Enhancing User Experience in Human-Robot Interaction in Manufacturing

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Abstract

Robotic systems hold significant potential for transforming industrial environments; however, ensuring a positive and effective User Experience (UX) in Human-Robot Interaction (HRI) remains a major challenge. While technical performance is crucial, factors such as user trust, cognitive load, and collaboration satisfaction are equally vital for the success of Human-Robot Collaboration (HRC). This thesis adopts a User-Centred Design (UCD) approach, tailored to the manufacturing context, to systematically evaluate and enhance UX in HRI.

Through semi-structured interviews with 19 factory employees and subsequent qualitative analysis, the study identifies 12 key UX themes spanning five facets, including physical interaction, cognitive load, and emotional response. These findings inform the development of the HRI UX Assessment Framework, which offers structured guidance for designing more intuitive and user-friendly robotic systems in industrial settings.

Two case studies explore the integration of Augmented Reality (AR) into HRC tasks to address challenges related to trust and cognitive load. In the first case, AR-based robot facial expressions were compared with screen-based displays during a collaborative task. In the second case, a UCD-driven AR-assisted assembly system significantly enhanced task accuracy (97.49%) and user satisfaction, while also reducing cognitive workload.

To facilitate broader implementation, a self-report questionnaire was developed based on the UX framework and validated through surveys conducted with 358 workers across 35 factories. Exploratory factor analysis identified two core dimensions, comprehensive operational efficiency and cognitive usability, thus establishing a reliable UX measurement tool for industrial applications.

Overall, this research presents a scalable, human-centred approach to the design and evaluation of robotic systems in manufacturing, contributing to the advancement of HRI practices and laying the groundwork for safer, more efficient, and user-friendly robotic collaboration.

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List of Abbreviations

AI: Artificial Intelligence

AR: Augmented Reality

AVs: Autonomous Vehicles

Cobots: Collaborative Robots

EFA: Exploratory Factor Analysis

HRC: Human-Robot Collaboration

HRI: Human-Robot Interaction

KPIs: Key Performance Indicators

KMO: Kaiser-Meyer-Olkin

NASA-TLX: NASA Task Load Index

QUIS: Questionnaire for User Interaction Satisfaction

PSSUQ: Post-Study System Usability Questionnaire

SUMI: Software Usability Measurement Inventory

SUS: System Usability Scale

UCD: User-Centred Design

UEQ: User Experience Questionnaire

UX: User Experience

TiA: Trust in Automation

VUIs: Voice User Interfaces

VR: Virtual Reality

WCAG: Web Content Accessibility Guidelines

W3C: World Wide Web Consortium

List of Mathematical Symbols

DF: Degrees of Freedom

Sig.: Significance

μ: Mean

σ: Standard Deviation

t: T-Value

P: Probability Value

M: Mean

F: F-Statistic

Research Outputs

Journal Papers:

TONG, Y., ZHANG, Q., GALEANO, F. M. & JI, Z. Enhancing User Experience in Engine Assembly: Integration of Augmented Reality and Human-Robot Collaboration. (*Manuscript submitted to International Journal of Human-Computer Studies*)

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TONG, Y., ZHANG, Q., GALEANO, F. M. & JI, Z. AR and HRC integration for Enhanced Pragmatic Quality. 2024 IEEE International Conference on Industrial Technology (ICIT), 2024a. IEEE, 1-6.

TONG, Y., ZHANG, Q., GALEANO, F. M. & JI, Z. Designing an AR facial expression system for human-robots collaboration. 2023 28th International Conference on Automation and Computing (ICAC), 2023. IEEE, 1-6.

Chapter 1 Introduction

1.1 Background and Motivations

Robotic design is a rapidly evolving field that encompasses engineering, analysis, and implementation of robots that interact with humans in diverse settings (Chibani et al., 2013, Licardo et al., 2024, Goodrich and Schultz, 2007). These interactions hold the potential to substantially transform various domains, including industrial manufacturing, healthcare, education, agriculture, and restaurant, by integrating robotics to enhance efficiency and innovation (Dautenhahn, 2007b). For instance, robots are revolutionizing automotive industrial manufacturing by enhancing production efficiency, reducing workplace injuries, and enabling precise assembly tasks (Javaid et al., 2021). In healthcare, robotic-assisted surgeries, such as those performed by the Da Vinci Surgical System, illustrate how robots can deliver unparalleled precision and consistency, improving patient outcomes (Surgical, 2013). Similarly, in the education sector, robots like SoftBank's Pepper are being used to engage students in interactive learning, teaching programming skills, and supporting special education needs (Pandey et al., 2018). For example, Pepper has been implemented in Japanese schools to foster interactive learning experiences and in Boston classrooms as a tool for teaching programming and aiding students with autism spectrum disorders (Guizzo, 20204). In the restaurant industry, Miso Robotics, based in Pasadena, USA, created a mobile robotic platform called Flippy, featuring a 6-axis collaborative robot designed to work alongside humans at kitchen equipped with griddles and fryers (Pereira et al., 2022). In agriculture, robots like John Deere's autonomous tractors and Blue River Technology's precision weed control systems are transforming farming practices by reducing labour demands, optimizing resource use, and improving crop yields (Albiero et al., 2021, Panpatte and Ganeshkumar, 2021). The retail sector is also embracing robotics with solutions like Amazon's Kiva robots, which streamline warehouse operations by efficiently sorting and transporting goods, drastically reducing delivery times (Jain and Sharma, 2017). As robots become more integrated into these sectors, understanding how humans perceive, interact with, and accept these systems is crucial (Thrun, 2004, Sheridan, 2016, Bragança et al., 2019, Dautenhahn, 2007b, Ajoudani et al., 2018).

Human-Robot Interaction (HRI) refers to the interdisciplinary study and design of interactions between humans and robots, aiming to create systems that allow intuitive, and efficient collaboration (Bartneck et al., 2024). Under the broad conceptual umbrella of HRI, the field of Human-Robot Collaboration (HRC) specifically focuses on scenarios where humans and robots work side by side, sharing tasks and environments (Simões et al., 2022, Ajoudani et al., 2018). HRC focuses on fostering seamless collaboration between humans and robots, drawing on insights from disciplines such as robotics, psychology, cognitive science, and human-computer interaction (Wamba et al., 2023, Hentout et al., 2019, Sheridan, 2016). The goal of HRI is to bridge the gap between robotic capabilities and human expectations by addressing the technical, psychological, and social dimensions of these interactions (Feil-Seifer and Mataric, 2009, Kwon et al., 2016). As robots become increasingly integrated into daily life, the importance of designing systems that are not only technically advanced but also user-friendly and trustworthy cannot be overstated (Khan, 2024, Usmani et al., 2023, Engelhardt et al., 1992).

To integrate robots seamlessly into operators' daily routines, it is essential for them to deliver purpose-driven and enjoyable interactions that foster a positive experience (Chen et al., 2020, Boden et al., 2017, Kahn Jr et al., 2007, Lindblom and Alenljung, 2020, Prati et al., 2021a, Apraiz et al., 2023). Previous research has primarily concentrated on developing technically advanced robots, often neglecting the importance of UX (Shourmasti et al., 2021, Nielsen et al., 2024, Huang et al., 2021, Vaiani and Paternò, 2024). User experience (UX) is important in the interaction between humans and robots. ISO 9241-210 defined UX as the perceptions and responses of a person resulting from the use or anticipated use of a product, system, or service (Standardization, 2019). Traditional UX evaluation frameworks, developed for consumer products or digital applications, fail to address the unique challenges of industrial HRI (Tong et al., 2024). These tools UEQ (Laugwitz et al., 2008) and UMUX (Finstad, 2010) often overlook critical dimensions such as trust, safety, and operational accuracy, leaving organizations without systematic methods to assess and improve their HRI systems. This gap hampers progress in designing user-centred robotic systems that align with industrial requirements.

Currently, UX in HRI encompasses several dimensions, including cognitive load (Ahmad et al., 2019), trust (Yagoda and Gillan, 2012), safety (Lindblom and Wang, 2018) and Emotional engagement (Ahmad et al., 2017). Cognitive load refers to the mental effort required for users to interact with robotic systems, where intuitive interfaces can minimize mental strain and enhance productivity, while poorly designed ones can overwhelm users and lead to errors (Ahmad et al., 2019, Muradore et al., 2015). As robots become more advanced, the cognitive load on users increases. Poorly designed interfaces and workflows can overwhelm operators, resulting in errors, reduced productivity, and even safety risks (Öztürk et al., 2024, Hu, 2023). For example, The Three Mile Island nuclear accident in 1979 exemplifies how poor interface design can lead to catastrophic outcomes. Operators, overwhelmed by ambiguous indicators and excessive alarms during a coolant malfunction, misinterpreted the situation, delaying corrective actions. Addressing these cognitive challenges is critical for ensuring that humans and robots can collaborate effectively. Trust in automation is defined as “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability” (Lee and See, 2004). Robotics represents a key area within automation, focusing on machines designed to perform intricate tasks within dynamic and physical settings (Groover, 2016). Trust plays a critical role in ensuring effective collaboration, as appropriate levels of trust enable users to rely on robots without excessive supervision or overreliance, particularly in safety-critical environments (Coeckelbergh, 2012, Kok and Soh, 2020, Yagoda and Gillan, 2012, Lewis et al., 2018). Without appropriate levels of trust, users may avoid relying on robotic systems, choosing manual alternatives that undermine the potential benefits of automation. For instance, in November 2023, a South Korean agricultural centre saw tragedy when a robotic arm misidentified a worker as a box, fatally injuring him (Harris, 2023). Conversely, over-reliance on robots due to misplaced trust can lead to catastrophic failures in high-risk settings. For example, on March 18, 2018, the first pedestrian fatality involving a self-driving car occurred in Tempe, Arizona. Elaine Herzberg, 49, was pushing her bike across a four-lane road when she was struck and killed by an Uber test car in self-driving mode (bbc, 2020). Striking this balance is a fundamental challenge in HRI, especially as systems become more autonomous and complex. Safety encompasses both physical and psychological aspects, ensuring collision avoidance and instilling confidence in users when interacting with robots (Zacharaki et al., 2020, Haddadin et al., 2009, Villani et al., 2018, Lasota et al., 2017). Emotional engagement reflects the user's emotional responses during interaction, where expressive behaviours or friendly interfaces can foster positive feelings and long-term acceptance (Khosla et al., 2017, Ahmad et al., 2017). Understanding these dimensions and their impact on HRC is essential for designing effective and user-friendly robotic systems (Tong et al., 2024). As the complexity of tasks and the need for seamless collaboration increase, UX considerations in HRI become particularly critical in manufacturing environments, where robots and humans must work closely together under dynamic and high-stakes conditions."

Manufacturing environments present unique challenges for HRI because of their dynamic, high-risk nature and the need for deeper collaboration between humans and robots (Hjorth and Chrysostomou, 2022, Jahanmahin et al., 2022). Despite technological advancements, robotic systems often prioritize functionality over user experience (Chen et al., 2010). This technical focus has resulted in systems that are highly efficient but difficult to operate, creating a steep learning curve for users (Tortorella et al., 2024). In manufacturing, operators often struggle with unintuitive control systems, leading to frustration, inefficiency, and diminished productivity (McQuillen, 2021). For example, according to a 2016 study, the task Settings of robotic systems in many smart factories are too rigid to be dynamically adjusted to the operator's personal preferences or different work rhythms. It is difficult for operators to flexibly adapt to the default processes of robotic systems, resulting in productivity suffering and impacting the user experience (Weiss and Huber, 2016). The other key challenge is managing cognitive load in dynamic tasks. Manufacturing tasks often require frequent reconfiguration of robotic systems to accommodate shifting production demands (Morgan et al., 2021). However, existing user interfaces are often not intuitive, forcing operators to rely on trial-and-error methods, which increases cognitive strain and leads to delays and errors (Ahmad et al., 2019, Apraiz et al., 2023). Another critical challenge is establishing and calibrating trust. Trust is essential for effective collaboration but remains a double-edged sword. Insufficient trust may lead operators to underutilize robotic systems, while over-reliance can pose safety risks. Current HRI systems often fail to provide the transparency required to build appropriate levels of trust (Kok and Soh, 2020). Ensuring safety and user satisfaction also presents significant challenges. While physical safety measures such as collision avoidance are well-established, psychological safety and user satisfaction are often neglected, especially in environments where robots operate in close proximity to humans (Haddadin et al., 2009, Villani et al., 2018). Moreover, the limited transparency in current HRI systems, combined with abrupt or non-intuitive robot behaviours, further exacerbates this challenge by preventing operators from fully understanding or anticipating robotic actions (Lasota et al., 2017, Kok and Soh, 2020). Workers have reported discomfort and decreased productivity when working alongside robots with abrupt and unpredictable movements, highlighting the need for smoother, more human-like interaction patterns. There is a lack of comprehensive frameworks for evaluating UX in HRI within manufacturing contexts. Most existing assessments focus narrowly on task efficiency, neglecting broader factors such as emotional engagement and adaptability.

To summarise, the rapid integration of robotics into industrial and societal settings has unveiled significant challenges that hinder the seamless adoption of these systems. While robots have demonstrated remarkable capabilities in domains like manufacturing, critical gaps persist, primarily in how humans perceive, interact with, and ultimately trust these systems. In this context, I define four key points to address these issues:

1. The Neglect of UX

2. The Erosion of Trust in High-Stakes Collaboration

3. Escalating Cognitive Demands

4. The Lack of Comprehensive UX Evaluation Tools

Based on the challenges and gaps identified in the background and motivations, this research focuses on addressing key questions related to UX in Human-Robot Interaction (HRI). Specifically, it aims to develop user-centred frameworks and tools to improve trust, reduce cognitive load, and enhance adaptability in industrial HRI systems. These insights will guide the formulation of research questions and objectives in the next section.

1.2 Research Question and Objectives

Informed by the background and motivations, this thesis aims to investigate how UX can improve in HRC/HRI in manufacturing setting. By identifying key UX factors and structuring them into a systematic assessment framework, the study seeks to provide actionable insights and design strategies that can directly enhance the intuitiveness, efficiency, and user satisfaction of HRI systems in manufacturing environments. The following research questions have been formulated:

RQ1: How can user experience factors be identified and systematically incorporated into a UX assessment framework to evaluate HRI in manufacturing environments?

RQ2: How should I evaluate the effectiveness of a solution (e.g., AR assistive technology) to improve UX in a manufacturing setting?

RQ3: How can a specialized UX assessment tool be developed and validated for evaluating HRI in manufacturing settings, and what dimensions should it measure to effectively capture UX?

To ensure transparency and coherence in research design, Table 1.1 presents a structured mapping between the primary research challenges identified in the motivation, the corresponding research questions, and the chapters where these questions are systematically addressed. This overview provides a consolidated perspective on how each component of the thesis aligns with the central research objectives.

Table 1.1 Mapping of Research Challenges, Questions, and Chapter Structure.

Challenge	Research Question	Chapter
The Neglect of UX	RQ1	Chapter 3
The Erosion of Trust in High-Stakes Collaboration	RQ2	Chapter 4
Escalating Cognitive Demands	RQ2	Chapter 5
The Lack of Comprehensive UX Evaluation Tools	RQ3	Chapter 6

With the identification of the research questions, the research objectives following these research questions are listed below:

1 **To develop an assessment framework for UX in HRI within manufacturing settings** by analysing key UX factors, such as cognitive load, trust, and safety, derived from in-depth user feedback. This framework will serve as a foundation for evaluating the user experience in collaborative robotics across various manufacturing scenarios.

2 **To demonstrate a method for evaluating the effectiveness of AR interventions improving UX in HRC tasks through experimentation.** This objective focuses on using experimental methods to assess how AR technologies, such as facial expressions and immersive

interfaces, impact operator trust, task performance, and overall user experience in real-world industrial settings.

3 **To create a specialized UX assessment tool for HRI in manufacturing**, based on the developed framework, with a focus on dimensions like operational efficiency and cognitive usability. This tool will be specifically tailored for manufacturing environments, addressing gaps left by traditional UX assessments.

1.3 Thesis Outline

Designing for a positive user experience in HRI involves a structured process known as the user experience design process (Marcus and Wang, 2017). This process provides a systematic approach to understanding and addressing user needs, ensuring that robotic systems are not only functional but also user-friendly and satisfying to interact with. The process typically includes the following stages (Figure 1.1): user research (Baxter et al., 2015), problem definition and goal setting (Norman, 2013), conceptual design and prototyping (Arnowitz et al., 2010), testing (Nielsen, 1994a) and iteration and implementation and validation (Preece et al., 2015). This workflow serves as a guiding framework for ensuring that UX considerations are deeply integrated into the design and functionality of product or systems (Deaton, 2003). The rest of this thesis is structured around the UX design approach**.** This UCD process guide the development of HRI systems in manufacturing sector. Chapters 3 to 5 align with a specific phase of the UCD process.

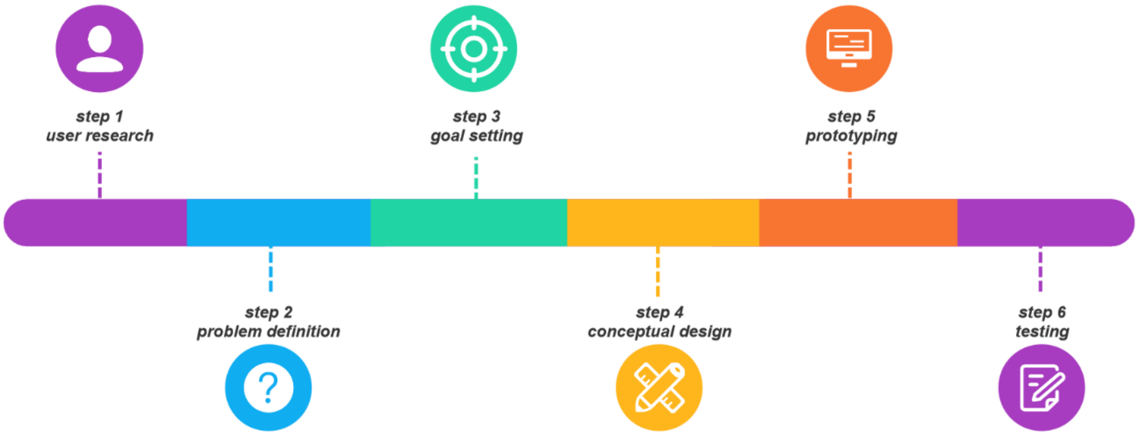

Figure 1.1 User experience design process.

Chapter 2 examines existing research on HRI, concentrating on key concepts like cognitive load, UX, trust, and safety in collaborative environments. The review highlights the interdisciplinary nature of HRI, where insights from psychology, engineering, and human-computer interaction converge to inform effective human-robot collaboration. Research shows that managing cognitive load is critical to achieving efficient and intuitive interactions, especially in high-stakes industrial settings. Additionally, UX is recognized as a multi-dimensional construct that includes emotional engagement, task satisfaction, and usability, all of which contribute to the acceptance and effectiveness of HRI systems.

Chapter 3 introduces a specialized framework for assessing UX in manufacturing HRI. It outlines the development process and methodology for creating a comprehensive UX evaluation model, focusing on critical factors such as operational efficiency, reliability, safety, and cognitive load. This framework is designed specifically for industrial settings, where traditional approaches to user experience assessment may not fully capture the unique challenges of human-robot collaboration in manufacturing.

Chapter 4 delves into the role of AR in fostering trust during human-robot interactions. This section presents an experimental study that compares the effectiveness of AR and screen-based systems in communicating safety-critical information, such as facial expressions, during collaborative tasks. The findings reveal insights into how AR can enhance or hinder trust in robotic systems, offering practical implications for the design of future HRC environments.

Chapter 5 focuses on the research in exploring the potential of augmented reality to enhance the user experience in industrial assembly tasks. It investigates how AR can be integrated into human-robot collaboration to reduce cognitive load, improve task accuracy, and boost overall efficiency. The chapter presents experimental results demonstrating the advantages of AR over traditional methods, highlighting its ability to streamline complex assembly tasks in real-world manufacturing settings.

Chapter 6 builds on the UX framework by developing and validating a tailored UX evaluation tool. This tool provides a practical mechanism for measuring and analysing the user experience in industrial HRC scenarios, ensuring that both technological performance and human-centred design factors are considered. The chapter details the tool's design, implementation, and validation, offering an empirical basis for its effectiveness in improving HRI.

Chapter 7 concludes the thesis by summarizing the key findings and contributions of the research. It outlines the achievements made in developing AR-assisted HRC systems and specialized UX evaluation tools, while also reflecting on the challenges encountered during the research. This chapter also presents future directions for expanding the application of AR and HRI technologies in more complex industrial contexts.

1.4 Contribution

This thesis makes significant contributions to the fields of HRI, UX, and AR interface, with a particular focus on integrating UX principles into the design and implementation of industrial HRC systems. These contributions are organized following the key stages of the UX design approach: user research, problem definition, prototyping, testing, and implementation.

A primary contribution of this research is the development of a tailored UX assessment framework specifically designed for industrial environments. Unlike traditional UX models which focused on consumer products, this framework addresses the unique demands of manufacturing settings, incorporating critical factors such as operational efficiency, cognitive load, safety, and trust. By providing a comprehensive understanding of UX in HRI, this framework bridges the gap between user-centred design principles and the technical requirements of industrial robotics, offering a foundation for further advancements in collaborative workspaces.

Building on the UX framework, this research introduces a specialized UX evaluation tool designed to systematically measure user experience in industrial HRI scenarios. Validated through empirical studies, the tool identifies key dimensions, including "Operational Efficiency" and "Cognitive Usability," and provides a practical mechanism for assessing and optimizing HRI systems. This contribution equips organizations with a reliable method to enhance both system performance and worker satisfaction, addressing a critical gap in the current research on industrial robotics.

This thesis introduces a UX paradigm, with AR technology serving as a representative example. Experimental studies reveal both the benefits and limitations of using AR to communicate safety-critical messages and enhance transparency in collaborative scenarios. While the findings indicate challenges in achieving consistent improvements in trust levels, they underscore the potential of AR for flexible and immersive interaction designs. These insights provide critical lessons for the future development of trust-centric HRI systems.

A major contribution of this thesis is the integration of the UX design process into HRI system development, demonstrating how each stage—user research, problem definition, prototyping, testing, and validation—can be applied to address real-world industrial challenges. By tailoring solutions to worker needs through iterative design and feedback, the research bridges the gap between academic theory and practical implementation, offering a cohesive methodology for developing user-centred HRC systems. This approach not only ensures usability and efficiency but also creates systems that are adaptive, intuitive, and aligned with the psychological and ergonomic needs of workers in industrial environments.

1.5 Assumptions

To ground the methodology in the context of the research questions and contributions outlined above, I operate under a number of key assumptions. I assume that participants will follow instructions and engage sincerely with the interaction tasks, such that their observed behavior reflects genuine user–robot collaboration in a manufacturing context.

I also assume that the data collection instruments (such as sensors, video recordings, and questionnaires) provide accurate and reliable measurements of system states and user responses. Furthermore, I assume that the scenario tasks chosen for evaluation are representative of real manufacturing activities; this means I treat the laboratory environment and task design as a valid proxy for analogous industrial situations. These methodological assumptions ensure that participant behavior and data quality align with the intended research context.

In addition to methodological assumptions, I make explicit technological assumptions regarding the experimental setup. I assume that the robotic hardware and its control system operate stably and perform as intended throughout each trial, so that any hardware malfunctions or erratic behavior would be treated as anomalies outside the intended evaluation. Similarly, I assume that the augmented reality interface (for example, AR glasses or a tablet-based AR app) works reliably, with accurate tracking, stable registration, and negligible latency. This implies that the AR overlays or guidance cues appear correctly in the user's field of view without significant errors. By assuming reliable technology operation, I can focus the study on user experience and interaction, accepting that any rare technical issues fall outside the core research scope.

1.6 Limitations

Nevertheless, I acknowledge that this study involves several important limitations. I note that I conducted the experimental evaluation in a controlled laboratory setting with a specific set of tasks, which may not capture the full variability of real-world manufacturing environments. This constrained setup means that contextual factors such as dynamic production line conditions, time pressure, or operator fatigue were not fully represented. The sample size of participants was also limited by practical constraints, as only a small number of subjects could be recruited; this limitation may reduce the statistical power of the findings and their generalizability to the broader population of manufacturing workers. Furthermore, each participant's exposure to the AR-assisted system was relatively brief, preventing the study from assessing longer-term user adaptation or learning effects. Together, these factors suggest caution when extrapolating the findings to broader contexts.

Furthermore, the broader applicability of the developed framework and tools is inherently limited by the scope of this research. The prototype system and UX assessment framework were validated only for the specific tasks, robot model, and AR hardware used in this thesis, so applying them to different manufacturing contexts or interaction scenarios may require further adaptation. I recognize that factors such as different task types, production scales, or diverse user populations were not explored; these could influence how users experience the system. Additionally, the evaluation primarily focuses on short-term subjective and performance measures, so future work would be needed to assess long-term usability, learning, and organizational factors. These limitations imply that while the contributions of this thesis advance understanding of AR-supported HRI, their generalizability to all manufacturing situations is constrained by the defined research scope.

Chapter 2 Literature Review

2.1 Introduction

This chapter aims to provide a comprehensive literature review of HRI and UX, particularly in industrial settings. It critically examines key concepts, interaction modalities, and evaluation tools, laying the groundwork for the development of a domain-specific UX assessment framework for manufacturing HRI. The review is structured around four themes: the fundamentals of HRI, the principles of UX, current evaluation approaches, and the core dimensions of UX in collaborative robotics.

Human-Robot Interaction (HRI) refers to the interdisciplinary study and design of interactions between humans and robots, aiming to create systems that allow intuitive, and efficient collaboration (Bartneck et al., 2024, Blessing and Klaus, 2024). This interaction is crucial in many applications, ranging from industrial automation to healthcare, education, and service industries (Dautenhahn, 2007b). The growing integration of robots into these sectors necessitates a comprehensive understanding of how humans perceive, interact with, and accept these robotic systems (Song and Kim, 2022, Thrun, 2004, Blessing and Klaus, 2024).

The significance of HRI lies in its potential to enhance productivity, safety, and efficiency in various tasks (Moustris et al., 2011). For instance, in manufacturing, cobots work alongside human workers to perform repetitive, dangerous, or precision tasks, thereby improving overall productivity and safety (Bogue, 2016). In a notable example (Figure 2.1), BMW's manufacturing plant in Spartanburg, South Carolina, integrates UR cobots to handle repetitive tasks such as inserting gear sticks into car chassis. These cobots not only reduce the physical strain on workers but also ensure consistent precision, thereby improving overall productivity and safety (Robots, 2020). In healthcare, robots assist in surgeries, rehabilitation, and eldercare, providing significant benefits in terms of precision, consistency, and personalized care (Moustris et al., 2011). A prime example is the da Vinci Surgical System (figure 2.2), developed by Intuitive Surgical, which is used in over 6,000 hospitals worldwide. At the Cleveland Clinic, this robot performs minimally invasive procedures such as prostatectomies with enhanced precision and reduced recovery times for patients (Clinic, 2025).

Figure 2.1 Universal Robots in factory. Source: (Robots, 2020).

Figure 2.2 daVinci Surgical System. Source: (Center, 2025).

However, the success of HRI depends heavily on the quality of the UX (Prati et al., 2021a). A positive UX in HRI can lead to higher acceptance rates, better performance, and increased trust between humans and robots (De Graaf and Allouch, 2013). Key dimensions of UX in HRI include cognitive load, emotional engagement, trust, and safety (Ali et al., 2023). Understanding these dimensions and how they impact human-robot collaboration is essential for designing effective and user-friendly robotic systems (Prati et al., 2021a).

This chapter aims to provide a review of the literature on HRI, focusing on the fundamental principles, key dimensions of UX. The following sections will delve into the historical development of HRI, theoretical models, evolution of interaction modalities, and the impact of cognitive, emotional, and social factors on user experience.

2.2 Fundamentals of Human-Robot Interaction (HRI)

2.2.1 Historical Overview

While robots have long existed, HRI as a field of research only began to take shape in the mid-20th century, thanks to advances in robotics and human factors (Sheridan, 1992, Sheridan et al., 2002, Goodrich and Schultz, 2008). In manufacturing, one of the earliest and most notable examples is the Unimate (show in Figure 2.3), introduced in 1961 by General Motors. Developed by George Devol and Joseph Engelberger, Unimate was capable of performing welding and material handling tasks with high precision and efficiency (Awards, 1977). Early industrial robots lacked adaptive capabilities and sensors, making it difficult to ensure human safety. As a result, physical isolation was often required to protect operators from the robots (Goodrich and Schultz, 2008). To address these issues, solutions such as proximity sensors, emergency stop devices, and safety standards like ISO 10218 were introduced (Fryman, 2014). The initial robot user interfaces were complex and not user-friendly, causing significant challenges for operators during learning and usage. To overcome this, researchers developed simpler programming interfaces and teach pendants, which significantly reduced the learning curve and improved the UX (Goodrich and Schultz, 2008). Contributions from psychology, engineering, and cognitive science converged in the mid-1990s, cementing HRI as a distinct field (Goodrich and Schultz, 2008, Sheridan, 1992).

The revolution in robotics enabled factories to automate hazardous and repetitive tasks, greatly enhancing productivity and improving safety on the assembly line (Engelberger, 2012), such as performing pick-and-place operations, collaborative tasks, and inspection-related activities (Javaid et al., 2022). The success of Unimate marked the beginning of widespread industrial automation and set the stage for future advancements in robotics. In recent years, collaborative robots, or cobots, have made significant strides in industrial automation. Unlike traditional industrial robots that operate in isolated environments, cobots are designed to work safely alongside human workers. Rethink Robotics' Baxter and Sawyer robots are prime examples of this new generation of robots (Rosenbaum, 2022 , Guizzo, 2015). These cobots feature advanced sensors and intuitive programming interfaces, allowing them to assist with various tasks on the factory floor, such as assembly, packaging, and quality control (Cremer et al., 2016, Javaid et al., 2022, Liu et al., 2024). By handling repetitive and precision tasks, the intention behind the development of cobots is to enhance productivity while creating a safer working environment for human workers. The history of HRI also includes the development of military and exploration robots designed to undertake dangerous and complex tasks. NASA's Mars rovers, such as Spirit, Opportunity, and Curiosity, have demonstrated advanced HRI capabilities through their interactions with ground control teams. These robots navigate challenging terrains, conduct scientific experiments, and send valuable data back to Earth, showcasing the potential of robots in exploration and defense (Williford et al., 2018).

Figure 2.3 Unimate robot. Source: (IEEE, 1961).

