure. To evaluate this, statistical reliability testing is used, where the frequency of robot operations without faults over a specific period is analysed. Additionally, accelerated life testing is applied under heightened stress conditions to predict a robot's longevity and uncover potential failure modes more rapidly than under normal operating conditions.

Availability, another critical aspect, involves ensuring that robotic systems are ready for use when needed. Markov models are adeptly employed to forecast the availability of robotic systems, taking into account various operational and failure states. Downtime analysis further contributes by measuring system inactivity and formulating strategies to enhance uptime, thus improving overall efficiency.

In the realm of safety, techniques such as Fault Tree Analysis (FTA) and Event Tree Analysis (ETA) play crucial roles. These methods identify and scrutinize potential safety hazards, thereby facilitating comprehensive risk assessments. Techniques such as Preliminary Hazard Analysis (PHA) are instrumental in evaluating risks and establishing necessary controls to safeguard against identified dangers.

Maintainability concerns how easily robotic systems can be preserved or restored to optimal working conditions. Tools like Maintainability Prediction assess the ease of maintaining robots, aiming to reduce downtime and lifecycle costs. Furthermore, Failure Modes, Effects, and Criticality Analysis (FMECA) extends beyond identifying failure modes to include an evaluation of the criticality of each failure, enhancing strategic maintenance planning.

The security and integrity of robotic systems are paramount, especially given the increasing sophistication of cyber threats. Penetration testing and red team exercises are employed to test the robustness of security measures, identifying vulnerabilities and strengthening the robot's resistance to security breaches. These tests ensure that the integrity of data and network communications within robotic systems remains uncompromised.

To support these methodologies, a variety of tools are utilized. MATLAB/Simulink and ReliaSoft offer powerful simulation and modelling capabilities, essential for predictive analysis in robotics. Statistical tools like Minitab and Python provide the necessary data analysis capabilities to support reliability and availability studies. Additionally, Weibull++ specializes in life data analysis, commonly used in reliability engineering to predict when components might fail.

For real-time monitoring and diagnostics, condition monitoring systems and SCADA systems are crucial, allowing for the continuous observation of critical robot parameters and the overarching control of industrial robots, respectively. In terms of security, SIEM systems and vulnerability scanners offer real-time security alert analysis and system scanning to detect known vulnerabilities, fortifying the security framework within which robots operate.

3.4.2 Literature review

Dependability analysis in Human-Robot Interaction (HRI) is critical for ensuring safe and effective interactions between humans and robots. Various methods have been developed to assess the dependability of robotic systems, each with its unique advantages and limitations. This comprehensive analysis will explore several prominent methods, including Fault Tree Analysis (FTA), Failure Modes and Effects Analysis (FMEA), Markov Models, Bayesian Networks, Simulation, Formal Verification, User Studies, and Expert Review. By synthesizing the relevant literature, we can better understand how these methods contribute to the dependability of HRI systems.

Fault Tree Analysis (FTA) is a systematic, top-down approach used to identify potential faults that could lead to system failures. The process involves constructing a hierarchical diagram that illustrates the various combinations of events that might result in a failure. FTA is particularly advantageous because it allows for a clear visualization of the relationships between different faults and their potential impacts on system performance. However, one of the significant drawbacks of FTA is its complexity when applied to large systems, which can make it challenging to manage and interpret the resulting diagrams [153],[154]. The systematic nature of FTA has been highlighted in various studies, emphasizing its effectiveness in identifying critical failure points in robotic systems [154],[155].

Failure Modes and Effects Analysis (FMEA) is another widely used method for assessing dependability in HRI. FMEA focuses on identifying potential failure modes within a system and analysing their effects on overall performance. This method involves listing potential failure modes, assessing their severity, occurrence, and detectability, and prioritizing risks based on these factors. The primary advantage of FMEA is its ability to prioritize risks, allowing engineers to focus on the most critical issues first. However, FMEA can be time-consuming, particularly for large and complex systems, which may require extensive analysis to cover all potential failure modes [156],[35]. The iterative nature of FMEA has been shown to enhance the reliability of robotic systems by systematically addressing potential failures before they occur [35].

Markov Models provide a probabilistic framework for modelling the behaviour of a system over time, considering various states and the probabilities of transitions between them. This method is particularly useful for complex systems with multiple states, as it allows for the analysis of system behaviour under different conditions. The primary advantage of Markov Models is their ability to capture the dynamic nature of HRI systems, enabling researchers to predict how systems will behave over time [35],[157]. However, the effectiveness of Markov Models is heavily dependent on the accuracy of the transition probabilities, which can be challenging to estimate accurately in real-world scenarios [157].

Bayesian Networks represent another powerful tool for analysing dependability in HRI. These networks provide a graphical representation of probabilistic relationships between variables, allowing for the modelling of uncertainty and dependencies within a system. The primary advantage of Bayesian Networks is their ability to handle complex interdependencies, making them particularly useful in scenarios where multiple factors influence system behaviour [35],[158]. However, the computational demands of Bayesian Networks can be significant, especially for large networks, which may limit their applicability in certain contexts [158].

Simulation is a widely adopted method for modelling the behaviour of robotic systems under various conditions. By creating a virtual representation of the system, researchers can simulate its operation and test its performance in different scenarios. The primary advantage of simulation is its ability to provide insights into system behaviour without the risks associated with real-world testing [35],[30]. However, the accuracy of simulations is heavily reliant on the quality of the modelling and the tools used, which can introduce errors if not carefully managed. Simulation has been shown to be particularly effective in evaluating HRI systems, as it allows for the exploration of various interaction scenarios and the identification of potential issues before deployment [35],[30].

Formal Verification is a rigorous method that mathematically proves the correctness of a system's behaviour against its specifications. This approach uses mathematical techniques to ensure that a system behaves as intended under all possible conditions. The primary advantage of Formal Verification is its ability to provide strong guarantees of system correctness, which is particularly important in safety-critical applications [155],[159]. However, the computational complexity of formal verification can be a significant barrier, especially for complex systems with numerous states and interactions [159]. Recent advancements in formal methods have shown promise in addressing these challenges, making them more applicable to HRI systems [155],[159].

User Studies and Field Trials are essential for evaluating the dependability of robotic systems in real-world scenarios. By conducting experiments with actual users, researchers can gain valuable insights into system performance and identify user-specific concerns that may not be apparent in controlled settings [160]. The primary advantage of user studies is their ability to capture the nuances of human-robot interactions, providing a more comprehensive understanding of system behaviour in practice. However, one of the significant limitations of user studies is that they may not cover all possible scenarios, potentially overlooking critical issues that could arise in different contexts [160].

Expert Review involves consulting domain specialists to assess the design, implementation, and potential risks associated with a robotic system. This method leverages the expertise of experienced professionals to identify potential issues and provide recommendations for improvement [161]. The primary advantage of expert review is its ability to draw on the knowledge and experience of specialists, which can be invaluable in identifying potential pitfalls. However, the subjective nature of expert opinions can introduce bias, making it essential to consider multiple perspectives to ensure a balanced assessment [161].

In practice, a combination of these methods is often employed to achieve a comprehensive assessment of dependability in HRI systems. The choice of methods depends on the specific characteristics of the system being analysed, the desired level of assurance, and the available resources. For instance, integrating FTA and FMEA can provide a robust framework for identifying and prioritizing risks, while simulation can offer insights into system behaviour under various conditions [35],[154]. Similarly, combining formal verification with user studies can enhance the reliability of HRI systems by ensuring that they meet rigorous safety standards while also addressing user needs [155],[159].

Table 10. A table with short summary of results related to methods for dependability analysis

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[153]	Fault Tree Analysis in HRI Dependability	How can Fault Tree Analysis (FTA) be applied to identify potential faults leading to system failures in robotic systems?	FTA is effective in identifying critical failure points in robotic systems but can become complex and challenging to manage for large systems due to the intricate relationships between faults and system components.
[154]	Systematic Dependability Assessment using FTA	How does FTA contribute to the systematic identification of critical failure points in robotic systems?	Emphasized the effectiveness of FTA in systematically identifying critical failure points in robotic systems; highlighted its utility in visualizing fault relationships but noted increased complexity with system size.
[155]	Formal Verification in HRI Dependability	How can formal verification methods ensure system correctness in HRI systems, and what are the recent advancements in this area?	Recent advancements have addressed computational complexity challenges, making formal verification more applicable to HRI systems by mathematically proving system correctness against specifications, crucial for safety-critical applications.
[156]	FMEA and Formal Verification in HRI	How can Failure Modes and Effects Analysis (FMEA) and formal verification enhance the reliability of HRI systems?	FMEA helps prioritize risks by identifying potential failure modes, while formal verification provides strong correctness guarantees; both methods enhance reliability but can be time-consuming and complex for large, intricate systems.
[35]	Dependability Analysis Methods in HRI	What are the advantages and limitations of various dependability analysis methods like FMEA, Markov Models, Bayesian Networks, and Simulation in HRI?	Discussed strengths and limitations of various methods: FMEA's prioritization of risks, Markov Models' dynamic system behaviour modelling, Bayesian Networks' handling of uncertainties, and Simulation's risk-free system behaviour insights, highlighting the need to choose methods based on context.
[157]	Markov Models for Dynamic Behaviour in HRI	How can Markov Models be utilized to model the dynamic behaviour of HRI systems over time?	Markov Models effectively capture the dynamic nature of HRI systems and predict system behaviour under different conditions, but their effectiveness depends on accurately estimating transition probabilities, which can be challenging in real-world scenarios.

[158]	Bayesian Networks in Dependability Analysis	How can Bayesian Networks model uncertainty and dependencies within HRI systems, and what are the computational challenges?	Bayesian Networks handle complex interdependencies and model uncertainties in system behaviour, beneficial for HRI systems; however, they can be computationally demanding, especially for large networks, potentially limiting their applicability without significant computational resources.
[30]	Simulation in HRI Dependability Evaluation	How effective is simulation in modelling robotic system behaviour under various conditions for dependability assessment in HRI?	Simulation allows for safe testing and provides insights into system behaviour across different scenarios without real-world risks; accuracy depends heavily on the quality of models and tools used, which can introduce errors if not carefully managed.
[160]	User Studies and Field Trials in HRI Dependability	How do user studies and field trials contribute to evaluating the dependability of robotic systems in real-world HRI scenarios?	User studies capture the nuances of human-robot interactions, providing comprehensive insights into system performance and user-specific concerns; however, they may not cover all possible scenarios, potentially overlooking critical issues in different contexts.
[161]	Expert Review in Dependability Assessment	How can consulting domain specialists enhance the dependability assessment of robotic systems through expert review?	Expert reviews leverage specialist knowledge to identify potential issues and recommend improvements; subjective opinions may introduce bias, so incorporating multiple expert perspectives is essential for a balanced and thorough assessment.

4 Methods for analysis of worker's subjective assessment

4.1 Introduction

As robotic systems increasingly integrate into workplace environments traditionally dominated by human labor, understanding the subjective assessments of those who interact with these robots daily becomes crucial. The introduction of MANiBOT robots into various sectors poses questions not only about the technical and operational impacts but also about the psychological and social influences they exert on human workers and customers. This chapter outlines the methodology employed to evaluate these subjective perceptions, focusing on factors that contribute to the overall acceptance and effectiveness of robotic technology in enhancing workplace dynamics.

The assessment of workers' and customers' perceptions is pivotal in determining the success of integrating new technologies into established human environments. By analysing a range of factors from trust in the technology's safety to the sense of job control and satisfaction, the MANiBOT project aims to develop a deep understanding of the social fabric into which these robots are being woven. Such insights will inform strategies to improve robot design, functionality, and interaction protocols to better align with human expectations and needs.

4.2 Factors planned to be analysed

4.2.1 Trust in technology safety

The exploration of trust in collaborative robots (cobots) is a multifaceted endeavor that necessitates a thorough understanding of various factors influencing this trust. Among these factors, the perceived safety of cobot technology stands out as a critical component. Trust in technology safety is paramount in human-robot interactions, as it directly impacts user acceptance and the overall effectiveness of collaborative systems. This section will delve into the various dimensions of trust in cobots, particularly focusing on the perceived safety of the technology, drawing upon a wide array of scholarly references to substantiate the claims made.

Perceived safety in cobot technology is influenced by several factors, including the transparency of safety measures and the robustness of the technology itself. Aasvik et al. [162] emphasizes that transport providers can enhance user trust by being transparent about the rigorous testing and safety measures implemented in autonomous systems, which is equally applicable to cobots. This transparency fosters a sense of security among users, as they become more aware of the safety protocols in place. Furthermore, the study by Pinto et al. [52] highlights the need for a specialized trust scale for human-robot interaction, indicating that existing tools often fail to adequately assess trust in cobots specifically. This suggests that a tailored approach to measuring trust, particularly regarding safety perceptions, is essential for fostering user confidence in cobots.

Additionally, the research conducted by Isbel et al. [163] indicates that trust, confidence, and safety are crucial factors in the acceptance of new technologies, especially among older adults. This demographic often exhibits heightened concerns regarding the safety of emerging technologies, making it imperative for developers to address these concerns through effective design and communication strategies. Rossato et al. [164] further corroborate this notion, revealing that while both seniors and younger adults reported a sense of safety when interacting with cobots, seniors expressed greater apprehension about potential damage to the cobots. This highlights the necessity of understanding the varying perceptions of safety across different age groups, which can inform the design and implementation of cobots to enhance user trust.

The role of perceived safety extends beyond individual users to organizational contexts as well. Montague et al. [165] found that healthcare professionals, such as nurses, who perceived smart technologies as enhancing safety were more likely to trust and effectively utilize these technologies. This finding underscores the importance of establishing a culture of safety within organizations that adopt cobots, as it can significantly influence the overall trust in these systems. Moreover, Krenn et al. [166] discuss how proxemics and nonverbal communication between humans and robots can affect trust and safety perceptions during collaborative tasks, suggesting that the design of cobots should consider these interpersonal dynamics.

