

THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Cognitive Augmentation Technologies

VR, AI and Social Robots for Industry 5.0

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Department of Industrial and Materials Science
Chalmers University of Technology
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The cover, designed by the author, uses a VR headset as a frame to merge with the vision of the future factory. This factory is portrayed as a tourist destination featuring human-machine interaction to enhance both work experience and pedagogical purposes. Created using Adobe Illustrator and GPT-4o for base image generation.

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To love, freedom, and the beauty of life.

Abstract

Digital innovations and an increasingly integrated global economy are transforming manufacturing systems—complex sociotechnical arrangements that integrate technology, information systems, and human labor. For European industry in particular, the COVID-19 pandemic, supply chain disruptions, and trade tensions have heightened uncertainty and exposed vulnerabilities in conventional production models. Besides, manufacturing is undergoing rapid transformation amid an aging workforce, prompting a shift toward Industry 5.0's human-centric vision. This paradigm seeks to harmonize advanced technologies with inclusive design, worker empowerment, and well-being, addressing widening skill gaps and the need for resilient, sustainable operations. Within this context, cognitive augmentation technologies—such as video-based instruction, virtual reality (VR), and AI-enabled humanoid social robots—offer new pathways to support learning and day-to-day operations, but also introduce mental workload demands that must be carefully measured and managed.

Comparative studies show that augmentation yields the greatest value when systems are designed for accessibility, usability, and well-being. Video instruction proved most cognitively efficient for onboarding; VR delivered superior spatial understanding but imposed the highest mental workload; AI-driven humanoid social robots occupied a middle ground. Overreliance on AI guidance increased mental workload and error risk, underscoring the need for calibrated assistance, transparent interaction, and thoughtful human–AI task allocation. Human-centered interface design, clear information pacing, and adaptive guidance emerged as key levers to reduce unnecessary complexity, support universal design demands, and enhance satisfaction and motivation.

The thesis demonstrates that a mixed-measures approach—integrating subjective ratings (e.g., NASA-TLX, RSME), physiological signals (e.g., HRV), and performance indicators (completion time, error rate)—provides a robust basis for quantifying mental workload and comparing modalities. Triangulation enabled detection of overload and underload, informed iterative interface refinements, and supported closed-loop adaptations in future research (e.g., tuning information density and pacing, simplifying interaction flows, switching assistance modality) to maintain workload within an optimal band.

Conceptually, the work reframes Industry 5.0 as a human-centric ecosystem where technologies symbiotically augment and empower workers, supporting dignity, wellbeing, and inclusion. Methodologically, it contributes a validated pipeline for mental workload assessment in real manufacturing contexts based operations. Practically, it offers guidance for technology development and adoption in adaptive and inclusive systems for universal design for vulnerable groups, which is also the future direction to continue after the licentiate study. Together, these contributions lay a foundation for resilient, inclusive, and sustainable manufacturing aligned with the goals of Industry 5.0.

Keywords: Human-centricity, Cognitive Augmentation, Mental Workload, Interaction Design, Virtual reality, Social Robots

List of Publications

Appended publications

This thesis is based on the following publications:

1. **Exploring the current applications, limitations and potential of extended reality for sustainability in manufacturing**

Huizhong Cao, Henrik Söderlund, Mélanie Despeisse, Björn Johansson

Presented at *2023 Eco Design Conference*, Nara, Japan, 29 November to 1 December 2023.

Published in *EcoDesign for Circular Value Creation: Volume I*, Springer Nature Singapore.

https://doi.org/10.1007/978-981-97-9066-5_32

Huizhong Cao initiated the paper and wrote it together with the co-authors. Huizhong was the corresponding author together with Henrik and presented the paper at the Eco Design conference.

2. **Cognitive Augmentation in Industry 5.0: Comparing Mental Workload in VR, Humanoid Conversational Robot and Video Learning**

Huizhong Cao, Emmie Fogelberg, Peter Thorvald, Elias Tengelin, Omkar Salunkhe, Johan Stahre

Submitted to a scientific **journal** - *Computer and Education*.

Huizhong Cao initiated the paper and wrote it together with the co-authors. Huizhong was the corresponding author.

3. **Cognitive ergonomics: Triangulation of physiological, subjective, and performance-based mental workload assessments**

Emmie Fogelberg, Huizhong Cao, Peter Thorvald

Published in **Journal** *Frontiers in Industrial Engineering*.

<https://doi.org/10.3389/fieng.2025.1605975>

Huizhong Cao developed the HRV assessment method and did the quantitative analysis together with Emmie. Emmie was the corresponding author.

4. **Human-centered design of VR interface features to support mental workload and spatial cognition during collaboration tasks in manufacturing**

Huizhong Cao, Francisco Garcia Rivera, Henrik Söderlund, Cecilia Berlin, Johan Stahre, Björn Johansson

Published in **Journal** *Cognition, Technology and Work*, June 20, 2025.

<https://doi.org/10.1007/s10111-025-00809-6>

Huizhong Cao initiated the paper and wrote it together with the co-authors. Huizhong was the corresponding author.

Other publications

The following publications were published during my PhD studies as co-author, supplementary to the licentiate thesis work. However, they are not appended to this thesis due to content overlap or lack of direct relevance.

- 1. VR interaction for efficient virtual manufacturing: mini map for multi-user VR navigation platform**
Huizhong Cao, Henrik Söderlund, Mélanie Despeisse, Francisco Garcia Rivera, Björn Johansson
In 2024 Swedish Production Symposium (SPS) (pp. 335-345). Advances in Transdisciplinary Engineering.
<https://ebooks.iospress.nl/doi/10.3233/ATDE240178>
Huizhong Cao initiated the paper and wrote it together with the co-authors. Huizhong was the corresponding author.
- 2. Beyond Videoconferencing: How Collaborative Tools Make Virtual Design Reviews Work**
Francisco Garcia Rivera, Asreen Rostami, Huizhong Cao, Dan Högberg, Maurice Lamb
In 2025 International Conference on Human-Computer Interaction (HCII) (pp. 96-112). Virtual, Augmented, and Mixed Reality. HCII 2025. Lecture Notes in Computer Science, vol 15790. Springer, Cham.
https://doi.org/10.1007/978-3-031-93715-6_7
Huizhong was the co-author for this conference paper. Francisco was the corresponding author and presented the paper.
- 3. Challenges and opportunities to advance manufacturing research for sustainable battery life cycles**
Björn Johansson, Mélanie Despeisse, Jon Bokrantz, Greta Braun, Huizhong Cao, et al.
Published in Frontiers in Manufacturing Technology, Sec. Sustainable Life Cycle Engineering and Manufacturing, Volume 4 - 2024.
<https://doi.org/10.3389/fmtec.2024.1360076>
Huizhong Cao contributed the XR part for the battery production application development together with Henrik. Björn was the corresponding author.
- 4. Integrating Dynamic Digital Twins: Enabling Real-Time Connectivity for IoT and Virtual Reality**
Lejla Erdal, Ammar Gubartalla, Paulo Victor Lopes, Huizhong Cao, Guodong Shao, Per Lonnehed, Henri Putto, Abbe Ahmed, Sven Ekered, Björn Johansson
In 2024 Winter Simulation Conference (WSC), Orlando, FL, USA, 15-18 December 2024, published in 2024 IEEE.
<https://ieeexplore.ieee.org/document/10838921>
Huizhong Cao supervised the thesis work and wrote it together with the co-authors. Lejla was the corresponding author and presented the paper.

Definition

XR	Extended Reality (XR) is the umbrella term for technologies that act as interfaces between the real and virtual worlds. The term includes Virtual Reality (VR), Mixed Reality (MR), and Augmented Reality (AR) (Fast-Berglund et al., 2018).
VR	Virtual reality applications completely immerse the user in a virtual world, usually using a head-mounted display (HMD) or projections that encapsulate the users with a full visual experience of a virtual world (Fast-Berglund et al., 2018).
AR	Augmented reality technology allows us to remain in the real world while overlaying digital information and augmented visuals on top of our perception of the real world(Fast-Berglund et al., 2018).
MR	Mixed reality technology can help us to mix and overlay 3D elements from both the real and virtual worlds in the same experience and environment. Usually, this is done via an HMD in combination with visual inputs from the real world using cameras or AR headsets with a transparent display (Fast-Berglund et al., 2018).
Mental workload	Identified as the amount of mental resources and cognitive effort required by an individual to accomplish a task at a given time (Realyvásquez-Vargas et al., 2023).
Learning	Refers to the process through which an individual acquires, organizes, and applies new knowledge or skills (Realyvásquez-Vargas et al., 2023).
Cognitive augmentation	Implies the extension of cognition, such as the ability to memorize, problem-solve, perceive, cooperate, and perform efficiently.
Cognitive augmentation technology	Technology that is added to a sociotechnical system to enhance operators' cognitive capability.
ICF catagorization	The International Classification of Functioning, Disability and Health (ICF) provides a standardized way to describe health and health-related states at individual and population levels, and was endorsed by WHO Member States for universal application across contexts (WHO, 2001).
Human-centric techniques	The technologies that helps and angments the users' talents for decision-making, problem-fixing, and creativity (Rajkumar et al., 2024).

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CHAPTER 1

Introduction

1.1 Background

Digital innovations and an increasingly integrated global economy are driving significant changes in manufacturing systems, which are a complex fusion of technology, information systems, and human labor (Johansson et al., 2024). Particularly in European industry, recent challenges—such as the COVID-19 pandemic, supply chain interruptions, and trade tensions—have increased uncertainty and exposed weaknesses in traditional production (Marta Pinzone et al., 2024). Within the framework of the Industry 5.0 revolution, there is growing emphasis on re-designing manufacturing to be more robust, sustainable, and, most importantly, human-centric (Breque et al., 2021), as illustrated in Figure 1.1. The application of human-centricity is a crucial component of this change. To fully realize human-centricity in Industry 5.0, several key imperatives must be prioritized (Ghosh et al., 2024).

The ongoing digital transformation in industry is shaped by major global trends such as the COVID-19 pandemic and geopolitically induced uncertainty, including supply chain tensions, tariffs, and difficulties in global collaboration (Amankwah-Amoah et al., 2021). The emergence of a contested, increasingly inward-looking, and unstable multipolar world has been paralleled by profound technological change and the deepening digitalization of economies and societies (Szczepański, 2024). Technology has become a battleground in the geopolitical quest for power, and the accelerated adoption of advanced digital technologies has increased the demand for digital proficiency to advance the “Made in Europe” partnership (McCormack and commission, 2020).