In the past, issues related to robot autonomy have mainly focused on safe interaction with the physical environment, but the growth of the field of personal robots acting in human environments has led to a greater need for robots to act on the social and emotional aspects of interaction (Lindblom and Andreasson, 2016). In 2000, Honda introduced ASIMO, a humanoid robot designed to assist with everyday tasks and interact socially with humans. ASIMO could walk, run, navigate stairs, and understand human gestures and commands, showcasing the potential for robots to operate in human environments (Sakagami et al., 2002). Around the same time, Sony launched AIBO (figure 2.4), an autonomous robotic pet that responded to voice commands and exhibited playful behaviors, demonstrating how robots could provide emotional companionship (Paws, 2018). This marked a significant shift in robotics, as robots began to be seen not just as tools for manufacturing, but as companions and assistants in daily life.

Figure 2.4 Aibo. Source: (IEEE, 1999).

In addition to industrial and exploration applications, HRI has made significant contributions to the healthcare sector. Robots are now being used to assist in surgeries, rehabilitation, and eldercare, providing significant benefits in terms of precision, consistency, and personalized care. Surgical robots, such as the da Vinci Surgical System, allow surgeons to perform minimally invasive procedures with enhanced precision and control. Rehabilitation robots help patients recover mobility and strength through guided exercises, while social robots provide companionship and support to elderly individuals, improving their quality of life (Silvera-Tawil, 2024).

Overall, HRI research has gradually shifted from a technology-driven focus to a user-centred approach (e.g., safety and emotional interaction), encompassing industrial and social interaction domains. This shift has not only driven technological innovation but also highlighted a profound understanding of human-robot coexistence and the importance of human factors. With the rise of collaborative and socially interactive robots, research has expanded beyond task efficiency and precision to explore how robots can better adapt to human environments and enhance UX.

2.2.2 Theoretical Models in HRI

The study of HRI relies on various theoretical models to understand and enhance the interactions between humans and robots. Such models play a crucial role in advancing the design of robots capable of interacting with humans effectively and safely across diverse environments, although challenges remain in adapting these interactions to dynamic and unpredictable contexts.

Trust and transparency are critical components in HRI. In HRI, according to Hancock et al. (2011) trust in robots is built through clear communication and predictable behaviour. The definition of trust is: "A multidimensional latent variable that mediates the relationship between past events and the former agent's subsequent decision to rely on the latter in an uncertain environment" (Kok and Soh, 2020). Models of trust emphasize the need for robots to provide real-time feedback and transparent decision-making processes. For instance, in healthcare, surgical robots must ensure that their actions and decisions are visible and understandable to surgeons and patients, thereby fostering trust and confidence in their use (Hancock et al., 2011). Balancing transparency and cognitive load in human-robot interaction is crucial, as excessive information can overwhelm users, while insufficient information may undermine trust.

Research indicates that increased transparency can enhance user trust without significantly affecting workload (Sanders et al., 2014). However, providing too much information can lead to cognitive overload, adversely impacting trust. Therefore, it's essential to calibrate the level of transparency to optimize both trust and cognitive load (Ahmad et al., 2019).

Theories from human-computer interaction (HCI) have significantly influenced HRI, particularly in understanding cognitive load and emotional engagement. Cognitive load theory, as discussed by Wickens (2008), helps optimize robot interfaces to reduce the mental effort required by users during interaction (Wickens, 2008). Reducing cognitive load is crucial in high-stakes environments like surgery or manufacturing, where users must make quick and accurate decisions. However, the application of cognitive load theory in HRI often assumes uniform user responses, potentially overlooking individual differences in cognitive capacities and task complexity. Research has shown that factors such as personality traits can influence cognitive workload and task performance during human-robot interactions. For instance, a study by Cha et al. (2023) found that while personality traits did not have a direct effect on task performance, they were correlated with variations in cognitive load and affective responses during remote robot control tasks (Cha et al., 2023). Similarly, emotional engagement models, such as those explored by Breazeal (Breazeal, 2003)(2003), provide a framework for designing robots capable of recognizing and responding to human emotions. While such models have shown promise in enhancing user acceptance and satisfaction—particularly in eldercare—they often rely on pre-defined emotional categories, which may not fully capture the nuances of human affective states. These limitations highlight the need for further research to refine these theories, ensuring their applicability to diverse HRI contexts and user groups (Breazeal, 2003).

Social interaction is another critical aspect of HRI, particularly in applications requiring natural communication, such as customer service and education. Early work by Dautenhahn (2007) laid the foundation for understanding social robotics, emphasizing the importance of conversational capabilities, facial expression recognition, and social cue adaptation. (Dautenhahn, 2007b). Subsequent studies, such as Fong et al. (2003), have expanded on these ideas, exploring how robots can seamlessly integrate into human social environments (Fong et al., 2003). Despite these advancements, achieving naturalistic and contextually appropriate interactions remains a significant challenge, particularly in diverse and multicultural settings where social norms and expectations vary widely.

Despite significant advancements, several challenges persist in HRI theoretical models. First, there is a need to integrate these models more comprehensively, as current approaches often address isolated aspects of interaction (e.g., trust, cognitive load, or social cues) without considering their interdependence. For instance, the integration of social cue processing into trust models has been explored to achieve more natural human-robot interactions (Taliaronak et al., 2023). Second, many models rely on controlled experimental data, limiting their applicability to real-world scenarios characterized by unpredictability and complexity. Experimental studies in HRI often face methodological constraints that threaten the validity of their interpretations, highlighting the need for more ecologically valid research approaches (Innes and W. Morrison, 2021). Third, cultural and individual differences remain underexplored, with most research focusing on homogeneous user groups. Studies have shown that personalization and localization in robotics need to move beyond simple language preferences to encompass intricate details of interface design, service expectations, and individual and cultural communication styles (Gasteiger et al., 2023). Future research should aim to address these gaps by developing integrative, context-aware models that account for the dynamic nature of human-robot interactions. Such efforts will be crucial for advancing the field and enabling robots to operate effectively in diverse environments (Dautenhahn, 2007a, Goodrich and Schultz, 2008).

2.2.3 Evolution of Interaction Modalities

The evolution of interaction modalities in HRI reflects significant advancements in technology and understanding of human needs and capabilities. This section explores the transition from basic command-based interactions to sophisticated multimodal interfaces that enhance the user experience and effectiveness of robots in various applications.

In the early stages of HRI, interactions between humans and robots were predominantly command-based, relying on predefined inputs through keyboards, buttons, and simple programming languages. These interactions were often limited and required users to have technical knowledge to operate the robots effectively (Fong et al., 2003). However, as technology advanced, the focus shifted towards creating more intuitive and accessible interaction methods.

The introduction of multimodal interaction, which combines multiple forms of communication such as voice, gesture, touch, and visual feedback, marked a significant milestone in HRI. Azuma discusses the role of Augmented Reality (AR) in providing intuitive and immersive interfaces that improve spatial understanding and interaction with robots. These interfaces allow users to interact with robots in a more natural and efficient manner, enhancing the overall user experience (Azuma, 1997).

Voice and gesture recognition technologies have become integral components of modern HRI. These technologies enable users to communicate with robots using natural language and body movements, making interactions more intuitive and reducing the cognitive load on users. For example, voice-controlled assistants like Amazon's Alexa and Google's Assistant use advanced speech recognition algorithms to understand and respond to user commands. Similarly, gesture recognition systems, such as those used in Microsoft's Kinect, allow users to control robots and devices through simple hand movements (Turk, 2014).

Haptic feedback technologies have further enriched the interaction modalities in HRI (Milgram and Kishino, 1994). These technologies provide users with tactile sensations that mimic the feel of real objects, enhancing the realism and immersion of interactions. Milgram and Kishino emphasize the importance of haptic feedback in creating more engaging and effective user experiences. Haptic gloves and force feedback devices are widely used in medical training and remote operations to improve user precision and experience (Milgram and Kishino, 1994).

The integration of AR and VR technologies has opened new possibilities for HRI. Billinghurst et al. highlight the application of AR and VR in creating immersive environments where users can interact with robots in real-time. AR overlays digital information onto the physical world, allowing users to receive contextual information and guidance during interactions. VR, on the other hand, creates entirely virtual environments where users can practice tasks and interact with virtual robots without physical constraints. These technologies are particularly useful in fields such as surgery, where precise, real-time guidance can significantly impact outcomes (Billinghurst et al., 2015).

Designing for natural interaction is a key focus in HRI research. Norman emphasizes that intuitive and user-friendly interfaces are crucial for enhancing user experience and acceptance of robotic systems (Norman, 2013). Natural interaction design aims to mimic human behaviour and responses, making interactions with robots seamless and efficient. For example, robots designed for social interaction often use natural language processing and machine learning to understand and respond to human speech and gestures, creating more engaging and effective interactions (Goodrich and Schultz, 2007, Breazeal, 2003).

While HRI research has made substantial progress in developing theoretical models and interaction modalities, several challenges remain unresolved. Current theoretical models often address isolated aspects of interaction, such as trust, cognitive load, or social engagement, without considering their interdependence, limiting their ability to capture the holistic nature of HRI (Goodrich and Schultz, 2008, Dautenhahn, 2007b). Furthermore, these models frequently rely on controlled experimental data, which restricts their applicability to dynamic, real-world environments (Innes and W. Morrison, 2021). The diversity of users, including cultural and individual differences, is also underexplored, leading to designs that may fail to meet the needs of heterogeneous user groups (Gasteiger et al., 2023). In terms of interaction modalities, significant advancements have been achieved—from command-based systems to multimodal interfaces incorporating voice, gesture, and AR/VR technologies (Azuma, 1997, Billinghurst et al., 2015). However, designing for natural, context-aware, and efficient interactions remains a formidable challenge, particularly in manufacturing and other dynamic environments where cultural and individual variability influences interaction success (Dautenhahn, 2007b, Turk, 2014). Integrating intuitive and adaptive interfaces that account for diverse user capabilities and preferences further compounds these issues. To address these challenges, future research should focus on developing integrative, User-Cantered frameworks that prioritize the role of UX in HRI. By placing greater emphasis on UX, researchers can create robots that are not only technically effective but also intuitive, accessible, and adaptable to diverse user contexts (Norman, 2013, Breazeal, 2003). This shift toward UX-driven HRI research will enable the design of systems that promote trust, reduce cognitive load, and enhance overall satisfaction, paving the way for seamless and effective human-robot collaboration in both industrial and social settings (Wickens, 2008, Lee and See, 2004).

While HRI has made significant strides in developing sophisticated interaction modalities and theoretical models, many of these frameworks remain fragmented, context-limited, or narrowly focused on task performance. There remains a need for integrative models that address cognitive, emotional, and social dynamics, particularly within manufacturing environments where safety and trust are critical.

2.3 Fundamentals of User Experience (UX)

2.3.1 Definition and Importance of UX

UX refers to the overall experience a person has when interacting with a product or system, encompassing all aspects of the end-user's interaction, including usability, accessibility, and emotional response (Norman, 2013, Sauer et al., 2020, Mahlke, 2007). UX design is not just about creating products that are usable, but also about creating products that are enjoyable to use and that meet the user's needs and expectations (Kraft, 2012, Allam and Dahlan, 2013). It includes various factors such as the interface, graphics, industrial design, physical interaction, and the users' manual (Jesse, 2011, Hartson and Pyla, 2018). The goal of UX design is to create products that provide meaningful and relevant experiences to users, addressing their needs effectively while ensuring a seamless and enjoyable interaction (Hassenzahl, 2010). This involves an understanding of psychology, design, and user research to create a holistic experience.

Good UX is crucial for the success of technology and design, as it directly impacts user satisfaction, engagement, and loyalty. High-quality UX can lead to increased user retention, positive word-of-mouth, and competitive advantage (Jesse, 2011). For example, a well-designed website or application that is easy to navigate and meets user needs can enhance user satisfaction and encourage repeat usage (Nielsen and Loranger, 2006). Conversely, poor UX can result in frustration, reduced efficiency, and abandonment of the product (Albert and Tullis, 2013). For example, in industrial settings, interfaces that are not user-friendly can lead to confusion and errors among operators, potentially causing production delays and safety hazards (Team, 2023a). A real-world example is the initial rollout of Microsoft's Clippy, the animated paperclip assistant introduced in Microsoft Office 97. While designed to help users with common tasks, Clippy was widely criticized for being intrusive, offering irrelevant suggestions, and interrupting workflows. Users found its behaviour frustrating and distracting, leading to negative public perception and widespread abandonment of the feature. Microsoft eventually retired Clippy from Microsoft Office in the early 2000s, acknowledging its failure as a user-friendly assistant (Balevic, 2024). The significance of UX is also evident in various successful products and companies that prioritize UX, such as such as Apple and Google, known for integrating intuitive interfaces and user-centred design into their product (Kujala et al., 2011). This contrasts with companies like BlackBerry, which, despite early leadership in the smartphone market, failed to adapt to changing user experience trends in the early 2010s. Its devices, while known for secure email and physical keyboards, lagged in offering intuitive touch interfaces and app ecosystems compared to competitors like Apple's iPhone. This lack of focus on user-friendly design and evolving UX trends contributed to BlackBerry's dramatic decline in market share and relevance (Bharath et al., 2023). Thus, investing in UX design can yield significant returns by improving user satisfaction and business outcomes (Donaire, 2009), such as Apple. Apple's emphasis on design and user experience has been a driving force behind its success and global influence. This focus has resulted in iconic products that define industries and contribute to Apple's profitability (Aksu, 2024). So good UX also can reduce the need for extensive customer support, as users are less likely to encounter problems that require assistance (Albert and Tullis, 2013).

The field of UX has evolved significantly from its early stages, where the focus was primarily on usability. The concept of UX originated from the field of IT products, with its foundation laid in the 1980s through the development of Human-computer Interaction (HCI) principles. These principles emphasized the importance of user-centred design and cognitive ergonomics, initially aimed at improving the usability and effectiveness of IT systems and interfaces (Johnson, 2020). The 1990s saw the rise of user-centred design methodologies, which focused on involving users throughout the design process to ensure products met their needs (Norman, 1995). During this period, the concept of usability became central, with researchers like Jakob Nielsen developing heuristics for usability evaluation, these heuristics are commonly applied in heuristic evaluations, where experts systematically assess a product against established usability principles. The method involves evaluators independently inspecting the interface to identify issues that violate these heuristics, such as consistency, error prevention, or aesthetic simplicity(Nielsen, 1994a). A deeper understanding of human behaviour, supported by fields such as psychology and neuroscience, has highlighted the importance of emotions in decision-making and user satisfaction. Studies have shown that emotional engagement can influence long-term user loyalty and product adoption (Hassenzahl and Tractinsky, 2006). More recently, the focus has expanded to include emotional and aesthetic aspects of user interaction, recognizing that positive emotional experiences can enhance overall satisfaction and brand loyalty (Hassenzahl, 2010). This shift has led to the incorporation of fields such as psychology and sociology into UX research and design. Key milestones in the development of UX as a field include the formalization of usability principles by Nielsen, the rise of interaction design as a discipline, and the integration of UX practices into agile and lean development processes (Gothelf, 2013). The integration of UX practices into agile and lean development processes marked a turning point in how UX was incorporated into product development. Jeff Gothelf’s work on "Lean UX" highlighted the importance of iterative, collaborative approaches that align UX design with rapid prototyping and frequent user feedback. This approach enabled teams to address user needs more effectively while maintaining the flexibility to adapt designs based on real-world insights(Gothelf, 2013). By embedding UX into agile methodologies, organizations could better ensure that usability, accessibility, and user satisfaction were prioritized throughout the development lifecycle. The advent of mobile computing and the proliferation of digital interfaces have further driven the evolution of UX, highlighting the need for responsive and adaptive design (Wroblewski, 2012). Mobile devices, with their smaller screens and varying resolutions, introduced unique challenges for designers. Traditional fixed-layout interfaces were no longer sufficient to meet the needs of users who interacted with products across different devices. This shift necessitated the development of responsive design—a methodology that ensures interfaces adapt seamlessly to different screen sizes and orientations, providing a consistent user experience across devices. Ethan Marcotte's 2011 introduction of responsive web design principles, including flexible grids, fluid images, and media queries, became a cornerstone for modern UX design in the mobile era (Marcotte, 2017). These milestones collectively transformed UX from a niche focus on usability into a comprehensive discipline that integrates psychology, design, and engineering to create meaningful and engaging UX.

2.3.2 Key Principles and Frameworks of UX Design

User Experience (UX) design is grounded in several key principles that guide the creation of intuitive, efficient, and enjoyable interactions between users and products. These principles have evolved over time, incorporating foundational concepts like usability while expanding to encompass modern frameworks such as user-centered design and effective feedback mechanisms(Nielsen, 1994a, Gould and Lewis, 1985, Shneiderman, 1980). Usability refers to how effectively, efficiently, and satisfactorily a user can interact with a product. Key aspects of usability include ease of learning, efficiency of use, and error frequency and severity. Usability ensures that users can achieve their goals with a product without encountering significant obstacles (Nielsen, 1994a). A product with high usability is intuitive, allowing users to perform tasks with minimal effort and confusion. The design should anticipate user needs and provide clear paths to achieve them. Simplifying complex processes and reducing the number of steps required to complete a task can significantly enhance usability (Donaire, 2009). Jakob Nielsen's heuristics, such as visibility of system status, match between system and real world, and user control and freedom, are foundational principles that guide usability practices (Nielsen, 1994a).

User-centered design (UCD) is a foundational framework that operationalizes key UX principles, such as usability and empathy, by placing the user at the center of the design process. It ensures that user needs, preferences, and limitations are systematically addressed throughout the design lifecycle. This approach involves continuous user involvement through techniques such as personas, user journeys, wireframes, prototypes, and usability testing (Pea, 1987). UCD emphasizes the importance of iterative design, where feedback from users is used to refine and improve the product

(Gould and Lewis, 1985). The ultimate goal of UCD is to create products that are not only functional but also provide a satisfying and enjoyable user experience.

Feedback is a foundational principle of UX design, derived from early research in human-computer interaction (HCI) that emphasized the importance of communication between systems and their users (Shneiderman, 1980). Effective feedback keeps users informed about system status, guides them toward desired actions, and helps them recover from errors. It can take various forms, such as visual indicators (e.g., progress bars), auditory cues (e.g., error sounds), or haptic feedback (e.g., vibrations on touchscreens) (Shneiderman, 1980). Providing feedback not only enhances usability but also supports user confidence by ensuring transparency in interactions. For example, visual feedback in e-commerce platforms, such as a confirmation message after placing an order, reassures users that their action has been successfully completed. Similarly, error prevention strategies, like requiring confirmation before performing irreversible actions, reduce the likelihood of mistakes and improve user satisfaction (Shneiderman and Plaisant, 2010). When errors do occur, providing informative error messages that explain the problem and suggest a solution is crucial for helping users recover from mistakes.

In addition to traditional principles like usability and feedback, recent advancements in UX design have introduced new frameworks and approaches that address evolving user needs and expectations. Microinteractions, for instance, focus on small, purposeful responses to user actions, such as animations or sound cues, which enhance feedback by making interactions more engaging and intuitive (Saffer, 2013). Similarly, anticipatory design leverages artificial intelligence to predict user needs, enabling systems to provide proactive assistance. For example, predictive algorithms in industrial systems can optimize workflows by suggesting the next step based on real-time data (Maeda, 2006). Modern UX design also emphasizes emotional and inclusive dimensions. Emotion-centered design highlights the importance of fostering positive emotional experiences, ensuring products not only meet functional requirements but also create a sense of delight and satisfaction (Hassenzahl, 2010). Meanwhile, inclusive design prioritizes accessibility and diversity, employing multi-modal feedback mechanisms—such as combining visual, auditory, and haptic feedback—to accommodate users with varying abilities and preferences (W3C, 2018). Ethical considerations have also gained prominence in recent years. The avoidance of dark patterns, which manipulate users into unintended actions, has become a critical aspect of ethical design practices. Instead, persuasive design aims to influence behavior positively, using techniques like progress indicators or gamification to motivate users while respecting their autonomy (Fogg, 2002). These emerging principles and theories demonstrate how UX design continues to evolve, addressing the complex interplay between functionality, emotion, and ethics. By integrating these modern approaches, designers can create systems that are not only efficient and intuitive but also inclusive, engaging, and aligned with user values.

2.3.3 Cognitive Aspects of UX

Designing effective user experiences requires not only addressing visual and functional aspects but also considering how users process information and interact with systems cognitively (Norman, 2013, Shneiderman and Plaisant, 2010). Cognitive aspects of UX focus on how mental effort, memory, and internal representations shape user behavior and decision-making (Sweller, 1988, Baddeley, 1992, Johnson-Laird, 1983). By understanding these cognitive processes, designers can create interfaces that are intuitive, reduce mental strain, and align with user expectations (Hassenzahl, 2010).

Cognitive load refers to the amount of mental effort required to process information and perform tasks. In the context of UX design, minimizing cognitive load is crucial to ensure users can efficiently interact with a product without becoming overwhelmed or frustrated (Sweller, 1988, Nielsen, 1994a, Norman, 2013). In 1988, Sweller's Cognitive Load Theory identifies three types of cognitive load: intrinsic, extraneous, and germane. Intrinsic load is related to the complexity of the information itself, extraneous load is associated with how the information is presented, and germane load pertains to the effort put into creating a schema (Sweller, 1988). UX designers aim to reduce extraneous cognitive load by simplifying interfaces, using clear and concise language, and providing visual hierarchies that guide the user's attention effectively (Norman, 2013). Techniques such as chunking information, using progressive disclosure, and maintaining consistency in design elements can significantly reduce cognitive load (Miller, 1956, Albert and Tullis, 2013).

There are many ways to manage cognitive workload, one of which is to reduce memory load plays a critical role in how users interact with and learn about a product. Memory is believed to consist of two components: short-term memory (often referred to as working memory) and long-term memory (Baddeley, 1992, Cowan, 2008). Short-term memory is thought to hold a limited amount of information temporarily, while long-term memory is associated with the storage of information over extended periods. These concepts are widely discussed in cognitive science, although their exact nature and mechanisms remain theoretical (Baddeley, 1992; Cowan, 2008). Working memory has limited capacity and is sensitive to overload, which poses challenges in designing user experiences. According to Baddeley (1992), working memory can only hold a small amount of information at a time, making it vulnerable to cognitive strain when overloaded (Baddeley, 1992). Strategies like recognition over recall, where users recognize options rather than recall information from memory, can aid in reducing cognitive load (Nielsen, 1994a). Additionally, leveraging familiarity and repetition can help users build long-term memory schemas, improving their efficiency and effectiveness when using a product. Consistent design patterns and familiar metaphors also facilitate quicker learning and better user retention (Shneiderman and Plaisant, 2010).

Mental models are the internal representations that users create to understand and interact with a system. These models are based on users' previous experiences and knowledge, influencing how they expect a system to work (Norman, 2014). For example, users familiar with traditional desktop computer interfaces might expect a file system on a new application to include folders, drag-and-drop functionality, and a search bar. If these expected elements are missing or behave inconsistently, users may feel frustrated or confused, as the system violates their mental model. Aligning design elements with common user expectations can significantly improve usability and reduce cognitive load (Nielsen, 1995, Norman, 2013). When designing user interfaces, it is essential to align the design with users' mental models to reduce confusion and enhance usability. If a system behaves in ways that are consistent with users' expectations, it is easier to learn and use (Johnson-Laird, 1983). User research techniques, such as interviews and usability testing, can help designers understand users' mental models and design interfaces that match their expectations. Providing clear affordances, using familiar icons, and maintaining consistency in navigation can support the development of accurate mental models (Lidwell et al., 2010).

In summary, cognitive aspects such as cognitive load, memory, and mental models play a pivotal role in shaping user experiences. By understanding and addressing these elements, UX designers can create interfaces that align with users' cognitive capabilities, reducing frustration and enhancing usability. These insights into cognitive processes provide a foundation for exploring how users emotionally connect with systems, which is discussed in the next section.

2.3.4 Emotional and Social Aspects of UX

Emotional design focuses on creating products that elicit positive emotions and enhance user satisfaction. According to Norman (2007), there are three levels of emotional design: visceral, behavioural, and reflective (Norman, 2007). Visceral design pertains to the initial impact of a product's appearance; behavioural design relates to the pleasure and effectiveness of use; and reflective design involves the personal meaning and value a user attaches to a product (Norman, 2013). For example, consider a smartphone: its sleek and modern design, such as a slim body and vibrant display, appeals to users on a visceral level, creating a strong initial impression. At the behavioural level, the intuitive interface and smooth functionality, such as responsive touch gestures and easy access to apps, enhance the pleasure and effectiveness of its use. Reflectively, the smartphone might carry personal value for the user, such as being a status symbol, a source of entertainment, or a tool for personal productivity, which shapes their long-term emotional attachment to the product. Emotional engagement can significantly influence user loyalty and brand perception (Desmet and Hekkert, 2007). Techniques to enhance emotional design include using aesthetically pleasing visuals, creating intuitive interactions, and providing rewarding feedback. Gamification elements, such as achievements and progress indicators, can also increase emotional engagement by making interactions more enjoyable and motivating (Deterding et al., 2011).

Social interaction is closely linked to the emotional aspects of UX because positive social experiences can evoke strong emotional responses and shape users' perceptions of a product (Preece et al., 2015). Social UX design considers the ways users interact with each other through a product and aims to facilitate meaningful and positive social interactions. This involves designing features that support social connectivity, such as messaging, sharing, and collaborative tools (Preece et al., 2015, Boyd and Ellison, 2007, Biocca et al., 2003). Social presence theory suggests that higher levels of social presence in digital interactions can lead to greater user satisfaction and engagement (Biocca et al., 2003). For example, integrating social media features into applications can enhance social connectivity and create a sense of community among users (Boyd and Ellison, 2007). Ensuring privacy and security in social interactions is also critical to maintaining trust and comfort among users (Kramer et al., 2014).

Building trust is an integral part of emotional and social aspects of UX, as it underpins long-term user engagement and satisfaction. Trust is particularly relevant in social interaction contexts, where users share personal information or collaborate with others. Without trust, even the most emotionally appealing or socially engaging features may fail to retain users. For instance, social platforms that lack transparent data policies or display inconsistent behaviour can erode user confidence, undermining both emotional attachment and social connectivity (Corritore et al., 2003). Strategies to build trust include providing clear and honest information, ensuring consistent and reliable performance, and implementing robust security measures. The appearance and behaviour of user interfaces also influence trust; for example, professional design and intuitive navigation can enhance perceived credibility (Fogg et al., 2003). Additionally, personalized experiences that address individual user needs and preferences can strengthen user relationships and foster loyalty (Hassenzahl and Tractinsky, 2006). Regularly updating the product with improvements and new features based on user feedback can also show users that their opinions are valued and that the company is committed to providing a high-quality experience (McKnight et al., 2002).

In summary, emotional and social aspects of UX are deeply intertwined and play a critical role in shaping user experiences. Emotional design focuses on creating positive feelings through aesthetics, usability, and personal relevance, while social interaction fosters a sense of community and belonging, both of which significantly influence user satisfaction and loyalty. Trust acts as a foundational element that bridges these aspects, ensuring users feel secure and valued in their interactions with products and other users. By integrating emotional, social, and trust-building strategies, UX designers can create holistic experiences that not only meet functional needs but also evoke lasting emotional connections.

2.3.5 UX Evaluation and Metrics

Usability testing is a crucial method for evaluating the effectiveness and efficiency of a product's user interface. It involves observing users as they interact with the product to identify usability issues and areas for improvement (Rubin and Chisnell, 2011). Common methods include task-based testing, where users complete specific tasks while researchers observe and record their performance and feedback. Usability testing helps designers understand how real users experience a product, revealing pain points and obstacles that might not be apparent through other forms of analysis (Nielsen, 1994a). Techniques such as think-aloud protocols, where users verbalize their thoughts during interaction, and eye-tracking, which records where users look on the screen, provide deeper insights into user behaviour (Lewis, 2014). Additionally, remote usability testing allows researchers to gather data from users in their natural environments, providing context-rich insights (Andreasen et al., 2007).

User satisfaction is a critical metric for evaluating UX, reflecting how well a product meets user needs and expectations (Norman et al., 1998). Surveys and questionnaires are common tools for gathering user feedback on satisfaction. The System Usability Scale (SUS) is a widely used questionnaire that provides a quick and reliable measure of usability (Brooke, 1996a). The SUS consists of 10 items rated on a five-point Likert scale, covering various aspects of usability, including ease of use and satisfaction. Additionally, the Net Promoter Score (NPS) measures user loyalty by asking users how likely they are to recommend the product to others (Reichheld, 2003). The NPS categorizes respondents into promoters, passives, and detractors, providing a straightforward metric for gauging user loyalty. Collecting qualitative feedback through open-ended survey questions or user interviews can also provide valuable insights into user satisfaction and areas for improvement (Albert and Tullis, 2013). Tools like the User Experience Questionnaire (UEQ) and the After-Scenario Questionnaire (ASQ) can also be used to assess different dimensions of user satisfaction (Lewis, 1991, Laugwitz et al., 2008). The UEQ, for example, covers six dimensions: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty, offering a comprehensive view of the user experience (Laugwitz et al., 2008).

Performance metrics and analytics provide quantitative data on how users interact with a product. Key performance indicators (KPIs) such as task completion rates, error rates, and time on task help assess the efficiency and effectiveness of the user interface (Albert and Tullis, 2013). Analytics tools like Google Analytics or custom-built solutions can track user behavior, such as page views, click paths, and drop-off points, providing insights into how users navigate the product (Clifton, 2012). Heatmaps and session recordings can visualize user interactions, highlighting which areas of the interface receive the most attention and where users encounter difficulties (Boag, 2014). Combining these quantitative metrics with qualitative insights from usability testing and user feedback offers a comprehensive view of the user experience (Albert and Tullis, 2013). Tools like Crazy Egg and Hotjar are popular for their heatmap and session recording capabilities, providing valuable visual data on user interactions (Boag, 2014).

Heuristic evaluation is an expert review method where usability experts evaluate a product against a set of established usability principles, known as heuristics (Nielsen and Molich, 1990). This method is efficient for identifying usability problems early in the design process (Nielsen and Molich, 1990). Jakob Nielsen’s ten heuristics for user interface design, such as visibility of system status, match between system and real world, and user control and freedom, provide a structured framework for evaluation (Nielsen, 1994b). Heuristic evaluations can uncover usability issues that might not be detected through user testing alone, offering a valuable complement to other evaluation methods (Nielsen, 1994b). Additionally, combining heuristic evaluation with cognitive walkthroughs can enhance the depth of the usability analysis by focusing on user goals and problem-solving processes (Spencer, 2000).

UX scorecards are a method for systematically evaluating and comparing the user experience across different products or versions. They provide a structured way to assess various aspects of UX, such as usability, accessibility, performance, and user satisfaction (Sauro and Lewis, 2016). Scorecards typically use a combination of qualitative and quantitative measures to provide a holistic view of the user experience. They can be used to track improvements over time, benchmark against competitors, and communicate the state of the UX to stakeholders (Sauro and Lewis, 2016). UX scorecards can be tailored to the specific needs of a project, focusing on the most relevant metrics and KPIs (Albert and Tullis, 2013). The scorecards can include metrics like the SUS, NPS, and specific performance metrics relevant to the product, providing a comprehensive evaluation tool.