In the context of automated vehicles, which share similarities with cobots, Hensch et al. [167] explored how malfunctions in electronic Human-Machine Interfaces (eHMIs) can impact trust and acceptance among users. Their findings indicate that trust can be easily compromised in the face of technological failures, emphasizing the need for reliable and fail-safe systems in cobot design. This aligns with the broader literature on technology acceptance, where perceived safety and reliability are critical determinants of user trust [168].

Moreover, the study by Gangadharaiah [169] indicates that users prioritize safety when evaluating new technologies, suggesting that perceived safety is a fundamental criterion for acceptance. This is further supported by the work of Ezzati [170], who identifies trust in safety features as a significant predictor of technology acceptance, particularly in the context of vehicles. These insights collectively highlight the necessity of prioritizing safety in the development and deployment of cobots to foster user trust.

The perceived safety of cobots can also be influenced by the design and operational characteristics of the robots themselves. Tusseyeva et al. [171] found that users reported higher safety perceptions when interacting with cobots that employed fixed-path motion planning compared to those using real-time motion planning algorithms. This suggests that predictable and controlled movements can enhance users' feelings of safety, which is crucial for building trust in collaborative environments. Berx et al. [172] further emphasize the importance of stakeholder perspectives on safety in human-robot collaborative scenarios, advocating for a comprehensive understanding of safety-related concerns from various stakeholders involved in cobot deployment.

Table 11. A table with short summary of results related to trust in technology safety

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[162]	Transparency and Trust in Autonomous Systems	How does transparency about safety measures and rigorous testing impact user trust in autonomous systems (and cobots)?	Transparency enhances user trust by making users aware of safety protocols; being transparent about safety measures fosters a sense of security among users, which is applicable to cobots.
[52]	Trust Measurement in Human-Robot Interaction	Is there a need for a specialized trust scale for HRI, specifically for cobots?	Existing tools often fail to adequately assess trust in cobots; a tailored approach to measuring trust, particularly regarding safety perceptions, is essential for fostering user confidence in cobots.
[163]	Trust, Confidence, and Safety in Technology Acceptance among Older Adults	How do trust, confidence, and safety influence the acceptance of new technologies among older adults?	Trust, confidence, and safety are crucial for technology acceptance in older adults, who often have heightened concerns regarding the safety of emerging technologies; addressing these concerns is imperative for developers.
[164]	Age-Related Differences in Safety Perceptions of Cobots	How do seniors and younger adults perceive safety when interacting with cobots?	Both seniors and younger adults reported a sense of safety when interacting with cobots, but seniors expressed greater apprehension about potential damage to the cobots, indicating varying perceptions of safety across different age groups.

[165]	Trust and Perceived Safety in Healthcare Technology	How do healthcare professionals perceive smart technologies in terms of safety and trust?	Healthcare professionals who perceive technologies as enhancing safety are more likely to trust and effectively utilize them, underscoring the importance of establishing a culture of safety within organizations that adopt cobots.
[166]	Proxemics, Nonverbal Communication, Trust, and Safety in HRI	How do proxemics and nonverbal communication affect trust and safety perceptions during collaborative tasks?	Proxemics (personal space) and nonverbal communication significantly impact trust and safety perceptions; the design of cobots should consider these interpersonal dynamics to enhance trust during human-robot collaboration.
[167]	Trust and Acceptance in Automated Vehicles; Impact of eHMI Malfunctions	How do malfunctions in electronic Human-Machine Interfaces impact trust and acceptance among users of automated vehicles?	Malfunctions can easily compromise trust and acceptance, emphasizing the need for reliable and fail-safe systems in design; this finding is applicable to cobots, where technological failures can significantly impact user trust.
[168]	Technology Acceptance, Perceived Safety, and Reliability	What are the critical determinants of user trust in technology acceptance?	Perceived safety and reliability are critical determinants of user trust in technology acceptance; ensuring these factors can enhance user trust in cobots and other emerging technologies.
[169]	User Priorities in Evaluating New Technologies	What factors do users prioritize when evaluating new technologies?	Users prioritize safety when evaluating new technologies; perceived safety is a fundamental criterion for acceptance, highlighting the necessity of prioritizing safety in cobot development and deployment to foster user trust.
[170]	Trust in Safety Features and Technology Acceptance in Vehicles	How does trust in safety features predict technology acceptance, especially in vehicles?	Trust in safety features is a significant predictor of technology acceptance; emphasizing and communicating safety features in cobots can enhance user trust and acceptance, particularly in sectors like transportation where safety is paramount.
[171]	Perceived Safety in Cobot Motion Planning	How do different motion planning algorithms affect users' safety perceptions when interacting with cobots?	Users reported higher safety perceptions when interacting with cobots employing fixed-path motion planning compared to real-time motion planning algorithms; predictable and controlled movements enhance users' feelings of safety in collaborative environments.
[172]	Stakeholder Perspectives on Safety in Human-Robot Collaboration	What are the safety-related concerns from various stakeholders involved in cobot deployment?	Emphasizes the importance of understanding safety concerns from various stakeholders, including users, developers, and organizations, to ensure safe cobot deployment and enhance user

			trust in human-robot collaborative scenarios.

4.2.2 Trust in the robotic technology worker support

The exploration of trust in robotic technology, particularly in the context of collaborative robots (cobots), is a multifaceted issue that encompasses various dimensions of human-robot interaction. Trust is a critical factor influencing how employees perceive cobots as valuable tools that enhance their work performance and provide support. This perception is shaped by several factors, including usability, cognitive load, safety, and the overall work environment.

Usability plays a significant role in shaping trust in cobots. Research by Fournier et al. [173] indicates that the introduction of cobots does not increase the complexity of tasks, even for operators with cognitive impairments, suggesting that cobots can be designed to be user-friendly and supportive in industrial settings . This usability is further supported by studies that assess cognitive workload and subjective perceptions of technology acceptance among workers, particularly in high-demand tasks [174]. The findings emphasize that when cobots are perceived as easy to use and integrate into existing workflows, trust in their capabilities increases, leading to enhanced collaboration and performance.

Cognitive load is another critical factor influencing trust in cobots. Zakeri's [175] work highlights the importance of assessing cognitive workload in smart factory settings, where the introduction of secondary tasks can complicate the primary task. By understanding how cognitive load affects human performance in conjunction with cobots, organizations can design systems that minimize overload and enhance trust. Furthermore, studies have shown that when workers feel that their cognitive resources are not being overstretched by the introduction of cobots, their trust in these technologies increases, leading to a more positive attitude towards collaboration [175].

Safety is paramount in fostering trust in cobots. Berx et al. [176] discuss the inherent trade-offs between safety and efficiency in cobot technologies, noting that while cobots can enhance productivity, they also introduce new risks that must be managed effectively. The perception of safety is crucial; when employees feel secure in their interactions with cobots, their trust in these systems grows. This is echoed in the work of Kopp et al. [177], which identifies safety and appropriate cobot configuration as essential factors for fostering employee trust and acceptance. The implementation of safety features, such as collision detection and force-limiting mechanisms, further reinforces this trust by ensuring that cobots can operate safely alongside human workers [178].

The psychosocial impacts of cobot integration also play a significant role in shaping employee perceptions and trust. Cheon et al. [179] found that cobots can facilitate social interactions among workers, which can enhance the overall work environment and contribute to a sense of community. This social aspect is vital, as positive interpersonal relationships can enhance trust not only in colleagues but also in the technologies they use. When employees perceive cobots as partners rather than threats, their trust in these systems is likely to increase, leading to improved collaboration and performance.

Moreover, the ethical considerations surrounding human-cobot collaboration cannot be overlooked. Chromjaková et al. [180] emphasize the importance of ethical frameworks in ensuring that cobots are integrated into workplaces in ways that respect human dignity and promote positive interactions. When organizations prioritize ethical considerations in their deployment of cobots, they foster an environment of trust and acceptance among employees. This ethical approach can mitigate fears of job displacement and enhance the perception of cobots as supportive tools rather than replacements.

The design of cobots also significantly impacts trust. Patil's [178] review of collaborative robotics highlights the importance of user-centered design principles that prioritize the needs and preferences of workers. When cobots are designed with the end-user in mind, including considerations for ergonomics and ease of use, employees are more likely to perceive them as valuable assets to their work processes. This perception is crucial for building trust, as employees need to feel that the technology is designed to enhance their capabilities rather than complicate their tasks.

Training and education play a vital role in building trust in cobots. Studies have shown that when employees receive adequate training on how to interact with cobots, their confidence in using these technologies increases [181]. This training not only enhances their skills but also addresses any misconceptions or fears they may have about working alongside robots. As employees become more familiar with cobot functionalities and safety protocols, their trust in these systems grows, leading to more effective collaboration.

Furthermore, the role of organizational culture in shaping trust in cobots cannot be understated. A culture that promotes innovation, openness, and collaboration is likely to foster a more positive perception of cobots among employees. Research indicates that when organizations actively involve employees in the decision-making processes related to cobot implementation, trust levels increase significantly [177]. This participatory approach ensures that employees feel valued and heard, which can enhance their acceptance and trust in the technologies being introduced.

Table 12. A table with short summary of results related to trust in the robotic technology worker support

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[173]	Usability and Cognitive Impairments in Cobot Interaction	Does the introduction of cobots increase task complexity for operators with cognitive impairments in industrial settings?	Found that cobots do not increase task complexity even for operators with cognitive impairments; cobots can be designed to be user-friendly and supportive, enhancing trust through improved usability in industrial environments.
[174]	Cognitive Workload and Technology Acceptance	How do cognitive workload and subjective perceptions affect technology acceptance among workers in high-demand tasks?	Emphasized that when cobots are perceived as easy to use and integrate into existing workflows, workers' trust increases, leading to enhanced collaboration and performance; assessing cognitive workload is crucial for technology acceptance.
[175]	Cognitive Workload and Trust in Smart Factories	How does cognitive workload affect human performance and trust in cobot-assisted tasks within smart factory settings?	Highlighted the importance of assessing and minimizing cognitive overload to enhance trust; workers' trust in cobots increases when they feel their cognitive resources are not overstretched, leading to a positive attitude towards collaboration.
[176]	Safety and Efficiency Trade-offs in Cobot Technologies	What are the inherent trade-offs between safety and efficiency in cobot technologies, and how can risks be managed effectively?	Discussed that while cobots can enhance productivity, they also introduce new risks that must be effectively managed; perception of safety is crucial for trust, and proper risk management strategies are essential to foster employee trust in cobots.
[177]	Safety, Configuration, and Employee Involvement	How do safety measures, appropriate cobot configuration, and employee involvement affect trust and acceptance	Identified safety and appropriate cobot configuration as essential for fostering employee trust and acceptance; involving employees in decision-making processes related to cobot implementation significantly increases trust levels and acceptance.

		of cobots in the workplace?	
[178]	Safety Features and User-Centered Design in Cobots	How do safety features and user-centered design principles impact trust in collaborative robots among workers?	Found that implementing safety features like collision detection and force-limiting mechanisms reinforces trust by ensuring safe operation; user-centered design that prioritizes workers' needs and preferences increases trust and perception of cobots as valuable assets.
[179]	Psychosocial Impacts of Cobot Integration	How do cobots facilitate social interactions among workers, and what is the impact on the work environment and trust?	Discovered that cobots can enhance social interactions among workers, improving the overall work environment and contributing to a sense of community; positive interpersonal relationships foster increased trust in both colleagues and the technologies used.
[180]	Ethical Considerations in Human-Cobot Collaboration	What is the importance of ethical frameworks in ensuring that cobots are integrated into workplaces respectfully and positively?	Emphasized that ethical considerations are crucial for respecting human dignity and promoting positive interactions; prioritizing ethical frameworks in cobot deployment fosters an environment of trust and acceptance among employees, mitigating fears of job displacement.
[181]	Training and Education in Building Trust	How does adequate training on cobot interaction affect employees' confidence and trust in using these technologies?	Showed that when employees receive sufficient training, their confidence in using cobots increases; training addresses misconceptions and fears, leading to enhanced trust and more effective collaboration between humans and cobots in the workplace.

4.2.3 Organisational trust

Organizational trust is a critical factor that significantly influences employees' perceptions and acceptance of new technologies, such as collaborative robots (cobots). Trust within an organization can shape employees' attitudes towards technological innovations, impacting their willingness to engage with these tools. The literature highlights several dimensions of organizational trust, including trust in leadership, trust among colleagues, and trust in the organization itself, which collectively contribute to a supportive work environment conducive to technological adoption.

The relationship between organizational trust and employee engagement with new technologies is well-documented. For instance, Attiq et al. [182] emphasize that a supportive work environment fosters trust, which in turn nurtures self-efficacy among employees, enhancing their capacity to adapt to new technologies. This notion is echoed by Sun et al. [183], who discuss how organizational justice influences commitment and, by extension, trust, suggesting that fair treatment within the organization can bolster trust and facilitate the acceptance of innovations. Furthermore, the findings of Muhadi et al. [184] indicate that trust significantly affects organizational citizenship behaviour, which can be crucial when integrating new technologies like cobots, as employees who feel trusted are more likely to embrace changes positively.

Moreover, the role of leadership in cultivating trust cannot be overstated. Research by Rajabi et al. [185] illustrates that trust perceptions are integral to various organizational processes, including commitment to leaders' decisions and overall job performance. This is particularly relevant in the context of technological changes, where employees look to their leaders for guidance and reassurance. The findings of Jiang and Luo [186] further support this, revealing that authentic leadership and transparent communication significantly enhance employee trust, which is essential for the successful implementation of new technologies.

In addition to leadership, the organizational environment plays a pivotal role in shaping trust. Deswira et al. [187] found that organizational trust positively influences performance through mediating factors like knowledge management and organizational learning capabilities. This suggests that a culture of trust can enhance the overall learning environment, making it easier for employees to adapt to and utilize new technologies effectively. Similarly, Hashemiamin's [188] systematic review highlights that trust in organizational actions is fundamental for fostering a positive organizational culture, which is crucial during technological transitions.