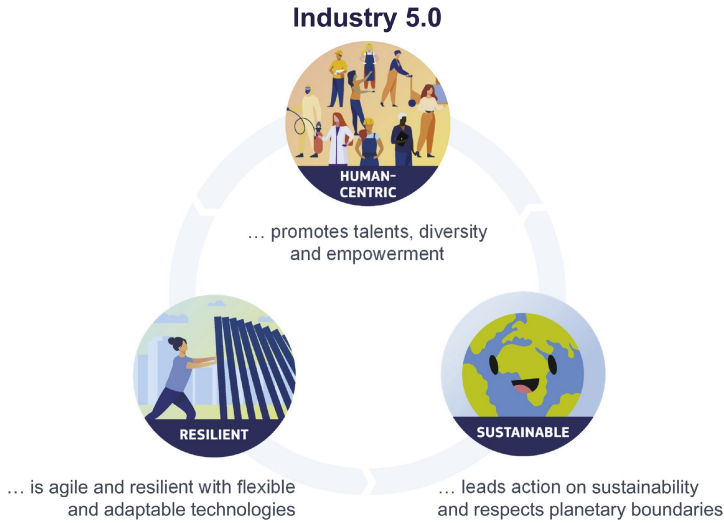


Figure 1.1: Industrial revolution - Industry 5.0 (Breque et al., 2021)

However, as the workforce ages and digitalization accelerates, significant skill gaps are emerging (Greta Braun, 2023). According to the OECD, the labor force participation rate of workers aged 50–64 in 27 European Union countries increased from 37.9% in 2000 to 67% in 2023, with Sweden ranked highest globally at 87.4% (OECD, 2023). A work environment that does not accommodate age-related cognitive decline can exacerbate health problems among older workers, negatively affecting their well-being and productivity (Lilah Rinsky-Halivni et al., 2022). Thus, effective management of mental workload remains critical.

The emergence of profound technological change and growing dependence on digitalization has brought challenges not only for aging workers but also for people with visual impairments (Kerdar et al., 2024), neurodiverse populations (Adler, 2024), people with hearing impairments (Balcevic and Aravind, 2023), and people with cognitive impairments (Van Holstein et al., 2021) due to the lack of universal design. For example, as Adler notes, digital applications with cluttered interfaces can overwhelm users with ADHD, while platforms that rely heavily on text-based instruction can make it harder for individuals with dyslexia to process information.

As global attention intensifies on geopolitical uncertainty, aging trends, climate change, and resource depletion, the manufacturing sector faces pressure to transition to operations that are sustainable, resilient, and fundamentally human-centric, embracing ethics, inclusivity, and empowerment (Rajkumar et al., 2024). While the Industry 5.0 vision aspires to harmonize advanced digital technologies, effective information systems, skilled workforces, and sustainable practices within a human-centric framework, a significant gap persists between this ideal and current industrial realities (De J Pacheco and Iwaszczenko, 2024). The research problem, therefore, is to bridge this gap by identifying and addressing the chal-

lenges that hinder the adoption of emerging digitalization technologies, adaptive information systems, upskilling pathways, and sustainability initiatives within a human-centric production ecosystem (Bucci et al., 2024).

1.2 Research gaps

Based on that research problem, we need to identify the challenges further to specify the gaps between ideal and current industrial realities and to specify the research initiatives.

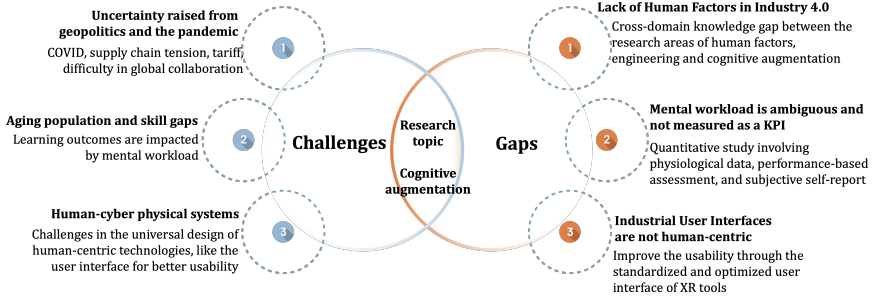


Figure 1.2: Problem structure

To address these research problems and challenges, as illustrated in Figure 1.2, this research focuses on digitalization, human–technology interaction, and cognitive enhancement. The aim is to empower the workforce through advanced cognitive acceleration technologies for human-centric production.

The first gap identified in this study is the cross-domain knowledge gap among human factors, manufacturing, and cognitive augmentation. The emergence of Industry 5.0 has shifted workplace dynamics, requiring workers to make rapid decisions using real-time data while overseeing collaborative robots (cobots) and advanced digital technologies such as XR, AI, and digital twins (Ricci et al., 2025). As a result, workers’ mental workload has intensified, necessitating constant adaptation to evolving technologies, and it can significantly correlate with physical fatigue and human error (Arturo Realyvázquez-Vargas et al., 2023).

Current approaches lack robust, quantitative methods for measuring mental workload in empirical manufacturing environments to assess digital and virtual training. There is a need for integrated studies that combine physiological data, performance-based assessment, and subjective self-report to better understand and manage cognitive demands. In addition, affordable, portable, and flexible equipment is needed to collect physiological data suited to industrial work environments (Lucchese et al., 2025).

Previous studies show that virtual training environments are often used when real-world training is impractical due to high costs, safety risks, time constraints, or substantial resource requirements (Moskaliuk et al., 2013). This digital ap-

proach reduces reliance on physical machinery and equipment, supporting the transition toward more sustainable industrial practices. Virtual reality (VR), in particular, offers features that can help manage cognitive overload and tailor experiences to users' needs (Ratmono et al., 2024).

However, a key barrier to broader adoption is that VR tools can impose higher mental workload, often resulting in dizziness, navigational challenges, and poor learning outcomes—especially among novice users. Moreover, most extended reality (XR) applications to date remain confined to single use cases and lack scalability, which significantly hinders practical adoption. Transitions between tasks or technologies often require costly configuration changes and force users to relearn interaction methods (Memmesheimer and Ebert, 2022). Addressing these issues requires the development of standardized, universally designed, and optimized user interfaces for VR tools to enhance usability and support effective learning (H. Cao, Rivera, et al., 2025).

Human-centric technologies are designed to augment rather than replace human capabilities to create more adaptive and responsive systems.

—Ben Shneiderman (Shneiderman, 2022)

1.3 Vision, Mission and Aim

Instead of focusing on what humans can do with new technology, Industry 5.0 asks what technology can do for humans?

—European commissioning, Industry 5.0

The vision of the research is a future industry where a human-centric paradigm for Industry 5.0 has been adopted, where technology and production processes have been designed to adapt to the diverse needs of the workforce, rather than requiring workers to adapt to them (Ghosh et al., 2024).

1.3.1 Mission

The shift requires more natural, adaptive, and effective human-technology interactions, augmenting and empowering operators to work alongside advanced systems.

This vision manifests in three core imperatives as missions:

- **Transition from smart to cognitive technology:** Develop and implement sophisticated digital technologies with intuitive, natural, and adaptive user interfaces that can be flexible for complex human needs and contexts.

- **Empower the workforce:** Equip employees with essential digital proficiency, cognitive and emotional intelligence, and foster continuous learning within flexible work environments. By upskilling shop floor workers and supporting diverse learning pathways, the workforce becomes ready for the demands of Industry 5.0 and can bridge emerging skill gaps.
- **Enhance worker well-being and resilience:** Prioritize the physical and mental health of employees by implementing comprehensive safety measures, reducing injury risks, and ensuring dignity and data privacy. The aim is to leverage digital solutions and create workplaces that are safe, satisfying, and resilient, supporting both individual and organizational well-being.

The research aims to leverage cognitive augmentation technologies—including VR, AI agents, social robots, and video instructions—to empower shop floor workers and enhance cognitive ergonomics in digital proficiency upskilling processes.

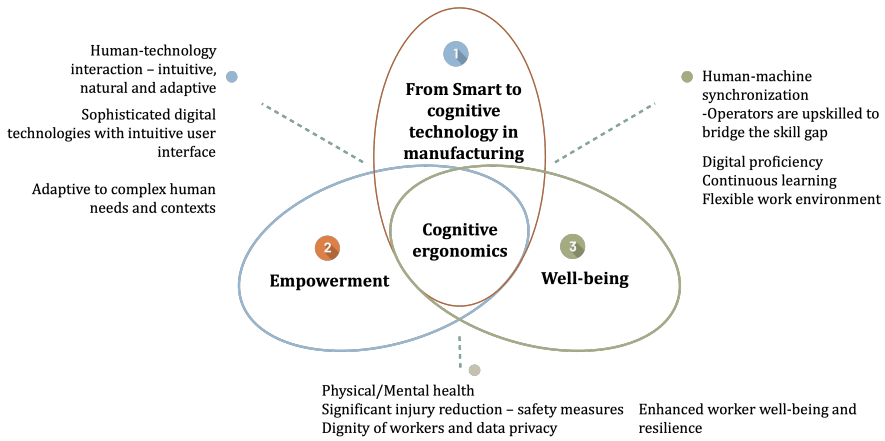


Figure 1.3: Mission—the three core imperatives

1.3.2 Research Questions (RQs)

To advance the mission of evolving industrial systems from smart to cognitive—with human well-being achieved through augmentation and empowerment—cognitive augmentation technologies are proposed as a research focus to realize this vision.

The cognitive augmentation technologies examined include video instruction, VR, and humanoid social robots for Industry 5.0. To enact the vision through the mission pathways, the research questions are formulated. The first research question (RQ1) establishes a basis for understanding the impact of current cognitive augmentation technologies on users in the context of Industry 5.0:

***RQ1** How do cognitive augmentation technologies influence shop floor workers during the learning and operational phase in the Industry 5.0 manufacturing context?*

Cognitive augmentation technologies—such as VR, robotic assistants, and advanced visualization tools—promise to enhance human performance by offloading, supporting, or amplifying cognitive processes. “Learning phase” refers to guided instruction with the augmentation tool, whereas “operational phase” denotes unaided task execution. However, these systems can also introduce novel mental demands, making it imperative to objectively quantify the workload they impose. Mental workload reflects the interplay between task requirements and an individual’s cognitive capacity and influences usability, performance, and user acceptance (S. G. Hart and Staveland, 1988). A triangulated evaluation (subjective, physiological, and performance) is used as the methodological spine for RQ2 to capture complementary facets of mental workload and to reduce single-measure bias. Research Question 2, therefore, asks:

***RQ2** How can quantification of mental workload be utilized for improvement of cognitive augmentation technologies?*

This thesis examines how these technologies are applied in instructional design during both the learning and operational phases, as well as the development of user interfaces that prioritize intuitive and effective human–technology interaction.

1.4 Scope and Delimitation

Although a cross-discipline view are emphasized, the thesis is limited to the following:

- The cognitive augmentation technology application and adoption scenario are focused in a factory setting in manufacturing. The layout planning, design review, and instruction design are mainly studied use cases in this thesis; other use cases, like human-robot interaction or data monitoring and visualization, are briefly discussed but without an empirical study.
- The thesis is based on the full design and evaluation cycle of the digital platform development in VR, Humanoid social and Video, other cognitive augmentation technologies like AR are delimited.
- The thesis provides a focused angle in mental workload assessment and regards it as an indicator for usability; a more holistic or comprehensive understanding of trust, satisfaction, and engagement is briefly discussed but not quantitatively measured.
- The triangulation of measurement modalities focuses on physiological, performance based, and subjective data. At the same time, in each category,

the metrics are selected based on the feasibility, availability, portability, and the optimal indicator discussion, which are briefly included.