A/B testing, or split testing, is a method used to compare two versions of a product to determine which one performs better. It involves randomly assigning users to different versions and measuring their interactions to assess which version yields higher engagement, satisfaction, or other desired outcomes (Kohavi et al., 2009). A/B testing provides empirical evidence about which design elements are more effective, allowing for data-driven decision-making (Siroker and Koomen, 2015). This method is particularly useful for optimizing specific features or elements of a product, such as call-to-action buttons, headlines, or page layouts (Kohavi et al., 2009). Advanced A/B testing tools like Optimizely and VWO (Visual Website Optimizer) provide robust platforms for conducting experiments and analysing results (Siroker and Koomen, 2015).

Journey mapping and service blueprinting are techniques used to visualize and analyse the user experience across different touchpoints and interactions with a product or service. Journey mapping involves creating a visual representation of the user's journey, highlighting key interactions, pain points, and emotional highs and lows (Stickdorn and Schneider, 2012). Service blueprinting extends this by mapping out the behind-the-scenes processes and systems that support the user journey, providing a comprehensive view of the user experience and operational context (Bitner et al., 2008). These techniques help identify opportunities for improving the user experience and optimizing service delivery.

Hedonic quality refers to the pleasure and enjoyment users derive from a product, while pragmatic quality relates to the product's functionality and usability (Hassenzahl, 2001). Both aspects are essential for a comprehensive evaluation of UX. The AttrakDiff questionnaire is a tool designed to measure both hedonic and pragmatic qualities of a product. It includes pairs of opposite adjectives that users rate, providing insights into how users perceive both the usability and the enjoyment aspects of the product (Hassenzahl et al., 2000). Incorporating hedonic and pragmatic quality evaluations helps ensure that the product not only meets functional requirements but also provides a satisfying and enjoyable user experience (Hassenzahl and Monk, 2010). Hedonic qualities often address users' emotional and aesthetic needs, enhancing their overall experience and satisfaction (Tractinsky et al., 2000). Meanwhile, pragmatic qualities ensure the product is efficient, reliable, and functional, meeting users' practical needs (Jordan, 2000).

Although numerous frameworks and principles of UX design exist, most are developed for desktop or mobile applications and lack the specificity required for high-stakes, real-time industrial contexts. Current UX literature insufficiently addresses the psychosocial and cognitive demands unique to human-robot collaboration in manufacturing.

2.4 Key Dimensions of User Experience in HRI

The UX in HRI is multi-faceted and involves various dimensions that collectively influence how users perceive and interact with robots. Understanding these key dimensions is crucial for designing effective and user-friendly robotic systems. This section explores several critical aspects of UX in HRI, including performance, cognitive load, emotional and social connection, trust and safety, and methods for assessing and measuring UX.

2.4.1 Performance

Performance is one of the most extensively evaluated factors in HRI studies, referring to how users execute tasks in collaboration with robotic systems (Bethel and Murphy, 2010, van den Brule et al., 2014, Chanel et al., 2020). User performance is shaped by individual capabilities—such as interface complexity, attention, and flexibility—as well as the human factors embedded in the system's design. A human-centred approach to HRI highlights the importance of incorporating performance considerations into system evaluations. Performance-related indicators, which directly or indirectly reflect user performance, offer valuable insights into human factors and the broader UX.

Among the various indicators used to evaluate system performance and user interaction, error frequency consistently emerges as one of the most commonly assessed metrics. It plays a pivotal role in measuring task efficiency, often serving as a benchmark for comparing different interface designs or interaction methodologies. Studies such as Daniel et al. (2013) emphasize the relevance of the number of interactions performed, which not only highlights the efficiency of task execution but also pinpoints potential flaws in the user interface, such as poorly designed input fields or confusing navigation structures. For instance, in their analysis of a data entry system, Daniel et al. observed that an increase in interaction steps often correlated with a higher incidence of input errors, suggesting that interface complexity is a critical factor influencing user performance (Daniel et al., 2013). Similarly, errors have been examined in depth by Almeida et al. (2020), who categorized mistakes based on their occurrence during task execution. Their findings underscored that errors often arise due to misaligned user expectations and inadequate system feedback. For example, in their study on industrial robotics interfaces, they demonstrated that simplifying visual feedback mechanisms significantly reduced error frequency, thereby improving task accuracy and user satisfaction. These studies collectively establish error frequency and interaction metrics as essential tools for identifying areas of improvement in interface design, particularly in complex or high-stakes environments (Almeida et al., 2020).

Robot idle time, assessed in studies by Lasota et al. (Lasota and Shah, 2015) and Hietanen et al. (Hietanen et al., 2020), measures the duration for which robots remain inactive, indicating inefficiencies in task synchronization. Correspondingly, person idle time, evaluated by Lasota et al. (Lasota and Shah, 2015), reflects the period during which human operators are inactive, offering insights into task allocation and human-robot integration. Variability in production times, identified by Colim et al.(Colim et al., 2021), assesses the consistency of task execution, serving as an indicator of system stability and predictability.

Additionally, production rate, also evaluated by Colim et al. (Colim et al., 2021), quantifies the number of items produced within a specific time frame, such as units per hour, highlighting the system's operational efficiency. Lastly, the ratio of task completion time with and without robotic assistance, examined by Beschi et al. (Beschi et al., 2020), evaluates the impact of robot movements on human productivity, particularly during unsynchronized tasks. This measure helps determine whether robotic systems enhance or impede task efficiency in collaborative scenarios. By analysing these performance indicators, researchers gain a holistic understanding of how system design influences user performance, task outcomes, and overall operational efficiency.

2.4.2 Emotional and Social Connection

Emotional engagement is critical in HRI, particularly in contexts such as healthcare, education, and customer service. According to Dautenhahn, sociable humanoid robots are designed to engage with users on an emotional level using techniques such as facial expression recognition, tone of voice analysis, and context-aware behaviours (Dautenhahn, 2007b). These robots create meaningful interactions by responding to users' emotional states, enhancing the overall user experience (Dautenhahn, 2007b). For instance, in eldercare settings, robots can detect and respond to the emotional needs of residents, providing companionship and improving their quality of life (Kidd and Breazeal, 2008).

Social presence refers to the extent to which a robot can create a sense of being with a social entity. Studies such as those by Wada and Shibata highlight the importance of social presence in HRI, showing how robots designed to exhibit human-like behaviours foster stronger social connections (Wada and Shibata, 2007). Robots that mimic human gestures, maintain eye contact, and adapt their behaviour based on social cues are more likely to be accepted and trusted by users (Wada and Shibata, 2007). Research by Bartneck et al. demonstrates that robots with high social presence can significantly improve user satisfaction and engagement (Bartneck et al., 2009).

The social and emotional capabilities of robots significantly influence their acceptance and effectiveness in various applications. A study by Li found that robots capable of expressing emotions and understanding social cues are more likely to be accepted in domestic environments (Li, 2015). This acceptance is crucial for the successful integration of robots in daily life, as it determines how comfortably users can interact with them (Li, 2015). Additionally, social robots in educational settings have been shown to enhance learning outcomes by creating a supportive and interactive environment for students (Vogt et al., 2017).

In healthcare, social robots play a vital role in providing emotional support and companionship to patients. A study by Broadbent et al. demonstrated that patients interacting with socially capable robots experienced reduced anxiety and improved overall well-being (Broadbent et al., 2009). These robots, equipped with the ability to recognize and respond to patient emotions, provided personalized interactions that addressed the emotional needs of patients (Broadbent et al., 2009). Additionally, research by Wada and Shibata demonstrated that elderly residents interacting with social robots experienced reduced feelings of loneliness and increased social interaction, contributing to their overall well-being (Wada and Shibata, 2007).

Despite the advancements in emotional and social robotics, challenges remain. Designing robots that can accurately interpret and respond to a wide range of human emotions is complex and requires sophisticated algorithms and sensors (Breazeal et al., 2016). Additionally, cultural differences in emotional expression and social norms must be considered to ensure that robots are effective and acceptable across different contexts (Nomura et al., 2008). Future research should focus on improving the emotional intelligence of robots and exploring new ways to enhance their social presence and engagement capabilities. Advances in machine learning and affective computing could provide new opportunities for developing robots that can understand and respond to complex emotional states more effectively (Picard, 1999).

2.4.3 Trust and Safety

Trust is fundamental to the acceptance and effective use of robots. Hancock et al. highlight that trust in robots is influenced by factors such as the robot's performance, transparency, and reliability (Hancock et al., 2011). Users are more likely to trust robots that perform consistently and provide clear, understandable feedback (Hancock et al., 2011). Trust is particularly important in high-stakes environments like healthcare and industrial automation, where errors can have significant consequences (Hancock et al., 2011).

Several factors influence trust in HRI. According to Lee and See, these factors include the robot's reliability, predictability, and transparency. Reliability refers to the robot's ability to perform tasks accurately and consistently over time. Predictability involves the robot behaving in ways that users can anticipate based on previous interactions. Transparency is the degree to which the robot's actions and decision-making processes are understandable to the user (Lee and See, 2004). Studies have shown that enhancing these factors can significantly increase user trust and satisfaction (Desai et al., 2012). For example, robots that clearly explain their actions and provide feedback can help users understand and anticipate their behaviours, leading to greater trust (Desai et al., 2012).

Safety is paramount in HRI, particularly in environments where robots and humans interact closely. Robots must be designed to prevent accidents and injuries. Riek discusses the importance of incorporating safety measures such as collision detection and avoidance, emergency stop mechanisms, and compliant control systems. These measures ensure that robots can operate safely even in dynamic and unpredictable environments (Riek, 2016). For instance, in collaborative manufacturing settings, robots equipped with sensors and adaptive control systems can detect human presence and adjust their actions accordingly to avoid collisions (Colgate et al., 1996).

Healthcare is a field where trust and safety are critical. For example, surgical robots like the da Vinci Surgical System are designed with multiple safety features, including redundant control systems, real-time monitoring, and precise movement control, to ensure patient safety (Lanfranco et al., 2004). These features help build trust among surgeons and patients, leading to broader acceptance and adoption of robotic surgery. Additionally, social robots in healthcare settings must be designed to interact safely with vulnerable populations, such as the elderly or children, ensuring that their interactions are supportive and non-threatening (Broadbent et al., 2009).

Autonomous vehicles (AVs) represent another area where trust and safety are paramount (Adnan, 2024). Studies have shown that users' trust in AVs is influenced by the vehicle's ability to provide clear information about its actions and ensure the safety of its passengers (Schoettle and Sivak, 2014). AVs equipped with advanced sensors, real-time data processing, and machine learning algorithms can predict and respond to road conditions more effectively, enhancing both safety and trust (González et al., 2015). Ensuring that AVs can handle complex driving scenarios and communicate their intentions to passengers and other road users is critical for their widespread adoption (Schoettle and Sivak, 2014).

Despite advancements in enhancing trust and safety in HRI, challenges remain. One significant challenge is balancing robot autonomy with the need for human oversight. Over-reliance on automation can lead to complacency and reduced situational awareness among human operators (Schoettle and Sivak, 2014). Another challenge is designing robots that can adapt to diverse user needs and preferences while maintaining high safety standards. Future research should focus on developing more sophisticated models of trust and safety that account for the dynamic nature of HRI and the evolving capabilities of robotic systems (Hancock et al., 2011). Additionally, integrating ethical considerations into the design and deployment of robots will be crucial to ensure that they operate in ways that are aligned with societal values and expectations (Lin et al., 2011).

Designing for a positive UX in HRI involves a structured process known as the user experience design workflow (Marcus & Wang, 2017). This workflow provides a systematic approach to understanding and addressing user needs, ensuring that robotic systems are not only functional but also user-friendly and satisfying to interact with. The workflow typically includes the following stages: user research (Baxter et al., 2015), problem definition and goal setting (Norman, 2013), conceptual design and prototyping (Arnowitz et al., 2010), testing (Nielsen, 1994a) and iteration and implementation and validation (Preece et al., 2015). This workflow serves as a guiding framework for ensuring that UX considerations are deeply integrated into the design and functionality of product or systems (Deaton, 2003). By applying these principles, researchers and designers can address critical UX dimensions like trust, safety, and cognitive load, ultimately creating more effective and intuitive HRI. In summary, this research is driven by the need to systematically address these challenges through a user-centred approach to HRI design and evaluation. By bridging the gap between robotic capabilities and human expectations.

Despite the diversity of UX measurement instruments, such as SUS, UEQ, and AttrakDiff, they often lack relevance to the complexities of HRI in manufacturing. These tools are typically not designed to assess trust, safety, or cognitive load in physically dynamic, multi-agent environments, which are central to industrial HRI. This shortcoming underscores the necessity of domain-specific evaluation approaches.

2.5 Research Gap and Motivation

Despite the increasing integration of collaborative robots into manufacturing environments, there remains a notable disconnect between technical system design and human-centered evaluation. Most existing studies on Human-Robot Interaction (HRI) emphasize performance optimization and safety compliance, while relatively few address the broader UX from the perspective of cognitive, emotional, and social factors. This gap limits the effective deployment and user acceptance of robotic systems in real-world industrial contexts.

Furthermore, although a range of UX assessment tools exists—such as the SUS, UEQ, and AttrakDiff—these instruments were originally developed for general HCI scenarios. As such, they do not fully capture the unique demands of HRI in manufacturing, particularly regarding cognitive workload, operator trust, emotional engagement, and real-time adaptability in shared physical spaces.

In addition, the theoretical models of HRI often treat key concepts such as trust, cognitive load, and social interaction as isolated constructs, without adequately accounting for their interdependence in high-stakes, collaborative settings. This fragmentation hinders the development of cohesive, empirically grounded evaluation frameworks.

Therefore, this research is motivated by the urgent need to develop a domain-specific

UX assessment framework tailored to manufacturing HRI. Such a framework must incorporate interdisciplinary insights and be validated through empirical studies to ensure it reflects the complex realities of industrial work environments. Addressing this research gap not only contributes to academic discourse but also provides practical tools for improving the design and deployment of collaborative robotic systems.

2.6 Summary

This chapter reviewed the key theoretical foundations and empirical developments related to HRI and UX, with a particular focus on their application in manufacturing settings. It outlined how HRI has evolved through various modalities and conceptual models, and how UX, though well-studied in general HCI contexts, remains underexplored within industrial HRI.

Several core dimensions of UX in HRI were identified—such as performance, cognitive load, emotional engagement, and trust—which are particularly relevant in complex, collaborative manufacturing environments. The chapter also examined a range of existing evaluation tools, noting that most are inadequate for capturing the nuances of UX in this context due to their general-purpose design and limited consideration of domain-specific challenges.

Through this review, a critical research gap has been identified: the absence of a validated, domain-specific UX assessment framework tailored to the unique demands of HRI in industrial environments. This motivates the following chapter, which outlines the methodological approach taken to address this gap through the development and validation of a novel HRI UX Assessment Framework for manufacturing applications.

Chapter 3 A Framework for Assessing User Experience in Human-Robot Interaction (HRI) within Manufacturing

3.1 Introduction

This chapter builds upon the discussions in Chapter 2, where the foundational concepts and challenges of HRI in manufacturing were explored. While the previous chapter provided a comprehensive review of the technological advancements and research gaps in HRI, this chapter shifts focus towards addressing the critical need for a structured framework to assess and enhance UX within manufacturing environments. By doing so, it bridges the theoretical understanding of HRI with practical implications, laying the groundwork for developing human-centred solutions in industrial settings. UX plays a pivotal role in determining the success of HRI systems, particularly in high-stakes environments such as manufacturing, where productivity, safety, and worker satisfaction are tightly interlinked (Ntoa, 2025, Peruzzini and Pellicciari, 2018, Lin, 2018). However, as highlighted in Chapter 2, existing HRI systems often prioritize technical efficiency over UX, leading to suboptimal human-robot collaboration and limited technology adoption. To address these issues, this chapter introduces an HRI UX Assessment Framework specifically tailored to manufacturing contexts, designed to evaluate and improve the overall user experience in collaborative scenarios.

In this chapter, I aim to lay the foundation for a user-centred HRI framework to evaluate and enhance the user experience within manufacturing environments. Employing a qualitative approach, which comprise semi-structured interviews (as depicted in Figure 3.1), I primarily recruited people from manufacturing factories to gather insights that directly inform the development of my assessment framework. This approach enables us to uncover and define the essential elements necessary to evaluate and improve the HRI user experience. My primary objective is to facilitate the optimization of HRI within the manufacturing industry through the development of my tailored HRI UX Assessment Framework. The specificity of my framework ensures its efficacy as an instrumental resource for meeting the unique requisites of the industry. I posit that my methodological approach will yield theoretical and empirical guidelines for the design of HRI systems in advanced manufacturing settings, thereby contributing significantly to the discipline by promoting more effective, secure, and human-oriented interactions between robots and humans.

The growing emphasis on tailored products and bespoke manufacturing solutions has intensified the need for flexibility in production systems, as companies strive to accommodate diverse and dynamic customer expectations (Zhang et al., 2003). In the manufacturing industry, with the increasing demand for product personalization and customize with the requirements for small batches and high customization production, traditional fixed automation robot systems, designed primarily for large-scale and single-product production modes, often struggle to cater for these rapidly changing demands (Giberti et al., 2022). Smart factories have emerged as a promising solution to address the growing demands for manufacturing flexibility. By leveraging advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and real-time data analytics, these factories enable adaptive production processes, optimized resource utilization, and enhanced operational efficiency (Kusiak, 2018, Schlechtendahl et al., 2015). However, achieving the full potential of smart factories is contingent upon overcoming critical challenges in HRI. As robots take on increasingly complex and dynamic roles within these environments, traditional modes of interaction—designed for static, repetitive tasks—are insufficient for addressing the fluid and unpredictable nature of modern production lines (Giberti et al., 2022). To ensure effective collaboration, new HRI paradigms must be developed, emphasizing intuitive communication, shared decision-making, and mutual adaptability between humans and robots (Ghodsian et al., 2023).

HRI refers to the process of communication, collaboration, and joint operation between humans and robots in a shared work environment (Prati et al., 2021a). Although the development of HRI technology (such as gesture recognition) has provided new possibilities for human-machine cooperation, existing research on HRI mainly focuses on technological challenges and solutions, with relatively less consideration of the importance of UX (Lindblom and Andreasson, 2016). UX refers to the feelings, cognition, and responses formed by users in the process of interacting with products or systems, directly affecting users' acceptance of technology, satisfaction with use, and work efficiency (Hassenzahl, 2008, Law et al., 2009).

Figure 3.1 Semi-structured interviews in enterprises.

3.2 Related Works

3.2.1 HCI in Manufacturing

In the manufacturing sector, HRI plays a critical role in addressing the growing demand for product customization and enhancing manufacturing flexibility (Wang et al., 2020). It enables a more adaptable production line where robots can assist in tasks requiring precision and endurance, while humans contribute with decision-making and problem-solving skills (Alessio et al., 2022). This collaboration is vital in creating efficient workflows that can adjust to small batches and high customization demands - a common challenge in modern manufacturing processes (Umbrico et al., 2022).

The effectiveness of HRI in manufacturing heavily relies on the design of user interfaces that facilitate natural and intuitive communication between humans and robots (Marvel et al., 2020). These interfaces range from visual displays, gestures, and speech to more advanced natural language and haptic interactions, each suited to different levels of interaction (Gentile et al., 2011). For instance, graphical user interfaces and augmented reality interfaces are prevalent for tasks requiring coexistence, while more complex cooperative and collaborative tasks may benefit from speech, gesture, and physical interactions (Gentile et al., 2011). The choice of interface impacts the efficiency of human-robot teams, emphasizing the need for designs that are intuitive, adaptable, and capable of supporting a seamless flow of information, thereby ensuring safety and enhancing productivity in manufacturing environments (Prati et al., 2021b).

3.2.2 Role of User Experience in Manufacturing HRI

In the realm of manufacturing, integrating UX within HRI is crucial, especially as cobots become standard, designed to operate alongside humans within shared workspaces (Lorenzini et al., 2023). These cobots adhere to ISO safety standards (Valori et al., 2021), focusing on behaviours like speed and power adjustments based on human proximity, yet often overlook the critical role of interfaces in facilitating effective human-robot communication (Ghodsian et al., 2023). This oversight highlights the need for a human factors perspective in designing communication strategies that allow for intuitive and effective cooperation between humans and robots, incorporating principles from Human-Computer Interaction (HCI) and Human-

Machine Interaction (HMI) to ensure that technological advancements in HRI genuinely benefit human operators (Kopp et al., 2021). For instance, studies have shown that poorly designed interfaces in HRI systems can increase cognitive load, leading to operator errors and reduced task efficiency (Goodrich and Schultz, 2007).

The necessity of a structured human-centered approach in HRI design is underscored by the significant impact robots have on human work dynamics in manufacturing (Kopp et al., 2021). This approach should prioritize clear communication and intuitive information exchange between operators and robots, addressing not only the technical but also the cognitive and psychosocial aspects of human-robot collaboration (Dautenhahn, 2013). By using a human centred methodology aims to seamlessly integrate cobots into industrial settings, enhancing efficiency and the overall user experience by leveraging insights from qualitative HCI methods to inform interface design and interaction strategies (Apraiz et al., 2023). However, to effectively implement this approach, it is essential to first establish reliable tools for assessing UX in HRI settings. Such tools would provide a structured means of evaluating critical factors like usability, cognitive load, and emotional response, thereby guiding the design and optimization of HRI systems. This need underscores the importance of developing a comprehensive UX assessment framework, as detailed in the next section.

3.2.3 Assessment of User Experience

Incorporating UX into manufacturing HRI is pivotal, enhancing operational efficiency and user satisfaction within constrained interactions (Lorenzini et al., 2023). In the literature on UX, various questionnaires are instrumental in assessing the multifaceted nature of user interactions with systems. Beginning with an evaluation of overall satisfaction and system usability, the Post-Study System Usability Questionnaire

(PSSUQ) and the System Usability Scale (SUS) stand out for their ability to offer rapid, yet insightful metrics (Lewis, 2002, Brooke, 2013). These foundational assessments are complemented by more focused inquiries into software and interface satisfaction, as evidenced by the Software Usability Measurement Inventory (SUMI) (Kirakowski, 1996) and the Questionnaire for User Interaction Satisfaction (QUIS) (Norman et al., 1998).

In the broader context of technology acceptance and comprehensive UX assessment, the Technology Acceptance Model (TAM) (Marangunić and Granić, 2015) provides a theoretical framework to predict user acceptance, while the modular evaluation of Components for User Experience (meCUE) questionnaire (Minge et al., 2017), the User Experience Questionnaire (UEQ) (Schrepp et al., 2017), and AttrakDiff (Schrepp et al., 2017) offer a multi-dimensional exploration of user experience, encompassing efficiency, stimulation, and the hedonic and pragmatic quality of HRI systems.

These tools highlight the multifaceted nature of UX in HRI. However, there is no evaluation tool that is suitable for the UX of HRI, especially in the manufacturing. The tools reviewed earlier, such as PSSUQ, SUS, AttrakDiff, and UEQ, provide valuable insights into various dimensions of UX but fall short in capturing the full complexity of HRI in manufacturing. For instance, tools like PSSUQ and SUS primarily focus on pragmatic aspects, such as usability and operational efficiency, but they lack the depth needed to assess how these systems impact collaboration between human operators and robots in dynamic and high-stakes manufacturing tasks. Similarly, while AttrakDiff and UEQ incorporate both pragmatic and hedonic dimensions, these tools are often too generic to address domain-specific concerns, such as the cognitive load associated with operating industrial robots, or the emotional responses triggered by physical interaction in manufacturing contexts. Moreover, many of these tools were originally developed for general HCI scenarios, which typically involve desktop or mobile applications. When applied to HRI in manufacturing, they fail to account for critical factors such as real-time task adaptability, safety protocols, and the ergonomic requirements of shared workspaces. For example, the modular evaluation framework of meCUE might offer a balanced exploration of hedonic and pragmatic qualities but does not consider the hierarchical and procedural workflows inherent in industrial settings. This mismatch could lead to incomplete or misleading evaluations, where the tools overlook key aspects such as the physical and cognitive demands placed on operators or the interplay between human and robotic roles during collaborative tasks. Applying these tools without adaptation could result in significant issues. For instance, ignoring the specific safety and reliability concerns in manufacturing could lead to designs that compromise worker trust and satisfaction. Similarly, the failure to address how manufacturing workers learn and adapt to robotic systems might result in an underestimation of the training required, ultimately reducing the effectiveness of HRI implementations. These limitations highlight the urgent need for a domain-specific UX assessment framework that can integrate these unique requirements and provide actionable insights for improving HRI in manufacturing.

3.3 Methodology

This study adopts a qualitative approach by semi-structured interviews to investigate HRI (such as usability, cognitive load, efficiency, safety, trust, physical interaction, ergonomics and system adaptability) in manufacturing environments. And based on interview, I developed a pioneering HRI UX Assessment Framework tailored for the manufacturing industry.

3.3.1Research factories background

In this study, I selected 3 different scales of manufacturing enterprises. Factory 1 which belongs to CITIC Dicastal (the world's largest automobile wheel hub and automobile chassis parts manufacturing enterprise, website: https://www.citic.com/ar2016/en/dicastal.php) and JIEL joint-venture factory is shown in Figure 3.2 (a). Factory 2 which is a small and medium-sized outdoor production machinery factory (HWASDAN, website: http://www.hwasdan.com/) is shown in Figure 3.2 (b). Factory 3 (KHM, website: http://en.cqkhm.com/) which is Cummins Engine key parts supplier, shows in Figure 3.2 (c). The robot completes the parts processing and operators checks the quality of the parts. And 3 factories have different levels of automation. Factory 1 achieved a high level of automation maturity with the assistance of ABB and FANUC in 2009. Due to the complexity and variety of its products, Factory 2 utilizes human-robot collaboration, with workers and Chinese AGVs (Automated Guided Vehicles) jointly completing assembly tasks. However, its automation level is low, and workers are not yet fully accustomed to working alongside robots. Factory 3 focuses on precision production and has achieved complete robot autonomous production (by Nachi) in key process parts.

(a) (b) (c)

Figure 3.2 Pictures from the three factories where I interviewed personnel. (a) Factory 1 (b) Factory 2 (c) Factory 3.

3.3.2 Participants

In this study, 19 employees directly involved with robotic systems, ranging from novices to experts and spanning various manufacturing roles, were selected. A comprehensive selection process was employed to include all workers interacting with robotic systems across three distinct manufacturing plants, ensuring a diverse analysis of interactions stemming from various operational roles, experience levels, and intensities of engagement with robotic technology. Participants' backgrounds varied in terms of their ages (average age is 43), education backgrounds (from high school to college), and genders (seventeen males, two females), ensuring diverse insights into HRI experiences. Table 3.1 shows different factory operators interacted with robots in different ways.

Table 3.1 The way of interacting with robots.

	Number of participants	**Interacting with robots**
Factory 1	4	After completing the task, the operators reposition the robot and change the tool.
Factory 2	8	Operators complete the assembly task on the AGV, the AGV is sent to the next task flow.
Factory 3	7	Operators reposition robots and change tools while inspecting the quality of manufactured products.

3.3.3 Materials

The research design incorporates semi-structured interviews (example of semi-structured interviews questions were shown in Table 3.2) to capture qualitative insights into the experiences and perceptions of manufacturing employees regarding HRI. The semi-structured interview questions were developed through a systematic process to ensure they comprehensively addressed the research objectives related to UX in HRI within manufacturing environments. This process began with an extensive literature review to identify key themes such as usability, safety, cognitive load, and emotional responses, which are critical in HRI studies. Drawing on insights from existing research and practical industry needs, the questions were aligned with the study's focus on evaluating worker interactions with robotic systems. Input from experts in robotics and manufacturing was sought to refine the questions, ensuring their relevance to real-world applications. An iterative review process within the research team further enhanced clarity and relevance, resulting in open-ended questions designed to elicit in-depth responses about physical interaction, intuitive design elements, learning processes, and the impacts of robotics on productivity and safety. This approach ensured that the questions were both theoretically grounded and practically meaningful. The interview guide was developed with semi-structured, open-ended questions to facilitate a flexible yet focused dialogue, ensuring thorough exploration of key themes such as usability, collaboration efficiency, and safety. With participants' consent, interviews were conducted and recorded audibly. The recording was transcribed into text and translated into English and later transcribed verbatim for a detailed thematic analysis to uncover recurring patterns and insights.

Table 3.2 Example of semi-structured interview questions.

How do you feel about the physical interaction with the robot?
What positive and negative impacts do you think it has had?
During the operation, which parts of the robot do you find intuitive, and which parts might need improvement?
How did you learn to operate the robot?
During the learning process, which resources or methods were most helpful to you?
What specific difficulties or challenges did you encounter when you first started using the robot?
What specific changes have you noticed in your work efficiency?
What positive or negative impacts do you think robot technology has had on your productivity?

3.4 Result

3.4.1 Data Processing

The qualitative data was collected through semi-structured interviews. Analysis in NVivo 12 (NVivo, 2020) revealed different themes representing the aspects of HRI assessment experienced by participants. In the qualitative analysis conducted using NVivo, 28 themes were initially identified (figure 3.3), each representing a distinct aspect of HRI pertinent to the user experience in manufacturing environments. These themes encompass critical dimensions such as 'Usability,' denoting the ease and intuitiveness of interaction with HRI systems; ‘Adaptability,' reflecting the system's ability to adjust to user and environmental variables; ‘Safety,' indicating the presence of protective measures for users; 'Efficiency,' relating to the system's contribution to productivity; along with other specific themes including 'Emotional Response,' 'Cognitive Load,' and 'Physical Ergonomics.' This comprehensive identification ensures a nuanced understanding of the multifaceted HRI user experience. Each theme was supported by direct quotes or summaries of participant responses.

Figure 3.3 Qualitative Data Analysis Conducted in NVivo. Including 28 themes and their occurrence frequencies

Name	Files	References	Created On
working environment	1	1	2024/2/20 6:04
User satisfaction	1	23	2024/2/19 9:30
Usability	1	16	2024/2/19 9:30
trust	1	20	2024/2/19 9:26
traning quality	1	9	2024/2/19 9:32
task	1	16	2024/2/19 10:08
source of learning	1	15	2024/2/19 9:50
Safety Feeling	1	16	2024/2/19 9:31
role dofferetitaion	1	2	2024/2/19 9:32
reliability	1	50	2024/2/19 9:30
Reaction time	1	4	2024/2/19 10:38
price	1	1	2024/2/20 9:25
Personification	1	11	2024/2/19 9:58
Personalization settings	1	27	2024/2/19 9:31
operation experience	1	15	2024/2/19 9:33
Memory Burden	1	10	2024/2/19 9:30
Interaction Interface Design	1	12	2024/2/19 9:30
gender	1	2	2024/2/20 5:58
ergonomics	1	24	2024/2/19 9:30
enmotion	1	11	2024/2/19 10:13
efficiency	1	23	2024/2/19 9:29
education	1	14	2024/2/19 9:27
Ease of Learning	1	31	2024/2/19 9:30
culture	1	1	2024/2/19 10:26
age	1	13	2024/2/19 9:28
After-sales	1	2	2024/2/19 23:00
accuracy	1	20	2024/2/19 9:29
Acceptance	1	8	2024/2/19 23:05

The process of condensing the themes extracted from the qualitative dataset involved a systematic and iterative methodology (Service, 2009). Initially, open coding was employed to identify preliminary themes directly from the data. This was followed by axial coding, where these initial themes were categorized based on their relationships and relevance to the study's objectives. To ensure rigor, this coding process was conducted independently by two researchers, followed by a consensus meeting to resolve any discrepancies and to refine the themes further. Subsequently, selective coding was applied to distill these themes into broader categories that encapsulate the core aspects of HRI within manufacturing contexts. This multistep process ensured that the final set of themes was both comprehensive and aligned with the research questions, providing a structured basis for the analysis.