The impact of organizational trust extends to job satisfaction and employee retention. Nurhayati et al. [189] highlight that organizational trust significantly moderates the relationship between job satisfaction and turnover intention. Their findings suggest that higher levels of trust can enhance job satisfaction, which in turn reduces turnover intentions. This is particularly crucial in the context of adopting new technologies, as organizations characterized by high levels of trust are more likely to facilitate smoother transitions and improve employee retention during periods of change.

Furthermore, the interplay between organizational trust and technological readiness is significant. Hmoud and Várallyai's [190] research indicates that trust in technology influences the adoption of AI in human resources, suggesting that employees' trust in their organization can similarly affect their readiness to engage with cobots. This relationship underscores the importance of building trust not only in leadership but also in the technologies being introduced.

The implications of organizational trust on technological adoption are further supported by studies examining the mediating effects of trust on various organizational outcomes. For example, the work of Kalischko [191] highlights that electronic performance monitoring can negatively impact organizational trust, which in turn affects employee engagement and performance. This finding suggests that organizations must be mindful of how technological implementations are perceived by employees to maintain trust levels.

Table 13. A table with short summary of results related to organisational trust

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[182]	Organizational Trust and Employee Self-Efficacy	How does a supportive work environment foster trust and enhance employees' capacity to adapt to new technologies?	Found that a supportive work environment fosters trust, which in turn nurtures self-efficacy among employees, enhancing their capacity to adapt to new technologies.
[183]	Organizational Justice, Commitment, and Trust	How does organizational justice influence commitment and trust, facilitating acceptance of innovations?	Demonstrated that fair treatment within the organization bolsters trust and facilitates the acceptance of innovations.
[184]	Trust and Organizational Citizenship Behaviour	How does trust affect organizational citizenship behaviour during the integration of new technologies like cobots?	Found that trust significantly affects organizational citizenship behaviour; employees who feel trusted are more likely to embrace changes positively.

[185]	Trust Perceptions and Organizational Processes	How are trust perceptions integral to commitment to leaders' decisions and job performance, especially during technological changes?	Illustrated that trust perceptions are integral to various organizational processes, including commitment to leaders' decisions and overall job performance, particularly relevant during technological changes.
[186]	Authentic Leadership, Communication, and Employee Trust	How do authentic leadership and transparent communication enhance employee trust during technological implementations?	Revealed that authentic leadership and transparent communication significantly enhance employee trust, which is essential for the successful implementation of new technologies.
[187]	Organizational Trust, Performance, and Knowledge Management	How does organizational trust influence performance through mediating factors like knowledge management and organizational learning capabilities?	Found that organizational trust positively influences performance through mediating factors like knowledge management and organizational learning capabilities, enhancing the learning environment for effective technology adaptation.
[188]	Trust in Organizational Actions and Culture	How is trust in organizational actions fundamental for fostering a positive organizational culture during technological transitions?	Highlighted that trust in organizational actions is fundamental for fostering a positive organizational culture, which is crucial during technological transitions.
[189]	Organizational Trust, Job Satisfaction, and Turnover Intention	How does organizational trust moderate the relationship between job satisfaction and turnover intention?	Demonstrated that higher trust levels can lead to greater job satisfaction and lower turnover rates, important during the adoption of new technologies, as organizations with high trust experience smoother transitions.
[190]	Trust in Technology and Adoption of AI in HR	How does trust in technology influence the adoption of AI in human resources, and how does this relate to cobots?	Indicated that trust in technology influences the adoption of AI in HR; similarly, employees' trust in their organization affects their readiness to engage with cobots, underscoring the importance of building trust in both leadership and new technologies.
[191]	Electronic Performance Monitoring and Organizational Trust	How does electronic performance monitoring impact organizational trust, and what are its effects on employee engagement and performance?	Found that electronic performance monitoring can negatively impact organizational trust, which in turn affects employee engagement and performance; organizations must be mindful of perceptions to maintain trust during technological implementations.

4.2.4 Feeling of predictability in the work environment

The feeling of predictability in the work environment, particularly in the context of human-robot collaboration (HRC), is a critical factor influencing trust among employees. Predictability refers to the extent to which individuals can anticipate the actions and behaviours of their robotic counterparts, which is essential for fostering a stable and reliable work atmosphere. The integration of collaborative robots (cobots) into workplaces necessitates a thorough understanding of how these machines operate and interact with human workers. This understanding is pivotal in establishing a sense of predictability, which can significantly enhance trust in these robotic systems.

Research indicates that trust in human-robot interactions is multifaceted, encompassing reliability, transparency, and the perceived competence of the robots involved. For instance, Kluy and Roesler [192] highlight that the reliability and transparency of robots directly affect human perceptions and trust, suggesting that predictable robot behaviour can lead to increased trust. This is further supported by Xu and Dudek [68], who propose that modelling trust in asymmetric human-robot collaborations can enhance predictability and, consequently, trust.

Moreover, the emotional and social dynamics between humans and robots play a significant role in establishing predictability. Jerčić et al. [136] explore how emotions and social behaviours impact performance in collaborative tasks, indicating that positive emotional engagement can enhance predictability in human-robot interactions. This emotional aspect is crucial, as it can lead to a more stable environment where employees feel secure in their interactions with cobots. The ability of robots to adapt their behaviours based on human emotional cues further contributes to a predictable work environment, reinforcing trust.

The design of robots also influences predictability. Aliev and Antonelli [193] discuss how monitoring systems for cobots can predict outages and assess reliability factors, which directly impacts the perceived predictability of these machines in the workplace. This predictive capability is essential for employees to feel confident in the robots' performance, thereby enhancing trust. Additionally, the incorporation of dynamic graphical signage, as noted by Eimontaite et al. [194], can improve response times and decrease negative attitudes towards robots, further contributing to a predictable and trust-enhancing environment.

Furthermore, the role of communication in establishing predictability cannot be overstated. Effective communication strategies, as highlighted by Salehzadeh et al. [195], are vital for reducing uncertainties and enhancing trust in HRC. When robots can convey their intentions and capabilities clearly, employees are more likely to perceive them as predictable partners in collaboration. This aligns with the findings of Nikolaidis et al. [60], who emphasize the importance of mutual adaptation in collaborative tasks, where clear communication can significantly enhance trust and predictability.

The interplay between human factors and robot factors is also critical in shaping the predictability of interactions. Hopko et al. [245] argue that the success of HRC depends on understanding both human and robot behaviours, suggesting that a change in robot behaviour can be perceived differently depending on the human operator's state. This highlights the need for robots to maintain consistent and predictable behaviours to foster trust among human collaborators.

Moreover, the impact of anthropomorphism on trust and predictability is an area of growing interest. Roesler et al. [86] found that anthropomorphic features in robots can influence trust levels, suggesting that robots designed to exhibit human-like traits may be perceived as more predictable and trustworthy. This anthropomorphic design can enhance the emotional connection between humans and robots, further solidifying the predictability of interactions.

In addition, the concept of trust repair is crucial when predictability is compromised. Esterwood and Robert [54] discuss strategies for repairing trust after robot failures, emphasizing that effective communication and prompt corrective actions can restore predictability in human-robot collaborations. This underscores the importance of not only establishing predictability but also having mechanisms in place to address any disruptions that may occur.

The relationship between workload, trust, and predictability is another critical aspect to consider. Research by Story et al. [196] indicates that understanding the interplay between these factors is essential for designing collaborative work cells that ensure safety and productivity. When employees feel that their workload is manageable and that they can predict the robots' actions, their trust in the collaborative process is likely to increase.

Table 14. A table with short summary of results related to feeling of predictability in the work environment

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[192]	Reliability, Transparency, and Trust in HRI	How do the reliability and transparency of robots affect human perceptions and trust? Can predictable robot behaviour increase trust?	Found that the reliability and transparency of robots directly affect human perceptions and trust, suggesting that predictable robot behaviour leads to increased trust among employees in human-robot interactions.
[68]	Modelling Trust in Asymmetric HRC	How can modelling trust in asymmetric human-robot collaborations enhance predictability and trust?	Proposed that modelling trust in asymmetric human-robot collaborations can enhance predictability and consequently build trust between humans and robots, improving collaboration outcomes.
[136]	Emotions, Social Behaviours, and Predictability in HRI	How do emotions and social behaviours impact performance in collaborative tasks? Can positive emotional engagement enhance predictability in HRI?	Explored how emotions and social behaviours impact performance in collaborative tasks, indicating that positive emotional engagement can enhance predictability in human-robot interactions, leading to a more stable environment and increased trust.
[193]	Predictive Monitoring Systems for Cobots	How can monitoring systems for cobots predict outages and assess reliability factors, impacting perceived predictability in the workplace?	Discussed how monitoring systems for cobots can predict outages and assess reliability factors, directly impacting the perceived predictability of these machines in the workplace, thereby enhancing employee confidence and trust in the robots' performance.
[194]	Dynamic Graphical Signage and Attitudes Toward Robots	Can the incorporation of dynamic graphical signage improve response times and decrease negative attitudes toward robots, contributing to predictability?	Found that the incorporation of dynamic graphical signage can improve response times and decrease negative attitudes toward robots, further contributing to a predictable and trust-enhancing environment in human-robot collaboration.

[195]	Communication Strategies in HRC	How do effective communication strategies reduce uncertainties and enhance trust and predictability in human-robot collaboration?	Highlighted that effective communication strategies are vital for reducing uncertainties and enhancing trust in HRC; when robots convey their intentions and capabilities clearly, employees perceive them as predictable partners, improving collaboration.
[60]	Mutual Adaptation in Collaborative Tasks	What is the importance of mutual adaptation and clear communication in enhancing trust and predictability in collaborative tasks?	Emphasized the importance of mutual adaptation in collaborative tasks; clear communication between humans and robots significantly enhances trust and predictability, leading to more effective collaboration.
[53]	Human and Robot Behaviour in HRC	How does the interplay between human factors and robot factors shape the predictability of interactions in HRC?	Argued that the success of HRC depends on understanding both human and robot behaviours; changes in robot behaviour can be perceived differently depending on the human operator's state, highlighting the need for robots to maintain consistent and predictable behaviours to foster trust.
[86]	Anthropomorphism, Trust, and Predictability	How do anthropomorphic features in robots influence trust levels and perceived predictability?	Found that anthropomorphic features in robots can influence trust levels; robots designed with human-like traits may be perceived as more predictable and trustworthy, enhancing the emotional connection and predictability of interactions in HRI.
[54]	Trust Repair in Human-Robot Collaboration	What strategies can repair trust after robot failures and restore predictability in HRC?	Discussed strategies for repairing trust after robot failures; emphasized that effective communication and prompt corrective actions can restore predictability in human-robot collaborations, underscoring the importance of mechanisms to address disruptions and maintain trust.
[196]	Workload, Trust, and Predictability in HRC	How does understanding the interplay between workload, trust, and predictability help in designing collaborative work cells that ensure safety and productivity?	Indicated that when employees feel their workload is manageable and can predict the robots' actions, their trust in the collaborative process increases; understanding this interplay is essential for designing collaborative work cells that ensure safety and productivity in human-robot collaborations.

4.2.5 Support from coworkers and supervisors

The role of social support from coworkers and supervisors is a critical factor in shaping employees' trust in collaborative robots (cobots). Understanding this dynamic is essential as it can significantly influence employee attitudes towards technology integration in the workplace. Social support encompasses emotional, informational, and instrumental assistance provided by colleagues and supervisors, which can mitigate stress and enhance job satisfaction. Research indicates that coworker support can be particularly effective in fostering resilience and reducing psychological distress among employees, thereby positively impacting their perceptions of new technologies like cobots [197],[198].

Coworker support is often viewed as a buffer against workplace stressors. For instance, studies have shown that employees who perceive high levels of support from their coworkers report lower levels of job-related stress and higher job satisfaction [199],[200]. This support can manifest in various forms, such as emotional encouragement during challenging tasks or practical assistance in navigating new technologies. The presence of a supportive social network at work can enhance employees' confidence in their ability to adapt to changes, including the introduction of cobots, which may otherwise be perceived as threatening or disruptive [197],[198].

Moreover, the quality of coworker relationships plays a significant role in shaping employees' attitudes towards cobots. Positive interactions with colleagues can foster a sense of belonging and community, which is crucial when adapting to new technologies. Research suggests that employees who feel supported by their peers are more likely to embrace technological changes, as they perceive these changes as collaborative rather than competitive [199],[200]. This is particularly relevant in environments where cobots are introduced, as the perceived threat of job displacement can be alleviated through strong coworker relationships that emphasize teamwork and shared goals [197],[198] .

Supervisor support also plays a vital role in this dynamic. Supervisors who actively promote a culture of support and collaboration can significantly influence how employees perceive and interact with cobots. Studies indicate that when supervisors provide clear communication and encouragement regarding the use of new technologies, employees are more likely to trust and accept these innovations [199],[201]. The interplay between supervisor and coworker support creates a comprehensive support system that can enhance employees' overall trust in their work environment, including their trust in the technologies they are expected to use [201],[198].

Furthermore, the impact of social support on trust in cobots can be understood through the lens of social exchange theory. This theory posits that the quality of social interactions at work influences employees' perceptions of their environment and their willingness to engage with new technologies. When employees feel valued and supported by their coworkers and supervisors, they are more likely to reciprocate this support by engaging positively with workplace innovations, including cobots [197],[198]. This reciprocal relationship highlights the importance of fostering a supportive work culture that prioritizes employee well-being and collaboration.

In addition to emotional and instrumental support, the role of informational support cannot be overlooked. Coworkers and supervisors who share knowledge and resources related to the use of cobots can significantly enhance employees' understanding and comfort with these technologies. Research has shown that employees who receive adequate training and information about new tools are more likely to trust and effectively utilize them [197],[198]. This underscores the need for organizations to invest in training programs that not only focus on the technical aspects of cobot operation but also emphasize the importance of social support in the learning process.

The relationship between social support and trust in cobots is further complicated by individual differences among employees. Factors such as personality traits, previous experiences with technology, and individual coping mechanisms can influence how employees perceive and respond to social support in the context of technological change. For example, employees with higher levels of self-efficacy may be more receptive to coworker and supervisor support, leading to greater trust in cobots [197],[198]. Understanding these individual differences is crucial for organizations aiming to foster a supportive environment conducive to technology adoption.