- The main users studied in this licentiate thesis are novice/expert operators and engineers from manufacturing companies. The sampling in the experiment has a mixed testing group from both students and citizens, novice and experienced operators/engineers from manufacturing companies in Sweden, to represent the operator; the personas' representation is briefly discussed.
- The mental workload studied in this study focused on an ultra-short phase of experience; the corresponding technologies, longitudinal studies, or motivation of users are not currently studied in this thesis.

1.5 Thesis Outline

The theoretical framework are outlined in Chapter 2, followed by a description of the research approach and methods in Chapter 3. The summary of the appended papers is presented in Chapter 4. Chapter 5 provides a discussion of the results to answer RQ1 and RQ2, while Chapter 6 offers a summary of the main findings and conclusions. As shown in Table 1.1, the disposition of the thesis is presented.

Table 1.1: Overview of the chapters in this thesis

Chapters	Description	Key deliverables
1. Introduction	The chapter introduces the topic, background, aim and research questions of this thesis.	Background: Industry 5.0 aims to bridge the gap between its human-centric vision and current industrial practices. RQ1: How do cognitive augmentation technologies influence shop floor workers during the learning and operational phase in the Industry 5.0 manufacturing context? RQ2: How can quantification of mental workload be utilized for improvement of cognitive augmentation technologies? Scope: Evaluates cognitive tech in manufacturing via mental workload for training and design.

Continued on next page

Table 1.1: Overview of the chapters in this thesis (continued)

Chapters	Description	Key deliverables
2. Theoretical Framework	The chapter introduces key concepts and theories used to support the research. Providing contextualization and theory in the intersection between manufacturing, XR and learning theories.	Human-Technology Interaction: Designing for human capabilities Mental Workload: Cognitive task demand Cognitive Augmentation: Technology enhancing human cognition VR: Immersive training and simulation Social Robots: AI-driven humanoid assistant
3. Research Approach and Methods	The chapter explains the underlying worldviews and academic perspectives that have framed the research as well as the methods used in answering the research questions.	Research philosophy: Pragmatic-empiricist, critical realist. Research process: Prototype-based experiments, comparative studies, mixed-methods analysis. Research method: Quantitative (performance, physiological, subjective metrics) and qualitative (thematic) analysis.
4. Summary of the Appended Papers	The chapter provides an overview of the appended papers, focusing on the main results and contributions relevant for this thesis in answering the stated research questions.	Paper 1: Summary of method, main results and discussion of Paper 1. Paper 2: Summary of method, main results and discussion of Paper 2. Paper 3: Summary of method, main results and discussion of Paper 3. Paper 4: Summary of method, main results and discussion of Paper 4.

Continued on next page

Table 1.1: Overview of the chapters in this thesis (continued)

Chapters	Description	Key deliverables
5. Discussion	The chapter combines findings from the appended paper, and additional work, to answer the two research questions and forming the contribution of this thesis. Furthermore, this chapter also discusses the methods used and future research directions.	RQ1: Findings and discussion regarding RQ1. RQ2: Findings and discussion regarding RQ2. Contributions: Highlighting and discussing the scientific and practical contribution of this thesis. Limitations: Discussion on the scientific quality and limitation of the thesis. Future work: Proposed future work and studies as part of the authors continued PhD studied.
6. Conclusion	The chapter offers a summary of the thesis, focusing on providing an overview of the problem formulation, key contributions and answers to the research questions.	Summary of the key takeaways and contributions of the thesis.

CHAPTER 2

Theoretical Framework

This chapter orients the reader to the theoretical foundations that underpin cognitive augmentation in modern manufacturing. It begins by mapping the evolution from Industry 4.0’s digitally connected, automation-focused systems to Industry 5.0’s human-centric vision, highlighting how the role of technology shifts from replacing to empowering workers. It then frames human–technology interaction through cognitive ergonomics, explaining why mental workload is a pivotal lens for designing interfaces and workflows that are usable, inclusive, and efficient. Building on this, the chapter outlines how mental workload can be assessed with complementary subjective, physiological, and performance-based methods, and shows how these insights inform the design and deployment of augmentation technologies—such as XR and humanoid social robots. The aim is to provide a coherent narrative linking concepts, measures, and technologies so that subsequent sections can focus on how to augment skills, support learning and collaboration, and sustain well-being and resilience on the shop floor.

2.1 Transformation from Industry 4.0 to 5.0

Industry 4.0 foregrounded tightly integrated cyber–physical systems that link sensors, actuators, and embedded computation with cloud/edge analytics to enable real-time monitoring, control, and autonomous optimization across production networks (Da Xu et al., 2018; Zubrzycki et al., 2021). In contrast, Industry 5.0 reframes this digital foundation toward a human-centric paradigm that prioritizes empowerment, well-being, resilience, and sustainability, adapting technology to workers’ needs and elevating human creativity and decision-making rather than

replacing it (Breque et al., 2021). Representative Industry 4.0 technologies include CPS/CPPS, IIoT, edge-cloud computing, big-data/AI analytics, and digital twins (Da Xu et al., 2018). Representative Industry 5.0 technologies emphasize collaborative robots (cobots), human-digital twins, AI copilots/assistants, XR for training and support, and ergonomic, adaptive HMIs that augment skills and enable inclusive, resilient operations (Breque et al., 2021; Oeij et al., 2024).

Industry 5.0 aims to create a more harmonious relationship between humans and technology to address challenges arising from increasing reliance on automation and digitalization (Erlantz Loizaga et al., 2023). It seeks to promote worker well-being and establish sustainable, resilient systems through human-centered strategies that incorporate virtual reality (VR), artificial intelligence (AI), robotics, and digitalization (Joel Alves et al., 2023). However, interactive systems in automotive manufacturing settings have yet to catch up with consumer products in terms of interaction quality and user experience (Mucha et al., 2018). In the era of Industry 5.0, mental-workload optimization offers opportunities to boost shop-floor performance and efficiency while enhancing collaboration, well-being, and job satisfaction (Eva Geurts et al., 2022).

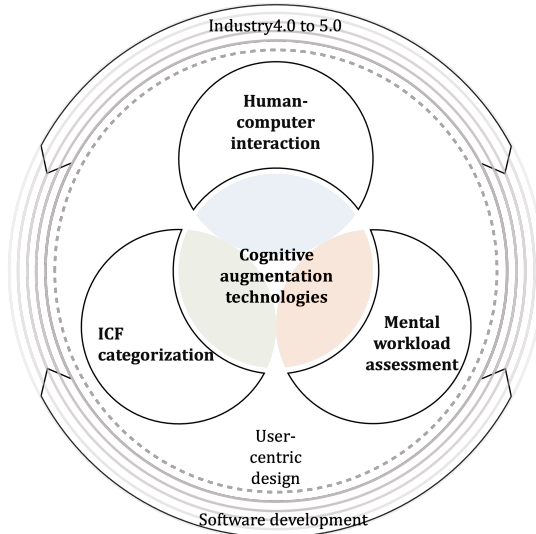


Figure 2.1: Theoretical framework

2.2 Human-technology Interaction

Industry 5.0 makes human–computer interaction the conduit for its human-centric vision, turning interfaces, guidance, and feedback into the means by which advanced automation actively augments human judgment, creativity, and well-being on the shop floor (Lihui Wang, 2021). Human–system interaction demands coordination of perceptual, cognitive, and motor functions (Neumann et al., 2020). Cognitive ergonomics addresses four major difficulties in human–computer interaction (HCI): long task completion times, low user satisfaction, high error rates, and extended response times (Cañas, 2008). Human factors and ergonomics research can improve system performance and well-being in manufacturing companies (Arto Reiman et al., 2021).

This changing landscape ushers in new challenges and opportunities, particularly in workforce development and lifelong learning, while raising new ethical considerations. Industry 5.0’s digital-twin technology underscores the importance of human expertise in the creation and application of these systems. Notably, not all industries and factories need to be fully automated or unmanned; technical and economic viability should also be considered when promoting intelligent manufacturing. For example, unlike the automotive industry, the aviation, aerospace, shipping, and construction sectors—owing to the complexity of their tasks and processes—have not yet realized full automation and unmanned production. They remain largely dependent on human–machine cooperation, the accumulation of human knowledge and experience, and human self-motivation (Neumann et al., 2020).

Emerging technologies—including the Internet of Things, AI, machine learning, collaborative robots, and virtual/augmented reality—have been crucial in shaping human-centered intelligent manufacturing (HCIM) (Neumann et al., 2020). Yet traditional industrial robots still struggle to meet new demands, largely due to inadequate human–machine interaction design (Neumann et al., 2020).

The human–technology interaction enabled by augmentation technologies includes real-time auditory feedback (Bustoni, 2025), tactile feedback, and visual interaction, which requires rapid information processing and can therefore impose a higher mental workload (Y.-T. Huang et al., 2025). The application of augmentation technology to empower users is associated with high intrinsic motivation and deep comprehension. This grants users full decision authority for critical task evaluation, meaningful choice, and autonomous expertise development and flexibility (Pan, 2022).

2.3 Mental Workload

Mental Workload can be defined as “the ratio of demand to allocated resources” (Luong et al., 2020). It is an essential metric for evaluating the impact of performing tasks and predicting operators’ performances and technology adoption (Cañas, 2008). Optimizing mental workload has been proven to reduce human errors, improve system safety, increase productivity, and enhance operators’ satisfaction with their working experience (Luong et al., 2020).

Cognitive load is a common word used interchangeably with mental workload. Longo and Orrú (2022) contend that while they may come from various fields, they are essentially the same (Luca Longo and Orrú, 2020). Cognitive load is mostly associated with educational psychology (Sweller et al., 1998), whereas mental workload is associated with ergonomics, human factors (MacDonald, 2003), psychology (Hancock et al., 2021), and aviation (Sandra G. Hart, 2006).

Mental workload can be measured in multiple ways, including subjective (or self-report), physiological, and task performance measures (Emmie Fogelberg, Peter Thorvald, et al., 2024). Self-report methods can be categorized into multidimensional or unidimensional scales (Luong et al., 2020). One of the most recognized and commonly used standardized multidimensional scales is the NASA-Task Load Index (TLX) (S. G. Hart and Staveland, 1988). Performance measures mainly depend on the type of task, and error rate and completion time are the common measures (Emmie Fogelberg, Peter Thorvald, et al., 2024). The physiological measures can be assessed through signals like electroencephalogram (EEG), pupillometry, heart rate variability (HRV) (Tao et al., 2019), etc.

Excessive levels of mental workload have been shown to alter physiological processes, including hormonal regulation. Similar to stress, high mental workload triggers elevated secretion of the hormone cortisol (Nomura et al., 2009). In addition, Kusnanto et al. (2020) found that blood sugar increases in correlation with mental workload (Kusnanto et al., 2020). Other associated symptoms are poorer body postures (Adams and Nino, 2024), fatigue, drowsiness (Borghini et al., 2012), and decreased HRV (Yannakakis et al., 2016).