In the meticulous refinement of themes for the HRI UX Assessment Framework, my inquiry adopted a systematic and iterative protocol to whittle down the initial enumeration of 28 themes to a pivotal cadre of 12. This cautious process commenced with an exhaustive evaluation of the thematic occurrences across the dataset, underscored by their significance to user experience within HRI scenario. Intersecting themes—defined as those that emerged across multiple user contexts and contributed to more than one dimension of user experience—such as ‘Acceptance’ and ‘Emotion,’ were amalgamated to fortify the framework's conceptual cohesion. Conversely, themes that did not significantly impact UX—based on low frequency, limited relevance, or minimal user emphasis—such as ‘Age,’ ‘Education,’ and ‘Price,’ were excised with judicious precision to refine the framework’s focus. This process of distillation resulted in the retention of 12 core themes, which were then systematically incorporated into 5 distinct facets, using a theory-informed thematic synthesis approach. First, the 12 emergent themes identified through qualitative coding were reviewed in light of established constructs in UX and HRI literature (e.g., Norman, 2013; Hassenzahl, 2010;

Ahmad et al., 2019). I identified conceptual overlaps and functional relationships among themes to enable higher-level abstraction. For instance, themes related to efficiency, accuracy, and reliability were consolidated into the Operational Performance Facet, capturing users' perceptions of how effectively and reliably robots supported task completion. Elements such as ergonomic and interaction interface design were conceptually clustered into the Physical Interaction Facet, reflecting the physical comfort, safety, and coordination during human-robot encounters. Themes addressing usability, ease of learning, and memory burden were mapped to the Cognitive Load Facet, representing the mental demands of understanding and operating robotic systems. User satisfaction, trust, and safety feeling informed the Emotional Response Facet, encapsulating users' psychological states during interaction. Lastly, themes related to personalization settings were organized under the System Adaptability Facet, emphasizing the robot system's ability to adapt to user needs and contextual variations. This categorization process involved iterative peer discussions to ensure internal consistency and theoretical alignment.

(Interview data: https://github.com/tongyanzhanggithub/UX-HRI-Farmework)

3.4.2 Example of Interview Data

In the process of formulating the HRI UX Assessment Framework, interview data played a pivotal role in elucidating the critical dimensions of user experience in human-robot interaction within manufacturing environments. This section aims to illustrate the rationale behind the delineation of the framework's facets, drawing on qualitative evidence from participant feedback to elucidate the genesis of each facet. It's important to clarify that the intention here is not to re-validate the framework with the same data from which it was conceived but to provide a transparent account of how participants' experiences and insights directly informed the framework's structure (Table 3.3).

For instance, the Operational Performance Facet was informed by participants' testimonials regarding efficiency, accuracy, and reliability in robot-assisted tasks. Similarly, the Physical Interaction Facet emerged from discussions on ergonomic interactions and user comfort, highlighting the significance of physical aspects in user experience. The Cognitive Load, Emotional Response, and System Adaptability Facets were similarly developed, each rooted in specific participant feedback that underscored the importance of ease of learning, emotional factors, and system flexibility, respectively.

Table 3.3 Examples of the semi-structured interview in UX assessment facets.

Facet	Participant Feedback
Operational Performance Facet	
Efficiency	"For the specific line it's used on, efficiency has increased by more than 30%."
Accuracy	"Previously, we had issues with the assembly line, but now, with the robots, the quality has significantly improved. The defect rate used to be around 30% before, and now the quality rate (or pass rate) is over 90%."
Reliability	"If properly trained, it's reliable. But without proper training, it can be risky, perhaps only two or three out of ten. I've heard of accidents where people were injured due to operational errors."
Physical Interaction	
Ergonomics	"The robots have significantly improved the work environment. Before, we used to work in uncomfortable postures which was quite taxing on our bodies. Now, with the robots, we work standing up, which is much more comfortable and has also improved the quality of our work."
Interaction Design	"Comparing ABB and Fanuc robots, I find ABB's interface to be more user-friendly. The setup and operation require fewer steps, which saves time and makes it easier for new operators to learn."
Cognitive Load Facet	
Ease of Learning	"Learning the basics and getting the robot to operate

	automatically takes about a day or two.”
Usability	“Using it can be frustrating. I’d rate the satisfaction as eight out of ten, as it can be quite troubling when it doesn’t work properly”
Memory Burden	“Its operating interface, some primary menus, secondary menus, those are more concise, those things are easy to remember. Some are not easy to operate, with some machine menus that you really have to press many times to enter, or some places are not easy to remember.”
Emotional Response Facet	
User satisfaction	“I actually really enjoy operating it.”
Trust	“I trust it quite a lot, maybe 90%.”
Safety Feeling	“Our automated line is enclosed with protective barriers, ensuring safety. Once the safety doors are opened, the system automatically shuts down”
System Adaptability Facet	
Personalization settings	“About seven or eight out of ten. Different robot brands have their own unique features and functions.”

3.4.3 HRI UX Assessment Framework in Manufacturing

The HRI User Experience Assessment Framework, through methodical analysis, integrates 12 selected themes into five rigorously defined facets (Figure 3.4):

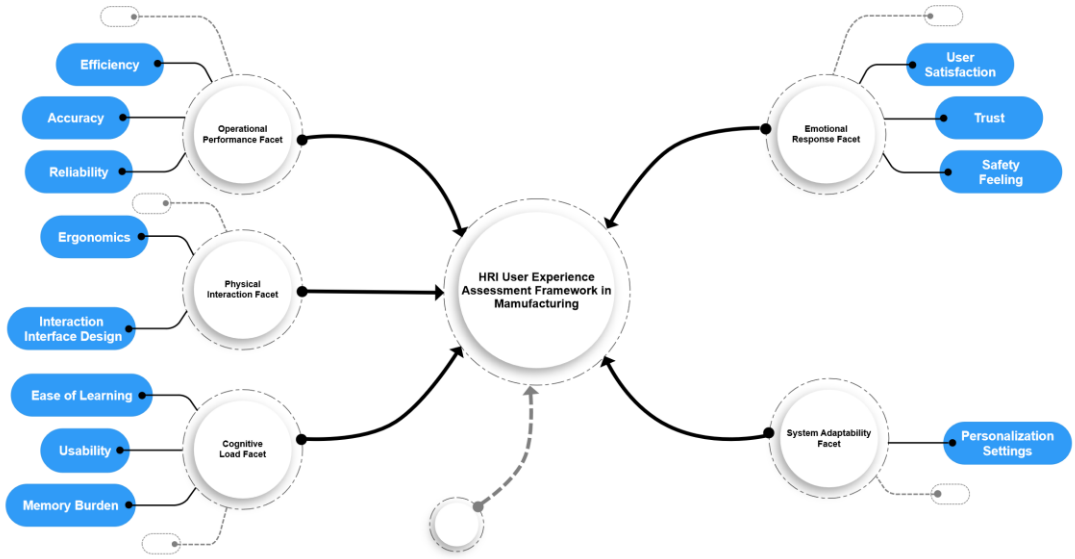

Figure 3.4 An HRI UX assessment framework in manufacturing. Dotted lines represent the framework's potential for expansion to incorporate additional user experience aspects.

Operational Performance Facet: Investigates efficiency, accuracy, and reliability of robot-assisted tasks, highlighting the critical role of these factors in optimizing manufacturing processes and outcomes.

Physical Interaction Facet: Focuses on the ergonomics of human-robot interfaces, the design and responsiveness of interaction systems, and the importance of effective operation feedback, underlining the need for physical comfort and effective communication between humans and robots.

Cognitive Load Facet: Addresses the ease of learning, usability, and memory burden associated with operating robotics, emphasizing the significance of intuitive design to minimize cognitive strain and enhance user engagement.

Emotional Response Facet: Explores user satisfaction, trust, and safety perceptions, acknowledging the profound impact of emotional factors on user acceptance and the overall success of HRI systems.

System Adaptability Facet: Assesses the system's capacity for personalization and role differentiation, as well as the ease of conducting system upgrades and maintenance, underscoring the need for flexible and adaptable HRI systems.

The HRI User Experience Assessment Framework, through methodical analysis, integrates 12 selected themes into five rigorously defined facets (Figure 3.4). Here, a facet refers to a higher-order conceptual category that encapsulates a group of interrelated UX themes sharing similar functions or psychological dimensions within the human-robot interaction context. These facets are designed to reflect distinct yet complementary domains of user experience. While conceptual boundaries were drawn to maintain analytical clarity, some degree of thematic overlap between facets is acknowledged—for example, the theme of trust may contribute to both the Emotional Trust Facet and Operational Performance Facet, as it relates to both affective perception and task confidence. These five facets group related UX themes into coherent categories. While some thematic intersections naturally occur, each facet is analytically distinct in its contribution to understanding UX in HRI.

3.5 Discussion

My exploration into optimizing HRI within the manufacturing industry, guided by my tailored HRI UX Assessment Framework, reveals critical insights into enhancing operational efficiency and worker engagement. This framework's suitability to manufacturing distinguishes it from generic models, making it a potent tool for addressing unique industry challenges.

The Operational Performance facet underscores the efficiency, effectiveness, and satisfaction derived from HRI systems. Theoretically, it challenges and extends current understandings of productivity in human-robot collaborations, The Operational Performance facet underscores the efficiency, effectiveness, and satisfaction derived from HRI systems. Interview results suggest a nuanced relationship between task performance and UX. Practically, insights into operational performance can guide the design of more responsive and intuitive HRI systems, emphasizing the balance between automation and human oversight.

Physical Interaction addresses the ergonomic and safety aspects of HRI. It highlights the importance of designing interactions that minimize physical strain and maximize safety. This facet contributes to a growing body of literature emphasizing the physical harmony between humans and robots, advocating for designs that accommodate human physical limitations and preferences (Chen et al., 2013).

The Cognitive Load facet examines the mental effort required to engage with HRI systems. suggesting that minimizing cognitive load can enhance user satisfaction and efficiency. From a practical standpoint, understanding cognitive load implications can lead to more intuitive system interfaces and interaction protocols, reducing barriers to HRI adoption.

Emotional Response captures the affective dimension of HRI, including feelings of trust, frustration, and satisfaction. I underscore the need for HRI systems to be designed with an understanding of human emotions, fostering positive emotional connections between users and robots.

System Adaptability focuses on the flexibility of HRI systems to accommodate diverse user needs and preferences. By emphasizing adaptability as a critical component of UX. The practical implications of this facet lie in the development of adaptable systems that can cater to a broad spectrum of operational contexts and user characteristics.

While the framework developed in this chapter offers a structured approach to evaluating UX in manufacturing HRI, its practical application requires further operationalization. To address this, the subsequent chapter focuses on translating the conceptual framework into a specialized, empirically validated UX evaluation tool. This transition marks a pivotal step in enabling quantitative assessment of HRI systems in real-world industrial contexts, building on the foundational work laid out here.

3.6 Comparison with Existing Frameworks

To contextualize our HRI-UX framework, we compare it with standard UX questionnaires (Table 3.4). Notably, the User Experience Questionnaire (UEQ) is a 26-item survey (7-point semantic scales) that measures six attributes including attractiveness and dependability (Schrepp et al., 2017). It is widely used for general interface evaluation, but it does not explicitly include dimensions like trust or cognitive effort. The Post-Study System Usability Questionnaire (PSSUQ) is a 16–19 item survey of overall system satisfaction (Lewis, 2002). PSSUQ yields an aggregate UX score and subscale scores for system usefulness, information quality, and interface quality. It is technology-agnostic and suited for usability studies, but again it focuses on pragmatic aspects (usability and satisfaction) rather than HRI-specific factors. The Usability Metric for User Experience (UMUX) is an ultra-brief, four-item scale aligned with ISO 9241-11 usability (Finstad, 2010). UMUX correlates strongly with the System Usability Scale (SUS) and provides a quick usability score, but like SUS it essentially captures general usability and does not cover emotional or cognitive load factors (Brooke, 1996a).

Table 3.4 Comparison of UX Evaluation Frameworks in HRI Contexts.

Framework	Item Count	Dimensions Covered	Trust Measured	Cognitive Load Measured	Tailored for Manufacturing HRI
UEQ	26	Attractiveness, Perspicuity, Efficiency, Dependability, etc.	✗	✗	✗
PSSUQ	16-19	System Usefulness, Information Quality, Interface Quality	✗	✗	✗
UMUX	4	Ease of Use, Utility	✗	✗	✗
Proposed HRI-UX	12	Operational Performance, Physical Interaction, Cognitive Load, Emotional Response (Trust), System Adaptability	✓	✓	✓

In summary, while UEQ/PSSUQ/UMUX are proven general UX tools, none were designed for the nuances of industrial HRI. For instance, Lindblom and Andreasson note that UX factors like trust and safety are often only "briefly touched" in HRI research (Lindblom and Andreasson, 2016). Standard questionnaires therefore cover usability and satisfaction but miss HRI-specific aspects. By contrast, our framework's dimensions (especially trust and cognitive load) were derived from operator feedback and are thus tailored to the unique requirements of human–robot collaboration. In practice, this means UEQ/PSSUQ/UMUX might provide a quick usability snapshot, but our framework offers deeper insight into factors (e.g. trust, mental workload, adaptability) that directly affect performance and acceptance in manufacturing HRI.

3.7 Contributions and Trust Emphasis

The proposed framework advances UX evaluation by introducing elements not covered in standard tools. It operationalizes trust as an explicit dimension of user experience. In our Emotional Response facet, we measure users' trust and safety perceptions alongside satisfaction. This is novel: previous work has noted that UEQ and similar questionnaires "have shown that UX factors are missing (e.g. Trust)", and that trust is a key aspect of HRI UX that is. By embedding trust directly into the framework, we provide a structured method to evaluate trust in HRI – an area where prior frameworks offered no specific metric. Likewise, the framework's Cognitive Load facet (ease of learning, memory burden) fills another gap: while UX broadly includes cognitive effort, common surveys usually do not measure it explicitly. Thus, our framework contributes new knowledge by adding targeted measures for trust and cognitive workload in HRI environments.

The focus of Chapter 3 was chiefly on constructing the multi-faceted assessment framework, rather than exclusively on trust. However, the importance of trust emerged naturally through this design process. The literature review (Chapter 2) had identified trust in HRI as an unsolved challenge, and we confirmed this through stakeholder interviews. In other words, while developing the framework to cover all relevant UX aspects, we found that trust was indeed a missing dimension highlighted by both literature and practitioners. Therefore, the framework's inclusion of trust is not an unrelated afterthought but a direct response to that gap. Chapter 3's outcome is the framework itself, but within it we explicitly address the previously recognized lack of trust evaluation. This dual focus means our contribution is both the novel structure of the HRI-UX framework and the insight into trust's critical role in human–robot interaction.

3.8 Summary

This chapter developed a pioneering HRI UX Assessment Framework tailored to the manufacturing industry. Through qualitative data analysis from semi-structured interviews, I identified and refined 12 key themes relevant to HRI UX. These themes were consolidated into five core facets: Operational Performance, Physical Interaction, Cognitive Load, Emotional Response, and System Adaptability. This framework serves as a structured tool for evaluating and improving HRI in manufacturing, providing valuable insights for both academic research and practical applications.

However, while this framework represents a significant step forward, it is still in the preliminary stages because the refinement process from 28 to 12 items, although focused on capturing core themes, may have omitted nuanced factors that could emerge in broader manufacturing contexts. The reduction was necessary for usability and focus, but it also necessitates further empirical validation to ensure the framework's comprehensiveness and reliability across diverse settings. Future research should deploy a broader questionnaire derived from this framework to test its applicability and robustness in various manufacturing environments, ensuring that the distilled factors adequately reflect the complexities of HRI. Additionally, focusing on specific key factors, such as trust and safety, could reveal deeper insights into these critical dimensions, which play a pivotal role in fostering effective and sustainable human-robot collaboration.

Building on the foundation of this UX assessment framework, the next phase of the research shifts focusses to trust, a critical dimension of user experience that plays a pivotal role in the success of HRC. Trust is integral to fostering effective and sustainable partnerships between humans and robots, especially in manufacturing environments where safety, transparency, and reliability are paramount (Maurtua et al., 2017, Lindblom and Wang, 2018). Insights from the UX assessment framework highlighted trust as a recurring theme influencing overall user satisfaction and system adoption. As a result, investigating how to enhance trust in collaborative robots emerges as a logical next step.

Chapter 4 Enhancing Operator Trust in Human-Robot Collaboration (HRC) by Facial Expression

4.1 Introduction

Building on the findings of Chapter 3, which emphasized the critical role of trust in enhancing UX in Human-Robot Interaction (HRI), this chapter delves into a specific strategy for fostering trust in HRC. Chapter 3 identified that while manufacturing flexibility necessity driven by the growing demand for product customization—requires hybrid systems where humans and robots collaborate, the effectiveness of these systems heavily depends on establishing trust as a cornerstone of the interaction. Furthermore, it revealed the limitations of existing HRI frameworks in addressing trust-related challenges in dynamic manufacturing environments. Insights from Chapter 3 highlighted the need for user-centered, intuitive communication mechanisms capable of supporting collaborative tasks in high-customization scenarios. This chapter extends that discussion by investigating the potential of AR-facilitated facial expression systems to enhance trust in HRC, leveraging AR's immersive and context-sensitive capabilities to address the gaps identified in prior frameworks.

As the demand for personalized and customized products continues to grow, manufacturing systems are increasingly required to handle diverse and dynamic customer requests—a capability referred to as manufacturing flexibility (Camison and Lopez, 2010). Traditional cage robots, optimized for large-scale, standardized production, struggle to meet the evolving needs of small-batch and high-customization workflows (Palmarini et al., 2018a). To address these challenges, smart factories are shifting towards hybrid systems that integrate human and robotic collaboration, enabling greater adaptability and efficiency in handling complex production demands (Prati et al., 2021a). The concept of HRC is very relevant and holds the potential for the future development of smart factories. However, most research on HRC is highly "robot-centred", primarily focusing on technological challenges and technical solutions, while lacking considerations of human aspects (Nordqvist and Lindblom, 2018), such as user experience (UX) (Prati et al., 2021a). According to recent research, trust is considered one of the three most critical factors, namely trust, safety, and operator experience, that affect HRC user experiences (Maurtua et al., 2017, Lindblom and Wang, 2018).

Facial expressions in robot design have been shown to play a pivotal role in fostering trust and facilitating intuitive communication between humans and robots. While many robots are designed without facial expressions, those equipped with expressive features offer several advantages. Research suggests that facial expressions enhance a robot's ability to convey emotional states, intentions, and feedback, making interactions more relatable and transparent for human users (Dunn and Schweitzer, 2005). For instance, facial expressions help bridge the gap in nonverbal communication, which is critical for establishing trust and reducing uncertainty during collaborative tasks (Krumhuber et al., 2007). Moreover, robots with facial expressions positively impact user perceptions, leading to higher levels of trust and acceptance. Studies have shown that users are more likely to interpret a robot's actions and intentions correctly when facial expressions are used to complement verbal or physical cues (Paradeda et al., 2016). For example, research by Krumhuber et al. (2007) revealed that facial dynamics influence trust-related decision-making, such as cooperative behaviours in social experiments (Krumhuber et al., 2007). Additionally, animated or dynamic facial features make robots appear more engaging and approachable, which is especially beneficial in safety-critical or high-stress environments (Galinsky et al., 2020). These findings underline the potential of facial expressions as a tool for improving HRC system design, making robotic interactions more human-like and effective.

The conventional approaches towards facial expressions in HRC usually rely on physical screens as the delivery medium, such as the animated face used in a Baxter robot (Fitter and Kuchenbecker, 2016). The advent of augmented reality (AR), a technology characterized by the superimposing of computer images on real-world objects or settings through a head-mounted device (HMD) or handheld display (Shen et al., 2010), provides a vast opportunity for researchers and industries to explore new ways of information exchange in the context of HRC (Dianatfar et al., 2021). In a semi-immersive AR environment, users can observe the real world while modelling the characteristics of digital products (Kaufmann and Schmalstieg, 2002). There is no need to model the background environment entities (Shen et al., 2010). The application of AR-mediated facial expressions in HRC presents a valuable research direction, grounded in AR's capacity for contextualized and intuitive interaction.

This chapter explores how AR may enhance trust in HRC by conveying safety-critical cues through facial expressions in a semi-immersive environment. The motivation for focusing on AR stems from its advantages over traditional screen-based approaches. Unlike fixed screens, which are limited by their static placement and narrow field of view, AR provides a dynamic and context-sensitive medium that allows digital elements, such as facial expressions, to be superimposed onto real-world environments in precise spatial locations (Shen et al., 2010). This flexibility offers an opportunity to create more intuitive and immersive communication channels between humans and robots, particularly in dynamic and collaborative tasks (Dianatfar et al., 2021). Prior research suggests that AR systems can improve task efficiency, reduce cognitive load, and enhance user engagement compared to traditional display technologies (Green et al., 2010, Alenljung and Lindblom, 2021). Additionally, AR's ability to integrate visual cues into the operator's field of view has been shown to improve the clarity of information delivery and user situational awareness (Liu and Wang, 2017). Based on these theoretical advantages, this chapter investigates how AR compares to traditional screens in delivering robot facial expressions and their impact on trust. The approach is tested through a controlled experiment in which participants experience two conditions: one using an AR headset and the other using a screen display to observe the robot's facial expressions during an HRC task. Trust is then measured using a validated questionnaire after each condition. The remaining sections of this chapter are structured as follows: first, a brief summary of previous research on the use of AR for facial expressions in HRC is provided. Next, the proposed paradigm for integrating AR-based facial expressions into HRC tasks is introduced, followed by an explanation of the trust measurement methodology. Finally, the experimental results are presented, along with a discussion of their implications and future research directions.

4.2 Related Works

4.2.1 Trust in HRC

Researchers believe that reliable HRC requires trust of the robot partner (Gaudiello et al., 2016). Trust directly influences users' willingness to engage with robots and their reliance on robot-generated outputs, such as data, suggestions, recommendations, and instructions, which are essential for task completion and decision-making (Hancock et al., 2021). For human-robot teams to function effectively, humans must believe that their robotic partners will act in ways that uphold the interests and welfare of the team (Hancock et al., 2011). Despite its importance, research on trust in industrial HRC has been relatively limited, with only a few studies exploring how trust develops in these settings (Charalambous and Fletcher, 2022). This gap is particularly significant given that trust is recognized as a critical factor in evaluating the UX goal framework for HRC (Lindblom and Wang, 2018). Building trust in Human-Robot Collaboration (HRC) has been a key focus in recent research, with various studies exploring different approaches to enhance trust. For instance, Kahn et al. (2015) found that people are generally open to forming close and trustworthy relationships with robots, suggesting a foundation of trustworthiness that can be nurtured through design and interaction strategies (Kahn Jr et al., 2015). Building on this, Palmarini et al. (2018) demonstrated that human confidence and trust in robots can be enhanced through the design of AR interfaces for HRC, which offer more intuitive and engaging interactions (Palmarini et al., 2018a). To address challenges in maintaining trust, Luo et al. (2021) proposed a trust repair framework based on human-to-robot attention transfer, providing a structured approach for regaining trust after errors (Luo et al., 2021). Similarly, Rabby et al. (2020) introduced a time-driven, performance-aware mathematical model for trust, enabling systematic evaluations of both human operators and robot performance (Rabby et al., 2020). Furthermore, Körber (2018) identified key factors—such as reliability, transparency, controllability, and effective communication—that significantly influence users' trust when evaluating new automation systems (Körber, 2018). Together, these studies underscore the multifaceted nature of trust in HRC and highlight various design and evaluation strategies that can enhance or restore trust. However, despite these advancements, a cohesive framework that integrates these diverse findings into practical applications for industrial HRC remains underexplored.

4.2.2 Role of Facial Expression

Facial expressions play a critical role in nonverbal communication, serving as a universal language that conveys emotions, intentions, and trustworthiness (Gendron et al., 2018, Galinsky et al., 2020). In the context of HRC, leveraging facial expressions can enhance intuitive communication and foster trust between humans and robots (Paradeda et al., 2016, Dunn and Schweitzer, 2005). Research in human psychology and human-agent interaction provides foundational insights into how facial expressions influence trust, which can be applied to robotic design (Krumhuber et al., 2007, Lindblom and Wang, 2018).

Trustworthiness is often evaluated through facial expressions, as humans instinctively rely on these cues to assess the intentions and emotional states of others (Krumhuber et al., 2007). In human-to-human interactions, dynamic facial expressions significantly impact decision-making and cooperative behavior, as shown in studies like the two-person trust game conducted by Krumhuber et al. (2007). While this research was not robot-specific, it highlights the fundamental role of facial expressions in building trust, which can be extrapolated to human-robot interaction scenarios.

In the domain of robotics, expressive facial features can make robots appear more relatable and trustworthy, enhancing the overall user experience. Robots equipped with animated facial expressions can convey emotional states and task-related feedback more effectively, helping reduce user uncertainty during collaborative tasks (Dunn and Schweitzer, 2005, Galinsky et al., 2020). For instance, robots with dynamic facial expressions have been shown to positively influence user trust and acceptance, particularly in high-stress or safety-critical environments (Paradeda et al., 2016). These findings suggest that facial expressions can bridge the gap in nonverbal communication between humans and robots, promoting intuitive interactions and improved collaboration.

The application of facial expressions in HRC often leverages technological solutions such as screen-based displays or AR systems. Traditional approaches, such as using static or animated faces on screens, have limitations in terms of flexibility and immersion (Fitter and Kuchenbecker, 2016). AR offers a more dynamic and context-sensitive medium for delivering facial expressions, enabling robots to superimpose expressive features onto real-world environments (Shen et al., 2010). This approach has the potential to enhance user engagement and situational awareness, making HRC more effective and satisfying.

While expressive facial features can foster trust, other factors such as cultural perceptions, task context, and the appropriateness of expressions must also be considered. For example, research shows that cartoon-like appearances often increase perceptions of approachability and trustworthiness due to their association with pleasant memories and positive emotions (Sun and Botev, 2021). However, the design of robotic facial expressions must balance these factors with the functional requirements of the task to avoid creating unrealistic expectations or over-reliance on emotional cues (Caudwell and Lacey, 2020).

In conclusion, integrating facial expressions into HRC systems presents a promising pathway for improving trust and communication in collaborative environments. By leveraging AR technologies to deliver expressive features, future research can explore how these systems can be optimized for diverse industrial tasks. The following sections will investigate the use of AR to enhance facial expressions in HRC, focusing on its impact on trust, task efficiency, and user satisfaction.

4.2.3 Augmented Reality (AR) Solution in HRC

Based on the review of existing research and applications, AR solutions have three main advantages in human-robot collaboration: increased efficiency, improved safety, and enhanced UX (Dianatfar et al., 2021). AR technologies can help workers complete tasks more quickly and accurately, simulate dangerous environments for training purposes, and improve the immersion and interactivity of human-robot interaction (Dianatfar et al., 2021). However, there are challenges related to technical costs and operability that need to be addressed for the wider adoption of AR (Green et al., 2010). Green et al. presented an HRC system based on AR technology and evaluated its performance (Green et al., 2010), in which the proposed system significantly improved work efficiency and reduced error rates. Compared to traditional human-machine collaboration methods, the AR-based system was widely accepted and positively evaluated by workers.

Alenljung et al. (2021) introduced the user experience evaluation results of a prototype system for assembly instructions based on the AR technology. They found that AR technology has a great potential to improve user efficiency and accuracy and provide more intuitive and easy-to-understand guidance to follow assembly instructions. Amtsberg et al. designed a human-robot collaboration interface based on the AR technology (Amtsberg et al., 2021). This system has many advantages, such as reducing communication costs, improving task execution efficiency, and reducing error rates (Amtsberg et al., 2021). In addition, the system can dynamically adjust the collaboration relationship between robots and personnel according to the characteristics of the task and work requirements to achieve more flexible and intelligent task sharing (Amtsberg et al., 2021). Therefore, an AR-based Worker Support System was designed, consisting of an AR-based teaching system, task sequence planning and re-planning system, worker monitoring system, and industrial robot control system that was used for investigation of the possibilities of AR applications in HRC (Liu and Wang, 2017). However, the user experience of AR technologies is also influenced by factors such as system stability, user training, and technology acceptance (Alenljung and Lindblom, 2021).

Recent studies have begun to explore the integration of AR and facial expressions in collaborative scenarios. For example, Palmarini et al. (2018) demonstrated that AR interfaces could enhance trust in HRC by making robot intentions more transparent and intuitive (Palmarini et al., 2018a). Similarly, Dianatfar et al. (2021) identified AR's potential to improve safety and efficiency in collaborative tasks but emphasized the need for further research on its application in emotional and trust-related interactions. These findings suggest that while AR has already proven effective in task execution, its role in nonverbal communication and trust-building remains a largely untapped area of investigation (Dianatfar et al., 2021). Compared to traditional human-machine collaboration, AR-based HRC offers significant potential advantages in terms of user experience, task efficiency, and operational safety, as demonstrated by recent studies (Dianatfar et al., 2021). Additionally, AR has been shown to improve task efficiency by enabling faster part identification and reducing assembly errors (Green et al., 2010). Meanwhile, there is still a lack of research on AR facial expressions in HRC. To fill this research gap, I introduce an AR approach that uses facial expressions to convey safety-critical messages in HRC tasks.