Moreover, the context in which social support is provided can also affect its impact on trust in cobots. For instance, during periods of organizational change or crisis, the availability and quality of social support may fluctuate, influencing employees' perceptions of their work environment and the technologies they are expected to use [197],[198]. Organizations must be mindful of these contextual factors and strive to maintain a consistent level of support, particularly during transitions involving new technologies.

Table 15. A table with short summary of results related to support from coworkers and supervisors

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[198]	Coworker Support and Adaptation to New Technologies	How does coworker support affect employees' stress levels and their ability to adapt to new technologies like cobots?	Coworker support significantly reduces job-related stress and enhances employees' confidence in adapting to changes, including the introduction of cobots, positively impacting their perceptions and acceptance of new technologies.
[197]	Social Support and Psychological Well-being	How does social support from coworkers and supervisors impact employees' psychological distress and perceptions of new technologies?	Social support mitigates psychological distress among employees and positively influences their perceptions of new technologies such as cobots, fostering a supportive environment conducive to technology adoption.
[200]	Coworker Relationships and Job Satisfaction	How do positive coworker relationships affect job satisfaction and acceptance of technological changes in the workplace?	Positive interactions with colleagues enhance job satisfaction and make employees more likely to embrace technological changes as collaborative efforts rather than competitive threats, facilitating smoother integration of cobots.
[199]	Coworker and Supervisor Support in Technological Adaptation	What role do coworker and supervisor support play in employee job satisfaction and adaptation to new technologies?	High levels of support from coworkers and supervisors lead to lower job-related stress and higher job satisfaction, thereby positively impacting employees' acceptance and effective utilization of new technologies like cobots.
[201]	Supervisor Support and Trust in New Technologies	How does supervisor support and communication influence employee trust and acceptance of new technologies such as cobots?	Supervisors who provide clear communication and encouragement regarding the use of new technologies significantly enhance employee trust and acceptance of these innovations, contributing to a comprehensive support system within the workplace.

4.2.6 Job satisfaction

The relationship between job satisfaction and trust in collaborative robots (cobots) is a multifaceted issue that encompasses various psychological and organizational dynamics. Job satisfaction is often influenced by the level of trust employees have in their work environment, including their relationships with colleagues and management, as well as the technologies they interact with, such as cobots. This exploration is particularly relevant in the context of modern workplaces where automation and human-robot collaboration are becoming increasingly prevalent.

Research indicates that trust plays a critical role in shaping job satisfaction. For instance, Mitterer and Mitterer [202] highlight the mediating effect of trust on psychological safety and job satisfaction, suggesting that a trusting environment can significantly enhance employees' job satisfaction by fostering a sense of safety and belonging in the workplace. This is further supported by Zheng et al. [203], who found that trust in colleagues significantly enhances job satisfaction and reduces emotional exhaustion, underscoring the importance of interpersonal trust in the workplace.

Moreover, the role of organizational trust in influencing job satisfaction cannot be overstated. Dalati et al. [204] provide empirical evidence that organizational trust among co-workers significantly impacts job satisfaction within higher education institutions. This aligns with findings from Huda et al. [205], who assert that trust directly influences job satisfaction, reinforcing the notion that higher levels of trust correlate with increased job satisfaction. Additionally, organizational trust has been shown to act as a mediator in various contexts, linking leadership styles and job satisfaction, as discussed by Butt et al. [206] and Gopalan et al. [207]. These studies collectively suggest that fostering trust within organizations can lead to enhanced job satisfaction, which is crucial for employee retention and overall organizational effectiveness.

The impact of transformational leadership on job satisfaction is another critical factor. Research Top et al.

[207] Gopalan, N., Beutell, N., & Alstete, J. (2023). Can trust in management help? job satisfaction, healthy lifestyle, and turnover intentions. International Journal of Organization Theory and Behavior, 26(3), 185-202. https://doi.org/10.1108/ijotb-09-2022-0180

[208] found that transformational leadership significantly affects job satisfaction, organizational commitment, and trust among healthcare professionals. The ability of leaders to inspire trust and commitment is vital for enhancing job satisfaction, particularly in environments where collaboration with technology, such as cobots, is essential.

Furthermore, the dynamics of trust extend to the interaction between employees and cobots. As organizations increasingly integrate automation into their workflows, the trust employees place in these technologies becomes paramount. Kamaraj's [209] study on the influence of trust in automation reveals that trust significantly affects employees' responses to automation, including their job satisfaction levels. This highlights the necessity for organizations to not only foster trust among employees but also to build trust in the technologies they utilize, including cobots. The relationship between trust in automation and job satisfaction is critical, as employees who trust the technology they work with are likely to experience higher job satisfaction and engagement.

In addition to trust, the quality of interpersonal relationships within the workplace plays a significant role in shaping job satisfaction. Bulińska-Stangrecka and Bagieńska [210] argue that positive employee relations are fundamental to job satisfaction, particularly in the context of mental health promotion during challenging times such as the COVID-19 pandemic. This suggests that organizations should prioritize building strong interpersonal relationships to enhance job satisfaction, especially in environments where collaborative technologies are employed.

The interplay between job satisfaction, trust, and the use of cobots is also influenced by organizational culture. Research by Håvold et al. [211] indicates that trust in leaders and a supportive organizational culture significantly enhance work satisfaction, which is crucial in environments where automation is prevalent. This implies that organizations must cultivate a culture that promotes trust and collaboration to maximize job satisfaction among employees working alongside cobots.

Moreover, the role of communication in fostering trust and job satisfaction cannot be overlooked. Effective communication is essential for building trust among colleagues and between employees and management. As highlighted by Hidayat and Patras [212], trust in management significantly influences job satisfaction, suggesting that transparent communication practices are vital for enhancing employee satisfaction. This is particularly relevant in the context of cobots, where clear communication about the roles and capabilities of these technologies can help alleviate concerns and foster trust.

Table 16. A table with short summary of results related to job satisfaction

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[202]	Trust, Psychological Safety, and Job Satisfaction	How does trust mediate the relationship between psychological safety and job satisfaction among employees?	Found that a trusting environment significantly enhances employees' job satisfaction by fostering a sense of safety and belonging in the workplace; trust acts as a mediator between psychological safety and job satisfaction.
[203]	Trust in Colleagues and Job Satisfaction	How does trust in colleagues affect job satisfaction and emotional exhaustion among employees?	Found that trust in colleagues significantly enhances job satisfaction and reduces emotional exhaustion, underscoring the importance of interpersonal trust in the workplace for employee well-being.
[204]	Organizational Trust and Job Satisfaction	Does organizational trust among co-workers impact job satisfaction within higher education institutions?	Provided empirical evidence that organizational trust among co-workers significantly impacts job satisfaction, highlighting the critical role of trust in enhancing employee satisfaction within organizations.
[205]	Trust and Job Satisfaction	How does trust directly influence job satisfaction among employees?	Asserted that trust directly influences job satisfaction, reinforcing the notion that higher levels of trust correlate with increased job satisfaction among employees.
[206]	Organizational Trust as a Mediator	Does organizational trust mediate the relationship between leadership styles and job satisfaction?	Demonstrated that organizational trust acts as a mediator linking leadership styles to job satisfaction, indicating that fostering trust within organizations can enhance job satisfaction influenced by leadership approaches.
[207]	Leadership, Trust, and Job Satisfaction	How does leadership influence job satisfaction through the mediation of trust within organizations?	Showed that leadership styles impact job satisfaction through the mediation of trust, emphasizing the importance of cultivating trust to enhance employee satisfaction and retention.
[207] Gopalan, N., Beutell, N., & Alstete, J. (202	Leadership, Trust, and Job Satisfaction in Healthcare	What is the effect of transformational leadership on job satisfaction, organizational commitment, and trust among healthcare professionals?	Discovered that transformational leadership significantly affects job satisfaction, organizational commitment, and trust among healthcare professionals, highlighting the role of leadership in fostering trust and enhancing job satisfaction.

3). Can trust in management help? job satisfaction, healthy lifestyle, and turnover intentions. International Journal of Organization Theory and Behavior, 26(3), 185-202. https://doi.org/10.1108/ijotb-09-2022-0180 [208]			
[209]	Trust in Automation	How does trust in automation influence employees' responses to	Revealed that trust in automation significantly affects employees' responses to automation, including their job satisfaction levels;

	and Job Satisfaction	automation and their job satisfaction levels?	employees who trust the technology they work with are likely to experience higher job satisfaction and engagement.
[210]	Employee Relations and Job Satisfaction	How do positive employee relations contribute to job satisfaction, particularly during challenging times like the COVID-19 pandemic?	Argued that positive employee relations are fundamental to job satisfaction, especially in the context of mental health promotion during challenging times; strong interpersonal relationships enhance job satisfaction in environments employing collaborative technologies.
[211]	Organizational Culture, Trust, and Work Satisfaction	How does trust in leaders and a supportive organizational culture influence work satisfaction in environments with prevalent automation?	Indicated that trust in leaders and a supportive organizational culture significantly enhance work satisfaction; organizations must cultivate a culture that promotes trust and collaboration to maximize job satisfaction among employees working alongside cobots.
[212]	Trust in Management and Job Satisfaction	How does trust in management influence job satisfaction, and what role does communication play?	Highlighted that trust in management significantly influences job satisfaction; transparent communication practices are vital for enhancing employee satisfaction, particularly relevant when integrating technologies like cobots where clear communication can foster trust.

4.2.7 Job control

The analysis of job control, particularly in the context of human-robot collaboration (HRC), is essential for understanding how employees perceive their autonomy and control over work processes involving collaborative robots (cobots). Job control refers to the degree of autonomy employees feel they possess in their roles, which can significantly influence their trust in robotic systems and their overall job satisfaction. The literature indicates that employees' perceptions of autonomy are closely linked to their willingness to engage with robotic technologies, which can ultimately affect productivity and workplace dynamics.

One critical aspect of job control is the employees' readiness and communication skills, which are vital for effective human-robot interaction (HRI). According to Kim [213], employees' comfort levels in HRI are influenced by their attitudes toward robots, which can be shaped through proper training and development initiatives. The design of collaborative tasks and the perceived safety of working alongside robots also play a crucial role in shaping these attitudes. Parvez et al. [214] further emphasize that employees' perceptions of the benefits and drawbacks of robots can significantly affect their acceptance and trust in robotic systems. This highlights the importance of fostering a positive perception of robots through targeted training and communication strategies.

Moreover, the psychological impact of working alongside robots cannot be overlooked. Kim's [215] research on frontline service robots indicates that when employees recognize the competence of service robots, their negative psychological reactions diminish, leading to increased willingness to collaborate. This finding underscores the importance of perceived competence in enhancing job control and trust in robotic systems. Similarly, Siri et al. [216] discuss how perceptions of a robot's mental states can influence performance in collaborative tasks, suggesting that understanding and aligning perceptions between humans and robots is crucial for effective collaboration.

The interplay between job control and trust in robotic systems is further illustrated by the findings of Aliev and Antonelli [193], who propose that effective monitoring systems for cobots can enhance reliability and predict potential outages, thereby increasing employees' trust in these technologies. This aligns with the notion that transparency and reliability in robotic systems are essential for fostering a collaborative environment where employees feel in control of their work processes.

Trust in robots is also influenced by the perceived autonomy of these systems. Khavas et al. [85] highlight that existing trust models in HRI often focus on specific types of robotic agents, suggesting that a more generalized understanding of trust dynamics is necessary for various collaborative contexts. This indicates that as robots become more autonomous, employees' perceptions of their control over work processes may shift, necessitating a revaluation of training and support mechanisms.

Furthermore, the relationship between job autonomy and employee outcomes is well-documented. Jong and Ford [217] argue that increased autonomy is generally associated with positive perceptions of organizational support, which can enhance employee satisfaction and performance. This is particularly relevant in the context of HRC, where employees may feel a greater sense of control when they perceive that their contributions are valued and supported by their organizations.

In addition to autonomy, the social context of the workplace plays a significant role in shaping employees' perceptions of job control. Lauring and Kubovcikova [218] found that the relationship between job autonomy and work outcomes is moderated by the quality of the relationship with supervisors, suggesting that a supportive social environment can amplify the positive effects of autonomy. This highlights the importance of fostering a collaborative culture that encourages open communication and trust between employees and management.

Moreover, the integration of robots into the workplace can lead to changes in job characteristics, which may impact employees' perceptions of autonomy. Fréour et al. [219] discuss how digital technologies, including robotics, modify work characteristics and influence employee experiences. This transformation necessitates a careful examination of how job control is perceived in increasingly automated environments, as employees may experience both enhanced autonomy and new challenges related to their roles.

The concept of collaborative autonomy, where robots assist rather than replace human workers, is gaining traction in the literature. Cantucci and Falcone [220] emphasize that robots should provide varying levels of assistance to users, thereby enhancing the collaborative experience and maintaining a sense of control for human operators. This approach aligns with the findings of Romay et al. [221], who argue that shared autonomy can improve task completion times and overall team reliability in HRC scenarios.

As organizations continue to adopt robotic technologies, understanding the factors that influence job control and trust in these systems becomes increasingly critical. The literature consistently points to the importance of training, communication, and the design of collaborative tasks in shaping employees' perceptions of their roles in HRC. By fostering a supportive environment that emphasizes autonomy and collaboration, organizations can enhance employee engagement and satisfaction while effectively integrating robotic systems into their workflows.

Table 17. A table with short summary of results related to job control

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[213]	Employees' Comfort Levels in HRI	How do employees' attitudes toward robots influence their comfort levels in human-robot interaction (HRI), and how can training shape these attitudes?	Employees' comfort levels in HRI are influenced by their attitudes toward robots; proper training and development initiatives can improve these attitudes, enhancing comfort levels and willingness to engage with robotic technologies.