2.3.1 Mental workload assessment

Mental workload can be understood as the balance between task complexity and an individual’s cognitive capacity to meet those demands (MacDonald, 2003; B. Wang et al., 2024), although the lack of a universal definition makes it difficult to claim exact boundaries of the construct. When this balance aligns with an individual’s skills, studies report better performance along with higher motivation and productivity (Bartram and Turley, 2009; L. Longo et al., 2022; Venkatesh and Ram, 2015). Conversely, when mental workload is either too high or too low, performance suffers (Xie and Salvendy, 2000; Young et al., 2015). Elevated workload, in particular, is associated with increased errors and longer response times (Foy and Chapman, 2018; Ryu and Myung, 2005).

Assessment methods are commonly grouped into three categories: subjective, physiological, and performance-based (Matthews, De Winter, et al., 2020). Over the past three decades, multimethod assessments have become more prevalent (Di Stasi, Alvarez-Valbuena, et al., 2009), and several authors recommend combining instruments because single measures cannot capture signals outside their own scope (Veltman and Gaillard, 1998).

Subjective measures rely on self-ratings of perceived workload and are popular because they are easy to administer (Zarjam et al., 2015), relatively insensitive to time constraints (Marino et al., 2021), able to capture small variations (Paas et al., 2016), show strong validity (Grandi et al., 2022; Torres et al., 2021), are non-interruptive (Bommer and Fendley, 2018; Grandi et al., 2022; Torres et al., 2021), and are low cost (Arana-De las Casas et al., 2023; Bommer and Fendley, 2018; Grandi et al., 2022; Torres et al., 2021). Widely used scales include NASA-TLX (S. G. Hart and Staveland, 1988), the Cooper–Harper Rating Scale (Cooper and Harper, 1969), and the RSME (Zijlstra and Van Doorn, 1985).

Physiological assessments are increasingly popular because they provide “hard” evidence via traceable bodily and neural changes (Annett, 2002; Fairclough and Houston, 2004), and they have become more accessible due to improvements in device cost and size (Guzik and Malik, 2016). Common measures include eye tracking (Hertzum and Holmegaard, 2013)—such as pupil diameter (Argyle et al., 2021; Batmaz and Ozturk, 2008) and blink frequency (Faure et al., 2016)—skin conductance (Lagomarsino et al., 2022; Shimomura et al., 2008), neural activity (Wilson and Eggemeier, 2020), heart rate (HR) (Argyle et al., 2021; Henelius et al., 2009), and heart rate variability (HRV) (Delliaux et al., 2019; Grandi et al., 2022). When used for workload, HRV serves as an indicator of cardiovascular responses to heightened demands (Miyake, 2001). Unlike HR, which is measured in beats per minute, HRV captures fluctuations in the intervals between heartbeats (McCraty and Shaffer, 2015; Shao et al., 2020), can be measured non-intrusively, and can be computed in under two minutes (Bläsing and Bornewasser, 2020). HRV is often collected via photoplethysmography (PPG), which detects changes in blood volume in the microvasculature (Allen, 2007), with signals obtainable from multiple body sites such as fingers and earlobes (Kiselev et al., 2016). With lightweight sensors, participants can, for example, assemble a drone without meaningful restrictions from instrumentation. HRV is the variation in the length of heartbeat intervals (Malik et al., 1996). HRV represents the heart’s ability to respond to a wide range of physiological and environmental stimuli (Acharya et al., 2006). Low HRV indicates a monotonously regular heart rate. Furthermore, reduced HRV is linked to decreased regulatory and homeostatic autonomic nerve system (ANS) activities, reducing the body’s ability to deal with internal and external stimuli.

Performance-based assessments focus on observable actions and execution and help quantify how individuals allocate limited cognitive resources and differ in performance profiles (Butmee et al., 2018). Typical industrial assembly metrics include speed, accuracy, time, reaction time, and error counts (Drouot et al., 2022; Lagomarsino et al., 2022). These variables can be measured in the main task to check goal success or in a secondary task to see how much mental capacity remains.

2.4 The International Classification of Functioning

The International Classification of Functioning, Disability and Health (ICF) provides a standardized way to describe health and health-related states at individual and population levels, and was endorsed by WHO Member States for universal application across contexts (WHO, 2001). It conceptualizes functioning as a dynamic interaction between health conditions and contextual factors, allowing description in both neutral (functioning) and negative (disability) terms (WHO, 2001; Battistella and De Brito, 2002).

ICF comprises three coded components—Body Functions and Structures, Activities and Participation, and Environmental Factors—plus Personal Factors as contextual elements, with components operationalized using qualifiers such as capacity and performance for activities/participation (WHO, 2001; Battistella and De Brito, 2002). The unit of classification is domains within these components; importantly, ICF “does not classify people,” but describes each person’s situation across domains (WHO, 2001).

ICF’s body functions explicitly include mental functions, aligning the framework with cognitive ergonomics and mental workload constructs in which working memory limits, task demands, and environmental conditions jointly shape performance (Battistella and De Brito, 2002; L. Longo et al., 2022). Building on ICF, the analysis connects mental workload and users’ cognitive functions (body functions) with task performance (activities/participation) and the digital work environment (environmental factors).

Body functions are the physiological functions of body systems (including mental functions), and body structures are anatomical parts such as organs and limbs (WHO, 2001). Activities and participation span learning, general tasks and demands, communication, mobility, self-care, domestic life, relationships, major life areas, and community life, assessed via capacity and performance qualifiers (WHO, 2001; Battistella and De Brito, 2002). Environmental factors cover the physical, social, and attitudinal environment, and are explicitly coded as facilitators or barriers that influence functioning (WHO, 2001; Battistella and De Brito, 2002).

Personal factors (e.g., age, lifestyle, coping habits) are included conceptually as contextual elements but are not formally classified in ICF due to cultural variability and scope concerns; their assessment is left to users and domain-specific applications (WHO, 2001). Scholarly work discusses ongoing efforts to structure personal factors (e.g., self-efficacy, attitudes, motivation) while emphasizing the need for conceptual clarity to avoid overlap with other components (Fehrmann et al., 2022). But in this thesis, the personal factors are delimited from the discussion of mental workload, as a more objective perspective of mental workload imposed by digitalization tools is raised, but not the motivation or lifestyle of each user. But we acknowledge the importance of personal factors regarding future universal design.

2.5 Cognitive Augmentation Technology

Cognitive enhancement—understood as the augmentation of brain processes—has been a prominent topic in academic and public debates about increasing physical and mental capabilities (Nitish Singh Jangwan et al., 2022). In recent years, numerous recommendations have been proposed for improving cognitive functions, and physical and behavioral treatments have been investigated in the context of cognitive enhancement (Nitish Singh Jangwan et al., 2022).

Cognitive augmentation can be framed in four compact dimensions: spatial cognition (where the assembly is), memory cognition (what the assembly/parts are), comprehension cognition (how the assembly state is), and decision-making cognition (how to perform the operation). These dimensions cooperate to support the task flow from locating and recognizing to understanding and acting (Pang et al., 2024).

Cognitive augmentation technologies are designed to provide rich feedback with reduced mental workload, making them well suited for progressive learning and symbiosis between working systems and operators (Lucchese et al., 2025). The technologies serve to support and empower the workforce, fostering more high quality jobs and prosperity beyond efficiency. By relieving individuals of physical and cognitive strain, stress, and workplace risks, these technologies offer effective means to support and amplify human capabilities on the modern shop floor (HORIZON, 2025). In manufacturing, cognitive enhancement technologies aim to improve human perception, cognition, and decision-making by integrating advanced digital tools—such as extended reality (XR), AI agents, social robots, and digital twins—into industrial environments (Lihui Wang, 2021).

2.5.1 VR as cognitive augmentation technology

VR systems represent innovative solutions that merge technological advances with human centric design, aligning with Industry 5.0 principles (Escallada et al., 2025). However, despite progress in VR technologies and hardware, if a VR task is not designed with an appropriate level of mental workload that matches users' expertise, both task performance and technology utilization can be constrained (Zhang et al., 2016).

In manufacturing, VR is a key enabler supporting layout planning, design reviews, virtual prototyping, machine/robot interaction, ergonomics assessment, and virtual training (Erlantz Loizaga et al., 2023). Enhancing the cognitive ergonomics of VR application interfaces aims to align technology with human needs and capabilities, promoting efficiency, effectiveness, and user satisfaction in manufacturing processes.

The gamified multi-user VR experience described here combines essential technology components and approaches established in current research. The Unity 3D game engine (*Unity Engine* 2025) is one of the platforms used to construct XR applications in this study, and its customization and adaptability make it suitable for industrial and academic applications (Tytarenko, 2023). The integration of

Photon Networking for multi-user capabilities aligns with established practices in collaborative VR. Furthermore, implementing VR Builder for task sequencing and interaction design is consistent with documented methodologies for constructing instructional VR training applications without substantial C programming (Söderlund et al., 2024).

As another gamified platform, Unreal Engine (*Unreal Engine* 2025) can bridge gaps by providing more realistic environmental rendering, detailed avatar customization, and seamless communication for user enhancement and social interaction in immersive worlds. This platform can address issues such as AI integration, improved haptic feedback, and optimization of large-scale VR projects (Berrezueta-Guzman and Wagner, 2025).

For engineering and industrial application design, commercial software such as IC.IDO (IC.IDO, 2025)—which combines high-end visualization with real-time physics simulation to enable authentic human-centered process validation—can also be used. The fundamental architecture of VR prototypes is based on established CAD data formats, specifically the JT (Jupiter Tessellation) format, an ISO-standardized solution for 3D data interchange and visualization.

VR prototypes frequently use head mounted displays (HMDs), such as the Meta Quest series, which hold over 70% market share due to their wireless capabilities and mixed-reality features (Wheeler, 2024). The wireless operating mode eliminates tethering restrictions while preserving high-fidelity rendering via a streaming architecture that separates computational processing from display hardware (Petersen, 2024).

2.5.2 Humanoid social robots

A humanoid social robot (HSR) is defined as “human-made technologies that can take physical or digital form, resemble people in form or behavior to some degree, and are designed to interact with people” (Fox and Gambino, 2021). This definition emphasizes that HSRs exhibit both form anthropomorphism (human-like voice or appearance) and behavioral anthropomorphism (gestures, spoken messages, nonverbal expressions) (Fox and Gambino, 2021). To enhance the social-interaction functionality and social capital of humanoid social robots, a natural language model can be introduced to enable fluent communication, and computer vision can be used to enable eye contact and facial expression (Dogan, 2021).

The HSR demo in this study is built on a tabletop humanoid social robot from Furhat (Furhat, 2025). The back-projected face technology used by Furhat robots creates lifelike expressions by projecting animated faces onto a translucent mask. The Furhat OS platform offers speech, facial-animation, and gesture-control APIs. The HSR can be customized with context, sequential assembly instructions, and other task information by connecting to the GPT-4o API via Python for external integration. In addition, it can function as a virtual mentor—presenting with a human persona, voice, and face—and deliver customized teaching based on the operator’s skill level.

2.5.3 Mental workload in VR and humanoid social robots

Navigation in VR can impose substantial mental load on users, affecting short-term memory, attention, perception, and response time (Han et al., 2021). Elevated mental workload during visuomotor adaptation in immersive VR has been associated with poorer long-term motor memory and reduced context transfer (Juliano et al., 2021). Increases in mental load also manifest in ocular metrics—such as larger relative pupil size and fewer fixations—indicating impacts on attention (Schirm et al., 2023). Collectively, these effects can degrade overall user experience and the effectiveness of VR applications.