4.3 System Design

4.3.1 AR for HRC framework

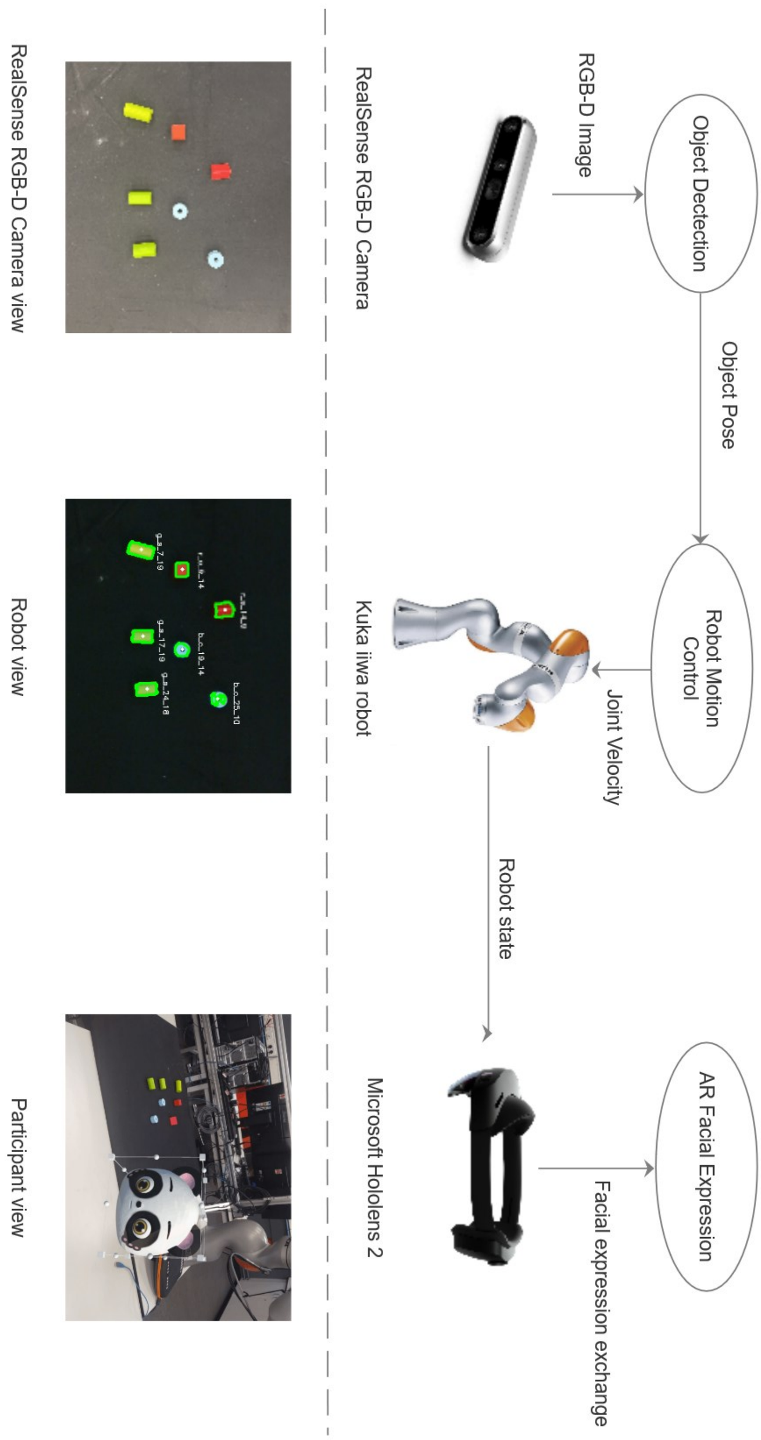

Figure 4.1 The AR facial expression system diagram. The ellipse software blocks.

This section describes the paradigm used for the experiments in this study (Figure 4.1), which comprises three modules: Object detection, Robot control, and AR facial expression. The Robot Operating System (ROS) is used to coordinate message communication among modules, acquire and display information, and control the robot. For my HRC scenario, I used a Kuka iiwa robot arm with 7 degrees of freedom and a Robotiq 3-finger gripper attached to the flange. Besides that, an Intel RealSense camera is mounted on the top of the table. The designated AR device is the Microsoft HoloLens 2, which provides relatively accurate spatial tracking and enables the AR facial expressions to be fixed in precise locations. The HoloLens and the robot were linked on the same local area network, and the current robot state information was transmitted via TCP for AR facial expression switching.

4.3.2 Object Detection

This module segments the image from the camera based on the color of the blocks on the table. The RealSense camera, in conjunction with OpenCV libraries (team, 2023b), is used to extract the centroid position of each object in pixels. The depth cloud provided by the RealSense D435i camera enables the calculation of the object's position in meters, referenced from the robot's base.

The positional accuracy of the object detection system is approximately ±1.5 cm in the x and y directions and ±1 cm in the z direction (Tetsuri Sonoda, 2023). This level of accuracy is derived from the depth resolution of the Intel RealSense D435, which offers a depth precision of up to 1% of the distance from the camera. In this experimental setup, the average object distance from the camera is about 1 meter, yielding a tolerance of approximately ±1 cm (Tetsuri Sonoda, 2023).

This tolerance is adequate for the collaborative block-stacking task, as the blocks are relatively large (typically greater than 4 cm per side) and the robot's end-effector (a 3-finger Robotiq gripper) has sufficient compliance to compensate for minor misalignments during grasping. Moreover, because the robot is not required to perform precision placement at sub-millimeter levels, and the AR-based feedback does not rely on exact placement but rather on gross position estimation, the current level of accuracy is sufficient for maintaining task success and user confidence.

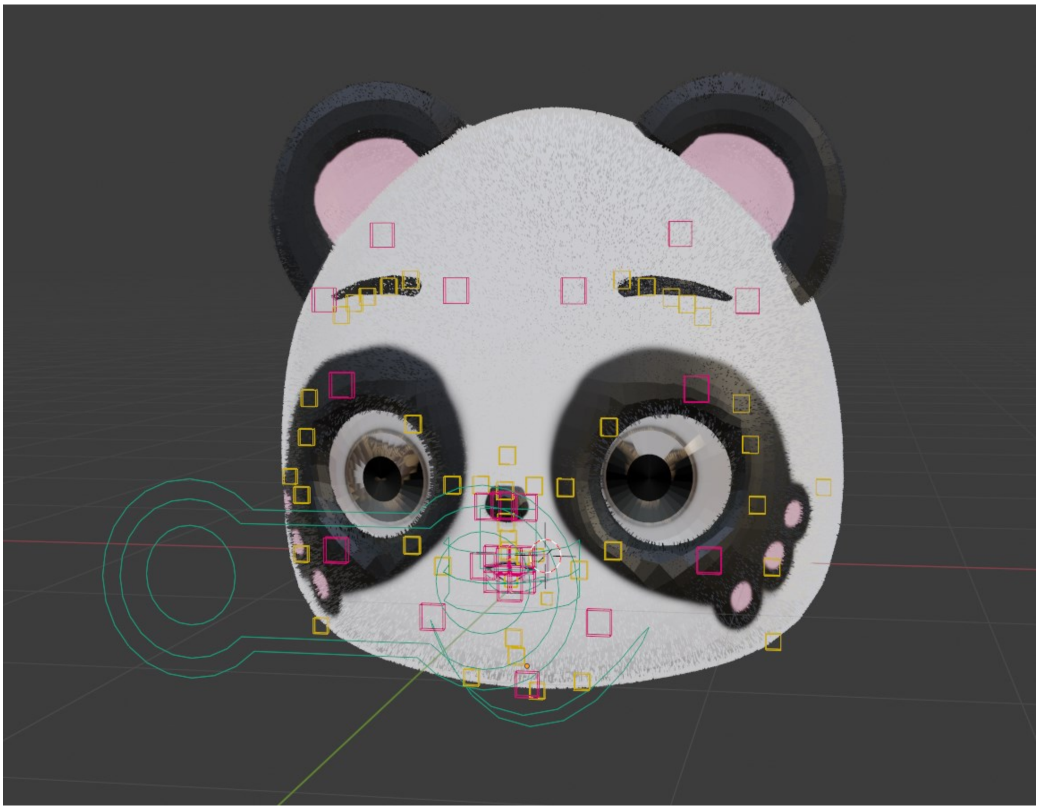

Figure 4.2 Panda model design and shape key creation.

4.3.3 Robot Control

This module aims to control the robot's actions while it collaborates with the user to complete a block-stacking task. During the execution of the task, the robot publishes state topics via TCP communication to the HoloLens2 or the screen, depending on the experiment. The image displayed on the device reacts according to the robot's state by switching facial expressions.

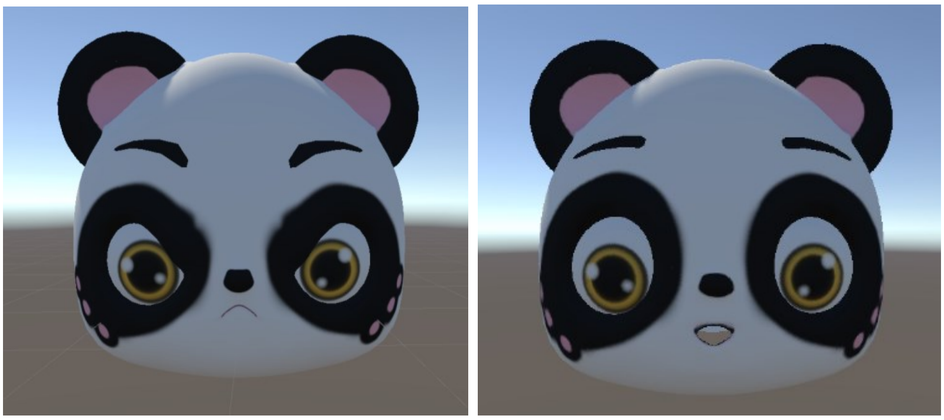

Figure 4.3 The expression on the left is angry, and the expression on the right is happy.

4.3.4 AR Facial Expression

Using cute objects as emotional triggers can prompt individuals to exhibit careful behaviours in certain situations, such as when driving or working in an office (Nittono et al., 2012). Cartoonish faces seem more trustworthy than other facial aesthetics (Pinney et al., 2022). Based on this research (Nittono et al., 2012, Pinney et al., 2022), I designed a cute panda model (Figure 4.2). First, I created a basic panda model in Blender and added details to it. The panda model consists of 4,749 polygons. Next, I drew and applied textures and materials to the model to give it a panda-like appearance. Then, I added bones to the model to enable facial movement and adjusted the bone weights to make the movements more natural. Finally, controlling the panda's facial expressions was implemented using the function of shape keys. This method enables the panda model to make any desired facial expressions.

Figure 4.3 shows two expressions: angry and happy. The angry expression is mainly displayed when the robot is moving. The happy expression indicates that the robot has completed the object-picking-and-placing task. The information about which facial expression must display is transmitted from the robot to the Hololens2 via the local area network (LAN) protocol.

4.4 Experiment Methodology

I hypothesize that in HRC tasks, facial expressions are more effective in facilitating trust in the robot if they are delivered by AR than if they are delivered by a fixed screen because they offer better visual effects and reduce some of the constraints imposed by the screen, such as reflections and fixed location. Based on my hypotheses, I expect to observe a higher level of trust after deploying AR facial expressions than using a screen display, operationalized by four subjective metrics, namely reliability, predictability, propensity to trust and trust in system.

This research was conducted in accordance with ethical guidelines and was approved by the Cardiff university Ethics Panel. All participants provided informed consent prior to their involvement in the study, and data collection was conducted in compliance with data protection regulations.

For more details, please see: https://github.com/tongyanzhanggithub/facial-expression

4.4.1 Participants

I recruited 14 participants from Cardiff University, including 10 males and 4 females, whose ages range from 24 to 31 years old. The participants were not compensated. Among them, 4 participants had prior experience with robots, while 10 participants had never interacted with a collaborative robot before. In addition, 4 participants had prior experience with AR devices, while 10 participants only heard about AR devices through media.

In determining the minimum number of participants required for the experiment, a priori power analysis was conducted using G*Power 3.1. Based on a two-tailed matched-sample t-test, a medium effect size (Cohen's $d = 0.5$), $\alpha = 0.05$, and power $(1 - \beta) = 0.8$, the minimum required total sample size was calculated to be 27 participants. However, due to constraints related to participant availability and experimental logistics, the final number of valid participants included in this study was 14.

4.4.2Materials

The materials used in this experiment included task-related artifacts, procedural elements, and hardware necessary for delivering facial expressions in two experimental conditions: AR and a fixed screen display. These materials were carefully selected and designed to simulate a collaborative industrial scenario while ensuring the reliability and consistency of the experiment.

The task required participants to collaborate with a robot to complete a block-stacking activity, designed to mimic a typical HRC scenario in industrial settings. The objective of the task was to evaluate how different visualization methods (AR versus screen) for delivering facial expressions influenced participants' trust in the robot. Participants were provided with task instruction cards illustrating the final block configurations they needed to build. The artifacts consisted of seven blocks, divided into three green rectangular prisms, two blue cylinders, and two red rectangular prisms. These blocks were chosen for their uniform sizes and distinct shapes and colors, ensuring that participants could easily identify and handle them during the task.

Two hardware configurations were used to deliver the robot's facial expressions. In the AR condition, facial expressions were projected into the participants' real-world environment using the Microsoft HoloLens 2. The HoloLens 2 provided precise spatial tracking, allowing facial expressions to appear directly adjacent to the robot's operational area. The device ensured an immersive and contextually relevant visualization experience. In the screen condition, the same facial expressions were displayed on a 24-inch high-definition LED monitor with a resolution of 1920 x 1080 pixels. The screen was placed at a fixed location on the participant's left side, approximately 1 meter away from the robot, at a 30-degree angle relative to their field of view. This placement ensured consistency in visibility while simulating a typical industrial screen-based interaction.

The task procedure required participants to complete the block-stacking activity under both visualization conditions, with the order counterbalanced across participants to minimize sequence effects. Facial expressions, such as "happy" to indicate task completion and "angry" to signal potential safety hazards, were delivered through animated panda models created in Blender. In the AR condition, these expressions were superimposed onto the physical environment near the robot's arm, while in the screen condition, they were displayed on the fixed monitor. These expressions were synchronized with the robot's operational states to provide real-time feedback to participants.

4.4.3 Design

In this study, I manipulated the visualization mode as a within-subject independent variable. Participants experienced both of these conditions below:

- AR: Participants will wear AR device and complete the human-robot collaborative task of block building (HRC-AR)
- Screen: Participants will observe the screen displayed changes in facial expressions and complete the human-robot collaborative task of block building. (HRC-S)

Each participant experienced both conditions, with the order of conditions counterbalanced across participants to mitigate potential sequence effects. This design ensured that individual differences, such as prior experience with robots or AR devices, did not bias the results.

4.4.4 Procedure

The experiment took place in the Robotics Lab of Cardiff University under the supervision of two experimenters. Upon arrival, participants were welcomed and provided with an information sheet detailing the purpose, structure, and ethical considerations of the study. They were given sufficient time to review the information sheet and ask any questions before signing a consent form to confirm their voluntary participation.

After providing informed consent, participants completed a short demographic questionnaire, collecting information such as age, gender, and prior experience with AR or robots. Following this, the experimenter explained the experimental process using a standardized script to ensure consistency across sessions. Participants were then introduced to the robotic arm and shown an example of the block-stacking task to familiarize them with the setup.

Participants were instructed to wear the Microsoft HoloLens 2 AR headset for the AR condition and to stand in a designated position in front of the robotic arm. In the screen condition, participants stood in the same position, but without the AR headset, and instead relied on a fixed 24-inch monitor placed on their left side, approximately 1 meter away from the robot, at a 30-degree angle. The monitor and AR system both displayed the robot's facial expressions during the task.

Participants received a task card indicating the specific block structure they needed to build. Once they verbally confirmed their readiness, the experimenter manually started the robot program. The robot assisted participants by picking and placing blocks, while facial expressions were used to communicate the robot’s state. For example, an "angry" expression appeared when the robot was in motion, signalling participants to maintain caution. Conversely, a "happy" expression indicated task completion, signalling that participants could proceed to pick up the blocks and continue building.

The AR system superimposed these facial expressions onto the physical environment, directly adjacent to the robot's operational area, ensuring that participants could easily perceive the expressions. In the screen condition, the same facial expressions were displayed on the fixed monitor, providing participants with a comparable visual experience.

After completing the task in each condition, participants were asked to complete the Trust in Automation (TiA) questionnaire, which was adapted to include specific references to either the AR or screen-based facial expression system. The questionnaire utilized a 100-point scale (0 - Strongly disagree; 25 – Disagree; 50 – Neutral; 75 – Agree; 100 - Strongly agree) and assessed four dimensions of trust: reliability, predictability, propensity to trust, and trust in system, shown in Table 4.1. To minimize sequence effects, the order of the conditions (AR and screen) was counterbalanced across participants. The total duration of the experiment, including the briefing, task completion, and questionnaire, was approximately 20 minutes. The same model and technical code were used for both visualization systems to ensure consistency across conditions.

Table 4.1 Questionnaire for facial expression system test.

	Subscale
	Reliability/Competence
Q1	The screen/AR facial expression system is capable of interpreting situations correctly
Q2	The screen/AR facial expression system works reliably
Q3	The screen/AR facial expression system malfunction is likely
Q4	The screen facial expression system is capable of taking over complicated tasks
Q5	The screen/AR facial expression system might make sporadic errors
Q6	I am confident about the system's capabilities
	Understanding/Predictability
Q7	The screen/AR facial expression system state was always clear to me
Q8	The screen/AR facial expression system reacts unpredictably
Q9	I can understand the reasons for things happening.
Q10	It's difficult to identify what the screen/AR facial expression system will do next
	Familiarity

Q11	I already know similar systems
Q12	I have already used similar systems
	Intention of Developers
Q13	The developers are trustworthy
Q14	The developers take my well-being seriously
	Propensity to Trust
Q15	One should be careful with unfamiliar screen/AR facial expression system
Q16	I rather trust a system than mistrust it
Q17	this system generally works well
	Trust in System
Q18	I trust the system
Q19	I can rely on the system

4.5 Experimental Results

I organised the ratings of the 19 questions in the questionnaire under 6 categories following the recommendations of TiA [21], (Cronbach's Alpha 0.617) calculated the mean for each category (after reverse-coding some items with a negative statement), and then performed pair-sample t-test analysis on the data to explore differences between conditions. The main results are presented in Table 4.2 showing the comparison between the AR and screen cases. The "t-test" values in Table 4.2 represent the comparison of means between the AR and Screen groups for each subscale, with significance evaluated using two-tailed independent samples t-tests.

Table 4.2 Results from the experiment comparing AR and screen.

	AR		Screen		t-test	*P*
	μ	σ	μ	σ		
Reliability/Competence	60.24	10.37	66.98	8.99	-1.84	0.04
Understanding/ Predictability	69.61	10.89	77.09	10.79	-1.83	0.04
Familiarity	21.89	21.26	28.93	31.40	-0.70	0.25
Intention of Developers	75.86	17.32	78.32	15.54	-0.40	0.35
Propensity to Trust	56.60	11.10	68.79	14.84	-0.44	0.33
Trust in System	70.25	14.96	67.00	12.04	0.63	0.26

Contrary to the initial expectation, the mean score of the AR group was lower than that of the screen group. However, on the understanding/predictability subscale (Q7–Q10), the AR group still scored above the neutral benchmark of 50, suggesting a generally positive response. According to the t-test, the difference between the two groups was statistically significant, though the direction was opposite to our hypothesis. Q11 and Q12 represent the familiarity subscale. Although the AR group's mean score on this subscale was 7.1 points lower than the screen group's, this difference was not statistically significant. The subscale of intention of developers is composed of Q13 to Q14. The results show a more favourable judgment of developers in the screen condition than in the AR condition, although the difference has not achieved the level of significance. With the second-to-last subscale, propensity to trust, including Q15 to

Q17, the average score of the AR group is 12.1 points lower than that of the screen group, although the difference is not significant. The last subscale is about "Trust in System", which includes Q18 to Q20. The t-test yielded a value of 0.63 ($p = 0.26$). This indicates that the difference in mean trust scores between the AR condition ($M = 70.25$, $SD = 14.96$) and the Screen condition ($M = 67.00$, $SD = 12.04$) was not statistically significant. The p-value exceeds the conventional alpha level of 0.05, suggesting that any observed difference could be due to random variation rather than a real effect of the display mode.

Although AR-based systems have been previously associated with enhanced user engagement and transparency, the results of this study showed no statistically significant difference in trust or cognitive load between the AR and Screen conditions. One possible explanation is user unfamiliarity with AR, which may have introduced cognitive distraction or novelty effects, thereby neutralizing the expected benefits. Moreover, the task complexity in this experiment was moderate, possibly making the visual augmentation less impactful compared to more demanding scenarios. Additionally, individual differences in technology acceptance and prior experience with AR could have influenced the results. This suggests that AR interfaces may require longer-term exposure or more complex task contexts to yield measurable benefits in trust and user experience. Future work could consider longitudinal studies or controlled exposure durations to isolate these effects.

4.6 Discussion

Based on the description of the results, I did not find evidence supporting my hypothesis that AR can improve trust in collaborative robots in comparison to a fixed screen by incorporating AR facial expressions into HRC. On the contrary, the measures of perceived reliability/competence and understanding/predictability indicate that AR facial expressions could damage trust. At the beginning of the experiment, participants' familiarity with AR and robots was measured using a demographic questionnaire. The familiarity scores revealed that only 4 out of 14 participants had prior experience using AR devices, while 10 participants reported familiarity with robots, primarily in non-collaborative contexts. In this experiment, prior experience with AR or robots could be a factor affecting participants' performance when using the system in an unfamiliar situation. It might be challenging for those without prior experience to operate and predict the system with the robot and AR. The familiarity and adaptation of participants to screen might explain why the mean scores of the screen group were higher than the AR group in reliability/competence and understanding/predictability subscales. Furthermore, the limitations of AR devices could also affect the reliability/competence and understanding/predictability subscales. For example, AR goggles have a limited field of view, and operator movements such as bending can cause dizziness (Dianatfar et al., 2021).

An observation from the experiment is that AR system can accurately convey information that can be used to express the state of robot. This interpretation is supported by the mean scores for the understanding/predictability subscale in the AR condition, which were relatively high (M = 69.61, SD = 10.89) despite being lower than the screen condition. While the AR system did not demonstrate any clear advantages over the screen in several aspects of the results, the mean score of the trust in system subscale suggests that the potential of the AR facial expression system to gain user's trust should not be dismissed. The AR approach incorporates facial expression communication into the real-world environment, providing participants with a more immersive experience during interactions. Additionally, the screen is difficult to move, while the AR model can be placed in the user's visual comfort zone according to their needs, enhancing the user experience. The AR facial expression system might have the potential to enhance trust in HRC because it allows for greater flexibility, enabling the model to generate any expression.

4.7 Contributions

In this Chapter of this thesis, a novel contribution is presented through the investigation of AR as a means to enhance operator trust in HRC by employing a facial expression system. Specifically, an AR-based system was developed using a stylized panda model capable of displaying dynamic facial expressions—such as "angry" during robot motion and "happy" upon task completion—to communicate the robot's internal states. The expressions were spatially anchored in the real-world environment via a head-mounted AR display (Microsoft HoloLens 2), aiming to provide more immersive and intuitive interaction cues compared to conventional screen-based interfaces.

To evaluate the effectiveness of this system, a controlled within-subjects experiment was conducted, comparing the AR condition with a traditional fixed-screen condition. Participants performed a block-stacking task collaboratively with a robot, while trust was measured using the Trust in Automation (TiA) questionnaire, which includes subscales such as reliability, predictability, propensity to trust, and overall system trust. Contrary to the initial hypothesis, the results indicated that AR-based facial expression delivery did not significantly outperform the screen-based condition in fostering trust. In fact, lower scores were observed in some trust dimensions under the AR condition, which may be attributed to users' unfamiliarity with AR technology and limitations such as restricted field of view and potential discomfort during use.

Despite the lack of significant improvement in trust outcomes, this study makes a valuable contribution by proposing and implementing an original method for integrating expressive AR content into HRC systems. It offers a comprehensive experimental paradigm for assessing trust in immersive interaction scenarios and provides practical insights into the design challenges and user experience considerations associated with AR deployment in industrial settings. This work thus lays the groundwork for future research seeking to leverage immersive technologies to enhance social transparency and trust in collaborative robotic systems.

4.8 Summary

In this chapter, I proposed an AR approach to improve operator trust by using facial expressions to convey safety-critical messages in HRC tasks. The AR facial expression system was designed to provide an immersive experience, allowing participants to perceive the robot's state directly within their field of view. Through experiments, I found no evidence that the AR approach could significantly improve trust in HRC compared to a screen display, as participants rated the screen condition higher in key trust metrics such as reliability and predictability. However, the AR system demonstrated flexibility and the ability to superimpose facial expressions in real-world environments, making it a promising tool for future applications. Although AR offers theoretical advantages, such as immersion and flexibility, the current task design may not have been optimal for showcasing these strengths. Participants were generally more familiar with screen-based interfaces, which likely influenced their perceptions of trust and usability in favor of the screen condition. Additionally, AR’s advantages, such as dynamic and spatially integrated visualizations, may have been underutilized in the block-stacking task, as the task itself required minimal cognitive engagement and spatial awareness.

In Chapter 5, I will explore a more complex and cognitively demanding task, specifically a working memory task, to better leverage the unique capabilities of AR. By selecting a task that requires real-time decision-making, spatial coordination, and higher levels of cognitive load, I aim to better demonstrate AR's potential to enhance user experience and trust in HRC environments. This transition will also provide a more robust evaluation of AR's effectiveness in supporting human-robot collaboration under more realistic industrial conditions.

Chapter 5 Augmented Reality (AR) for Improved User Experience in Industrial Assembly

5.1 Introduction

Building upon the findings from Chapter 4, this chapter explores a new case study to further investigate the potential of AR in HRC. In Chapter 4, I examined the use of AR for conveying robot facial expressions during a block-stacking task, aiming to enhance trust and communication. While the AR system demonstrated technical feasibility and flexibility, the block-stacking task was ultimately deemed suboptimal for showcasing AR's unique advantages. Specifically, the task lacked the cognitive and spatial complexity needed to fully leverage AR’s strengths, such as its ability to provide real-time, immersive, and spatially integrated visualizations. To address this limitation, I have designed a new case study focusing on a working memory task that incorporates higher levels of cognitive demand, decision-making, and spatial coordination. This task is intended to better utilize AR's potential for enhancing user experience in HRC.

As mentioned in chapter 3 and 4, the increasing demand for customized products has made manufacturing adaptability essential for addressing diverse consumer preferences (Camison and Villar Lopez, 2010). Conventional robotic systems, conceived for elevated throughput yet minimal diversity in production, often struggle to accommodate the rapidly increasing prerequisites of limited volumes yet elevated personalization (Palmarini et al., 2018a). Contemporary intelligent manufacturing facilities necessitate integrated configurations where the human workforce and robotic entities synergize (Prati et al., 2021a). However, a substantial proportion of scholarly work on HRC seems to have a stronger emphasis on the robotic aspect, primarily tackling technological issues and their solutions, while the human aspect (Nordqvist and Lindblom, 2018), such as UX considerations (Prati et al., 2021a), has been mainly left under-addressed.

In assembly operations, workers must adapt to product specification variations that come in diverse batch magnitudes (Wahlster, 2014). The predominant mode of information dissemination, typically defined by stationary and paper-based assembly directives, fails to meet these adaptability demands, leading to issues such as cognitive strain among employees and diminished operational efficiency (Falck et al., 2017). The emergence of augmented reality (AR) has the potential to reduce cognitive strain and improve operational efficiency (Dianatfar et al., 2021). AR is a technological innovation defined by its overlay of digital visuals onto physical entities or surroundings via devices, such as head-mounted displays (HMD) or portable screens (Shen et al., 2010). It offers a profound prospect for both scholars and industrial sectors to delve into novel paradigms of data communication within the HRC framework (Dianatfar et al., 2021).

Building on the findings from Chapter 4, which explored the potential of AR facial expression systems to enhance trust in HRC, this chapter further investigates operators' user experience in an AR-enhanced HRC assembly process. In Chapter 4, while the AR system demonstrated its ability to convey robot states effectively, the results highlighted challenges related to task suitability and participants' familiarity with AR technology. These insights inform the design of the AR-assisted HRC system discussed in this chapter, which has been tailored to a specific industrial use case. This system integrates observations and feedback from real-world applications and interviews to address the limitations identified previously, aiming to better leverage AR's immersive capabilities and enhance operator experience in more cognitively demanding tasks. Utilizing a comprehensive user experience design process, my research rigorously evaluates user satisfaction and cognitive load through the AttrakDiff Mini and NASA TLX questionnaires. This chapter aims to enhance assembly accuracy and efficiency through

AR integration, improve user satisfaction, reduce operator cognitive load, and provide a replicable methodology for future studies and practical applications in industrial settings. By focusing on the practical application of user-centred design in HRC systems, this research addresses a critical gap in the literature. My approach demonstrates the significant value of integrating real-world user feedback into the design and evaluation of AR-assisted HRC systems.

5.2 Related Works

5.2.1 AR-Based Solutions for HRC in Manufacturing

The increasing complexity and customization demands in modern manufacturing necessitate agile and adaptive assembly processes (Abele and Reinhart). Traditional assembly methods, which rely heavily on static, paper-based instructions, often fail to meet the dynamic requirements of varied product batches, leading to cognitive overload and worker inefficiencies (Falck et al., 2017). HRC has emerged as a pivotal solution to these challenges, integrating the precision and consistency of robots with the flexibility and problem-solving abilities of human worker (Eswaran et al., 2024).

HRC systems are designed to facilitate seamless cooperation between humans and robots, thereby enhancing productivity and reducing ergonomic risks (Cardoso et al., 2021). For example, Realyvásquez-Vargas et al. demonstrated that integrating collaborative robots in assembly tasks can significantly mitigate occupational hazards and improve operational efficiency (Realyvásquez-Vargas et al., 2019). Furthermore, Cherubini et al. developed a cooperative human-robot assembly cell that emphasizes the importance of physical interaction and task sharing between humans and robots (Cherubini et al., 2016). In this setup, the robot alternates between active and passive roles, effectively reducing human operators' cognitive and physical workload (Kaber et al., 2000). This dual-mode operation ensures that the robot can assist in both direct assembly tasks and support activities, creating a more balanced and efficient workflow (Wang et al., 2019). Their study highlighted how robots can take over repetitive and hazardous tasks, allowing human workers to focus on more complex and value-added activities (Benos et al., 2020).

The importance of ergonomics and human factors in the design of HRC systems cannot be overstated. Studies by Villani et al. and Nordqvist and Lindblom have shown that user-centred design approaches in HRC can significantly enhance operator satisfaction and productivity (Villani et al., 2018, Nordqvist and Lindblom, 2018). Their research emphasizes the integration of ergonomic principles and real-time feedback mechanisms to create adaptive interfaces that cater to human operators' needs (Fabio et al., 2025).

Despite these advancements, the success of HRC systems heavily relies on their integration into human-centric workflows. It is crucial to address human operators' cognitive and ergonomic needs to maximize the benefits of HRC. User-centered design approaches incorporating real-time feedback and adaptive interfaces can enhance the overall effectiveness of HRC systems. By focusing on the user experience, manufacturers can ensure that these systems are not only technically proficient but also intuitive and supportive for human operators (Prati et al., 2021a).