[214]	Employee Perceptions and Acceptance of Robots	How do employees' perceptions of the benefits and drawbacks of robots affect their acceptance and trust in robotic systems?	Employees' perceptions significantly affect their acceptance and trust in robotic systems; fostering positive perceptions through targeted training and communication strategies is essential for increasing acceptance and trust in robots.
[215]	Psychological Impact of Working with Service Robots	How does recognizing the competence of service robots affect employees' psychological reactions and willingness to collaborate?	When employees recognize the competence of service robots, their negative psychological reactions diminish, leading to an increased willingness to collaborate; perceived competence enhances job control and trust in robotic systems.
[216]	Perceptions of Robot Mental States in Collaboration	How do perceptions of a robot's mental states influence performance in collaborative tasks between humans and robots?	Understanding and aligning perceptions between humans and robots regarding the robots' mental states is crucial for effective collaboration; such perceptions can significantly influence performance in collaborative tasks.
[193]	Monitoring Systems for Cobots and Employee Trust	How can effective monitoring systems for collaborative robots enhance reliability and increase employees' trust in these technologies?	Effective monitoring systems enhance the reliability of cobots by predicting potential outages, thereby increasing employees' trust in these technologies; transparency and reliability are essential for fostering a collaborative environment where employees feel in control.
[85]	Trust Models in Human-Robot Interaction	Do existing trust models in HRI adequately cover various collaborative contexts, and is a generalized understanding of trust dynamics necessary as robots become more autonomous?	Existing trust models often focus on specific types of robotic agents; as robots become more autonomous, there is a need for a generalized understanding of trust dynamics to address shifts in employees' perceptions of control over work processes.
[217]	Job Autonomy and Organizational Support	How does increased job autonomy affect perceptions of organizational support, and what is its impact on employee satisfaction and performance?	Increased autonomy is generally associated with positive perceptions of organizational support, enhancing employee satisfaction and performance; employees feel a greater sense of control when their contributions are valued and supported by their organizations.

[218]	Job Autonomy, Supervisor Relationships, and Work Outcomes	How does the quality of the relationship with supervisors moderate the relationship between job autonomy and work outcomes?	The positive effects of job autonomy on work outcomes are amplified when there is a high-quality relationship with supervisors; a supportive social environment enhances the benefits of autonomy, highlighting the importance of open communication and trust between employees and management.
[219]	Impact of Robotics on Work Characteristics	How do digital technologies, including robotics, modify work characteristics and influence employee experiences in automated environments?	Digital technologies and robotics modify work characteristics, influencing employee experiences; this transformation requires careful examination of how job control is perceived, as employees may face both enhanced autonomy and new challenges related to their roles in automated settings.
[220]	Collaborative Autonomy and User Assistance	How can robots providing varying levels of assistance enhance the collaborative experience and maintain a sense of control for human operators?	Robots should provide varying levels of assistance to users, enhancing the collaborative experience and maintaining a sense of control for human operators; this approach supports better collaboration and ensures that humans feel empowered in HRC scenarios.
[221]	Shared Autonomy in HRC and Team Performance	How does shared autonomy between humans and robots impact task completion times and overall team reliability in HRC scenarios?	Shared autonomy improves task completion times and overall team reliability in human-robot collaboration scenarios; allowing both humans and robots to contribute control leads to more efficient and reliable task performance.

4.2.8 Feeling of self-efficacy as well as customers perception of robots presence

The integration of collaborative robots (cobots) in service industries, particularly in hospitality and tourism, has garnered significant attention in recent years. This interest is primarily driven by the potential of cobots to enhance customer experiences and improve operational efficiency. Two critical factors in this context are employees' self-efficacy in working with cobots and customers' perceptions of robots' presence. Understanding these factors is essential for maximizing the benefits of robotic integration in service settings.

Self-efficacy refers to an individual's belief in their capability to execute behaviours necessary to produce specific performance attainments. In the context of cobots, employees' self-efficacy can significantly influence their willingness to engage with these technologies. Research indicates that when employees feel confident in their ability to interact with cobots, they are more likely to embrace their presence and utilize them effectively in service delivery [222],[223]. For instance, Liu et al. [222] highlight that employees who perceive themselves as competent in using service robots experience reduced social discomfort, which in turn enhances their interaction quality with customers. This suggests that fostering a sense of self-efficacy among employees is crucial for successful cobot implementation.

Moreover, the perceived utility of cobots can further bolster employees' self-efficacy. When employees recognize that cobots can assist them in their tasks, they are more likely to view these technologies as valuable tools rather than threats to their job security [224]. This perception can lead to a more positive attitude towards the integration of cobots, ultimately enhancing service quality and customer satisfaction.

Ozturk et al. [224] emphasize that understanding the utilitarian and hedonic values associated with service robots can help organizations design better training programs that enhance employees' self-efficacy.

On the customer side, perceptions of robots' presence play a pivotal role in shaping their overall service experience. Customers' willingness to engage with service robots is often influenced by their perceptions of the robots' capabilities and the quality of interactions they provide [223],[225]. For instance, Molinillo et al. [223] found that positive interactions with service robots can lead to a greater willingness to use these technologies in restaurants, highlighting the importance of perceived interaction quality. Additionally, Huang's [226] research indicates that when service robots exhibit friendly behaviours, such as smiling and polite interactions, customers are more likely to perceive them positively, enhancing their overall experience.

The emotional responses elicited by service robots also contribute significantly to customer perceptions. Research has shown that customers tend to attribute human-like qualities to robots, which can influence their emotional engagement during service encounters [227],[228]. For example, when robots are designed with anthropomorphic features, customers may feel a greater emotional connection, leading to increased satisfaction and loyalty [227],[228]. This anthropomorphism can create a sense of familiarity and comfort, which is particularly important in hospitality settings where personal interactions are key to customer satisfaction.

Furthermore, the perceived competence and warmth of service robots can significantly affect customers' willingness to accept and engage with these technologies. Studies indicate that customers are more likely to tolerate service failures when they perceive robots as warm and competent [229,[230]. This finding underscores the importance of designing robots that not only perform tasks effectively but also engage customers on an emotional level. The balance between functional performance and emotional engagement is crucial for fostering positive customer perceptions and enhancing overall satisfaction.

In addition to emotional responses, customers' prior experiences with technology can shape their perceptions of service robots. Familiarity with robotic technologies can lead to more favourable attitudes and increased acceptance [231]. Conversely, customers with limited exposure to robots may exhibit scepticism or apprehension, which can hinder their willingness to engage with these technologies [232]. Therefore, organizations must consider strategies to educate customers about the benefits and functionalities of service robots to mitigate potential resistance.

The role of cultural factors in shaping customer perceptions of service robots cannot be overlooked. Different cultural backgrounds can influence how customers interpret and respond to robotic interactions [227],[233]. For instance, customers from cultures that prioritize personal interactions may be less receptive to robots, while those from cultures that embrace technological advancements may exhibit greater acceptance [227],[233]. Understanding these cultural nuances is essential for tailoring robotic services to meet diverse customer needs and expectations.

Moreover, the integration of cobots in service settings raises important ethical considerations. As robots become more prevalent in customer interactions, concerns regarding privacy, data security, and the potential dehumanization of service experiences emerge [234],[235]. Organizations must address these concerns transparently to build trust and foster positive customer relationships. Establishing clear guidelines for data usage and ensuring that robots enhance rather than replace human interactions can help mitigate these ethical dilemmas.

Table 18. A table with short summary of results related to feeling of self-efficacy as well as customers perception of robots presence

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[223]	Employees' Self-Efficacy and Customer Perceptions in Service Robot Interactions	How do positive interactions with service robots influence employees' self-efficacy and customers' willingness to use these technologies in restaurants?	Positive interactions with service robots enhance employees' self-efficacy and lead to greater customer willingness to use these technologies, highlighting the importance of perceived interaction quality in service settings.
[222]	Employees' Self-Efficacy and Social Discomfort in Using Service Robots	How does employees' perceived competence in using service robots affect social discomfort and interaction quality with customers?	Employees who perceive themselves as competent in using service robots experience reduced social discomfort, which enhances their interaction quality with customers; fostering self-efficacy is crucial for successful cobot implementation in service industries.
[224]	Perceived Utility of Cobots and Employee Self-Efficacy	How does recognizing the utilitarian and hedonic values of service robots influence employees' self-efficacy and attitudes towards cobot integration?	Employees who perceive cobots as valuable tools assisting in tasks are more likely to have enhanced self-efficacy and positive attitudes towards cobot integration; understanding these values can help design better training programs to enhance employee engagement.
[225]	Customers' Perceptions of Robots' Capabilities and Interaction Quality	How do customers' perceptions of robots' capabilities and interaction quality influence their willingness to engage with service robots?	Customers' willingness to engage with service robots is influenced by their perceptions of the robots' capabilities and the quality of interactions provided; positive perceptions lead to increased engagement with robotic technologies in service settings.
[226]	Service Robots' Friendly Behaviours and Customer Experience	How do friendly behaviours exhibited by service robots affect customer perceptions and overall service experience?	When service robots exhibit friendly behaviours such as smiling and polite interactions, customers perceive them more positively, enhancing their overall service experience and satisfaction in hospitality settings.
[227]	Anthropomorphism in Service Robots and Cultural Factors	How do anthropomorphic features in robots influence customers' emotional engagement, satisfaction, and loyalty? How do cultural backgrounds affect	Anthropomorphic robot designs lead to greater emotional connection, increased satisfaction, and loyalty among customers; cultural differences significantly affect customer receptiveness to robots, with some cultures being more accepting than

		customer perceptions of robots?	others, highlighting the need for cultural tailoring.
[228]	Anthropomorphism in Service Robots and Customer Satisfaction	How does designing robots with human-like qualities affect customer emotional connection, satisfaction, and loyalty?	Anthropomorphic features in robots enhance emotional connection, leading to increased customer satisfaction and loyalty; customers respond more positively to robots that exhibit human-like characteristics in service interactions.
[229]	Perceived Warmth and Competence of Service Robots Affecting Customer Tolerance	How do perceptions of warmth and competence in service robots affect customers' willingness to tolerate service failures?	Customers are more likely to tolerate service failures when they perceive service robots as warm and competent; emotional engagement with robots is crucial for fostering positive customer perceptions and enhancing overall satisfaction despite occasional shortcomings.
[230]	Perceived Warmth and Competence in Customer Acceptance of Robots	How do the perceived warmth and competence of robots influence customer acceptance and engagement in service settings?	Customers' acceptance and engagement with service robots are enhanced when robots are perceived as warm and competent; positive perceptions encourage customers to interact with robots even in the face of service failures, emphasizing the importance of emotional connection.
[231]	Customers' Prior Experience with Technology and Acceptance of Service Robots	How does familiarity with robotic technologies affect customer attitudes and acceptance of service robots in hospitality settings?	Familiarity with robotic technologies leads to more favourable attitudes and increased acceptance of service robots; prior experience reduces apprehension and enhances willingness to engage with robots in service environments.
[232]	Impact of Limited Exposure to Robots on Customer Scepticism	How do customers with limited exposure to robots perceive and engage with these technologies in service settings?	Customers with limited exposure to robots may exhibit scepticism or apprehension, hindering their willingness to engage; organizations need to implement education strategies to inform customers about the benefits and functionalities of service robots to mitigate resistance.
[233]	Cultural Factors Influencing Customer Perceptions of	How do different cultural backgrounds influence customer interpretation and response to robotic	Cultural backgrounds significantly influence customer perceptions and receptiveness to robots; understanding cultural nuances is essential for tailoring robotic services to meet

	Robotic Interactions	interactions in service industries?	diverse customer needs and expectations, improving acceptance and satisfaction across cultures.
[234]	Ethical Considerations in Robotic Service Interactions	What ethical concerns arise with the integration of cobots in service settings, and how do they impact customer trust and relationships?	Integration of cobots raises concerns about privacy, data security, and potential dehumanization of service experiences; addressing these concerns transparently helps build trust and fosters positive customer relationships, ensuring ethical deployment of service robots.
[235]	Ethical Implications of Robots in Customer Interactions	What are the ethical implications of increased robot prevalence in customer interactions, and how can organizations mitigate potential ethical dilemmas?	Concerns regarding privacy, data security, and dehumanization emerge with robots in customer interactions; establishing clear guidelines for data usage and ensuring robots enhance rather than replace human interactions can mitigate ethical issues and build customer trust.

4.2.9 Acceptance of robots

The acceptance of collaborative robots (cobots) in the workplace is a multifaceted issue that encompasses various factors influencing employees' perceptions and readiness to integrate these technologies into their daily tasks. Understanding these factors is crucial for organizations aiming to enhance productivity and employee satisfaction while minimizing resistance to technological change. This synthesis will explore the key determinants of robot acceptance, drawing on a range of scholarly articles and studies that provide insights into the psychological, social, and organizational dimensions of this phenomenon.

One significant factor influencing the acceptance of robots is employees' self-efficacy regarding their ability to work with robotic systems. Research indicates that high self-efficacy can lead to a more positive attitude towards the use of robots in the workplace, as employees feel more confident in their skills to adapt to new technologies [236]. The development of measures such as the Robot Use Self-Efficacy in Healthcare Work (RUSH) highlights the importance of assessing and enhancing employees' confidence in their ability to interact with robots effectively [236]. This is particularly relevant in sectors like healthcare, where the integration of robots can significantly alter workflows and patient interactions [214].

Moreover, the perceived benefits and drawbacks of robot integration play a critical role in shaping acceptance. Employees often weigh the advantages, such as increased efficiency and reduced physical strain, against potential drawbacks, including job displacement fears and the complexity of working alongside machines [214]. The Technology Acceptance Model (TAM) has been extended to include these perceptions, suggesting that employees' attitudes towards robots are influenced by their beliefs about the technology's usefulness and ease of use [237]. This model underscores the necessity for organizations to communicate the benefits of robot integration clearly and to provide adequate training to alleviate concerns about usability and job security.