Users frequently experience higher mental workload during complex motor tasks in head-mounted displays compared with traditional computer screens (Bernal, Jung, et al., 2024). Moreover, higher cognitive and affective load during VR navigation can diminish navigational performance (Parsons et al., 2023). Without mitigation, these mental-load factors can adversely affect collaborative activities in virtual environments—such as layout planning, design reviews, and remote assistance. It is therefore crucial to leverage user cognitive psychology and interface/scene-design features early in the VR design phase to improve information acquisition and task execution, enhance user experience, and reduce mental workload (Fu et al., 2024; H. Cao, Rivera, et al., 2025).

CHAPTER 3

Research Approach and Methods

This chapter describes the research approach, methods, and techniques used to achieve the research aim and mission. First, the research activities are presented with papers.

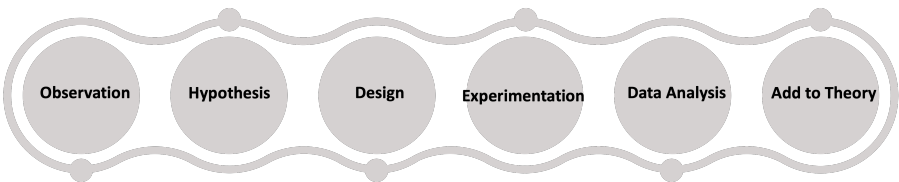


Figure 3.1: General scientific methods steps, adapted from (Pruzan, 2016)

3.1 The design of research

Scientists share certain beliefs in common: that scientific disciplines are reliant on evidence, the use of hypotheses and theories, and the logic used (AAAS, 1990). Science does not have a unified epistemology, but the overarching technique gives a consistent criterion of validity for all hypotheses. Inadequate data collection and processing might lead to subjective outcomes, thus it is crucial to evaluate different participants using consistent criteria (Harold, 1983).

My research is grounded in a pragmatic-empiricist worldview that privileges direct measurement and statistical validation to illuminate human–technology interactions. By systematically quantifying mental workload across objective (per-

formance, physiological) and subjective (self-report) domains, this epistemological stance asserts that reliable knowledge emerges from observable, reproducible data rather than intuition or expert conjecture alone. In adopting mixed-methods mental workload assessments, the study embodies a critical realist approach: it assumes that cognitive phenomena and user experience are real and measurable, yet acknowledges that no single metric can fully capture their complexity. This synthesis of quantitative rigor with complementary qualitative insights enables the empirical demonstration of how technology can symbiotically empower, augment, and include users. Ultimately, this philosophy holds that ambiguity in human–technology symbiosis is best resolved through transparent experiment design and comparative data analysis, yielding actionable, generalizable insights into usability and cognitive impact.

The term of ‘scientific method’ refers to a systematic procedure for carrying out a scientific investigation and justifying the privileged status of the research findings (Pruzan, 2016). The delineation introduces a step-by-step of an apparent logical and/or chronological progression in research activities; however, it is not always linear or sequential (Pruzan, 2016). The adapted scientific research methods steps are illustrated in the Figure 3.1. Objectivity, curiosity, creativity, and interpretation give the research process repeatability and transparency while also advancing our understanding of the hard and soft science socio-technical system sector.

3.2 Experimental approaches

3.2.1 Prototype-based experiment Method

There are various modeling and analytic methods for complex experimental setups. The use of quantitative data to compare and reveal significant differences between subjects can provide us with a clear picture of the usability of technology as well as quantify the interaction between humans and technology. It is difficult to determine the interaction between humans and technology without measuring or relying solely on qualitative data, as subjective assessments may not accurately reflect reality (Emmie Fogelberg, Peter Thorvald, et al., 2024), and expert opinion is not reliable in this new sector. The primary unique working methods used in this study were to quantify the user experience through mental workload assessment. How to understand the symbiosis, empowerment, augmentation, and inclusion of technology from a cognitive perspective? Mixed mental workload evaluation methods could be a feasible solution to demonstrate the significance of ambiguity and personalization by scientific comparison experiment design and data analysis.

A sandbox can be classified as either a technological sandbox or a regulatory sandbox (OECD, 2025). The former emphasizes responsible decision-making, safety risk simulation, norms, ethics, and training procedures. Technological sandbox, the latter, focuses on technical or production-related faults and system fluency while studying tools, systems, and innovation for training reasons. This research aims to identify the two sandbox types that have a measurable mental

workload. In this instance, we pay particular attention to the cycles of technology adoption and development as well as the cognitive strain and stress that shop floor operators experience.

The Stena Industry Innovation Lab (SII-Lab), a learning factory in Gothenburg, Sweden, serves as the basis for the research. By offering a controlled environment for experimenting with Industry 5.0 background, drone factories, assembly jobs, and human-centric digital tools, regulatory sandboxes are investigated as a tangible framework. For a limited period and in a restricted portion of a sector or area, the sandboxes are intended to provide a real-world setting for testing the uptake and usability of innovative technologies, products, services, or approaches—particularly in the context of digitalization—under regulatory supervision, guaranteeing that the necessary safeguards are in place. In order to validate the proof of concept of the digital tools for cognitive augmentation, the sandboxes primarily rely on experimentation to produce qualitative and quantitative study results.

This research employs prototype-based experiments to evaluate cognitive augmentation technologies, including VR, video instruction, and AI-driven social robots in realistic Industry 5.0 manufacturing settings. Besides, the research assessed the human-technology interaction and user interface of VR regarding mental workload.

3.2.2 Comparative Experiments

To answer RQ1 and illustrate the probable causality of an independent variable on a dependent variable, studies are frequently structured in such a way that the findings of an experimental sampling may be compared to one or more controlled samples (Pruzan, 2016).

A between-subjects 3x4 factorial design is a study where participants are randomly assigned to the control or the experimental group, with three subjects on four measurements. This study B aims to assess three common digital instructional tools - video instruction, VR, and AI-integrated humanoid social robots using a triangular combination of mental workload assessment measurement modalities (Emmie Fogelberg, Huizhong Cao, et al., 2025). The assessment incorporates four measurements - heart rate variability (HRV) as a physiological measure, the Rating Scale Mental Effort (RSME) for subjective evaluation, and performance-based metrics of completion time and error rate. By integrating these diverse measures, the study seeks to provide a holistic understanding of how different instructional methods impact learners during both the learning and operation phases of an assembly task in manufacturing. Evaluating mental workload through subjective assessments, physiological data, and performance-based metrics provides a comprehensive approach to understanding how different instructional methods affect learners.

3.2.3 Personas and Participants

Personas are imagined profiles that reflect the diversity of users or learners. A typical persona includes the user group's needs and goals, background information on the user group, and a picture of the group's representative (Weinhandl et al., 2023). In this research, the participants represent industrial practitioners ranging from novices to professionals, as well as students with little job experience. The following information has been collected with informed consent approved by the Chalmers Institutional Ethical Advisory Board (IEAB): gender, age, native language, level of education, occupation, VR experience and humanoid conversational robot experience in both Study B and C.

Participants were randomly divided into three groups, in which one group participated in a training session by watching the segmented videos on a 2D LCD screen, another group participated in a training session using HMD VR, and the last group participated in a training session with a humanoid social robots, as shown in Figure 3.2.

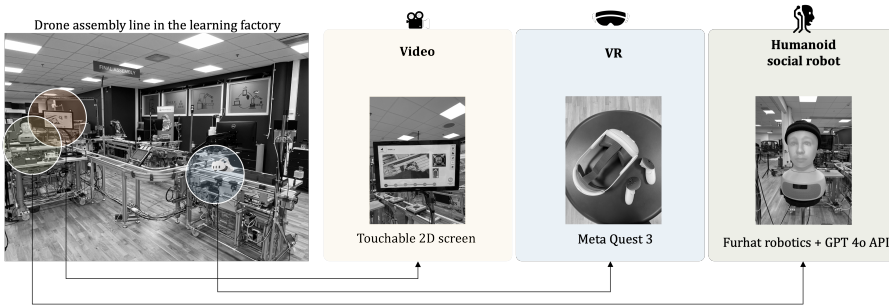


Figure 3.2: The experiment apparatus of three subjects—the simulated drone factory and its instruction station, equipped with 2D screens, a humanoid social robot, and a VR headset.

3.2.4 Hypothesis testing

In Paper 2 (instruction modality), the hypothesis is that instruction modality—video, VR, and humanoid social robots—elicits different mental workload profiles across learning and operation, leading to measurable differences in perceived effort (RSME), completion time, and errors during an industrial assembly task.

In Paper 3 (measure triangulation), the hypothesis is that Mental workload indicators from different classes—error rate and completion time (performance), RSME (subjective), and HRV (physiological)—correlate during assembly.

While in Paper 4 (VR mini-map UI features), the hypothesis is that three mini-map design features—portability, dimensionality (2D vs 3D), and tangibility—exert different, measurable effects on mental workload (NASA-TLX sub-scales) and spatial performance (navigation, layout perception, collaboration, time)

in collaborative industrial VR; portability will yield the strongest workload reduction and performance gains.

The criteria for hypothesis testing in this thesis are defined by the study design, measurement scales, and model assumptions, and are operationalized via nonparametric omnibus tests with corrected post-hoc comparisons (Paper 2), correlation analysis with power considerations (Paper 3), and mixed-effects ANOVA with predefined alpha and effect size reporting (Paper 4).

3.2.5 Data analysis methods

Answering RQ2 requires integrating multiple assessment methods—subjective self-reports, performance-based metrics, and physiological measures—to capture distinct facets of workload. By systematically comparing these measures under varying augmentation conditions, we aim to determine which metrics best reflect cognitive demands and how technology design features modulate perceived and actual mental effort. This quantitative triangulation lays the foundation for evidence-based guidelines in designing augmentation systems that optimize cognitive support without overburdening users.

Due to the fact that the studies involve inclusive representation of participant groups (both industrial/academic participants), paired/nested observations, and a mix of ordinal and continuous measures, the licentiate adopts analysis methods that fit each dataset rather than a single generic test. In practice, this means choosing robust non-parametric tests for ordinal or non-normal data, mixed-effects models to handle dependencies and unbalanced samples, and clear visualizations to expose how the data are distributed.

3.2.5.1 Non-parametric analysis

Non-parametric analysis refers to statistical methods that do not assume a specific probability distribution for the data, making them well suited for ordinal measures, small samples, or when normality assumptions are violated (Guittou and Siegel, 1958). These techniques operate on data ranks rather than raw values, providing robust inference under broader conditions. Common non-parametric tests include the Mann–Whitney U test for comparing two independent groups and the Kruskal–Wallis H test for three or more groups (Kruskal and Wallis, 1952). In paper 2, non-parametric analyses were employed to compare subjective workload ratings (RSME) across the video, VR, and humanoid robot conditions, ensuring valid results despite the ordinal scale and potential skewness of the self-report data.