5.2.2 Evaluating UX in HRC

As with all interactive systems, a positive user experience is essential for robots to achieve the anticipated benefits. If users feel negative towards interactions with robots, it may result in a reluctance to engage with them, which could prevent the acceptance of future robotic technologies (De Graaf and Allouch, 2013). A favourable user experience supports the widespread adoption of robots in society. Such a positive user experience does not materialize automatically but through deliberate, conscious systematic design and evaluation (Hartson and Pyla, 2012). Consequently, the user experience for robots should be at the forefront of considerations when developing such machines. According to prior studies in the realm of UX, the user experience is delineated by a system's pragmatic (often termed as 'instrumental product', 'task-focused', or 'ergonomic') attributes and its hedonic ('non-functional or 'non-task-focused') attributes (Hassenzahl, 2018, Merčun and Žumer, 2017). Pragmatic quality can be characterized by how much aspects like utility, efficiency, and ease of use are actualized, and are commonly denominated as usability and utility (Merčun and Žumer, 2017). ISO 9241-11 defines usability as the "extent to which specific users can use a system, product, or service to achieve specified goals with effectiveness, efficiency, and satisfaction in a specified context of use". It is worth emphasizing that usability pertains to the outcomes of system interactions. According to the definition of the ISO standard, usability is not an intrinsic attribute of the system. However, appropriate characteristics of the system can facilitate usability within a given usage environment (Bevan, 2001).

Researchers have devised various questionnaires to gauge subjective pragmatic quality (usability). For instance, the System Usability Scale (SUS) developed by DEC in the UK encompasses ten items and was unveiled in 1996 (Brooke, 1996b). Furthermore, the Technology Acceptance Model (TAM), designed initially to predict technological adoption likelihood, has been moderately adapted to function as a standardized user experience questionnaire, preserving its renowned factorial structure to measure perceived ease of use and utility (Silva, 2015). In recent years, aiming to offer more succinct assessment tools, the UMUX was formulated as a brief four-item perceived usability measure with scores designed to align with the SUS (Finstad, 2010). For further simplification, the UMUX-Lite consists of just two items, targeting the perceived utility and ease of use (Lewis et al., 2013). It serves not only as a compact version of the UMUX but also as a condensed version of TAM (Lewis et al., 2015). Its scores exhibit a high congruence with those of the SUS (Lewis et al., 2015). The AttrakDiff Mini is a brief, 10-item evaluation tool that assesses an interactive product's pragmatic quality, hedonic quality, and overall attractiveness (Hassenzahl et al., 2008). Attributes are rated on a 7-point Likert scale using bipolar semantic differentials (e.g., negative to positive) (Hassenzahl and Monk, 2010). I chose the AttrakDiff Mini because it is widely used to evaluate user experience, particularly in measuring usability, identity, stimulation, and appeal (Vieira et al., 2023). However, it does not address the cognitive workload involved in using the system (Hartson and Pyla, 2012). To provide a comprehensive assessment of UX, it is also important to consider cognitive workload and user satisfaction. The NASA Task Load Index (NASA-TLX) questionnaire is a well-established tool for measuring cognitive workload across six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration (Hart and Staveland, 1988). By evaluating these factors, researchers can gain insights into the cognitive strain experienced by users during their interactions with HRC systems (Hart and Staveland, 1988).

Studies have shown that incorporating user-centered design approaches in HRC systems can significantly enhance operator satisfaction and productivity (Villani et al., 2018, Prati et al., 2021a). By integrating ergonomic principles and real-time feedback mechanisms, adaptive interfaces can be created to meet the specific needs of human operators, ensuring that HRC systems are both technically proficient and user-friendly (Nordqvist and Lindblom, 2018). For example, Nordqvist and Lindblom found that trust and satisfaction among operators increased when HRC systems were designed with user experience in mind (Nordqvist and Lindblom, 2018).

My study leverages these established methodologies to evaluate the UX of an AR-enhanced HRC system tailored for a specific industrial case. By incorporating real-world observations and interviews into the design process, I ensure that the system addresses its users' practical needs and preferences. This comprehensive approach not only improves assembly accuracy and efficiency but also enhances overall user satisfaction and reduces cognitive load (Prati et al., 2021a).

5.2.3 AR-Based Solutions for HRC in Manufacturing

AR technology has emerged as a transformative tool for enhancing HRC by providing real-time, context-specific guidance and feedback to operators (Nee et al., 2012). AR systems can overlay digital information onto the physical workspace, facilitating more intuitive and efficient task execution (Syberfeldt et al., 2017). This integration is particularly beneficial in complex assembly processes where precision and adaptability are crucial (Villani et al., 2018).

The potential of AR in industrial applications has been highlighted in several studies. For instance, AR could significantly improve task performance and reduce the likelihood of errors in human-robot collaborative environments (Green et al., 2008). Their study showed how AR can provide immediate feedback and detailed instructions, helping operators perform tasks more accurately and efficiently (Wang et al., 2022). Similarly, Nee et al. emphasized the importance of AR in enhancing task performance by reducing cognitive load and providing clear visual cues (Nee et al., 2012).

Cherubini et al. also explored the benefits of AR in cooperative human-robot assembly cells. Their research emphasized that AR can enhance the physical interaction and task-sharing capabilities between humans and robots (Cherubini et al., 2016). By displaying digital instructions and real-time data onto the operator's field of view, AR helps in reducing cognitive load and minimizing errors, thus improving overall task performance (Alessa et al., 2023). Syberfeldt et al. further supported these findings, demonstrating that AR can significantly enhance the efficiency and accuracy of complex assembly tasks (Syberfeldt et al., 2017).

AR's ability to provide adaptive instructions based on real-time user feedback makes it a versatile tool in HRC settings. Studies by Villani et al. have shown that user-centred design approaches, which incorporate ergonomic principles and real-time feedback mechanisms, can significantly enhance operator satisfaction and productivity (Villani et al., 2018). By tailoring the AR interface to the specific needs of human operators, it is possible to create more user-friendly and efficient HRC systems (Subramanian et al., 2024). Similarly, Syberfeldt et al. highlighted that AR can improve operator performance and satisfaction by providing interactive and context-aware assistance (Syberfeldt et al., 2017).

Based on AR's benefits, the AR-assisted HRC system developed in my study offers a promising solution for enhancing the efficiency, accuracy, and safety of assembly processes. By leveraging AR technology, manufacturers can create more adaptable and user-friendly work environments, increasing productivity and reducing cognitive load on operators. This chapter’s findings contribute to the literature that supports the integration of AR technology in HRC systems and provide practical insights for future implementations.

5.3 Materials Development

5.3.1 Insight from Factory

In this study, observations and interviews were conducted at the HWASDAN conveyor belt assembly workshop in Chongqing (company website: http://www.hwasdan.com/) (see Figure 5.1). This production line primarily handles the assembly of small batches of diverse agricultural machinery products and general machinery. On average, the assembly line transitions between several to over a dozen different products daily. Over the course of a year, it assembles approximately 200 different types of machinery, with an annual output of around 100 units of agricultural machinery. This workshop is representative of medium-sized manufacturing enterprises in the western region of China, providing a valuable case study of the operational conditions within an assembly workshop.

Figure 5.1 HWASDAN conveyor belt assembly workshop.

Through observations and interviews conducted at the factory, several critical insights have been identified regarding the traditional conveyor belt assembly line. The factory is tasked with assembling a diverse range of over a dozen different products daily, which imposes significant learning demands on the workers and results in frequent assembly errors. The findings from these insights are crucial for understanding the current inefficiencies and identifying areas for improvement. A service blueprint was employed to systematically document and analyse these insights (Figure 5.2). This service blueprint provides a detailed mapping of the entire assembly process, highlighting key pain points and identifying potential areas for improvement. The main components of the service blueprint include:

Operator Actions: Detailed steps undertaken by workers during the assembly process for each type of product.

Frontstage (Visible Contact): Interactions between workers and the machinery or tools used in the assembly process.

Backstage (Invisible Contact): Support processes that are not visible to the workers but are crucial for the assembly line's functionality.

Support Processes: Auxiliary processes that support the assembly line, including inventory management, quality control, and maintenance.

Pain Points and Opportunities: Identify areas where errors and inefficiencies are most prevalent, along with suggestions for process optimization and enhanced training programs.

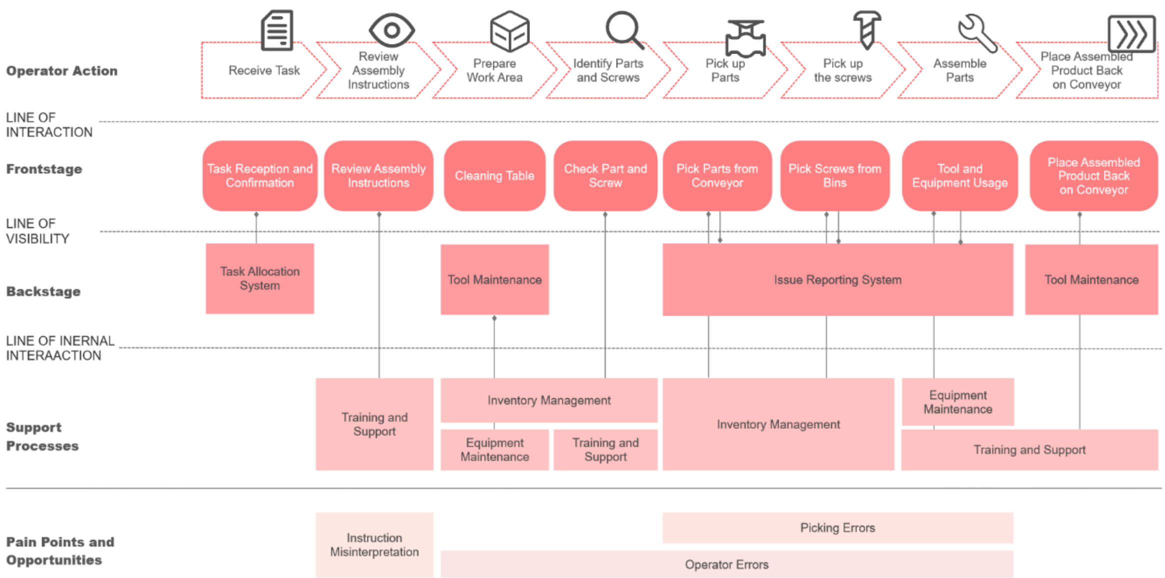

Figure 5.2 Service blueprint from HWASDAN conveyor's operator.

Figure 5.3 I observed the workers who were assembling parts.

The process begins with operators receiving their daily tasks through task sheets. Once tasks are received, operators review the assembly instructions to understand the steps and parts required. Preparing the work area is a crucial next step, ensuring all necessary tools and parts are available and organized. Operators then identify the different parts and screws required for the task. After identification, operators pick the necessary parts from the conveyor belt and separately pick the screws either from the conveyor belt or designated bins. The assembly of parts follows, where operators use specified tools such as screwdrivers and wrenches to assemble the parts onto the product correctly. Finally, the assembled product is placed back onto the conveyor belt, ready for the next process stage. Figure 5.3 shows the worker performing the assembly task.

The assembly process faces several challenges. Operator errors in identifying and picking parts and screws can affect product quality, while initial quality checks may not catch all issues. Errors in picking the correct parts and screws, as well as misinterpreting assembly instructions, can also lead to assembly mistakes (see Figure 5.4). However, there are numerous opportunities for improvement. Enhanced training focused on the identification and correct use of parts and screws, potentially using AR aids, can improve accuracy. Introducing automated inspection equipment can increase the accuracy of quality checks, and utilizing digital aids or AR systems can help operators accurately identify parts and screws, reducing assembly errors. Optimizing the picking process with systems such as color-coded bins or part identification labels can improve efficiency and improving instruction delivery through digital or AR-enhanced instructions can help operators better understand assembly steps, reducing errors.

Figure 5.4 Screws of different sizes that look similar.

5.3.2 AR-assisted HRC system design

This research adopts a multi-faceted approach integrating robot control, data communication, and Unity3D visualization (Figure 5.5). The detailed methodology is described below.

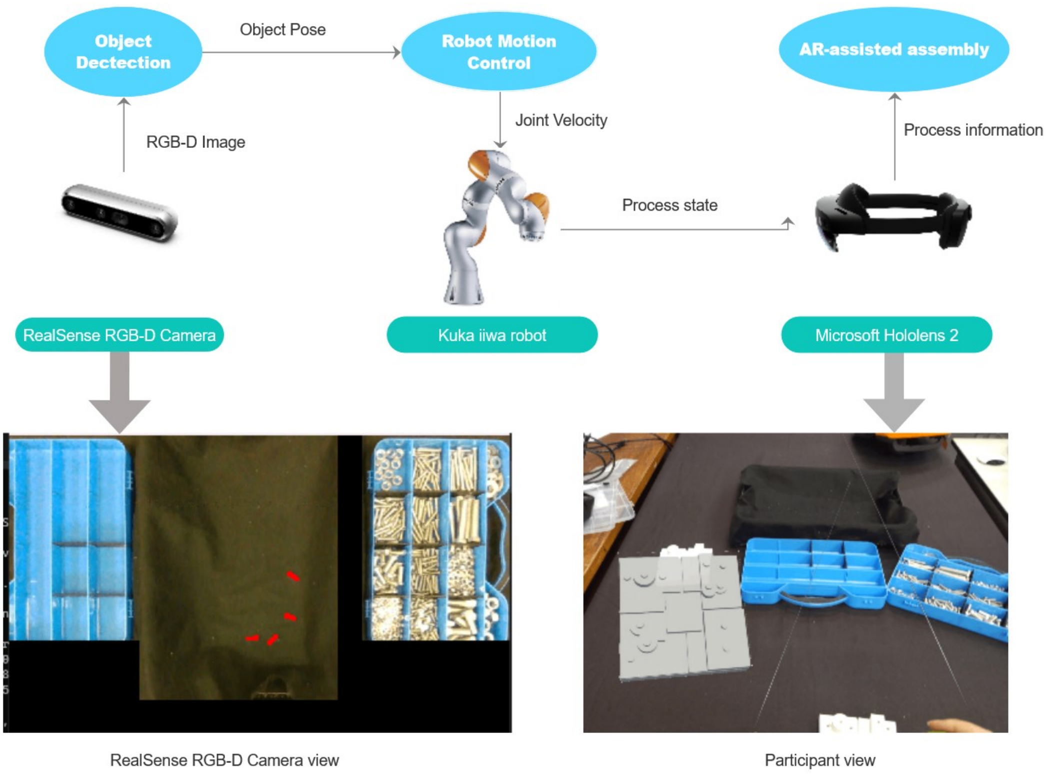

Figure 5.5 The AR-Guided Assembly Procedures diagram. The blue ellipse software blocks were developed in this system.

5.3.3 Robot Control

In this work, I introduce an assembly task, where the operator is required to complete an assembly of a part, as illustrated in Figure 5.6. The part comprises 4 components that require the user to select the screws of different sizes. In the task, the robot is responsible for picking and sorting the screws, and the user is mainly responsible for the actual assembly.

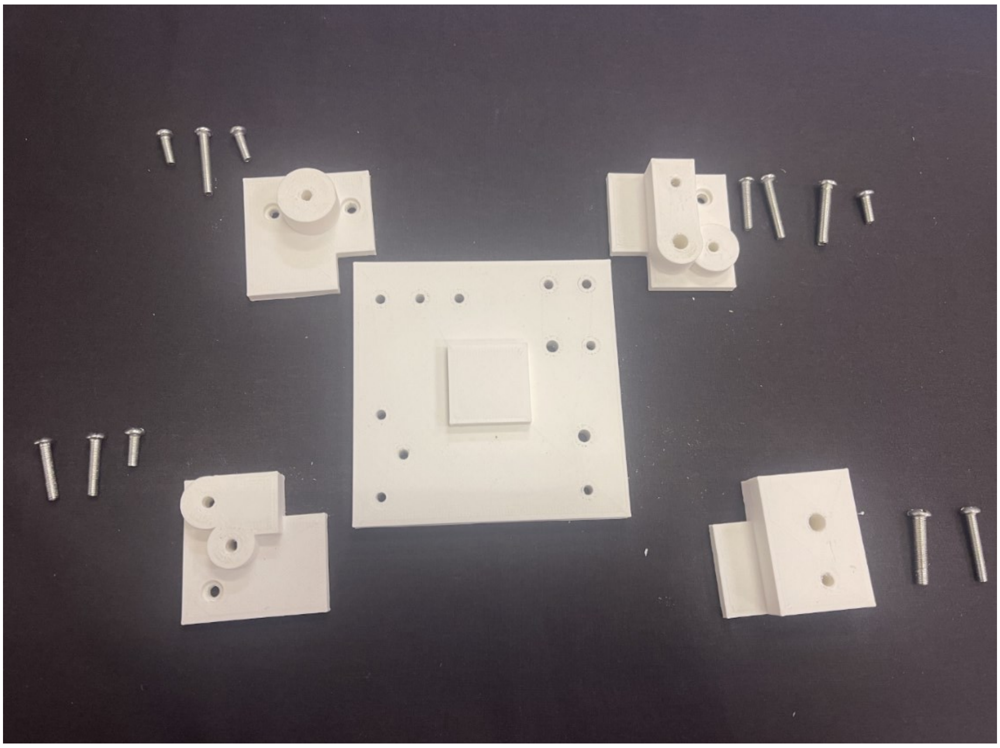

Figure 5.6 3D printed assembly parts.

A comprehensive robot control system was developed using Python as the primary programming language. This system served as an integrated platform based on MATLAB, centralizing various operations and tasks and ensuring consistency and continuity throughout the experiments.

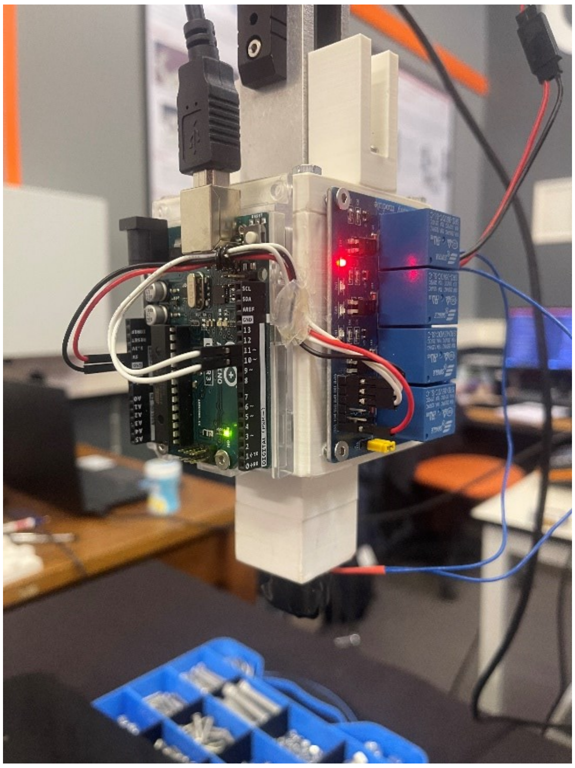

Figure 5.7 The robot's end-effector tool includes an electromagnet, which is controlled via an Arduino microcontroller.

For screw picking and sorting, I designed my own end-effector tool attached to the robot. The end-effector used in this experiment was custom designed and built by the research team. Rather than relying on off-the-shelf solutions, we developed a tailored tool featuring an Arduino-controlled electromagnet to meet the specific requirements of the screw sorting task (see Figure 5.7). The robot uses its end-effector to pick up a group of screws and then drops them into the tray. This process separates the screws, allowing the robot to pick them up one by one. The robot counts the number of screws in the tray, and if, after picking up a screw, the number of screws decreases by 2 or more, it means that more than one screw was picked. In this case, the robot drops the screws back into the tray. When there are no more screws in the tray, but the assembly process still requires more, the robot picks up additional screws from the screw tray and repeats the process. Once the robot has dispensed all the required screws, if there are any screws left in the tray, it returns them to the original screw tray. For a better understanding of the process, please refer to the video at https://www.youtube.com/watch?v=qoJvonsQUGk.

This tool can communicate with the control system through a serial port. The task is divided into three distinct boxes: in the first box, the robot selects the correct screws from a set of fourteen different parts. Using the magnet, it picks and sorts these screws into a central black box (see Figure 5.8). The correct screws are then placed in a box closer to the user, while surplus parts are returned to the first box. Each successful retrieval of the correct screw results in a change in the robot process state. These state

Figure 5.8 Assembly bench.

changes are recorded in a global state variable, preparing the data for subsequent transmission via the User Datagram Protocol (UDP).

5.3.4 User Datagram Protocol (UDP) Communication

In this system, efficient real-time communication facilitated by the UDP is crucial for the interaction between AR goggles and the robot control system. The choice of UDP, known for its low latency and less overhead than TCP, is pivotal in ensuring seamless data transfer and coordinated functioning. This communication framework, leveraging the strengths of UDP, is adept at handling the rapid exchange of information, which is essential for the responsive operation of the system. My focus on UDP highlights its suitability for scenarios where speed and efficiency are paramount, aligning perfectly with the system's fast and reliable communication requirements.

5.3.5 Unity3D Visualization

To achieve real-time visualization of the robot's operations, Unity3D was chosen as the development environment. Within Unity, a specialized UDP manager was developed, who was responsible for continuously monitoring a specified UDP port and awaiting state messages from the robot control system.

Once the UDP manager received these state messages, it promptly updated a variable. This allows other scripts or objects within the Unity scene to react in real-time based on the robot's state, displaying corresponding animation effects or other visualization elements (see Figure 5.9).

Exception-handling mechanisms were incorporated at each stage to enhance the overall system's stability. This not only ensured the timely resolution of any communication discrepancies but also fortified the system's robustness and stability during its operational course.

For more details, please see: https://github.com/tongyanzhanggithub/HRC-Scorting-screws

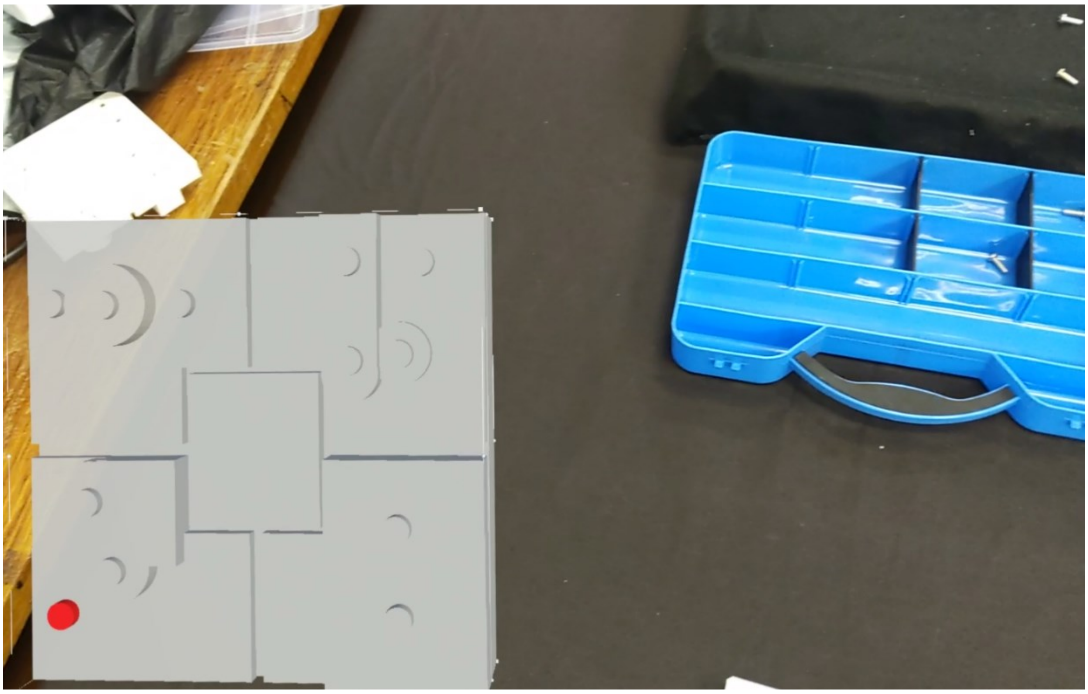

Figure 5.9 The corresponding screws are displayed on the HoloLens.

5.4 Experiment Methodology

5.4.1 Participants

Participants were recruited through personal acquisition and announcements at Cardiff University's School of Engineering, each receiving a 5-pound reward (Fig. 7 shows Participant in the experiment). Their ages ranged from 23 to 30 years. Of the participants, 7 (23%) were female and 23 (77%) were male. In this cohort, 8 individuals had previous experience with robots, whereas the other 22 had no prior interaction with collaborative robots. Moreover, 15 participants had firsthand experience with AR technology, while the other 15 were only familiar with AR through media channels. All participants reported no experience in factory assembly (Fig. 10 shows the experimental setup).

To ensure the statistical validity of the experimental findings in this study, the minimum required sample size was determined using a power analysis conducted via G*Power 3.1. Based on a repeated-measure ANOVA F test, a medium effect size ($f = 0.25$), $\alpha = 0.05$, and power $(1 - \beta) = 0.8$, the minimum required total sample size was calculated to be 28 participants.

Figure 5.10 A participant performing experiments.

5.4.2 Materials

The primary task of this experiment involved completing a complex industrial assembly process using an AR-supported collaborative robotic system. The task was designed to simulate scenarios requiring high precision and efficiency, emphasizing cognitive complexity and spatial coordination. Participants were required to perform a series of assembly steps, including selecting appropriate screws, positioning components accurately, and completing assembly instructions under varying conditions. The objective of the experiment was to evaluate the impact of the AR-enhanced collaborative robotic system on UX, assembly performance (including accuracy and efficiency), and cognitive workload. Specifically, the study sought to determine whether AR guidance, combined with collaborative robotic assistance, could significantly improve assembly accuracy, reduce cognitive load, and enhance user experience while optimizing task completion time.

The experiment followed a structured procedure. First, participants were briefed on the experimental setup and equipped with AR headsets (HoloLens 2) to familiarize themselves with the process. They were then asked to complete the assembly task under three conditions: (1) using AR guidance and a collaborative robot (AR-Robot), (2) referring to paper-based instructions alongside a collaborative robot (No AR-Robot), and (3) using paper-based instructions without robotic support (No AR-No Robot). Researchers recorded assembly time and accuracy for each condition, while subjective data, such as user experience and cognitive workload, were collected via the AttrakDiff Mini and NASA-TLX questionnaires. To ensure accurate results, the experimental tasks were closely monitored, and data analysis was conducted using IBM SPSS 27, employing repeated-measures ANOVA and paired t-tests to compare outcomes across conditions.

The equipment and hardware utilized in this study included the HoloLens 2 AR headset, a KUKA iiwa collaborative robot, a custom-designed electromagnet end-effector controlled via Arduino, an assembly workstation, and 3D-printed standardized assembly parts. The HoloLens 2 provided real-time digital guidance to assist participants throughout the assembly process. The KUKA iiwa robot played a pivotal role by using its electromagnet end-effector to pick and sort screws, ensuring precise delivery to participants. The robot's control system was developed using Python and MATLAB, facilitating consistent task execution and seamless integration with other components. Real-time data transmission between the robot and AR interface was achieved using the User Datagram Protocol (UDP), enabling dynamic updates in the Unity3D visualization module. These elements were carefully integrated to create a stable and efficient experimental platform capable of supporting both task execution and data collection.

The collaborative robot, KUKA iiwa, was central to the experiment. Equipped with a custom-built electromagnet end-effector, it handled screw sorting and dispensing tasks with precision. The robot communicated in real time with the AR system via UDP, ensuring low-latency and high-efficiency data exchange. The control platform, primarily developed in Python and MATLAB, provided a reliable and cohesive environment for robot operation.

5.4.3 Design

The experiment was set up at Cardiff University's Robotics and Autonomous Intelligent Machines Laboratory, which is equipped with the hardware necessary for the experiments. Under these conditions, 30 participants (N = 30) were to complete assembly tasks under three different conditions:

- Assembly with the assistance of an AR worker guidance system and a collaborative robot. (AR)
- Assembly referring to paper instructions alongside a collaborative robot. (HRC)
- Assembly referring to paper instructions manually. The dependent variables investigated included assembly time, assembly success rate, user experience, and subjective stress. (M)

5.4.4 Procedure

Participants followed a structured procedure to ensure consistency and reliability in the experiment. Upon arrival at the laboratory, participants were welcomed by the research team and guided through the experimental setup. They were provided with an information sheet detailing the purpose of the study, the tasks they would be performing, and any potential risks or benefits of participation. Before proceeding, participants were required to sign an informed consent form, acknowledging their understanding of the experiment and agreeing to take part voluntarily.

After providing consent, participants received a comprehensive instruction session, during which they were introduced to the experimental environment, including the collaborative robot (KUKA iiwa), AR headset (HoloLens 2), and the assembly task workflow. Researchers demonstrated the correct use of the AR guidance system and collaborative robot to ensure participants were familiar with the tools and understood the steps required for the task.

During the task, measures were taken to evaluate both objective and subjective performance. Assembly time and assembly quality were used as the primary indicators of performance. Assembly time was recorded from the moment participants picked up the first part until the entire assembly was completed, with pauses applied only in cases of unrelated interruptions (e.g., emergency maintenance). Assembly errors were defined as any deviations from the AR guidance or task instructions that negatively impacted assembly quality. In addition to objective measures, participants' user experience (UX) was assessed using the AttrakDiff Mini questionnaire (Diefenbach & Hassenzahl, 2010), which evaluates UX on a 7-point scale, and their subjective workload was assessed using the NASA TLX questionnaire (Hart & Staveland, 1988), quantified on a scale from 0 to 100.

The survey was conducted from January 2024 to February 2024 at the laboratory's collaborative robot workstation, equipped with all the tools needed for assembly, HoloLens 2, and an iiwa KUKA collaborative robot. Two investigators recorded the assembly time and accuracy. Other dependent variables were measured through an online survey questionnaire completed by participants after the assembly task. Statistical analysis of the hypothesized differences in measurements of dependent variables was conducted using paired t-tests with IBM SPSS Statistics 27. Due to the issue of multiple testing when re-testing the same samples, the α level was adjusted according to Hochberg with a Bonferroni correction (Hochberg, 1988). This means the threshold for statistical significance was corrected to reduce the risk of false positives when conducting multiple comparisons. An alpha level of $\alpha^* = 0.033$ was applied for this laboratory study.

5.4.5 Results

In this section, I present the results of my experimental study aimed at evaluating the effectiveness of an AR-assisted HRC system on user experience, assembly performance, and cognitive workload. To assess UX and cognitive workload, I utilized the AttrakDiff Mini questionnaire and the NASA TLX questionnaire, respectively. Statistical analysis of the hypothesized differences in measurements of dependent variables was conducted using repeated-measures ANOVA with IBM SPSS Statistics 27. Due to the issue of multiple testing when re-testing the same samples, the α level was adjusted according to Hochberg with a Bonferroni correction (Hochberg, 1988). Descriptive statistics of experiment results are shown in Table 5.1 and the results of inferential statistics were shown in Table 5.2.