Ethical considerations also emerge as pivotal in the acceptance of robots. Employees are more likely to embrace robotic systems when they perceive them as ethically designed and aligned with human values [237]. The Robot Acceptance Model for Care (RAM-care) emphasizes the importance of ethical and interpersonal factors in fostering acceptance, suggesting that organizations should address these concerns proactively. This includes ensuring that robots are designed to enhance human capabilities rather than replace them, thus fostering a collaborative environment where both humans and robots can thrive[237].

The social dynamics within the workplace significantly impact robot acceptance as well. Employees' perceptions of their colleagues' attitudes towards robots can influence their own acceptance levels. For instance, if a majority of employees express scepticism or resistance towards robotic systems, this can create a culture of fear and reluctance to adapt [238]. Conversely, positive social reinforcement and shared experiences with robots can enhance acceptance. This highlights the need for organizations to cultivate a supportive environment where employees can share their experiences and learn from one another regarding the use of robots [238].

Training and education are critical components in facilitating acceptance. Studies have shown that comprehensive training programs that not only focus on the technical aspects of robot operation but also address psychological and social dimensions can significantly improve acceptance rates [239]. Employees who receive adequate training are more likely to feel competent and less anxious about working with robots, leading to a more harmonious integration of technology into the workplace. Furthermore, ongoing support and opportunities for feedback can help employees adjust to new systems and foster a culture of continuous improvement [239].

The design and functionality of robots themselves also play a crucial role in acceptance. Research indicates that robots designed with user-friendly interfaces and anthropomorphic features tend to be more readily accepted by employees [240]. The appearance and behaviour of robots can influence how employees perceive their roles and capabilities, thus affecting their willingness to collaborate with these machines. For example, robots that exhibit human-like characteristics may elicit more positive emotional responses from employees, thereby enhancing acceptance [240].

Additionally, the context in which robots are introduced can significantly affect acceptance. Factors such as organizational culture, the nature of the work being performed, and the specific tasks assigned to robots can all influence how employees perceive and interact with robotic systems [241]. Organizations must consider these contextual factors when implementing robotic solutions to ensure that they align with employees' expectations and work practices [241].

Trust is another critical element influencing robot acceptance. Employees must trust that robots will perform their tasks reliably and safely. Research suggests that transparency in robot operations and clear communication about their capabilities can enhance trust. When employees understand how robots function and the rationale behind their deployment, they are more likely to accept them as reliable partners in their work [242].

Moreover, the emotional responses of employees towards robots cannot be overlooked. Negative emotions such as fear or anxiety can hinder acceptance, while positive emotions such as excitement and curiosity can facilitate it. Organizations should aim to create positive emotional experiences through engaging training sessions and hands-on interactions with robots, allowing employees to familiarize themselves with the technology in a supportive environment [243].

Table 19. A table with short summary of results related to acceptance of robots

Publication (Reference)	Thematic Area	Research Scope / Research Questions	Main Findings
[236]	Self-Efficacy in Robot Use in Healthcare	How does self-efficacy affect employees' attitudes toward robots, and how can it be measured in healthcare settings?	Developed the Robot Use Self-Efficacy (RUSH) scale; found that high self-efficacy leads to more positive attitudes toward robots; emphasizing the importance of assessing and enhancing employees' confidence in interacting with robots to improve acceptance.

[214]	Perceived Benefits and Drawbacks Affecting Acceptance	How do employees' perceptions of the benefits and drawbacks of robot integration influence their acceptance of robots in the workplace?	Employees weigh advantages like increased efficiency against drawbacks such as job displacement fears; organizations should communicate benefits clearly and provide adequate training to alleviate concerns, enhancing acceptance and trust in robotic systems.
[237]	Ethical Considerations in Robot Acceptance (RAM-care)	How do ethical and interpersonal factors influence the acceptance of robots, particularly in care settings?	Introduced the Robot Acceptance Model for Care (RAM-care); found that employees are more likely to embrace robots when perceived as ethically designed and aligned with human values; ethical considerations are pivotal in fostering acceptance of robotic systems.
[238]	Social Dynamics Influencing Robot Acceptance	How do colleagues' attitudes toward robots affect individual employees' acceptance levels in the workplace?	Negative attitudes among colleagues can create resistance and fear; positive social reinforcement and shared positive experiences with robots enhance acceptance; highlights the need for a supportive environment to facilitate robot integration.
[239]	Training and Education in Facilitating Acceptance	How do comprehensive training programs affect employees' acceptance of robots in the workplace?	Comprehensive training improves acceptance rates; employees who receive adequate training feel more competent and less anxious about working with robots; ongoing support and opportunities for feedback are essential for successful technology integration.
[240]	Design and Functionality Influencing Acceptance	How do user-friendly interfaces and anthropomorphic features in robots affect employees' willingness to collaborate with robotic systems?	Robots with user-friendly interfaces and anthropomorphic features are more readily accepted; the appearance and behaviour of robots influence employees' perceptions of their roles and capabilities, enhancing willingness to collaborate with these machines.
[241]	Contextual Factors in Robot Acceptance	How does the context of robot introduction, such as organizational culture and nature of work, influence employees' acceptance of robots?	The context significantly affects acceptance; alignment of robotic solutions with employees' expectations and work practices is crucial; organizations must consider contextual factors to ensure successful implementation of robotic technologies.
[242]	Trust and Transparency in Robot Operations	How do trust and transparency in robot operations influence employees' acceptance of robots in the workplace?	Transparency in robot operations and clear communication about capabilities enhance trust; when employees understand how robots function and the reasons for their deployment, they are more likely to accept them as reliable partners in their work.

[243]	Emotional Responses Affecting Robot Acceptance	How do employees' emotional responses toward robots impact their acceptance of robotic systems?	Negative emotions like fear and anxiety hinder acceptance, while positive emotions such as excitement facilitate it; creating positive emotional experiences through engaging training sessions helps employees familiarize themselves with robots, enhancing acceptance.

4.3 Examples of questionnaires available in the literature

4.3.1 TA-HRI

Following questionnaire was by Kraus et al. presented in [246].

Table 20. The Trustworthy and Acceptable HRI Checklist (TA-HRI)

Questions on Design		Design Recommendation
Trustworthy robot appearance		
1	Is the robot designed to look human-like for no compelling reason?	Human likeness of the robot is purpose-built and appropriate. The robot remains recognizable as a machine
2	Does the robot appear threatening?	The robot's dimensions are chosen to allow for optimal task completion with minimal threat. The robot's face is designed to be neutral to friendly to support a basic level of trust
3	Is the appearance of the robot meaningful?	All design features of the robot are linked to functions and do not create false expectations in users
4	Is the degree of humanlikeness appropriate to the task, meaningful, and adapted to the user group?	Human-likeness of robot behaviour is reasonably balanced and fits the users/operators, task, and situation
Reasonable and understandable autonomy		
1	Does the robot have an appropriate degree of autonomy/decision-making power?	It should be considered where it makes sense to grant robots autonomy and decision-making power. Higher acceptance by users can be expected if a monitoring/override function is implemented. The user/operator remains responsible for robot use
2	Can the scope and range of the robot's autonomous task execution be coordinated with the user/operator?	The robot only performs actions to be performed within the scope of the task assigned to it. The robot requires permission for each function/task from the user/operator before the robot can perform it
3	Does the robot signal autonomy?	If the robot is working in a fully autonomous mode, this is communicated in the interface (e.g., icon, lights); depending on the area of application and task this option can be implemented in a way that it can be deselected
4	Does the robot act autonomously to an appropriate degree within the scope of the tasks assigned to it and does it communicate efficiently?	If tasks are given to the robot, they are performed as effectively and efficiently as possible. This includes the reduction of task-related queries and information to a user-adaptive minimum
5	Is an optional successive increase in the level of autonomy implemented for standard tasks?	If desired by the users the robot can become successively more autonomous in the execution of standard tasks by learning from past interactions and reducing the extent of queries

6	Is the level of autonomy and proactivity of task execution adaptable to the task, area of use, and user group?	The level of autonomy and proactivity can be adjusted to the task according to user preferences
Trustworthy interaction		
1	Does the robot support a calibrated level of trust?	The robot and its interaction are designed in a way to support dynamic and situation-specific formation of a calibrated level of trust for each subtask. For this, the design recommendations of the category "Transparent communication" are fundamental prerequisites
2	Does the robot adapt immediately to user input?	The robot adapts its task execution directly after receiving an input. The task scope of the robot can be extended and restricted if necessary
3	Are the robot's current reliability and probability of error communicated?	The robot's design and interaction mechanisms allow for maximum reliability in task execution. The robot communicates errors and limitations to its reliability dynamically and in a timely manner
4	Does the robot coordinate the task execution with users to an appropriate degree?	The robot reassures itself to an appropriate degree with the users prior to action execution
5	Is a user-adaptive level of reassurance by the robot implemented?	The extent to which the robot coordinates its task execution with the user/operator can be configured by the user (e.g., all actions vs. unusual actions)
6	Does the robot use intuitive interaction mechanisms resembling social, interpersonal communication?	The robot uses intuitive mechanisms of interpersonal communication appropriately (without excessive anthropomorphising or an inappropriate degree of attachment)
7	Are deviations from expected objects or situations communicated?	If an object or task anomaly is detected by the robot, this is communicated to the user and clarification is attempted
Transparent communication		
1	Does the robot have the ability to show what movements it will perform (both locomotion and manipulator)?	The robot communicates the planned path and/or occupied movement space (e.g., projection on the floor)
2	Does the robot have the ability to communicate its current state and plans?	Robot states (e.g. battery status, errors), plans (e.g. schedule, remaining sub tasks) and degree of autonomy are communicated transparently and can be checked at any time
3	Does the robot show whether and which people and objects it has detected?	The robot makes the object/person recognition transparent and comprehensible for users, and thereby allowing for the identification of errors in the person recognition
4	Is the robot's communication modality adapted to the environment?	The interaction of the robot is adapted to the task environment and is (in the optimal case) implemented in a multimodal design to ensure universal usability.
		If applicable in private households, a voice dialog is recommended
		In public spaces and noisy environments, warning sounds and visual interaction are often more beneficial
5	Are system boundaries transparent and comprehensible?	The robot communicates situations for which system limitations exist, explains their consequences and warns about possible errors

6	Is the robot able to draw attention to itself?	The robot's interaction concept is designed in a way to allow to attract attention to the robot when necessary
7	Does the robot communicate unnecessary information?	The robot by default limits the communicated information to what is necessary for task execution, unless its task is communication
8	Does the robot give feedback on faulty operation/mistreatment?	The robot provides feedback when operation by the users is not in accordance with the task or could cause damage to the robot's hardware or software
9	Is the robot equipped with a possibility of announcing its entry into a room?	To prevent startling by sudden, unexpected entry, the robot signals its entry beforehand. To avoid excessive disturbance, this option can be switched off in accordance with the situation
10	Is there an adaptive level of coordination with users?	Users can adjust the robot's frequency of the coordination with the robot and the autonomy level for individual tasks
11	Does the robot demonstrate critical tasks before it first executes these?	The robot demonstrates critical tasks to users first, before final permission to perform these tasks in the future is given (e.g., demo mode or tutorial)
Appropriate social behaviour		
1	Does the robot adapt to the environment and its interaction partners when performing its tasks?	When people enter the robot's movement space, the robot adjusts its movement sequences in a way that people can move around undisturbed
2	Is the robot as inconspicuous, discreet, and non-disruptive as possible?	The robot performs its task discreetly, unobtrusively and with a minimum level of interference. Both noise generation of the task and communication are reduced to the minimum required for the task execution
3	Does the robot have an suitable and culturally appropriate level of politeness?	The robot adheres to social norms and communicates in a culturally compliant, friendly and polite manner that at the same time allows efficient task completion
4	Does the robot respect the personal distance zone?	The robot does not violate the human's personal space (a minimum distance of 1.5 m is recommended). Physical contact with humans is acceptable if it is relevant to the task and permission has been granted by the user
		The robot does not violate the human's personal space. A minimum distance of 1.5 m is recommended
5	Does the robot react appropriately to inattentive persons?	The robot recognizes when people in its environment are inattentive and adjusts its movements and actions accordingly
6	Does the robot assert itself only within defined limits (e.g. emergencies)?	The situations in which assertive behaviour by the robot is allowed are to be coordinated with the users. It should be possible for the user to stop the assertive action at any time
Perceptible data protection and protection of privacy		
1	Have the data protection regulations/laws of the respective country and the corresponding situation at the robot's operating location been considered in design?	Depending on the applicable law or regulation, the robot requires explicit consent for the use of cameras/microphones and the further processing of the collected data. The implemented data protection measures are communicated transparently to the users
2	The processing and storage of data is limited only to the personal data needed for the robot to perform the task?	The robot does not process and store any specific identification features of the surrounding persons beyond those required for task completion

3	Does the robot provide transparency as to when and what personal data is collected for what purpose and under what conditions it is deleted?	Data recording by the robot is recognizable to users and the scope and extent is comprehensible. If applicable, the purpose of data collection is communicated Appropriate procedures for (automated or user-initiated) data deletion are implemented and communicated transparently
4	Is personal identification by the robot without user consent avoided?	The robot protects peoples' privacy and personally identifies people only after their consent
		The robot protects privacy and avoids personal identification. If the robot needs to distinguish users, it does so in pseudonymous form whenever possible
5	Is the data transmission encrypted in a comprehensible way?	All data transferred between the robot and other parties is encrypted in a way that guarantees data security. This is communicated to the users in a comprehensible and transparent manner
6	Is the robot secured against hacking and misuse?	The robot's hardware and software are secured against unauthorized access (e.g. hacking, illegitimate access to user data). The users are reassured in this respect (actively or on request)
7	Does the robot respect privacy in the home?	The possibility of coordinating the area of use and reducing robot activity to the agreed rooms and task areas can increase acceptance. For particularly private rooms (e.g., bathrooms and bedrooms), the robot has an individualizable time- and situation-based coordination concept
Security & subjective feeling of safety		
1	Can the robot be switched off at any time?	The robot has a clearly marked and easily accessible emergency stop switch
2	Is the physical force of the robot limited to a maximum level that does not exceed the maximum necessary for the task?	Functionality, force application and speeds are limited to the maximum required for successful task completion. Accordingly, in this regard, realistic expectations of users are fostered by appearance and instruction
3	Are the robot and its components (e.g. manipulators) designed to be minimally hazardous?	The robot is designed and built e.g. as a lightweight construction, without clamping points and with soft/flexible surfaces
5	Does the robot handle sensitive and dangerous objects with care?	The robot recognizes critical and dangerous objects and interacts with them with limited force and speed and without endangering its environment
6	Does the robot avoid collisions and warns of them in a timely manner?	The robot is equipped with sensor technology that monitors distances to people in the immediate environment and has automatic emergency braking as well as a perceivable, preventive collision avoidance system
7	Does the robot keep a safe distance to people?	The robot detects persons and acts with a perceivable minimum distance
Subjectively normative robot behaviour		
1	Does the robot respect the dignity and rights of humans?	Actions of the robot do not affect human rights and respect human dignity
2	Does the robot coordinate moral decisions with a human?	To increase acceptance and trustworthiness of the robot, decisions involving a moral component are not made by the robot, but by a human
3	Does the robot follow generally applicable legislation?	Robot behaviour and robot interaction do not cross any legal boundaries