3.2.5.2 Mixed effect ANOVA test

The mixed effects modeling provides an ideal framework for our study as it combines the strengths of both fixed (design features) and random (user type variability) effects analysis, accommodating the nested structure of our data where observations were collected from participants working in pairs, creating inherent

dependencies (Badr and De Amicis, 2023). As noted by Moseley et al., “Mixed models can accommodate unbalanced data patterns and use all available observations and patients in the analysis” (Badr and De Amicis, 2023), which is particularly valuable given the different sample sizes, measurement quantities, and VR experience backgrounds between student and industrial practitioner groups.

Statistical analyses were implemented using Python for the mixed design ANOVA calculations. The significance level (type I error) was set to 0.05 (Giovanni Di Leo and Francesco Sardanelli, 2020).

The mixed-design ANOVA enables us to:

- Assess the main effects of each design feature across all participants, identifying universal design principles that transcend user groups.
- Examine potential interactions between design features and user groups, illuminating whether certain features are particularly beneficial for specific user populations.
- Maintain focus on design elements rather than group differences, while still accounting for group-level variance in the statistical model.

3.2.5.3 Density plot

A density plot is a graphical representation that illustrates the distribution of a continuous variable. The probability density function depicts a smooth curve, making it easy to determine where data points are concentrated, spot several peaks (modes), and compare distributions without the abrupt bins found in histograms (GeeksforGeeks, 2025). Density plots employ a technique known as kernel density estimation (KDE), which results in a fluid, continuous representation of the data distribution. The area under the density curve always equals one, indicating the entire probability (GeeksforGeeks, 2025).

3.2.5.4 Thematic analysis

Thematic analysis is a flexible, qualitative method for identifying, analyzing, and reporting patterns (“themes”) within textual data. Rather than testing hypotheses, it explores participants’ perspectives to reveal shared experiences and meanings. Braun and Clarke’s (2006) approach, widely adopted in HCI and ergonomics research, unfolds in five iterative phases (Virginia Braun and Victoria Clarke, 2006):

1. Familiarization – Immersing in the data by reading and re-reading participants’ narratives.
2. Generating initial codes – Labeling meaningful segments of text (codes) that capture features of the data relevant to the research question.
3. Searching for themes – Grouping related codes into broader candidate themes that represent patterned responses.
4. Reviewing themes – Refining candidate themes by checking their coherence against the coded extracts and the full data set.

5. Defining and naming themes – Finalizing clear definitions and names for each theme, ensuring they tell a compelling story about the data.

3.2.6 Statistical significance

To assess statistical significance rigorously and transparently, subsection 3.2.4 specifies the hypothesis tests used, their assumptions, and decision criteria (including p-value thresholds and multiple-comparison controls), ensuring that inferences reflect the data's scale and distribution rather than relying on a single omnibus procedure. The following methods are used to test the statistical significance of the comparison results.

Kruskal-Wallis H test: The Kruskal–Wallis H test is a nonparametric alternative to one-way ANOVA, used when the assumption of normally distributed residuals is violated or when dealing with ordinal data. It evaluates whether three or more independent groups originate from the same distribution by comparing the ranks of the combined data rather than their raw values (Kruskal and Wallis, 1952). In practice, each observation is replaced by its rank across all groups, and the test statistic H measures the degree to which these ranks differ between groups. A significant H indicates that at least one group's median differs from the others, though it does not specify which groups differ; post-hoc pairwise comparisons (e.g., Dunn's test with Bonferroni correction) are then required to identify specific contrasts. In our study, the Kruskal–Wallis H test was applied to compare mental workload scores across the video, VR, and humanoid robot conditions, accommodating the ordinal nature and potential non-normality of the subjective workload data.

Dunn's post-hoc test with Bonferroni correction: When the Kruskal–Wallis's test indicated a significant group effect, Dunn's post-hoc test was applied to perform pairwise comparisons between instructional methods. The Bonferroni correction was used to adjust for multiple comparisons and control the family-wise error rate (ref). Statistical significance was set at $p < 0.05$.

Pearson Correlation: Pearson's correlation coefficient (r) measures the strength and direction of a linear relationship between two continuous variables, ranging from -1 (perfect negative) through 0 (none) to $+1$ (perfect positive) (LaMorte, 2021).

3.2.7 Statistical power

Paper 3 report p-values to indicate statistical significance, representing the likelihood that observed differences occurred by chance rather than due to our manipulated variables. The mean and standard deviation were calculated for all dependent variables. Additionally, we report partial eta squared (η^2) as our primary effect size measure, following conventional guidelines where η^2 values of approximately 0.01 indicate small effects, 0.06 medium effects, and 0.14 or greater large effects (Muller and Jacob Cohen, 1989).

Table 3.1: Methods adopted in the selected papers

Study	Paper	Analysis methods	Significance	Subject variables	Measurables
A	1	Literature review, categorization	30 full papers reviewed	7 types of use cases among 3 pillars of sustainable production	NIST sustainability KPIs
B	2	Between-subject 3x4 factorial design, Non-parametric analysis	Kruskal-Wallis H test, and Dunn's post-hoc test with Bonferroni correction	Between-subjects factors (video instruction, VR, and humanoid social robots)	Subjective assessment (RSME and user surveys), physiological instruments (HRV), and performance-based methods (completion time and error rate)
B	3	Density plot	Pearson correlation coefficient	Independent Variable (Between-subjects): VR, humanoid social robots, video instruction	Four validated mental workload instruments across three measurement classes: Error rate, Completion time, RSME, HRV

Continued on next page

Table 3.1: Methods adopted in the selected papers (continued)

Study	Paper	Analysis methods	Significance	Subject variables	Measurables
C	4	Literature review, Prototype-based experiment, Mixed effect ANOVA test, Thematic analysis	P-value to indicate statistical significance, partial eta squared(η^2) as our primary effect size measure	Within-subjects factors (design features: portability, dimensionality, and tangibility). Between-subjects factors (student vs. practitioner groups)	NASA-TLX metrics (Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration) and spatial cognition measures (Layout Perception, Navigation, Collaboration, and Time)

3.3 Project overview

The research program comprises several ongoing projects that shape the experiments, paper themes, application domains, and overall publication trajectory; collectively, they also steer the thesis's future direction. In particular, the project portfolio has informed study design choices, target user groups, and methodological emphasis across the included works. The licentiate and the author's research over the past two years have been funded by these initiatives. Specifically, Papers 1 and 4 are supported by the PLENUM project (PLENUM, 2022), while Papers 2 and 3 are supported by the DIGITALIS project (DIGITALIS, 2022).

PLENUM is envisioned as a cost-effective, accessible, and sustainable multi-user platform aimed at transforming 3D factory design, simulation, and operator upskilling. Seamlessly working in distributed environments, it leverages mature technologies for 3D scanning, multi-user functionality, and XR demonstration with the Unity platform to bring design guidelines to industrial software IPS. PLENUM's broader objectives include enhancing training effectiveness using real factory data, promoting inclusive factory design, and ensuring workforce productivity and sustainability. Moreover, it advocates for a reduction in travel needs by enabling meetings in digital twins of production system environments. User telemetry data collection, mirroring online games, can further refine IPS simulation models, enhancing overall platform efficiency through Unity for quick iteration for proof of concept.

The DIGITALIS project explores the intersection of cognitive science, information design, and XR, AI, and social robots within automotive manufacturing. It aims to enhance quality and efficiency through developing cognitive support systems and improved information design methods for XR and social robots applications. The DIGITALIS project incorporates cognitive task analysis to understand the cognitive processes involved in machine/robot interaction. Design thinking will be employed to create intuitive and effective XR/social robots interfaces for these interactions.

During the kappa's development, SkillAIbility (SkillAIbility, 2025) has accompanied the work and helped clarify the thesis's future direction. It aims to build human-centric pathways to future skills and jobs in manufacturing by co-designing education, training, and augmentation tools with workers—especially vulnerable groups—to enable an inclusive, resilient, and equitable twin transition through complementary strengths of AI, automation, and human task redesign.

Summary of the Appended Papers

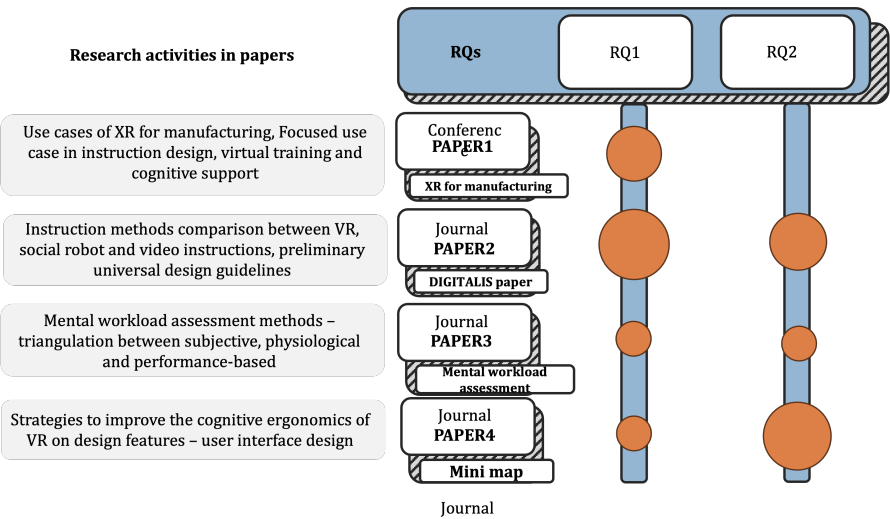


Figure 4.1: Research activities in this thesis connected to contributions to research questions and papers

Figure 4.2 provides a summary of the research activities. The activities clearly outline the research methodologies employed in each publication, which is a mixed research design that primarily uses prototype-based experimental research and integrates quantitative and qualitative research. A summary of the appended

papers is presented in the following sections, formatted as Background → Methods → Results → Discussion. The purpose of this section is to give a brief review of the attached paper with key references, and main findings with inspiring discussions. The relationship of each paper and the connection to vision/RQs will be elaborated in Chapter 4.

4.1 Paper 1

Exploring the current applications, limitations, and potential of extended reality for sustainability in manufacturing

4.1.1 Background

Manufacturing companies are facing increasing pressure to integrate sustainable and human-centric solutions to remain competitive, which aligns with the vision of Industry 5.0. This paradigm emphasizes resilient, smart, and sustainable production systems that balance economic, social, and environmental goals (Ren et al., 2019; Leng et al., 2022; European Commission, 2022). XR, encompassing VR, MR, and AR, has gained attention as a key enabling technology for this transition. XR has been shown to strengthen decision-making, improve knowledge transfer, and foster human-technology collaboration, thereby directly supporting social and economic sustainability dimensions (Fast-Berglund et al., 2018). However, its contributions toward environmental sustainability remain less systematically studied and often only indirectly demonstrated (Beier et al., 2020; Thiede et al., 2022).

4.1.2 Methods

Paper 1 presented real-world use cases of XR in manufacturing, highlighting how these technologies serve as both guidance and inspiration for future research and industrial implementation. 30 relevant papers were selected. Data from each was recorded in a spreadsheet, capturing XR technologies used, sustainability impacts, and evidence. Each use case was mapped to sustainability pillars (environmental, economic, social) based on NIST indicators. Impacts were classified as direct (quantitative evidence) or indirect (qualitative claims). This analysis highlighted how XR technologies contribute to different sustainability goals within manufacturing environments.