Table 5.1 Descriptive statistics of experiment results.

User Experience		
	μ	σ
AR-Robot	4.94	0.75
No AR-Robot	4.21	0.84
No AR-No Robot	3.47	1.08

Assembly Time		
	μ	σ
AR-Robot	8'37"	00'42"
No AR-Robot	8'19"	01'02"
No AR-No Robot	6'33"	02'01"

NASA TLX		
	μ	σ
AR-Robot	7.91	3.05
No AR-Robot	8.91	2.57
No AR-No Robot	11.10	2.89

Assembly Accuracy		
	μ	σ
AR-Robot	97.49%	0.95
No AR-Robot	81.94%	1.05
No AR-No Robot	71.66%	1.26

Table 5.2 Statistical analysis of experiment results.

User Experience		
	Mean Difference	*P*
AR-Robot vs **No AR-Robot**	0.723	<0.001
AR-Robot vs **No AR-No Robot**	1.470	<0.001
No AR-Robot vs **No AR-No Robot**	0.747	0.019

Assembly Time		
	Mean Difference	*P*
AR-Robot vs **No AR-Robot**	18.400	0.653

AR-Robot vs **No AR-No Robot**	124.167	<0.001
No AR-Robot vs **No AR-No Robot**	105.767	<0.001

NASA TLX

	Mean Difference	*P*
AR-Robot vs **No AR-Robot**	-1	0.178
AR-Robot vs **No AR-No Robot**	-3.194	<0.001
No AR-Robot vs **No AR-No Robot**	-2.194	0.001

Assembly Accuracy

	Mean Difference	*P*
AR-Robot vs **No AR-Robot**	15.557%	0.001
AR-Robot vs **No AR-No Robot**	25.836%	<0.001
No AR-Robot vs **No AR-No Robot**	10.280%	0.07

The analysis shows that the main effect of conditions on UX is significant, $F(2, 58) = 21.64$, $p < .001$, $\eta^2 = .427$, indicating that AR and robot use have a significant impact on UX. The post facto pair-comparison further shows that the AR-Robot condition produces a significantly higher UX score than the No AR-Robot and No AR-No Robot conditions ($p < .001$ for both comparisons), suggesting that augmented reality provides a more positive user experience compared to other methods. In addition, UX scores in the No AR-Robot condition were significantly higher than those in the No AR-No Robot condition (p =.019), which means that robot-assisted assembly improves user satisfaction compared to manual assembly without technical support. The average UX score for each condition showed that the AR-Robot condition produced the highest UX score (M = 4.94, SD = 0.75), followed by the No AR-Robot condition (M = 4.21, SD = 0.84) and the No AR-No Robot condition (M = 3.47, SD = 1.08). This model supports the hypothesis that technology-enhanced assistance, particularly through augmented reality, has a positive impact on user experience in complex assembly tasks.

For cognitive workload, the repeated measures ANOVA indicated a significant main effect of condition, F (2, 58) = 15, p < .001, η^2 = .341. This result suggests that the type of assembly support significantly influenced participants' cognitive workload. Pairwise comparisons revealed that the AR-Robot condition (M = 7.91, SD = 3.05) resulted in a lower cognitive workload compared to the No AR-No Robot condition (M = 11.10, SD = 2.89), with a mean difference of -3.194, p < .001. Additionally, the No AR-Robot condition (M = 8.91, SD = 2.57) also showed a significantly lower cognitive workload than the No AR-No Robot condition, with a mean difference of -2.194, p = .001. However, the difference in cognitive workload between the AR-Robot and No AR-Robot conditions was not statistically significant (mean difference = -1, p = 0.178).

In terms of assembly time, there was a significant main effect of condition, F (2, 58) = 19.43, p < .001, η^2 = .401. This result indicates that the type of assembly support significantly influenced the time required to complete the task. Pairwise comparisons showed that the AR-Robot condition (M = 8'37", SD = 42") and the No AR-Robot condition (M = 8'19", SD = 1'02") did not differ significantly in assembly time (mean difference = 18.4 seconds, p = 0.653). However, both conditions with robotic assistance took significantly longer than the fully manual No AR-No Robot condition (M = 6'33", SD = 2'01"). Specifically, the AR-Robot condition took an additional 124.167 seconds compared to the No AR-No Robot condition ($p < .001$), and the No AR-Robot condition took 105.767 seconds longer than the No AR-No Robot condition ($p < .001$).

The analysis for assembly accuracy revealed a significant main effect of condition, F (2, 58) = 19.76, $p < .001$, $\eta^2 = .405$. This result indicates that the type of assembly support significantly influenced the accuracy of task completion. Pairwise comparisons (see Pairwise Comparisons table) showed that the AR-Robot condition (M = 97.49%, SD = 0.95%) resulted in significantly higher assembly accuracy than both the No AR-Robot condition (M = 81.94%, SD = 1.05%) and the No AR-No Robot condition (M = 71.66%, SD = 1.26%). Specifically, the AR-Robot condition showed a mean difference of 15.557% compared to the No AR-Robot condition (p = .001) and a mean difference of 25.836% compared to the No AR-No Robot condition ($p < .001$). Although the No AR-Robot condition had a higher accuracy than the No AR-No Robot condition, this difference was not statistically significant (mean difference = 10.280%, p = .07).

5.5 Discussion

The findings from my study underscore the significant benefits of integrating AR into HRC systems in assembly operations. This discussion section will explore the implications of these results, emphasizing the uniqueness of my UX design process based on a real industrial case, comparing them with existing literature, and suggesting potential areas for future research.

My results are consistent with the findings of other studies that have explored the integration of AR in industrial applications. For instance, Liu and Wang demonstrated that AR-based worker support systems could enhance task performance and reduce error rates in human-robot collaborative environments (Liu and Wang, 2017). Similarly, Kousi et al. highlighted the benefits of AR in improving the flexibility and efficiency of production systems (Kousi et al., 2019).

What sets my study apart is the comprehensive evaluation of both UX and assembly performance metrics and the application of these findings to a real industrial case. By focusing on user-centric outcomes alongside traditional performance metrics, my research offers a more complete understanding of the impact of AR on assembly operations.

5.5.1 User Experience and Cognitive workload

The AR-assisted HRC system demonstrated substantial improvements in UX. These enhancements can be attributed to the intuitive and interactive nature of AR, which likely made the assembly tasks more engaging and less cognitively demanding. My findings align with prior research indicating that AR can significantly enhance user satisfaction and engagement in various interactive systems.

Cognitive workload, as measured by the NASA TLX questionnaire, was significantly lower in the AR-Robot condition and No AR-Robot condition compared to No AR-No Robot condition. This reduction in cognitive workload highlights that the presence of a collaborative robot can make complex tasks more manageable by providing physical assistance, which reduces cognitive demands. Although AR did not significantly lower cognitive workload compared to the HRC condition, it may still contribute additional real-time guidance and feedback that enhance task comprehension and efficiency. These results corroborate earlier studies that highlighted the potential of AR in mitigating cognitive strain in industrial settings.

5.5.2 Assembly Performance

My study revealed that the AR-assisted HRC system significantly improved assembly accuracy, achieving a mean accuracy of 97.49%, substantially higher than No AR-Robot condition and No AR-No Robot condition. This improvement is likely due to the precise and clear instructions provided through AR, which help minimize human errors. Previous research has also documented similar improvements in task accuracy when using AR systems in various applications, including manufacturing and maintenance.

However, the assembly time was slightly longer for the AR-assisted HRC system than the traditional HRC system, although this difference was not statistically significant. This minor increase in time could be due to the initial learning curve associated with using the AR system. Despite this, the significant improvement in accuracy may justify the marginally longer assembly time, as higher accuracy reduces the need for rework and increases overall efficiency in the long run.

5.5.3 Integration of User Experience Design in Real Industrial Context

A distinctive aspect of my study is integrating a UX design process based on a real industrial case. By conducting observations and interviews at the HWASDAN conveyor belt assembly workshop, I gathered authentic insights into the operational conditions and challenges that workers must face. This approach allowed us to tailor my AR-assisted HRC system specifically to the needs and behaviours of actual users in a real-world setting.

The service blueprint used to document and analyse these insights highlighted critical pain points in the traditional assembly process, such as cognitive strain due to varied product specifications and frequent errors in part identification and assembly. By addressing these pain points through my AR-HRC system, I were able to design a solution that not only improved performance metrics but also significantly enhanced user experience.

This real-world application of UX design principles is a key contribution of my study, demonstrating how user-centred design methodologies can be effectively applied to industrial settings to achieve meaningful improvements in both efficiency and worker satisfaction.

5.5.4 Transition from Classical Approaches to AR-based Systems

One significant gap worth discussing is the transition from classical approaches to AR-based systems. Implementing AR technology in an industrial setting can be a complex and time-consuming process, often taking several months. During this transition period, companies can adopt interim solutions to bridge the gap and gradually integrate AR. Literature suggests several approaches that can be applied before fully moving into AR: (1) Enhanced Training Programs: Implementing comprehensive training programs focused on AR principles and basic functionalities can prepare workers for the upcoming technological shift. Utilizing simulations and VR environments can help workers become familiar with AR interfaces and operations. (2) Incremental Integration: Gradually introducing AR components into the existing workflow can ease the transition. For instance, starting with AR-based instructional aids for complex tasks can help workers adapt to the new system without overwhelming them. (3) Hybrid Systems: Combining traditional methods with AR elements can create a hybrid system that leverages the strengths of both approaches. This can include using AR for specific high-error tasks while maintaining classical methods for routine operations.

5.5.5 Lack of Development Tools for Customizing AR system

Another critical gap is the lack of development tools that allow for the quick customization of AR systems for industrial applications. The current landscape shows a deficiency in libraries and frameworks tailored for rapid AR app development, which hinders the scalability and adaptability of AR technologies in manufacturing.

To address this, future work could focus on developing robust development frameworks and toolkits that provide: Modular Libraries: (1) Modular Libraries: These libraries can offer pre-built AR components that can be easily customized and integrated into different industrial processes. (2) User-Friendly Interfaces: Development tools with intuitive interfaces can enable non-expert users to create and modify AR applications, reducing dependency on specialized developers. (3) Interoperability Standards: Establishing standards for AR systems can ensure compatibility and integration with existing industrial software and hardware.

5.5.6 Implications for Practice

Integrating AR into HRC systems holds significant practical implications for the manufacturing industry. Enhanced user experience and reduced stress levels can increase worker satisfaction and retention, crucial for maintaining a skilled workforce. Moreover, the substantial improvement in assembly accuracy can translate into higher product quality and reduced rework and quality control costs.

To maximize AR's benefits, companies should invest in comprehensive training programs to familiarize workers with AR technologies. Additionally, iterative testing and refinement of AR interfaces are essential to ensure that they meet the specific needs of users and the tasks at hand.

Future research should explore the long-term effects of AR integration on worker performance and satisfaction. Studies could investigate how continuous use of AR affects learning curves, skill development, and job satisfaction over time. Additionally, research could examine the scalability of AR-assisted HRC systems in different manufacturing contexts and for various types of assembly tasks. Further investigation into the development of comprehensive toolkits for AR customization, focusing on modularity, user-friendliness, and interoperability, is also needed.

5.6 Contributions

Chapter 5 makes a significant contribution by introducing and empirically validating an AR-assisted HRC) system tailored for complex industrial assembly tasks. Grounded in real-world insights gathered from observations and interviews at the HWASDAN conveyor belt assembly workshop, the system was designed using a user-centered design (UCD) process that directly responds to practical challenges faced by operators, such as frequent part misidentification and cognitive overload. The AR system integrates real-time visual guidance via HoloLens 2, a collaborative robot equipped with a custom-designed electromagnet end-effector, and a robust control architecture to support adaptive, precise assembly workflows. This integration allows operators to perform tasks with greater clarity and accuracy, while the system dynamically adjusts to support user needs in cognitively demanding environments.

The effectiveness of the AR-assisted HRC system was validated through a controlled experiment involving thirty participants, comparing three conditions: AR with robot assistance, robot assistance without AR, and manual assembly using paper instructions. Results revealed that the AR-enhanced condition significantly outperformed the others in terms of assembly accuracy (97.49%), user experience (as measured by the AttrakDiff Mini), and reduced cognitive workload (NASA-TLX). Although assembly time was slightly longer with the AR system, this was offset by substantial gains in quality and user satisfaction. Notably, this chapter completes a full UX design workflow—from initial user research to iterative development and evaluation—within an industrial setting. This work not only demonstrates the tangible benefits of AR in improving user experience and task performance but also offers a replicable methodological framework for future research and implementation in smart manufacturing systems.

5.7 Summary

This chapter successfully demonstrated the application of an AR-assisted collaborative robotic system to enhance UX, assembly performance, and cognitive workload in a manufacturing context. By employing a user-centred approach, the study evaluated the effectiveness of AR and collaborative robotics in improving assembly accuracy, reducing cognitive strain, and enhancing user satisfaction. The structured methodology, which included both objective performance measures and subjective user feedback, provides valuable insights into the potential of integrating AR technologies into industrial assembly tasks.

Key findings from this chapter highlight the significant advantages of AR in reducing errors, improving assembly quality, and offering real-time guidance that supports users in complex tasks. The integration of collaborative robots further emphasized the benefits of shared tasks between humans and machines, balancing physical workload and cognitive demands. The use of tools such as AttrakDiff Mini and NASA TLX provided a comprehensive understanding of user perceptions, satisfaction, and workload, contributing to the validation of the AR-assisted system as a viable solution for industrial applications.

Importantly, this chapter illustrates the completion of the entire UX design workflow, encompassing user research, task analysis, system design, prototyping, testing, and evaluation. This comprehensive process ensures research aligns with real-world industrial needs while addressing critical gaps in literature. The findings pave the way for practical implementation in manufacturing environments and provide a solid foundation for future exploration.

Building on this work, the final chapter transitions to discussing broader measurement challenges in UX evaluation. Specifically, it identifies the limitations of existing tools, which are often too general and not tailored to manufacturing contexts. To address this, the next chapter proposes the development of a specialized tool grounded in the conceptual framework established in Chapter 3. This tool aims to refine and advance the measurement of UX in manufacturing, addressing domain-specific requirements and offering a more precise, impactful solution for evaluating human-robot interaction in industrial settings.

Chapter 6 Developing Specialized UX Evaluation Tools for Manufacturing Human-Robot Interaction (HRI)

6.1 Introduction

In previous chapters, this thesis has explored how modern manufacturing demands for product personalization and customization have created significant challenges for maintaining efficient production processes, necessitating the integration of advanced HRI systems. Chapter 3 established a conceptual framework for understanding the critical dimensions of UX in manufacturing HRI, such as operational efficiency, trust, and cognitive workload. Chapter 5 applied this framework in the context of an AR-assisted collaborative robotic system, demonstrating how user-centered design approaches can improve assembly performance, enhance user satisfaction, and reduce cognitive strain. These findings underscored the importance of aligning HRI technologies with the unique requirements of industrial environments, providing a strong foundation for further investigation.

Building on these insights, this chapter focuses on addressing a critical limitation identified in previous chapters: the lack of specialized tools for measuring UX in manufacturing HRI. While existing UX evaluation methods have been adapted from consumer-focused applications, they are often inadequate for capturing the complexity, precision, and unique demands of industrial tasks. The need for a domain-specific measurement tool that reflects the operational and cognitive challenges faced by human operators in manufacturing is evident.

This chapter introduces the development of a tailored UX evaluation tool for manufacturing HRI, grounded in the framework established in Chapter 3 and informed by the practical findings in Chapter 5. By focusing on operational efficiency, cognitive usability, and trust, this chapter aims to bridge the gap between generic UX evaluation tools and the specific needs of manufacturing environments. The proposed tool is designed to provide actionable insights for researchers and practitioners, enabling more effective and human-centred HRI system design.

6.2 Related Works

6.2.1 Research on HRI in Manufacturing

As discussed in previous chapters, HRI plays a pivotal role in modern manufacturing, driving improvements in productivity, safety, and adaptability. Prior research has emphasized the dual benefits of cobots, which combine robotic precision with human oversight to meet the growing demand for flexible, small-batch, and customized production (Villani et al., 2018, Prati et al., 2021a). While these advancements highlight the technological potential of HRI systems, many studies have focused on operational efficiency rather than addressing human-centred aspects, such as UX, cognitive workload, and trust (Wang et al., 2017, Kopp et al., 2021).

6.2.2 Role of User Experience in Manufacturing HRI

UX is increasingly recognized as a critical factor in the adoption and effectiveness of HRI systems. As discussed earlier, UX extends beyond usability to include dimensions such as reliability, safety, and personalization, which directly impact user satisfaction and system performance. However, existing UX evaluation tools, such as general usability scales (e.g., SUS, AttrakDiff), lack the specificity needed to address the unique demands of manufacturing environments (Hassenzahl, 2008, Diefenbach et al., 2014). This gap highlights the necessity of developing specialized UX evaluation tools tailored to industrial HRI contexts.

6.2.3 Assessment of User Experience

Over the years, many scales have been developed to assess user experience (UX) across various contexts. These scales reflect evolving trends and a deeper understanding of what constitutes a positive user experience. In early research concerning UX assessment, the focus was primarily on usability. The System Usability Scale (SUS), introduced by John Brooke in 1986, became one of the most widely used tools for quickly evaluating the usability of a system (Brooke, 1996a). SUS is a simple, ten-item questionnaire that allowed researchers to gauge how easy and pleasant a system was to use (Brooke, 1996a).

As the field matured, it became evident that usability alone could not capture the full spectrum of user experience. The User Experience Questionnaire (UEQ), developed by Schrepp et al., expanded the assessment criteria to include both pragmatic qualities like efficiency and dependability, and hedonic qualities such as stimulation and identification (Schrepp et al., 2017). This broader approach highlighted the importance of users' emotional and motivational responses to interacting with a product.

Similarly, the AttrakDiff scale, developed by Hassenzahl and colleagues, emphasizes the dual nature of UX by distinguishing between pragmatic and hedonic qualities. Using a semantic differential technique, this scale captures users' perceptions of both the functional and pleasurable aspects of a product (Hassenzahl et al., 2003b). For example, the hedonic aspects measured by AttrakDiff include how stimulating and novel the product feels, as well as the pleasure derived from using the product's design and features (Hassenzahl et al., 2003a). This reinforced the idea that a comprehensive UX assessment must account for both utilitarian and experiential dimensions.

As the focus on holistic UX assessment grew, researchers recognized the need for specialized tools tailored to specific contexts, since general UX measures often failed to capture unique factors relevant to different domains (Marques et al., 2021). For instance, the Game Experience Questionnaire (GEQ) was designed to measure unique aspects of user experience in gaming, including factors like immersion, flow, and competence (IJsselsteijn et al., 2013). Similarly, the Technology Acceptance Model (TAM) evolved to include perceived enjoyment as a critical factor influencing technology adoption, reflecting a broader understanding that positive emotional responses drive user engagement and acceptance (Silva, 2015).

While these scales are useful in their respective domains, applying them directly to manufacturing settings presents challenges. The unique environment of manufacturing involves complex, repetitive tasks that require high precision and seamless integration with existing industrial processes (Kopp et al., 2021). These specific conditions are not fully addressed by scales developed for consumer products or general UX assessment (Spatola et al., 2021). For instance, the emotional satisfaction and enjoyment (Hassenzahl et al., 2003a) derived from using a household product may not translate directly to the satisfaction experienced by an operator interacting with a cobot on an assembly line (Apraiz et al., 2023). Additionally, the stakes in manufacturing environments are higher, with potential impacts on safety, productivity, and worker well-being (Spatola et al., 2021). Therefore, specialized tools and methodologies tailored to the unique requirements of manufacturing HRI are necessary to capture the full spectrum of user experience in these settings

Incorporating UX into manufacturing HRI is crucial, as it enhances operational efficiency and user satisfaction within constrained interactions (Lorenzini et al., 2023). Despite these advances, current methodologies still lack robust, industry-specific UX evaluation frameworks. This study aims to address this gap by developing a specialized evaluation scale for assessing HRI UX in manufacturing environments. By doing so, it will provide a tool for practitioners to enhance both the design and implementation of HRI systems, ultimately improving efficiency and user satisfaction in industrial settings.

6.3 Experimental Methodology

6.3.1 Participants

The study recruited manufacturing professionals with direct experience in HRI from various industries, including automotive assembly, component processing, chip manufacturing, engine production, wheel hub processing, and household appliance manufacturing. Participants held diverse roles such as industrial line operators, maintenance engineers, safety managers, quality assurance personnel, and system designers to ensure a comprehensive representation of different perspectives within manufacturing environments.

An initial dataset of 358 responses was collected, but after data cleaning and quality checks, 215 valid responses were retained for analysis. The final sample included participants with varying levels of experience in HRI, ranging from those new to robot-assisted work environments to highly experienced professionals. To ensure relevance, only those who had direct interaction with robotic systems in manufacturing were included in the study. Participants also provided demographic information such as age, gender, education level, years of experience working with robots, and the types of robotic systems used in their workplaces. With accordance to the recommendation of Comrey (2013), as a rule of thumb, 200 is considered to be an adequate sample size for exploratory factor analyses (Comrey and Lee, 2013).

The data for this study were collected through a structured questionnaire distributed to employees in the manufacturing sector who interact or collaborate with robots. I selected a variety of manufacturing enterprises, including automotive assembly, component processing, chip manufacturing, engine manufacturing, wheel hub processing, and household appliance manufacturing, to ensure representativeness across the industry, company list see Table 6.1. To capture a broad spectrum of user experiences, I targeted different roles within these enterprises, such as Industrial Line Operators, Maintenance Engineers, Safety Managers, Quality Assurance Personnel, and System Designers and Developers, representing diverse job roles and departments as shown in Table 6.2.

Table 6.1 The Top 10 companies from which the participants came.

Company name
Haier Co., Ltd.
Lynk & Co (Geely Holding Group)
Bosch Hydrogen Power (Chongqing) Co., Ltd.
Dicastal Jieli Wheel Manufacturing Co., Ltd.
Chongqing Kanghui Machinery Manufacturing Co., Ltd.
Quanzhou Intelligent Manufacturing
Chongqing Genori Technology Co., Ltd.
Chongqing Automobile Muffler Co., Ltd.
Minsheng Logistics
Chongqing Zhicheng Machinery Co.,Ltd.
Chongqing Yanpu Auto Parts Co., Ltd.

Table 6.2 Participants and Sampling in Manufacturing.

Role	Action	Reason
Industrial Line Operators	Operate and monitor machinery with integrated robotic systems.	They directly interact with robotic systems, providing first-hand information on the usability and efficiency of HRI from an operator's perspective.
Maintenance Engineers	Perform regular maintenance and troubleshooting on robotic systems.	Their expertise in system functionality and maintenance gives insight into the long-term usability and serviceability of HRI.
Safety Managers	Implement safety protocols and conduct regular reviews of human-robot interaction zones.	They have a comprehensive understanding of the safety implications of HRI and the effectiveness of safety protocols.
Quality Assurance Personnel	Inspect and verify the quality of products produced with the assistance of robotic systems.	Their role in ensuring product quality offers a unique perspective on how HRI affect production outcomes and adherence to quality standards.
System Designers and Developers	Design user interfaces and develop software for robotics control systems.	They provide a critical view on the design and implementation of HRI, highlighting potential areas for improvement from a technical standpoint.

6.3.2 Materials

To develop an evaluation framework for UX in HRI within the manufacturing, my previous work used semi-structured interviews with factory robot operators to identify twelve themes most pertinent to HRI user experience in manufacturing: Efficiency, Accuracy, Reliability, Ergonomics, Interaction Interface Design, User Satisfaction, Trust, Safety, Personalization Settings, Ease of Learning, Usability, and Memory Burden. Based on these themes,

This study developed a scale which contains 44 items – 3 or 4 for each selected theme (See Table 6.3). Each item features a statement against which respondents indicate their degree of agreement on a 100-point scale – 1 (strongly disagree) to 100 (strongly agree).

To ensure the relevance of each question and the accuracy of its wording, a rigorous development process was implemented. This process involved a thorough review by three experts in the field. Each question was examined for clarity, appropriateness, and alignment with the research objectives. This iterative review process was conducted three times, with each round of review followed by necessary revisions.

Besides the 44 items in the HRI UX measures, the questionnaire also contains some demographic questions. The demographic section included questions on gender, age, company, education level, robot brand, work with robot experience and types of robots encountered in their jobs. Data were collected either in person or online. For online data collection in China, Chongqing, I used the Tencent Questionnaire platform, sending links to participants' mobile phones. The Chinese translation of the full questionnaire can be seen at the link: https://github.com/tongyanzhanggithub/UX-HRI-scale/tree/main/scale. The survey lasted for 20 days, and the average time to complete questionnaire was 568 seconds. All participants provided informed consent before participating.

Table 6.3 Preliminary HRI-UX assessment in manufacturing scale.

Themes	NO.	Question
Efficiency	Q1	The system's efficiency meets my expectations for the tasks at hand.
	Q2	I am able to complete tasks with the system within the expected time.
	Q3	The system's response speed meets my task needs.
	Q4	Using this system effectively reduces the working time for individual tasks.
Accuracy	Q5	The system's accuracy meets my expectations for the tasks at hand.
	Q6	The system performs tasks accurately with few errors.
	Q7	The information provided by the system is accurate and reliable for decision-making.
	Q8	The system's handling of complex tasks meets my accuracy requirements.
Reliability	Q9	I find the system reliable during operation.
	Q10	The system performs consistently during continuous use.
	Q11	I trust the system will not fail at critical moments.
	Q12	The system's maintenance and fault recovery capabilities give me confidence in its reliability.
Ergonomics	Q13	I have a comfortable working environment while interacting with the system.
	Q14	The system's physical layout is designed to make me feel comfortable.

	Q15	The physical interface of the system (such as buttons and switches) is easy to use.
	Q16	Prolonged interaction with the system does not cause me physical discomfort.
Interaction Interface Design	Q17	The design of the interactive interface is intuitive.
	Q18	The user interface design of the system is easy to operate.
	Q19	The design of interface elements (such as icons, buttons, and text) aligns with my usage habits.
	Q20	The interaction design of the system helps me complete tasks efficiently without causing confusion.
Ease of learning	Q21	I can quickly learn how to use the basic functions of the system.
	Q22	I do not feel a memory burden when using the system.
	Q23	I can easily learn how to use the system without extensive training.
	Q24	The learning difficulty of the system is reasonable for beginners.
Usability	Q25	The system is simple and easy to use.
	Q26	I find all the functions of the system useful in my daily work.
	Q27	I can use the system without frequently referring to the help documentation.
	Q28	The operation logic and user interface design of the system make daily use simple.
Memory Burden	Q29	I do not need to remember too much information to use the system effectively.
	Q30	The system's reminders and prompt features eliminate my memory burden.

	Q31	I rarely need to recall previous steps when operating the system.
User Satisfaction	Q32	I am satisfied with the overall experience of using this system.
	Q33	The system's performance and features meet my expectations.
	Q34	I would recommend this system to my colleagues.
Trust	Q35	I believe the system will maintain its performance standards.
	Q36	I trust the system to be secure and reliable in handling my information and tasks.
	Q37	I trust the system to respond correctly in unexpected situations.
Safety	Q38	I feel safe when interacting with the system.
	Q39	I feel safe during the operation of the system.
	Q40	The system's security measures give me confidence when using it.
	Q41	I am satisfied with the system's emergency response measures.
Personalization setting	Q42	The system provides sufficient personalization options to suit my work habits.
	Q43	I can easily adjust the system settings according to my preferences.
	Q44	The system's personalization settings help improve my work efficiency.

6.3.3 Design

The study followed an exploratory survey design with the primary goal of developing and validating a domain-specific UX evaluation tool for manufacturing HRI. The research objectives were: (1) to identify key UX factors in manufacturing HRI, (2) to refine the UX scale through factor analysis, and (3) to validate the instrument's internal consistency and construct validity.

Data were collected through a 20-day online and in-person survey distributed via workplace networks and professional contacts. To ensure robust measurement, the study employed exploratory factor analysis (EFA) to determine how UX-related factors clustered into meaningful subscales. The analysis was conducted using principal component extraction with Kappa 4 rotation, an oblique rotation method that allows factors to be interrelated.

To minimize response biases, the questionnaire included reverse-coded items, and responses with uniform ratings (e.g., all items marked as 50 or 100) were flagged and removed. Additionally, a minimum completion time of 200 seconds was enforced to ensure thoughtful responses.

6.3.4 Procedure

Participants were recruited through professional networks, workplace announcements, and direct email invitations. The survey was administered using the Tencent Questionnaire platform for online responses, while printed versions were distributed at selected industrial sites. Before participation, all respondents were presented with an information sheet detailing the study's objectives, risks, and expected contributions. They were required to sign an informed consent form acknowledging their voluntary participation and the confidentiality of their responses.

During the survey administration, participants were given clear instructions on how to complete the questionnaire, which took an average of 9.5 minutes (568 seconds). The survey included demographic questions, UX assessment items, cognitive workload measures (NASA-TLX), and an open-ended section for additional feedback.

After data collection, several preprocessing steps were conducted to ensure data quality. The initial dataset of 358 responses was filtered to remove (1) uniform or random responses, (2) submissions completed in above 200 seconds, and (3) respondents with no prior experience in HRI. After cleaning, 215 valid responses remained for analysis. According to established guidelines for EFA, a commonly recommended minimum sample size is between 5 to 10 participants per item, with an absolute minimum of 100 to 200 participants to ensure statistical validity and factor stability (Comrey and Lee, 2013, Hair, 2009). Given that the preliminary HRI-UX scale in this study included 44 items, the ideal sample size would range between 220 and 440 participants. The final valid dataset for this study includes responses from 215 participants, which is near the lower boundary of this recommended range and exceeds the minimum threshold suggested by several empirical studies. Therefore, the sample size is considered adequate for conducting EFA while ensuring the robustness of the findings.

6.4 Results

6.4.1 Descriptive Statistics

To gain a preliminary understanding of the demographic characteristics of the participants, I use SPSS 29.0 statistical software to conduct a general descriptive statistical analysis of the participants' gender, age, education level, and work with robot experience. The statistical results are shown in Table 6.4. The Table 6.5 describes the types of robots most used by the participants. The Table 6.6 shows six the robot brands most used by the participants.

Table 6.4 Description of Participants' Demographic Characteristics.

Attribute	Category	Frequency	Percentage
Gender	Male	191	88.8%
	Female	15	7%
	Prefer not to say	9	4.2%
Age	Under 18 years old	1	0.5%
	18 to 24 years old	23	10.7%
	25 to 30 years old	45	20.9%
	31 to 40 years old	78	36.3%
	41 to 50 years old	51	23.7%
	51 to 60 years old	9	4.2%
	Prefer not to say	8	3.7%
Education Level	Middle school and below	11	5.1%
	High school/Vocational school/Technical school	76	35.3%
	Associate degree	80	37.2%
	Bachelor's degree	31	14.4%
	Master's degree and above	5	2.3%
	Prefer not to say	12	5.6%
Work with Robot Experience	Less than 1 year	58	27%
	1 to 2 years	51	23.7%
	2 to 3 years	35	16.3%

3 to 4 years	31	14.4%
4 to 5 years	2	0.9%
More than 5 years	23	10.7%
More than 10 years	13	6%
More than 20 years	2	0.9%

Table 6.5 Type of robot for participants to work with.