4	Is discrimination of groups of people by the robot ruled out?	The robot does not discriminate (e.g., based on gender, age, ethnicity). User-adaptive interaction concepts build on factual requirements of users and not on stereotyped assumptions
5	Does the robot allow for universal usability and inclusion of vulnerable and impaired people in the interaction?	The interaction of the robot is internationally understandable and includes people with disabilities, for example, through multimodality. The robot can adapt its behaviour to the needs of vulnerable and impaired persons
6	Does the robot help to provide relief for humans?	The robot takes over monotonous, repetitive or stressful tasks. The robot is not used in competition with humans
7	Does the implementation of robots allow for complete tasks for humans?	The robot takes over tasks in the socio-technical system in a way that allows the design of complete tasks for humans as well as an experience of competence and self-efficacyg. As far as possible, the human does not come into the position of a mere supervisor of the task execution of the robot
8	Are the activities of the robot retrospectively reconstructible?	The robot has a black box that keeps an activity log to reconstruct task execution (e.g., after accidents); this recording is done in accordance with data protection regulations
9	Does the robot not replace interpersonal, social contacts, but complement these?	The robot does not simulate a human being. It encourages users to have real social contact with other people
10	Does the robot avoid emotional attachment of the users beyond a healthy level?	The robot is designed to prevent excessive emotional attachment of the users to it. In this regard, decisions regarding humanization, robot personality, and communication style of the robot are made in an informed manner

4.3.2 Human Robot Interaction (HRI) Trust Scale

The following questionnaire was presented by Yagoda et al. in [138].

The questionnaire uses a 7-item Likert scale (Strongly Disagree - Strongly Agree)

Table 21. Human Robot Interaction (HRI) Trust Scale

Scale Item
The operator is dependable.
The human team member is dependable.
The supervisor is dependable.
The subject matter expert provides expertise.
Team communication is reliable.
Team coordination is dependable.
Team dynamics are reliable.
Team situational awareness is dependable.
Team decision making dependable

Team planning is dependable.
Team replanning is dependable.
Team backup is reliable.
Team leadership is accessible.
The operation is reliable.
The task is reliable.
The physical environment is reliable.
The social environment is reliable.
My previous task knowledge is dependable.
My previous human team member experience is dependable.
My previous physical environment experience is reliable.
My previous system knowledge is reliable.
My skills required for the task are dependable.
The task allocation is reliable.
The task objectives are reliable.
The difficulty of the task is reliable.
The task feedback is dependable.
Task feedback from my human team members is timely.
Task feedback from the physical environment is timely.
Task feedback from the overall system is reliable.
The user interface is reliable.
The sensor data is dependable.
The navigation capabilities are consistent.
The signal/bandwidth is dependable.
The end effectors are reliable.
The remote information processing is timely.
The level of automation is reliable.
The type of control is reliable.

4.3.3 The Godspeed Questionnaire Series

The following questionnaire was presented by Bartneck et al. in [247].

Table 22. The Godspeed Questionnaire Series

Component	Scale Item						
GODSPEED I: Anthropomorphism	Please rate your impression of the robot on these scales:						
	Fake	1	2	3	4	5	Natural
	Machinelike	1	2	3	4	5	Humanlike
	Unconscious	1	2	3	4	5	Conscious
	Artificial	1	2	3	4	5	Lifelike
	Moving rigidly	1	2	3	4	5	Moving elegantly
GODSPEED II: Animacy	Please rate your impression of the robot on these scales:						
	Dead	1	2	3	4	5	Alive
	Stagnant	1	2	3	4	5	Lively
	Mechanical	1	2	3	4	5	Organic
	Artificial	1	2	3	4	5	Lifelike
	Inert	1	2	3	4	5	Interactive
	Apathetic	1	2	3	4	5	Responsive
GODSPEED III: Likeability	Please rate your impression of the robot on these scales:						
	Dislike	1	2	3	4	5	Like
	Unfriendly	1	2	3	4	5	Friendly
	Unkind	1	2	3	4	5	Kind
	Unpleasant	1	2	3	4	5	Pleasant
	Awful	1	2	3	4	5	Nice
GODSPEED IV: Perceived Intelligence	Please rate your impression of the robot on these scales:						
	Incompetent	1	2	3	4	5	Competent
	Ignorant	1	2	3	4	5	Knowledgeable
	Irresponsible	1	2	3	4	5	Responsible
	Unintelligent	1	2	3	4	5	Intelligent
	Foolish	1	2	3	4	5	Sensible
GODSPEED V: Perceived Safety	Please rate your impression of the robot on these scales:						
	Anxious	1	2	3	4	5	Relaxed
	Agitated	1	2	3	4	5	Calm
	Quiescent	1	2	3	4	5	Surprised

4.3.4 Trust in industrial human-robot collaboration

The following questionnaire was presented by Charalambous et al. in [248].

The questionnaire uses a 5-item Likert scale (Strongly disagree - Strongly Agree)

Table 23. Trust in industrial human-robot collaboration

Component	Scale Item
Robot's motion and pick-up speed	The way the robot moved made me uncomfortable
	The speed at which the gripper picked up and released the components made me uneasy
Safe Co-operation	I trusted that the robot was safe to cooperate with
	I was comfortable the robot would not hurt me
	The size of the robot did not intimidate me
	I felt safe interacting with the robot
Robot and gripper reliability	I knew the gripper would not drop the components
	The robot gripper did not look reliable
	The gripper seemed like it could be trusted
	I felt I could rely on the robot to do what it was supposed to do

4.3.5 Human-Robot Interaction Trust Scale (HRITS)

The following questionnaire was presented by Pinto et al. in [52].

The questionnaire uses a 5-item Likert scale (1-Strongly disagree - 5-Strongly Agree)

Table 24. Human-Robot Interaction Trust Scale (HRITS)

Component	Scale Item
Benevolence	I believe that a collaborative robot will act to help me fulfil my goals
	I believe that a collaborative robot will do what it is asked to do to help me
	I believe that a collaborative robot will act according to my needs and preferences
Competence	I believe that a collaborative robot is competent and effective at Maintaining a pre-defined safety distance from the human
	I think a collaborative robot fulfils its role as a human assistant very well
	I believe that a collaborative robot has all the necessary safety features To interact with the human
Reciprocity	When I share something with a collaborative robot, I expect to get meaningful feedback; effective response

	By sharing something with a pre-programmed collaborative robot To perform a certain action, I believe that I will receive a response according to the expected action

4.3.6 Checklist for trust between People and Automation

The following questionnaire was presented by Jian et al. in [249].

The questionnaire uses a 7-item Likert scale (not at all =1; extremely =7)

Table 25. Checklist for trust between People and Automation

Scale Item
The system is deceptive
The system behaves in an underhanded manner
I am suspicious of the system's intent action, or outputs
I am wary of the system
The system's actions will have a harmful or injurious outcome
I am confident in the system
The system provides security
The system has integrity
The system is dependable
The system is reliable
I can trust the system
I am familiar with the system

4.3.7 Questionnaire „Trust in Automation“ (TiA)

The following questionnaire was presented by Körber et al. in [250].

The questionnaire uses a 5-item Likert scale (1-Strongly disagree - 5-Strongly Agree)

Table 26. Questionnaire „Trust in Automation“ (TiA)

Scale Item
The system is capable of interpreting situations correctly.
The system state was always clear to me.
I already know similar systems.
The developers are trustworthy.
One should be careful with unfamiliar automated systems.
The system works reliably.

The system reacts unpredictably.
The developers take my well-being seriously.
I trust the system.
A system malfunction is likely.
I was able to understand why things happened.
I rather trust a system than I mistrust it.
The system is capable of taking over complicated tasks.
I can rely on the system.
The system might make sporadic errors.
It is difficult to identify what the system will do next.
I have already used similar systems.
Automated systems generally work well.
I am confident about the system's capabilities.

4.3.8 Copenhagen Psychosocial Questionnaire II (COPSOQ II)

The Copenhagen Psychosocial Questionnaire (COPSOQ II) is currently an international, standardized tool used by the International Labor Organization and the World Health Organization to assess psychosocial risks occurring in the work environment [244]. It has been translated into 25 languages and validated in many countries around the world.

The Copenhagen Psychosocial Questionnaire (COPSOQ II) consists of 41 dimensions of psychosocial working conditions, most of which consist of three or four items. The questionnaire in question contains questions relating to various levels of human functioning at work (e.g. organization, department, employee), and analyses can be carried out at various levels of generality - e.g. for the general level of requirements at work or for a specific type of requirements. (e.g. emotional demands). Moreover, the questionnaire takes into account not only potential sources of stress at work, but also human resources (e.g. social support), personality traits (e.g. self-efficacy beliefs), as well as mental health (e.g. depression) and well-being at work (e.g. job satisfaction).

The self-efficacy subscale includes questions relating to the employee's general beliefs that, regardless of the circumstances, he or she can cope with difficult problems and unexpected situations and is able to implement his or her own plans and intentions. The subscale includes 6 items.

The subscale for examining social support at work includes questions relating to two sources of support - from co-workers and from superiors. They provide help and advice on dealing with problems at work. Each type of support is measured with three items.

The job control subscale includes questions relating to the employee's beliefs about the influence he or she has at work in terms of making decisions, how work is performed, and the amount of work assigned to him or her. The subscale includes 4 items.

The subscale for examining the sense of predictability includes questions relating to the employee's beliefs that he or she receives a full range of information about important decisions, changes and plans in the workplace and that this information is provided in advance. The subscale includes 2 items.

The job satisfaction subscale includes questions relating to the employee's overall level of satisfaction with his or her job. The subscale contains 4 items.

The following questionnaire was presented by Pejtersen et al. in [251].

Table 27. Copenhagen Psychosocial Questionnaire II (COPSOQ II)

Component	Scale Item
Predictability	At your place of work, are you informed well in advance concerning for example important decisions, changes, or plans for the future? (To a very large extent, To a large extent, Somewhat, To a small extent, To a very small extent)
	Do you receive all the information you need in order to do your work well? (To a very large extent,…)
Support from Co-workers	How often do you get help and support from your colleagues? (Always, Often, Sometimes, Seldom Never/hardly ever)
	How often are your colleagues willing to listen to your problems at work? (Always, …)
	How often do your colleagues talk with you about how well you carry out your work? (Always, …)
Support from Supervisor	How often is your nearest superior willing to listen to your problems at work? (Always, Often, Sometimes, Seldom Never/hardly ever)
	How often do you get help and support from your nearest superior? (Always, …)
	How often does your nearest superior talk with you about how well you carry out your work? (Always, …)
Job satisfaction	Regarding your work in general. How pleased are you with:
	1. your work prospects? (Very satisfied. Satisfied. Unsatisfied. Very unsatisfied. Not relevant)
	2. the physical working conditions? (Very satisfied. Satisfied. Unsatisfied. Very unsatisfied. Not relevant)
	4. the way your abilities are used? (Very satisfied. Satisfied. Unsatisfied. Very unsatisfied. Not relevant)
	6. your job as a whole, everything taken into consideration? (Very satisfied. Satisfied. Unsatisfied. Very unsatisfied. Not relevant)
Job Control	Do you have a large degree of influence concerning your work?

	(Always, Often, Sometimes, Seldom Never/hardly ever)
	Do you have a say in choosing who you work with? (Always, …)
	Can you influence the amount of work assigned to you? (Always, …)
	Do you have any influence on what you do at work? (Always, …)
Self-Efficacy	I am always able to solve difficult problems, if I try hard enough. (Fits perfectly; Fits quite well; Fits a little bit; Does not fit)
	If people work against me, I find a way of achieving what I want. (Fits perfectly…)
	It is easy for me to stick to my plans and reach my objectives. (Fits perfectly…) I feel confident that I can handle unexpected events. (Fits perfectly…)
	When I have a problem, I can usually find several ways of solving it. (Fits perfectly…)
	Regardless of what happens, I usually manage. (Fits perfectly…)

4.4 Preliminary version of the questionnaire structure

The questionnaire should be designed to assess various aspects of human-robot interactions. By examining dimensions such as safety, trustworthiness, dependability, and psychosocial factors, the questionnaire should provide valuable insights into how humans perceive and engage with robotic entities.

It is assumed that the questionnaire will be structured around four key dimensions:

I. Safety: Assessing perceptions of the robot's ability to operate without causing harm or injury to humans or property.
II. Trustworthiness: Examining the degree to which individuals rely on the robot's capabilities and intentions.
III. Dependability: Evaluating the robot's consistency, reliability, and ability to fulfil its intended functions.
IV. Psychosocial Factors: Exploring the emotional, social, and psychological aspects of human-robot interactions, including feelings of comfort, acceptance, and empathy.

The results of the literature study shows that there is no single questionnaire which consider all above mentioned aspects of HRI. Therefore, a new questionnaire has to be developed, taking into account different questionnaires presented in the literature.