To measure sustainability within manufacturing processes, the U.S. National Institute of Standards and Technology (NIST) has established 213 sustainability indicators, of which 77 are specifically related to environmental performance (Joung et al., 2013; NIST, 2021; Kim et al., 2012). These indicators address crucial areas such as emissions reduction, energy and resource use, and waste minimization. While manufacturers and researchers can employ these metrics to track the ecological impact of production systems, the explicit ways in which XR technologies affect these indicators remain underexplored.

4.1.3 Results

The analysis of literature identified seven generic categories of XR use cases in manufacturing, covering a wide range of cross-industry applications. These categories demonstrate XR's capacity to support both operational efficiency and sustainability objectives.

Virtual prototyping showcases how XR can reduce the need for physical prototypes by enabling collaborative design and simulation with customers and engineers, thus minimizing material waste (Royo-Vela et al., 2022; Violante et al., 2019). Production and layout planning emphasize XR's ability to visualize and validate workstation and cell designs before implementation, helping avoid costly errors and optimize material and energy flows (Töröková and Török, 2021; Husár et al., 2022; Thiede et al., 2022; Abdelkhalik and Elngar, 2020). Ergonomic assessment illustrates XR's use with motion capture and digital human models to identify ergonomic risks early, improving worker safety and reducing redesign needs (Dreesbach et al., 2020; Hovanec et al., 2014).

Training applications indicate that XR supports improved learning outcomes, inclusivity, and skill transfer, with additional potential to integrate sustainability awareness into training programs (Gabajová et al., 2019; Araujo et al., 2019; Thiede et al., 2022). Machine/robot interaction demonstrates XR-based human-machine interfaces that improve efficiency and reduce risks during robot collaboration (Schmidt et al., 2022). Cognitive support/instruction highlights XR-enabled on-the-job support through AR devices, improving quality assurance and reducing unnecessary operator travel (J. Alves, Marques, et al., 2021; Kontovourkis et al., 2019; Lund and Ortova, 2022). Finally, data monitoring/analysis shows how XR, in combination with digital twins and sensing technologies, can visualize energy flows, emissions, and operational anomalies, contributing to environmental monitoring and worker safety (Thiede et al., 2022; Damiani et al., 2020).

Collectively, these use cases demonstrate XR's versatility and confirm its potential role in advancing environmentally sustainable manufacturing.

4.1.4 Discussion and Conclusion

The use cases show concrete pathways for XR's sustainable contributions. Virtual prototyping reduces waste and physical iterations (Chen et al., 2021; Royo-Vela et al., 2022; Violante et al., 2019). Production and layout planning ensure resource optimization and lower environmental risks (Thiede et al., 2022; Muñoz et al., 2019). Ergonomic assessments contribute to safer, more sustainable working conditions (Perezzi, Grandi, et al., 2018; Hovanec et al., 2014). Training simulations minimize unnecessary resource expenditures and embed sustainability awareness (Thiede et al., 2022; Palmarini et al., 2018). Further, machine/robot interaction, cognitive support/instruction, and data monitoring/analysis illustrate XR's ability to optimize energy flows, reduce errors, and present actionable environmental data (Schmidt et al., 2022; Sidiropoulos et al., 2021; J. Alves, Marques, et al., 2021; Lund and Ortova, 2022; Fukuda et al., 2019).

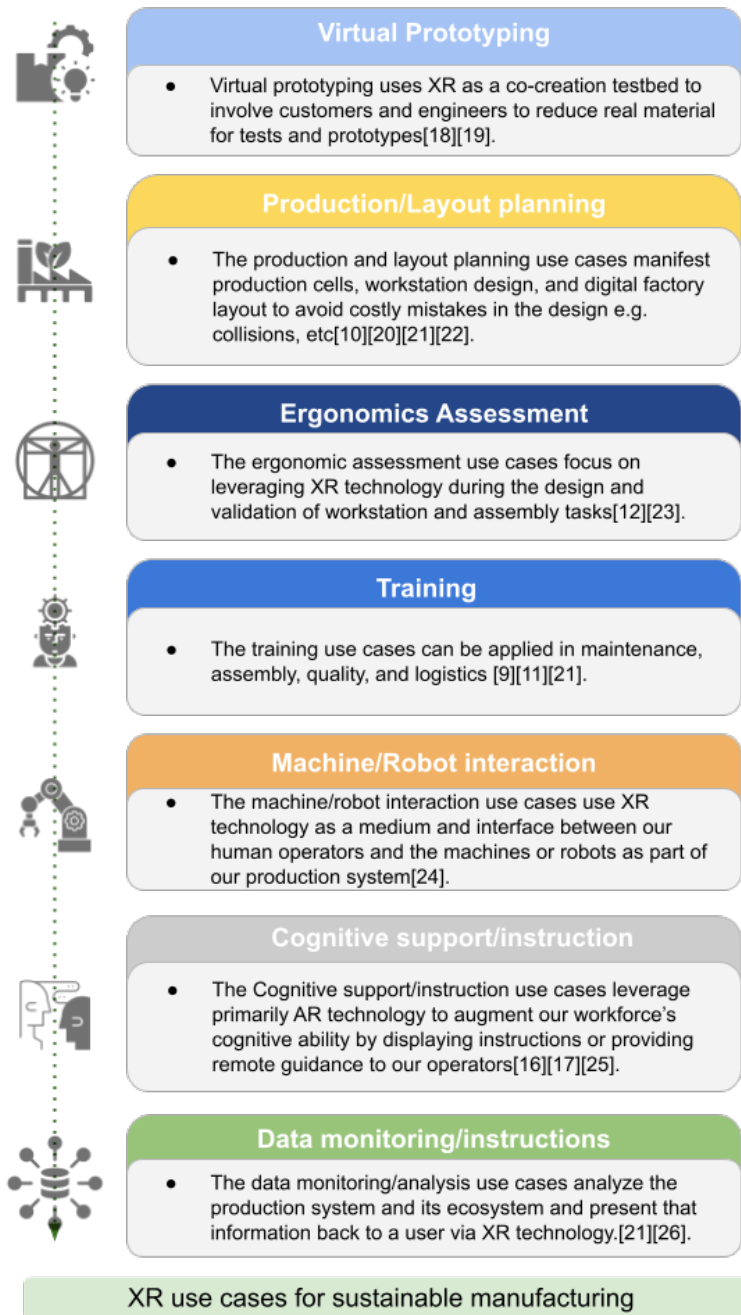


Figure 4.2: XR use case categorizations

4.2 Paper 2

Cognitive Augmentation in Industry 5.0: Comparing Mental Workload in VR, Humanoid Conversational Robot, and Video Learning

4.2.1 Background

As European industry and society confront persistent staffing shortages, a skilled and adaptable workforce is essential to sustain productivity and human-centric transformation in Industry 5.0 (M. Pinzone et al., 2024; Breque et al., 2021; Da Xu et al., 2018). Unlike Industry 4.0's emphasis on automation and connectivity, Industry 5.0 prioritizes robustness, sustainability, and worker well-being, spotlighting the need for optimized training—especially for novices—to accelerate upskilling without increasing cognitive strain (Breque et al., 2021; Da Xu et al., 2018; Romero and Stahre, 2021). Evidence shows 62% of manufacturers report competency shortages, while traditional training disrupts production and suffers from poor transfer, challenges amplified by an aging workforce and digitalization pressures (M. Pinzone et al., 2024; Greta Braun, 2023; G. Braun et al., 2024; L. Rinsky-Halivni et al., 2022). Cognitive augmentation—via XR, AI agents, social robots, and digital twins—seeks to enhance perception, cognition, and decision-making; yet multimodal, real-time interactions can elevate mental workload if timing and presentation are not cognitively aligned (Lucchese2025; L. Wang, 2021; N. S. Jangwan et al., 2022; Bustoni, 2025; Y. Huang et al., 2025; H. Cao, Rivera, et al., 2025). Mental workload, defined as the cognitive resources required to meet task demands, is tightly linked to performance, errors, and adoption outcomes; excessive load signals misaligned instruction or task design (A. Realyvásquez-Vargas et al., 2023; Galy, 2018; Galy et al., 2012). Triangulating subjective, physiological, and performance measures enables robust evaluation of instructional media—VR, AI-enabled humanoid robots, and video—to identify approaches that reduce workload while preserving consistency and fidelity in industrial assembly (Lindblom and P. Thorvald, 2014; L. Longo et al., 2022; Jafari et al., 2020; Di Stasi, Álvarez-Valbuena, et al., 2009).

4.2.2 Methods

Paper 2 used a between-subject 3×4 factorial design to compare the mental workload of three digital instructional methods—video instruction, VR, and AI-integrated humanoid social robots—used for training novice participants in a drone assembly task, as shown in Figure 4.3. Conducted in a realistic manufacturing lab, participants (N=37) were randomly assigned to one of the three instructional groups.

Prototypes were designed to reflect realistic industry practices while minimizing confounds. VR training (Meta Quest 3) provided an interactive digital twin of the assembly environment with step-mapped stations, collision notifications, haptic interaction cues, and constrained object interactions to prevent incorrect

sequences. The humanoid social robots (Furhat) delivered context-aware, step-by-step oral guidance with facial expressions and adjustable explanation granularity via a Python bridge to a large language model. Video instruction comprised segmented, first-person recordings of the same assembly sequence, accessed through an interactive interface enabling pause, replay, and step navigation.

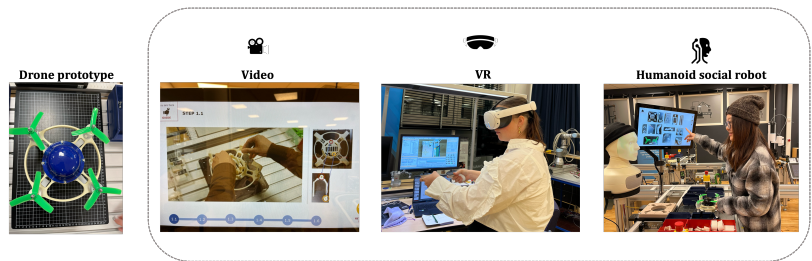


Figure 4.3: The experiment apparatus of three subjects—the simulated drone factory and its instruction station, equipped with 2D screens, a humanoid social robot, and a VR headset

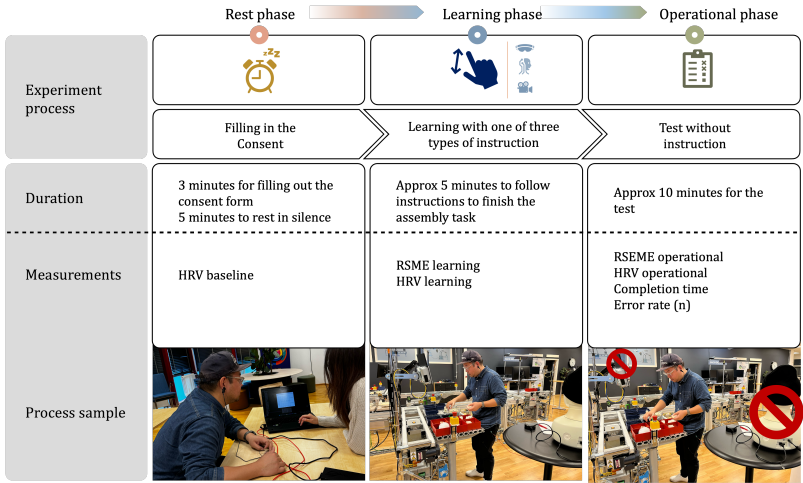


Figure 4.4: Experiment process of Paper 2 and Paper 3

Volunteers (n=37; 36 analyzed for performance; 28 for HRV after data quality screening) were primarily students/novices. Ethical procedures followed the Swedish Ethical Review Authority’s guidance; informed consent and demographics were collected, and a 5-minute seated rest established individual HRV baselines. The learning phase proceeded with the assigned modality; the operation phase required unaided assembly. HRV, time, and errors were recorded; RSME was collected after both phases. The process is illustrated in Figure 4.4.