Types of robots	Frequency	Percentage
Articulated Robots	158	73.5%
SCARA Robots	168	78.6%
Delta Robots	17	7.9%
Cartesian Robots	42	16.9%
Cylindrical Robots	37	17.2%
Polar or Spherical Robots	32	12.9%
Automated Guided Vehicles (AGV)	46	21.4%
Collaborative Robots (Cobots)	29	13.5%
Hybrid Robots	17	7.9%

Table 6.6 Robot brands for participants to work with.

Types of robot brand	Frequency	Percentage
KUKA	47	21.9%
ABB	52	24.2%
FANUC	21	9.8%
NANCHI	12	4.8%
Boston Dynamics	22	10.2%
KAWASAKI	16	7.4%

6.4.2 Inter-item Reliability and Validity Testing

Inter-item Reliability Analysis

Inter-item reliability is a crucial aspect of data consistency and dependability, reflecting the stability and authenticity of measurements. The Cronbach's alpha coefficient, ranging from 0 to 1, is the most widely used metric for assessing internal consistency, with values closer to 1 indicating higher reliability (Nunnally, 1975). Generally, a Cronbach's alpha value above 0.6 is acceptable, while values above 0.8 denote high reliability and practical value (Yockey, 2016).

Using SPSS 29.0 to analyse the reliability of my questionnaire. For my scale, the Cronbach's alpha coefficient is 0.989. Since the Cronbach's alpha value exceeds the acceptable threshold of 0.7, it indicates that the reliability of each scale is very high, and the questionnaire demonstrates excellent internal consistency.

Factor Analysis Suitability Assessment

Before conducting factor analysis, it's important to establish the validity of scale. Validity refers to the extent to which a scale accurately reflects the characteristics of the subject being measured, essentially assessing the effectiveness and correctness of the scale (Price et al., 2015). Higher validity indicates that the questionnaire results more accurately represent the true behaviours of the subjects being measured. Content validity and construct validity are commonly used indicators of validity. Content validity is a subjective indicator, and its evaluation primarily involves consulting experts to analyse and judge whether the measurement items effectively represent the content intended to be measured. Typically, the design process of a questionnaire can reflect its content validity. The questionnaire designed for this study was informed by previous research and was repeatedly revised and adjusted in consideration of the specific context of small and medium-sized enterprises; thus, it can be considered to have good content validity. Construct validity refers to the extent to which the measurement results explain a certain construct. Common indicators used to test construct validity include the Kaiser-Meyer-Olkin (KMO) value and Bartlett's Test of Sphericity. It is generally believed that a KMO value of 0.9 or higher is ideal, though values greater than 0.6 are also acceptable (Hair, 2009). The ideal significance level for Bartlett's Test of Sphericity is less than 0.05 (Hair, 2009).

If the KMO value exceeds 0.6 and the Bartlett's Test is significant with a p-value less than 0.01, exploratory factor analysis is considered appropriate. Given that my scale is derived is a relatively immature questionnaire, I conducted these tests on my scale as shown in the following Table 6.7.

Table 6.7 KMO and Bartlett's Test of Sphericity.

	KMO	DF	Bartlett’s Test of Sphericity	Sig.
HRI-UX Assessment in Manufacturing scale	0.969	946	11872.695	<0.001

Based on the results, the KMO values for the HRI-UX Assessment in Manufacturing scale is 0.968, respectively. The significance level of the Bartlett's Test of Sphericity is less than 0.001, meeting the requirements for conducting exploratory factor analysis.

6.5 Exploratory Factor Analysis (EFA)

In this study, SPSS 29.0 software was utilized to conduct an exploratory factor analysis on the HRI-UX Assessment in Manufacturing scale. EFA was chosen as the develop method because it simplifies the data structure by identifying a few latent factors that explain most of the observed variables, thereby enhancing the reliability and validity of the scale (Fabrigar et al., 1999). Principal Component Analysis (PCA) is employed for the factor analysis, with the extraction criterion set to eigenvalues greater than one. PCA for factor extraction because PCA effectively reduces the dimensionality of the data while retaining as much of the original information as possible, which helps identify the main components that best represent the data structure (Abdi and Williams, 2010). Additionally, I employed the Kappa 4 rotation method, an oblique rotation technique, which allows for correlations between factors, providing a clearer and more interpretable factor structure and simplifying the factor loading matrix (Browne, 2001). This method is more common in practical applications because the constructs being measured in real-world settings are often not entirely independent (Jennrich, 2002).

Items were screened based on the following criteria: items with factor loadings less than 0.4 were deleted, items with loadings greater than 0.4 on two or more common factors were also deleted, and items that did not match their expected category under the common factors were removed.

Subsequent analysis identified that the factor loading for item Q11 was below the threshold of 0.4, necessitating its exclusion from further analysis. Additionally, items exhibiting significant cross-loadings, with factor loadings exceeding 0.4 across two or more common factors—namely Q4, Q7, Q18, Q19, Q21, Q25, Q39 and Q41—were also removed. Items that did not conform to the established categories and lacked theoretical justification, such as Q9, Q16, Q28, Q30, Q36 and Q43, were further excluded. For example, item Q9, which was expected to load on the "Reliability" factor, did not align well with other items in this category and did not load significantly on any other factor either, indicating that it did not fit within the theoretical framework of the established categories. A revaluation through exploratory factor analysis subsequently revealed that the cumulative variance explained by the identified common factors was 72.935%, as presented in Table 6.8. It should be noted that only the first two components were retained based on the Kaiser criterion (eigenvalues > 1), and as such, Extraction and Rotation Sums of Squared Loadings are only reported for these components. For components 3 through 30, eigenvalues were below the threshold, and therefore no further extraction or rotation values were computed or displayed by the software. This is a standard outcome in exploratory factor analysis, as only components deemed significant are subjected

Table 6.8 Total Variance explained.

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	20.722	69.072	69.072	20.722	69.072	69.072	20.172
2	1.159	3.863	72.935	1.159	3.863	72.935	16.007
3	0.823	2.743	75.678				
4	0.612	2.039	77.716				
5	0.570	1.900	79.616				
6	0.523	1.744	81.360				
7	0.456	1.519	82.879				
8	0.432	1.439	84.319				
9	0.398	1.326	85.645				
10	0.382	1.272	86.917				
11	0.375	1.249	88.166				
12	0.354	1.180	89.346				
13	0.305	1.017	90.363				
14	0.301	1.004	91.368				

15	0.286	0.953	92.320
16	0.252	0.840	93.160
17	0.238	0.795	93.955
18	0.201	0.672	94.627
19	0.192	0.640	95.266
20	0.184	0.613	95.880
21	0.175	0.585	96.464
22	0.161	0.538	97.002
23	0.153	0.509	97.511
24	0.137	0.455	97.967
25	0.132	0.440	98.407
26	0.115	0.383	98.790
27	0.101	0.336	99.126
28	0.099	0.325	99.541
29	0.088	0.292	99.743
30	0.077	0.257	100

In this exploratory analysis, a total of two common factors were extracted from the scale, with each measurement item demonstrating a factor loading greater than the threshold of 0.5. Based on the specific measurement items included in each factor, these two common factors were named in sequence as: (1) Comprehensive operational efficiency. (2) Cognitive Usability. As presented in Table 6.9.

Table 6.9 Pattern matrix.

Component	Comprehensive operational efficiency	Cognitive Usability
Q1. The system’s efficiency meets my expectations for the tasks at hand.	0.783	
Q2. I am able to complete tasks with the system within the expected time.	0.780	
Q3. The system’s response speed meets my task needs.	0.805	
Q5. The system’s accuracy meets my expectations for the tasks at hand.	0.964	
Q6. The system performs tasks accurately with few errors.	0.710	
Q8. The system’s handling of complex tasks meets my accuracy requirements.	0.831	
Q10. The system performs consistently during continuous use.	0.908	
Q12. The system’s maintenance and fault recovery capabilities give me confidence in its reliability.	0.782	
Q13. I have a comfortable working environment while interacting with the system.	0.688	
Q14. The system’s physical layout is designed to make me feel comfortable.	0.825	
Q15. The physical interface of the system (such as buttons and switches) is easy to use.	0.920	
Q17. The design of the interactive interface is intuitive.	0.776	

Q20. The interaction design of the system helps me complete tasks efficiently without causing confusion.	0.743	
Q22. I do not feel a memory burden when using the system.		0.753
Q23. I can easily learn how to use the system without extensive training.		0.941
Q24. The learning difficulty of the system is reasonable for beginners.		0.662
Q26. I find all the functions of the system useful in my daily work.		0.476
Q27. I can use the system without frequently referring to the help documentation.		0.680
Q29. I do not need to remember too much information to use the system effectively.		0.927
Q31. I rarely need to recall previous steps when operating the system.		0.691
Q32. I am satisfied with the overall experience of using this system.	0.869	
Q33. The system's performance and features meet my expectations.	0.836	
Q34. I would recommend this system to my colleagues.	0.804	
Q35. I believe the system will maintain its performance standards.	0.813	
Q37. I trust the system to respond correctly in unexpected situations.	0.675	
Q38. I feel safe when interacting with the system.	0.631	

Q40. The system's security measures give me confidence when using it.	0.699
Q41. I am satisfied with the system's emergency response measures.	0.892
Q42. The system provides sufficient personalization options to suit my work habits.	0.606
Q44. The system's personalization settings help improve my work efficiency.	0.826

Table 6.10 Factor Structure and Corresponding Questionnaire Items.

Factor	Theme	Item Numbers	Cronbach's Alp
Factor 1: Comprehensive Operational Efficiency	Efficiency	Q1, Q2, Q3	0.983
	Accuracy	Q5, Q6, Q8	
	Reliability	Q10, Q12	
	Ergonomics	Q13, Q14, Q15	
	Interaction Interface Design	Q17, Q20	
	User Satisfaction	Q32, Q33, Q34	
	Trust	Q35, Q37	
	Safety	Q38, Q40, Q41	
	Personalization Settings	Q42, Q44	
Factor 2: Cognitive Usability	Ease of Learning	Q22, Q23, Q24	
	Usability	Q26, Q27	
	Memory Burden		

The Table 6.10 presents the results of the factor analysis conducted on the questionnaire items used to evaluate user experience in HRI within manufacturing environments. Two distinct factors emerged from the analysis: Factor 1: Comprehensive Operational Efficiency (Cronbach's alpha = 0.983) captures aspects related to the overall performance of robotic systems from the user's perspective. It encompasses multiple themes such as system efficiency, accuracy, reliability, ergonomics, interface design, user satisfaction, trust, safety, and personalization. This factor reflects how effectively and safely the robot functions in a production setting, as perceived by the users. Factor 2: Cognitive Usability (Cronbach's alpha = 0.920) focuses on the cognitive dimension of the user experience; particularly how easy it is for users to learn and operate the system. Themes under this factor include ease of learning, general usability, and the mental effort required (memory burden). This reflects users' cognitive workload and how intuitive the system is to use. High Cronbach's alpha values for both factors indicate strong internal consistency, suggesting that the items grouped under each factor reliably measure their respective constructs.

6.6 Discussion

This study successfully developed a specialized evaluation scale for assessing HRI UX in manufacturing environments. The scale, divided into 'Comprehensive Operational Efficiency' and 'Cognitive Usability', provides a robust framework for evaluating the effectiveness and usability of robotic systems in manufacturing. Through EFA, I ensured the reliability and validity of the scale, confirming its applicability in real-world settings

The new HRI UX evaluation scale has significant implications for the manufacturing industry. It offers a practical tool for companies to assess and improve the interaction between workers and robots, thereby potentially enhancing overall productivity and operator satisfaction. By addressing both technological performance and user experience aspects, this scale promotes a more holistic approach to integrating robotic technology in manufacturing, contributing to the sustainable development of the industry. Moreover, improving HRI UX can potentially lead to better working conditions for employees by making interactions with robots more intuitive and user-friendly.

The application of my HRI UX scale in various manufacturing settings demonstrates its versatility and relevance. For instance, in automotive assembly lines, the scale can help identify specific areas where the interaction between humans and robots can be improved, potentially leading to more efficient production processes. Similarly, in electronic component manufacturing, where precision and reliability are paramount, the scale can be used to evaluate how effectively robots are supporting human workers, which can inform strategies to reduce errors and enhance productivity. Nevertheless, the insights gained from applying this scale can inform the design and development of future robotic systems. By understanding the specific needs and challenges faced by human operators, designers can create more intuitive and user-friendly interfaces, ultimately enhancing the overall effectiveness of HRI in manufacturing settings. This user-centered approach is critical for the successful integration of advanced robotic technologies in industry.

However, one notable difference between my scale and other established UX scales is the apparent absence of a "hedonic" aspect, which pertains to the pleasure and enjoyment derived from using a system. Traditional UX scales, such as the AttrakDiff (Hassenzahl et al., 2003b) and the UEQ (Schrepp et al., 2017) emphasize both pragmatic and hedonic qualities to capture the full spectrum of user experience. While my scale focuses on operational efficiency and cognitive usability, the inclusion of hedonic elements could provide a more holistic understanding of UX in manufacturing HRI. Future research could explore the integration of hedonic aspects to evaluate how enjoyment and emotional satisfaction influence the acceptance and effectiveness of HRI systems in industrial contexts.

Despite the promising results, this study has several limitations. The sample size was relatively small, and data were collected from a limited number of manufacturing settings. Moreover, all data were collected in China, so the results might not be generalizable. Furthermore, the scale was translated into Chinese, and results need to be interpreted with caution due to possible translation errors. Future research should aim to include a larger and more diverse sample to validate and refine the scale further. Additionally, the exploratory factor analysis, while effective, may not fully capture all dimensions of HRI UX in diverse industrial contexts. Future research could benefit from incorporating more diverse data collection methods, such as direct observation and experimental designs, to gain a comprehensive understanding of HRI UX.

Expanding this research to include other types of industrial environments will ensure the robustness and versatility of the HRI UX evaluation scale. It is also crucial to investigate the impact of improved user interface designs on reducing cognitive load and increasing user satisfaction. Future studies should aim to design better user interfaces and interaction methods, potentially incorporating augmented reality (AR) and virtual reality (VR) technologies to provide more intuitive and interactive user experiences. Furthermore, integrating advanced technologies such as AI and machine learning into HRI systems could be explored to enhance UX further. These technologies have the potential to make robotic systems more adaptive and responsive to the needs of human operators, thereby improving the overall efficiency and satisfaction of HRI in manufacturing environments.

6.7 Contributions

This chapter represents a distinctive and culminating contribution of the thesis: the development of a specialized UX evaluation tool tailored for manufacturing HRI. Unlike traditional UX instruments that are often generic and not well-suited to industrial environments, the tool introduced here is grounded in the conceptual framework established in Chapter 3 and refined through rigorous empirical studies described in Chapters 4 and 5. Its design reflects real-world manufacturing challenges, incorporating insights from both qualitative interviews and large-scale survey data, thereby ensuring both theoretical robustness and practical relevance.

What sets this contribution apart is its dual capacity for precision and adaptability. While purpose-built for manufacturing contexts, the structure and methodology of the tool —such as the use of factor analysis to define key dimensions like operational efficiency and cognitive usability—can be adapted to other high-stakes or collaborative environments where humans interact with complex systems. For example, it holds potential for adaptation in sectors like healthcare robotics, warehouse automation, and collaborative AI interfaces. This positions the UX tool not only as an endpoint of the thesis's design process but also as a transferable resource that extends the impact of the research beyond its immediate domain.

6.8 Summary

This chapter successfully developed and tested a specialized evaluation scale for assessing HRI UX in manufacturing environments. The new scale, divided into two primary subscales – "Comprehensive Operational Efficiency" and "Cognitive Usability" – offers an effective framework for evaluating the effectiveness and usability of robotic systems in manufacturing settings. By focusing on both operational efficiency and cognitive usability, the scale addresses the multifaceted nature of user interactions with robotic systems. Through rigorous validation using EFA, the study ensures the reliability and validity of the developed scale. This validated tool can be used by manufacturing companies to assess and improve their HRI systems, leading to enhanced productivity and user satisfaction. The research fills a significant gap in the existing literature by providing a dedicated UX evaluation tool for manufacturing environments. It also offers practical insights for industries looking to integrate advanced robotic technologies while maintaining a focus on user experience.

Chapter 7 Achievements and conclusions

7.1 Achievements

This thesis adopts a structured UX Design Approach, systematically addressing critical UX dimensions in HRI to improve operational performance, user trust, and satisfaction in manufacturing environments. A key contribution of this research lies in presenting a comprehensive integration of UX design principles at each stage of the HRI development process, demonstrating how user-centred methodologies can be effectively applied to real-world industrial challenges. The key achievements are organized around the core stages of the UX design workflow: user research, problem definition and goal setting, conceptual design and prototyping with iterative testing, and implementation and validation.

The research begins with an extensive user research phase, involving qualitative interviews with manufacturing operators to identify critical UX dimensions in HRI. These dimensions include trust, cognitive load, efficiency, and ergonomics. Insights from this phase informed the development of a tailored HRI UX Assessment Framework, specifically designed to evaluate user interactions in industrial contexts. This framework identifies twelve key factors shaping effective human-robot collaboration and provides a foundation for subsequent design and evaluation efforts. This phase aligns with the discovery stage of the UX workflow, ensuring the research addresses real-world user needs.

Building on these insights, the thesis transitions to the problem definition and goal setting phase, addressing the identified gaps in evaluating UX in industrial HRI. The study formalized these findings into actionable goals, leading to the development of a specialized self-report evaluation tool, like chapter 6. This tool systematically measures dimensions such as operational efficiency and cognitive usability. Through EFA, the tool was validated as a reliable method for assessing and optimizing UX in manufacturing environments. By bridging qualitative insights and quantitative metrics, this stage provided a robust foundation for advancing UX evaluation in HRI.

The research further progressed to conceptual design and prototyping with iterative testing, presenting two AR-based case studies to address key UX challenges in manufacturing HRI. The first case study focused on AR facial expressions to enhance trust in collaborative robots. This prototype enabled robots to visually communicate task states and intentions through expressive animations displayed in AR, addressing critical UX dimensions of transparency and cognitive load. While this prototype demonstrated AR's potential for fostering trust and improving communication, the findings revealed several limitations. Participants found the AR-enhanced facial expressions helpful for understanding robot states but noted that the task itself—focused on conveying trust through simple visual cues—lacked the complexity and cognitive demands required to fully showcase AR's immersive capabilities. Moreover, the novelty of AR technology may have contributed to participants' mixed reactions, highlighting the need to explore its application in more intricate and task-specific industrial scenarios. Building on these reflections, the second case study was developed as an extension of the first, aiming to address the identified limitations by applying AR to a more demanding industrial context. This case study, an AR-assisted HRC system, targeted task performance by incorporating AR elements that reduced cognitive strain, improved assembly accuracy, and enhanced user engagement in precision-driven tasks. By integrating AR into the assembly process, the second study sought to capitalize on AR's strengths while addressing the shortcomings observed in the first study. Both prototypes were designed based on insights from the user research phase, ensuring alignment with industrial needs and providing a logical progression between the studies. Rigorous usability evaluations and trust testing followed the prototyping phase, employing methods such as the AttrakDiff Mini and NASA TLX questionnaires. The AR-assisted HRC system demonstrated significant improvements in task accuracy and user satisfaction, while further emphasizing AR's ability to reduce cognitive workload. Together, the findings underscore the importance of iterative testing in refining solutions and ensuring their effectiveness in real-world applications, with the second case study building directly on the lessons learned from the first.

Finally, in the implementation and validation phase, the AR-assisted HRC system was tested for its applicability in manufacturing environments. By integrating user-centred design principles, the system addressed both functional and psychological needs, providing a comprehensive solution for human-robot collaboration. This phase emphasizes the practical impact of UX-driven designs, demonstrating how AR-based solutions can bridge the gap between technical performance and user satisfaction.

A unique contribution of this thesis is the demonstration of how each stage of the UX design workflow can be seamlessly integrated into the development of HRI systems. By addressing user needs through research, defining actionable design goals, prototyping solutions, iteratively testing designs, and validating implementations in real-world contexts, this research provides a cohesive and practical roadmap for applying UX principles to industrial robotics. This integrative approach highlights the synergy between UX methodologies and HRI development, paving the way for more human-centred and effective collaborative systems.

7.2 Future Works

Expanding AR Applications to Complex Industrial Tasks

While this research focused on AR applications in collaborative assembly tasks, future work could explore its applicability in more complex and dynamic industrial environments. AR has been shown to facilitate real-time fault diagnosis by overlaying diagnostic information directly onto machinery, enabling operators to identify and address malfunctions efficiently (Nee et al., 2012, Dianatfar et al., 2021). Additionally, multi-step assembly processes requiring intricate sequences with multiple tools and components could benefit from dynamic AR systems that adapt to task complexity and operator performance (Syberfeldt et al., 2017, Kousi et al., 2019). These applications could extend AR's utility beyond repetitive or straightforward tasks to support real-time decision-making in high-pressure manufacturing environments.

Long-Term Impacts of AR on UX

While the short-term benefits of AR, such as improved task performance and user satisfaction, have been demonstrated in this study, understanding long-term usability and cognitive effects remains critical for sustainable implementation. Previous studies suggest that prolonged AR use may lead to mental fatigue and cognitive overload, particularly in tasks requiring sustained attention (Alessa et al., 2023). Conversely, extended exposure could also improve operator efficiency and trust, as familiarity with AR interfaces increases over time (Villani et al., 2018, Kopp et al., 2021). Future research should examine how long-term AR usage influences learning curves, operator satisfaction, and trust in HRI, particularly in high-stakes environments requiring precision and adaptability (Sharkawy and Koustoumpardis, 2022).

Integrating Artificial Intelligence into AR Systems

The integration of artificial intelligence (AI) into AR interfaces represents a promising direction for HRI. AI-powered AR systems can monitor user performance in real-time, dynamically adjusting guidance based on individual skill levels or task complexity (Palmarini et al., 2018b). For example, machine learning algorithms could predict common operator errors and provide contextualized feedback to minimize mistakes during assembly tasks (Green et al., 2008, Wang et al., 2022). AI-enhanced AR interfaces could also offer personalized training environments, ensuring adaptability for operators with different experience levels (Lorenzini et al., 2023). Future work should explore the design and development of adaptive AI-AR systems that dynamically adjust feedback and assistance to optimize human performance.

Advanced UX Design Tools for HRI

Although this research employed qualitative interviews and usability evaluations, integrating advanced UX methodologies could uncover deeper insights into user behavior and system interactions. Heuristic evaluations, which involve experts systematically reviewing an interface to identify usability issues, have been widely used in HRI to assess interaction quality (Clarkson et al., 2013). Similarly, cognitive walkthroughs evaluate a system's learnability by analyzing how easily new users can complete tasks (Nielsen, 1994a). Scenario-based design further helps researchers model how users interact with HRI systems in complex, real-world environments, aiding in identifying usability bottlenecks (Carroll, 2003). Integrating these methodologies systematically into HRI workflows would help refine interaction models and foster the development of more intuitive interfaces.

Designing Adaptive and Personalized HRI Systems

HRI systems that adapt to diverse user needs and preferences remain an underexplored frontier. Future research should focus on developing adaptive interfaces capable of tailoring interaction modalities in real-time. For instance, a system might detect heightened stress levels in an operator and switch from complex visual instructions to simpler auditory guidance. Such personalization could extend to task pacing, where the system dynamically adjusts based on operator performance metrics. Research into adaptive systems could also explore multi-sensory feedback mechanisms, combining haptic, auditory, and visual cues to accommodate operators with different sensory preferences or impairments (Rosin et al., 2024).

Exploring Cross-Domain Applications of AR-Enhanced HRI

While this research was conducted in manufacturing settings, AR-enhanced HRI systems have broader potential applications in various industries. For example, in healthcare, AR can assist surgeons by providing real-time anatomical overlays during complex procedures, improving precision and reducing errors (Nee et al., 2012). In public safety, AR-enhanced interfaces can improve situational awareness for first responders by displaying hazard zones and emergency exit routes in real-time (Alessa et al., 2023). Similarly, in education, AR-assisted robotic tutors can create immersive learning environments, making abstract concepts more tangible for students (IJsselsteijn et al., 2013). Exploring these cross-domain applications would provide valuable insights into how AR and HRI can improve efficiency and user engagement beyond manufacturing.

Addressing Ethical and Cultural Considerations

As HRI adoption expands globally, addressing ethical and cultural differences in system design is crucial. Research suggests that cultural variations influence user trust and acceptance of robotic systems, particularly in hierarchical societies where people may prefer robots that exhibit deference and humility in their interactions (De Graaf and Allouch, 2013, Sharkawy and Koustoumpardis, 2022). Additionally, data privacy concerns and algorithmic transparency are critical for building trust in AI-enhanced AR interfaces (Apraiz et al., 2023). Future research should investigate how cultural factors shape UX expectations in HRI and develop adaptive system designs that respect ethical guidelines and user privacy across diverse contexts.

Investigating Collaborative Robot Ecosystems

Future studies should explore the dynamics of multi-robot and human ecosystems, where collaborative robots interact not only with human operators but also with one another. AR could serve as an orchestrating interface, providing operators with a unified view of robot activities and enabling efficient task allocation. Research could examine how AR systems support real-time conflict resolution, ensuring seamless cooperation among multiple robots in dynamic environments (Liu et al., 2019).

Evaluating Social and Psychological Impacts of HRI

Beyond operational metrics, future research should delve into the social and psychological impacts of HRI systems. For example, studies could investigate whether prolonged interactions with collaborative robot's influence workplace dynamics, employee motivation, or mental well-being. Exploring how robots can foster team cohesion or alleviate workplace stress in high-pressure environments would provide valuable insights for holistic system design. Research has shown that robot social presence significantly influences human attitudes and behaviours, making it an essential factor in HRI design (Lee et al., 2006).

Exploring Future-Proofing Strategies for HRI Systems

The rapid evolution of technology necessitates designing HRI systems that remain relevant over time. Future work should explore future-proofing strategies, such as incorporating modular hardware components and upgradable software architectures. This would allow systems to adapt to emerging technologies like quantum computing, next-generation sensors, or novel AI algorithms, ensuring longevity and scalability (Murphy, 2019).

7.3 Conclusions

This thesis has explored the integration of UX methodologies into HRI for manufacturing, demonstrating how UX principles can enhance operational efficiency, user trust, and system adaptability. By adopting a structured UX design workflow, this research has contributed to bridging the gap between technical performance and human-centered system design. Through iterative studies, including AR-assisted HRI experiments and the development of a UX evaluation tool, the findings emphasize the interdependence between technology and human factors in industrial robotics.

Firstly, through qualitative interviews with manufacturing operators, the study identified twelve key UX factors—including trust, cognitive load, operational efficiency, and ergonomics—that impact the effectiveness of HRI in industrial settings. These insights informed the development of a specialized HRI UX Assessment Framework tailored to manufacturing, filling a gap where existing evaluation methods lacked contextual sensitivity.

Secondly, a questionnaire-based UX evaluation tool was developed and validated using exploratory factor analysis (EFA) with data collected from 358 manufacturing workers. The analysis yielded two subscales—"Comprehensive Operational Efficiency" and "Cognitive Usability"—which together offer a reliable, scalable method for assessing

HRI systems. This tool bridges qualitative user insight with quantitative validation and can be deployed in real-world industrial environments.

Thirdly, two AR-assisted HRC case studies demonstrated how immersive technology can address specific UX challenges. The first case investigated the use of AR facial expressions to convey robot intention and promote user trust. While participants found the system helpful, results showed limited trust enhancement due to the task's low complexity. The second case built on these findings, applying AR to a high-demand assembly task. Results showed that AR significantly improved task accuracy and reduced cognitive load, as measured by the NASA-TLX and AttrakDiff Mini tools.

Finally, the implementation and validation phase confirmed that AR-assisted HRC systems, grounded in a UX-centric approach, offer meaningful improvements in both performance and user satisfaction. This validates the proposed "framework–tool–application" pipeline as a repeatable model for designing effective human-robot systems in manufacturing contexts.

While this thesis has made meaningful contributions to HRI UX evaluation and AR-enhanced collaboration, its broader significance extends beyond specific experimental results. The research highlights a paradigm shift in industrial HRI—one that moves from technology-centric optimization toward human-centred intelligence. Future robotic systems will not only be judged by their precision and efficiency but also by their ability to seamlessly integrate into human workflows, anticipate operator needs, and foster long-term trust and collaboration.

As manufacturing landscapes evolve, the next frontier for HRI lies in autonomous adaptation and personalization. Advances in AI-driven interfaces, biofeedback-driven interaction models, and real-time cognitive state monitoring will transform how humans and robots collaborate. Future systems will need to be self-optimizing, learning from operators and adjusting workflows dynamically to accommodate skill levels, fatigue, and stress. This shift toward adaptive, responsive, and human-aware robots will require a fundamental rethinking of UX design principles in HRI.

Moreover, as robotic collaboration expands beyond manufacturing, industries such as healthcare, education, public safety, and personal assistance will present new challenges and opportunities for human-centred robotics. The principles developed in this thesis—UX evaluation frameworks, iterative human-centred design, and AR-enhanced interactions—can serve as a foundation for broader cross-domain applications.

Beyond technology, this research raises important ethical and societal considerations. As AI and robotics become deeply embedded in daily life, questions surrounding autonomy, transparency, and accountability will define the next era of HRI research. The future of robotic systems should not only prioritize performance but also align with human values, cultural expectations, and ethical frameworks to ensure meaningful and sustainable integration.

Although this research was conducted in three specific manufacturing factories with varying degrees of automation and involved participants from diverse roles such as operators, engineers, and designers, the findings provide a foundational framework that can be adapted to other industrial contexts. The HRI UX Assessment Framework and measurement tool were developed based on cross-factory insights and structured qualitative and quantitative analysis, offering relevance for similar smart manufacturing settings. However, it is important to acknowledge that the applicability of the results may be influenced by cultural, organizational, and technological differences across regions. As such, further validation in different industries and geographical settings is recommended to enhance the generalisability of the framework and tools.

Overall, this thesis has demonstrated how UX-driven methodologies can reshape the design, evaluation, and adoption of HRI systems. However, the true impact of this research lies in its vision for the future—a world where human-robot collaboration is not only functional and efficient but also intuitive, adaptive, and seamlessly embedded into human lives. To achieve this, the next wave of research must push beyond performance metrics toward holistic, context-aware, and ethically grounded robotic ecosystems that redefine how humans and intelligent machines work together.

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