The preliminary structure of the questionnaire is presented in the Table 28. The structure was prepared on the assumptions described in GA and results of the literature study. The final form of questionnaire will be developed after M12 as it is described in the fifth chapter (Future work). It should be noted, that to develop the questionnaire results of the other tasks are needed, especially the results described in D2.2 "*User requirements and use cases*" (M12) and D7.2 "*Report on pilot Specification and pilot sites preparation - v1*". It is assumed that for each subscale not more than four questions will be prepared to maintain reasonable length of the questionnaire.

Table 28. The structure of the questionnaire planned to use in the study

Main indicator / factor	Subscale
Safety	Physical safety
	Environmental Safety
	Emergency situations
Thrusthworthiness	Trust in technology safety and security
	Trust in the robotic technology and AI
	Technical Competence
	Trustworthy interaction
Dependability	Reliability
	Durability
	Adaptability
	Availability
	Perceived robot's work efficacy
Psychosocial factors	Worker support
	Organisational trust;
	Feeling of predictability in the work environment;
	Support from co-workers and supervisors;
	Job satisfaction;
	Job control;
	Feeling of self-efficacy
	Perception of robots presence

5 Future work

5.1 Introduction

Developing a highly sophisticated cobot can be a lengthy process. Hence, access to the fully functional robot may be possible in last months of the projects. In order to limit possible delays and reduce the risk of preparing a lower quality product, it was proposed in the Grant Agreement to conduct interactive simulations in a virtual environment. Basing on our previous experience it was assumed that simulations of a cobot in a VR will help developing the relevant methodology, e.g., to verify the questionnaire and research procedure.

5.2 Utilization of Virtual Reality Tools in Cobot Simulation for Methodology Development

5.2.1 Introduction

Collaborative robots, or cobots, have brought significant changes to the manufacturing industry, revolutionizing how humans and machines work together. Cobots are designed to assist human workers in a range of tasks, offering increased productivity, flexibility, and safety. However, to fully harness the benefits of cobots, it's essential to develop robust methodologies for their effective deployment. These methodologies must ensure that cobots perform their tasks efficiently while maintaining a safe environment for human workers.

In this context, Virtual Reality (VR) technology has emerged as an invaluable tool for simulating and refining cobot operations. VR provides an immersive and interactive environment where cobot simulations can be carried out, tested, and optimized without the need for costly and potentially hazardous real-world trials. This essay explores the utilization of VR tools in cobot simulations and examines how they contribute to the development of effective methodologies.

One of the primary benefits of VR in cobot simulation is immersive visualization. In a virtual environment, users can experience the cobot's operations from various angles and perspectives, which helps to better understand the spatial relationships between the cobot, its surroundings, and human workers. This clear visualization aids in optimizing cobot placement, task allocation, and ensuring efficient workflow integration.

Additionally, VR offers risk-free testing. Simulating cobot activities in a virtual environment eliminates the possibility of accidents or equipment damage, making it possible to test complex tasks or edge cases that might be too risky in the real world. This approach ensures a thorough exploration of cobot capabilities, allowing developers to identify potential issues before physical implementation.

Another key advantage is the cost efficiency of VR simulations. Creating physical prototypes or conducting real-world tests can be expensive and time-consuming, especially in the early stages of development. VR eliminates the need for these physical resources by providing virtual prototypes that can be tested and refined iteratively. This ultimately reduces the time and cost required for cobot deployment.

Furthermore, VR fosters enhanced collaboration among team members. In a virtual environment, engineers, designers, and stakeholders can interact with the cobot simulation simultaneously, regardless of their physical location. This collaborative aspect streamlines decision-making processes and enables quick adjustments based on feedback from various experts involved in the project.

Using VR in cobot simulations also provides significant advantages in terms of safety analysis and process optimization. In the virtual environment, safety risks posed by cobots can be thoroughly tested. For example, developers can simulate cobot interactions with humans, ensuring that the cobot behaves safely in scenarios involving sudden human movements or unexpected obstacles. This proactive testing helps to design cobots that prioritize safety without sacrificing efficiency.

From a process optimization perspective, VR simulations allow for testing different operational scenarios, such as task sequences and cobot movement patterns. By experimenting with various approaches in the virtual environment, developers can optimize cobot workflows, improve task completion times, and reduce energy consumption, all without halting real-world operations.

To implement these simulations effectively, specific VR tools and technologies are employed. Simulation software like Unity and Unreal Engine can create highly detailed virtual environments where cobots can be visualized and controlled. These platforms simulate realistic physics and enable dynamic interaction between virtual objects and users. VR hardware interfaces, such as headsets and haptic devices, further enhance the experience by immersing users in the environment and providing tactile feedback during cobot simulations. Additionally, integrating VR platforms with CAD and robotics software ensures that virtual models of cobots are as accurate as possible, based on real-world designs and control algorithms.

The process of using VR for methodology development follows several steps. First, the cobot and its operating environment are modelled in 3D, ensuring the virtual replica is accurate. Next, the cobot's behaviour is programmed, which includes defining its movement, sensor inputs, and responses to environmental factors. Once the virtual cobot is operational, scenario testing can begin. This involves simulating real-world tasks the cobot will perform, alongside potential human interactions, to evaluate safety and performance. During this stage, data collection and analysis play a critical role, as performance metrics such as task efficiency, error rates, and safety indicators are gathered for further refinement of the methodology.

Despite the advantages, utilizing VR for cobot simulations presents some challenges. Technical complexity is one such issue, as developing realistic VR simulations requires specialized knowledge in both VR technologies and robotics. Moreover, VR systems can involve significant resource investment, particularly in terms of high-quality hardware and software. Achieving the perfect balance between realism and performance is another challenge, as high-fidelity simulations often demand substantial computational resources. Finally, ensuring user acceptance of the technology is vital. Team members involved in the cobot development process must be trained and comfortable using VR to fully exploit its potential.

Looking to the future, advancements in VR technology are expected to further enhance its role in cobot development. Improved hardware like higher-resolution headsets and enhanced haptic devices will make VR simulations even more immersive. Additionally, the integration of artificial intelligence (AI) within VR simulations can lead to more adaptive cobot behaviours and provide predictive analytics for refining methodologies. Cloud-based VR collaboration will allow teams to work together from different locations in a shared virtual space, speeding up development cycles and reducing logistical barriers.

5.2.2 Development of interactive simulation in VR

To create a highly engaging and informative VR simulation for autonomous and collaborative robots, it is essential to construct a virtual world that closely mirrors real-life scenarios. This involves several key steps.

Firstly, the simulation must meticulously craft a 3D model of the robot, ensuring that its dimensions, movements, and capabilities are accurately represented. This includes modelling its arms, grippers, and base, as well as its ability to interact with objects in its environment. Simultaneously, detailed 3D models of the environments in which the robot will operate, such as airports and supermarkets, must be created. These environments should include all relevant objects, from luggage and shelves to aisles and people.

Next, a physics engine must be integrated into the simulation. This engine will simulate the interactions between the robot, its environment, and objects, ensuring that movements and collisions are realistic. Constraints must also be implemented to prevent the robot from moving outside of its intended boundaries or colliding with obstacles.

To make the robot truly autonomous, sophisticated algorithms that govern its behaviour must be developed. These algorithms should enable the robot to plan its movements, avoid obstacles, and interact with objects in a safe and efficient manner. Additionally, features that allow the robot to collaborate with human users, such as gesture-based commands, voice control, or haptic feedback, must be implemented.

Once the robot and its environments are created, they must be integrated into a VR experience using a device like the Meta Quest 3. This involves configuring the device to track the user's movements and provide a realistic VR experience. Additionally, the device's hand tracking capabilities must be utilized to allow users to interact with the robot directly.

To enhance the user experience, an intuitive and user-friendly interface must be designed. This interface should provide clear instructions and controls, allowing users to easily navigate in the simulated world and interact with the robot. Furthermore, the robot's responses to user actions must be realistic and appropriate.

Finally, a variety of interactive simulations must be created to test the robot's capabilities in different environments. These scenarios should include tasks such as loading and unloading luggage at an airport or restocking shelves in a supermarket. By conducting extensive testing and gathering feedback from users, the simulation can be refined to ensure that it provides a realistic experience.

5.2.3 Test in VR and questionnaire improvements

The interactive and VR-based simulation may be used to test and verify the questionnaire before the pilot test with the real robot. It is planned to perform such simulation to identify the potential drawbacks of the questionnaire. Having virtual environments specific for the MANIBOT project it will be easier to improve the questionnaire to better consider project requirements.

The VR-based experiments will be performed in CIOP-PIB's virtual reality laboratory, which has large enough are to properly simulate places like supermarket or a part of the airport (Figure 1).

It is important to notice that VR simulations will be also used to facilitate conducting safety analysis and analysing issues related to trustworthiness and dependability that are relevant to MANiBOT.

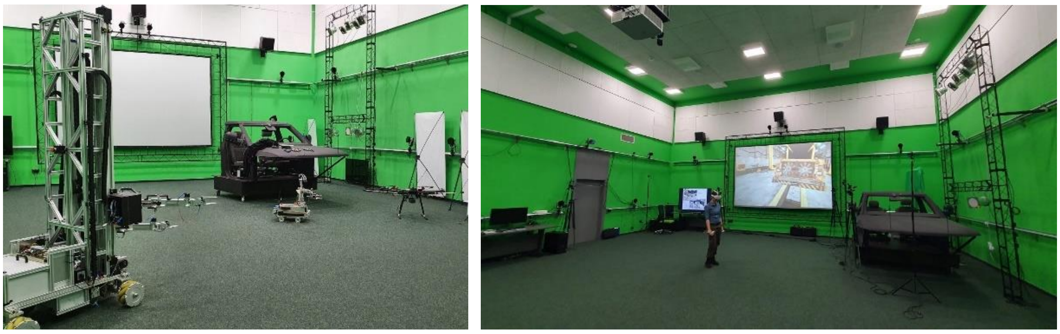

Figure 1. Virtual reality laboratory located in CIOP-PIB

5.3 Research using the real robot

The main objectives of Task 2.3 are:

- to conduct safety analysis and analyse issues related to trustworthiness and dependability that are relevant to MANiBOT,
- to develop a method for subjective assessment of workers' trust and satisfaction with working conditions in an automated work environment and to test this method during pilot studies.

To meet those objectives there is a need for:

- the access to the real robot,
- participation of the people with proper experience with cobot, who could fill the developed questionnaire. It is assumed that each participant will fill out two questionnaires. One corresponding to the situation without the cobot and the second with the cobot on the workplace. In this way the influence of the introduction of the cobot on e.g. psycho-social factors, like job satisfaction, will be investigated.

Therefore, the final version of this deliverable will be prepared during the pilot tests which are planned to conduct in WP7 "*MANiBOT framework testing, demonstration and validation*".

5.4 Research roadmap

This deliverable contains literature review and preliminary version of the questionnaire structure. To achieve results needed for final version of the deliverable, i.e. D2.6 “Trustworthiness and dependability analysis” (M36), following steps are needed:

- Development of virtual environment. To achieve this goal data from end-users as well as results of D7.2 “Report on pilot Specification and pilot sites preparation - v1” will be used [M24].
- Implementation of interactive simulations of all use cases in virtual reality according to the data provided in D2.2 “User requirements and use cases” [M30].
- Development of the questionnaire which takes into account all factors defined in the Grant Agreement [M30].
- Verification of the questionnaire using interactive simulation. CIOP-PIB employees will take part in interactive simulation and fill out the questionnaire. Considering those results and expert’s remarks the final version of the questionnaire will be developed [M36].
- Expert inspection method will be applied to perform hazards identification using interactive simulation in VR. Hazard identification is the first and crucial step in the process of risk analysis [M36].
- Subjective assessment of worker satisfaction with the working conditions present in the robotized working environment will be conducted during the pilot studies using developed questionnaire. It is assumed that workers having experience in working with robot will take part in the survey [M42].
- Subjective assessment of safety, trustworthiness and dependability will be conducted during the pilot studies using developed questionnaire. It is assumed that workers having experience in working with robot will take part in the survey [M42].
- Using data from pilot tests the safety analysis will be performed [M42].
- Results of the survey analysis as well as safety analysis will be performed [M42].

It should be noted that abovementioned roadmap will be adjusted to the testing plan which will be presented in: D7.1 “System testing and demonstration plan - v1” and D 7.5 “System testing and demonstration plan - v2”.

6 Summary and conclusions

This deliverable aims to investigate the factors influencing human-robot interaction (HRI) in collaborative robotic environments, focusing on safety, trustworthiness, dependability, and worker assessment.

Key areas explored include a comprehensive review of existing research on HRI issues, particularly trustworthiness, dependability, and safety analysis methods. It examines hazards posed by autonomous or collaborative robots, methods for safety analysis, relevant regulations and standards, and literature on safety analysis techniques. Additionally, the research reviews methods for assessing trustworthiness and dependability in HRI, including literature on existing techniques.

Furthermore, the deliverable investigates factors influencing workers' subjective assessments, such as trust in technology safety, trust in robotic technology worker support, organizational trust, predictability of the work environment, support from coworkers and supervisors, job satisfaction, job control, self-efficacy, customer perception of robots, and acceptance of robots. It also reviews existing questionnaires for measuring these factors, including TA-HRI, Human Robot Interaction (HRI) Trust Scale, The Godspeed Questionnaire Series, Trust in industrial human-robot collaboration, Human-Robot Interaction Trust Scale (HRITS), Checklist for trust between People and Automation, and Questionnaire "Trust in Automation" (TiA).

Finally, the deliverable presents a preliminary version of the questionnaire structure which will be developed for this study and discusses plans for utilizing virtual reality tools in cobot simulation for methodology development and facilitating the research using a real robot.

It should be noted, that this is the first version of the deliverable, mainly focussed on the literature review which was performed to choose or develop the preliminary methods for subjective assessment of workers' trust and satisfaction, as well as methods to analyse issues related to trustworthiness and dependability that are relevant to MANiBOT project. The second version of this deliverable will contain all required results, including the analysis results of the survey.

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