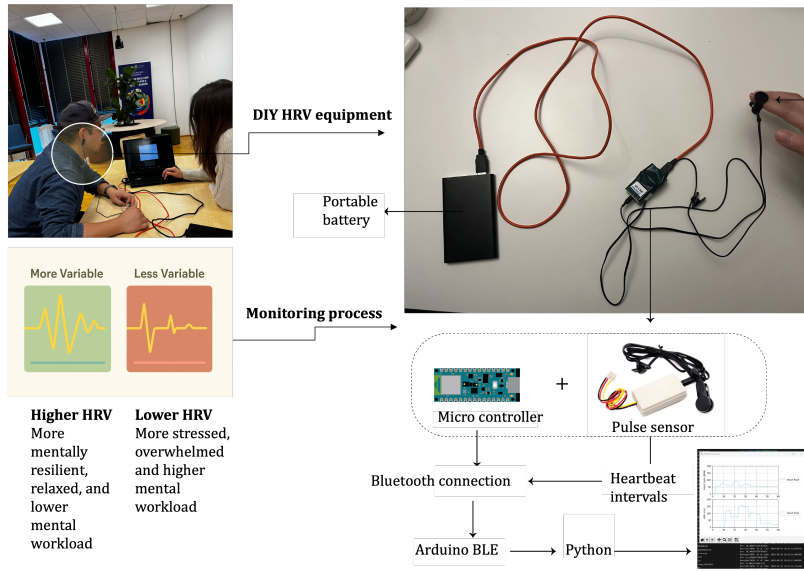


Figure 4.5: HRV collection equipment and development process

HRV was captured via ear-clip PPG to derive inter-beat intervals, transmitted to a PC, preprocessed to remove artifacts, and summarized using RMSSD with threshold-based correction windows. Nonparametric statistics evaluated group differences: Kruskal–Wallis tests for HRV, RSME, time, and errors; significant effects were followed by Dunn’s post hoc comparisons with Bonferroni correction ($\alpha = 0.05$).

Kruskal-Wallis H test: For each outcome variable (HRV, completion time, error rate, RSME), the Kruskal-Wallis H test was used to determine whether statistically significant differences existed among the three instruction groups. This test is appropriate for comparing more than two independent groups when the data do not meet the assumptions of normal distribution characteristics.

4.2.3 Results

Statistical analysis included Kruskal-Wallis H tests and Dunn’s post-hoc tests with Bonferroni correction due to the small sample size and non-normal data distribution. This combination of methods enabled a comprehensive evaluation of how different instructional technologies affect mental workload and task performance in manufacturing training.

Subjective Mental Workload (RSME)

To evaluate subjective mental workload, RSME scores were analyzed across the learning and operational phases for the three instruction types: video, robot, and

VR. Figure 4.6 presents box plots illustrating the distribution of RSME scores by condition.

Learning Phase: RSME scores varied across instruction types, with robot-based teaching producing the highest median mental effort (46.00), followed by video (26.00) and VR (25.50). Despite these differences, the Kruskal-Wallis test revealed no significant group effect ($H = 5.35$, $p = 0.0688$), with post-hoc analyses confirming no significant pairwise differences.

Operational Phase: VR instruction generated significantly higher mental workload (median = 77.50) compared to video (25.50) and robot (46.50) conditions. The Kruskal-Wallis test confirmed significant differences between groups ($H = 11.93$, $p = 0.0026$). Dunn's post-hoc testing revealed VR differed significantly from video ($p = 0.0018$), while robot instruction showed no significant differences from either condition.

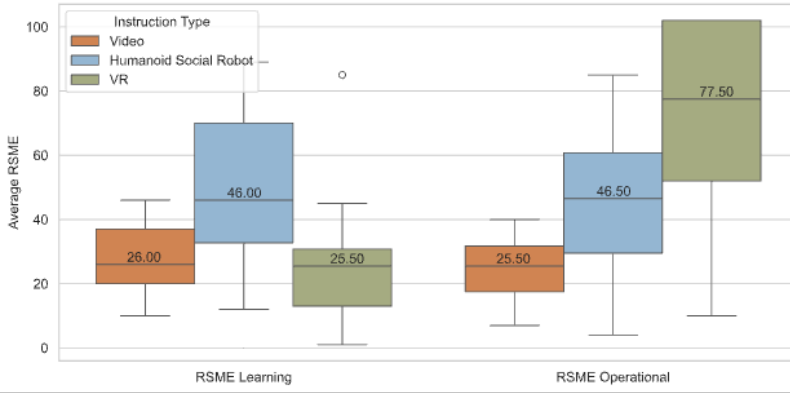


Figure 4.6: RSME (Rating Scale Mental Effort) scores across the learning and operational phases

Task Performance

To assess the impact of instruction modality on task performance of efficiency and accuracy, we analyzed Completion Time and Error Rate across three groups: Video, Robot, and VR. Figure 4.7 presents box plots summarizing these performance metrics.

Completion Time: Video instruction produced the fastest completion times (median = 165.50s), followed by robot (171.00s) and VR (490.00s). Significant group differences emerged ($H = 12.54$, $p = 0.0019$), with VR significantly slower than both video ($p = 0.0027$) and robot ($p = 0.0130$) conditions.

Error Rate: Video and robot groups demonstrated superior accuracy (median = 0.00 errors), while VR instruction resulted in substantially higher error rates (median = 8.00). Statistical analysis confirmed significant differences ($H = 17.53$, $p = 0.0002$), with VR significantly different from both video ($p = 0.00063$) and robot ($p = 0.00080$).

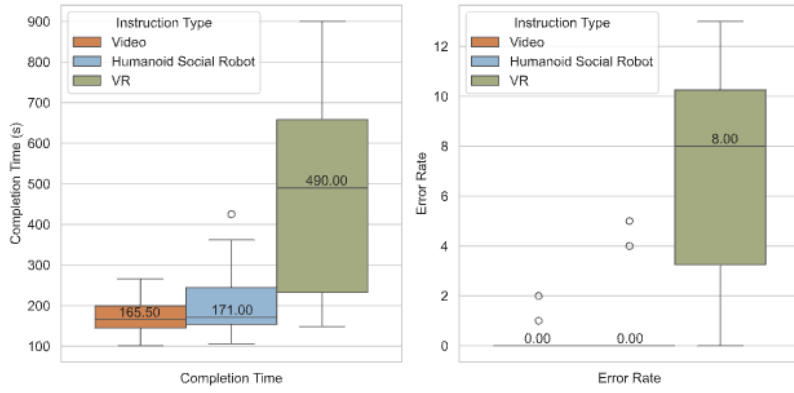


Figure 4.7: Task performance (completion time and error rate) metrics by instruction type scores across operational phases

Heart Rate Variability

HRV ratios showed no significant differences across instruction types during either learning ($H = 0.60$, $p = 0.7396$) or operational phases ($H = 0.18$, $p = 0.9124$), contrasting with subjective workload assessments as shown in Figure 4.8.

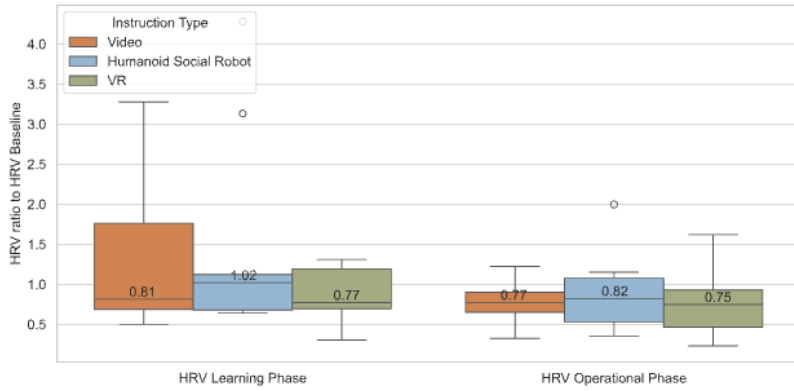


Figure 4.8: HRV ratio divided by HRV baseline during learning and operational phases. A higher ratio (above 1) means an HRV elevation from the baseline, indicating a lower stress level, mental resilience, and a lower mental workload imposed by the task.

4.2.4 Discussion and Conclusion

As shown in Figure 4.9, the mental workload assessment for video, the humanoid social robot, and VR instruction during learning and operational phases is com-

pared.

	RSME (Learning)	RSME (Operational)	Completion time	Error rate	HRV (Learning)	HRV (Operational)
 Video instruction	A tighter range centered around a median of 26.00	Lowest RSME scores during operation (median = 25.50)	Completing tasks fastest (median = 165.5 seconds)	Minimal errors (median = 0)	Median ratio of 0.81	Median ratios of 0.77
 Humanoid social robot	The most mental effort, with a median score of 46.00 and a broad interquartile range.	Subjective RSME workload was moderate (median = 46.50)	Completion times were slightly longer than Video (median = 171 seconds)	Error rates remained low (median = 0) with more outliers	Median ratio of 1.02, indicating slight elevation above baseline	Median ratios of 0.82
 VR	Lowest with a medium RSME score of 25.50	Highest subjective workload (median = 77.50).	Slowest completion times (median = 490 seconds)	Highest error rates (median = 8)	Highest mental workload increase with median ratio of 0.77	Highest mental workload increase with median ratio of 0.75
Statistical Significance	No	VR and Video conditions differed significantly ($p = 0.0018$)	VR was significantly different from both Video ($p = 0.0027$) and Robot ($p = 0.0130$)	VR was significantly different from both Video ($p = 0.00063$) and Robot ($p = 0.00080$)	No	No

Figure 4.9: Mental workload assessment comparison during learning and operational phases across instruction types

Video-based instruction delivered the most efficient and cognitively economical learning, combining the lowest perceived effort during both learning and operation (RSME medians 26.00 and 25.50), the fastest completion time (165.50 s), and near-perfect accuracy (median errors = 0). Moderate HRV ratios in both phases suggest stable autonomic responses consistent with low cognitive strain. This profile likely reflects the video’s visual clarity, procedural transparency, and natural compatibility with hands-on practice in low-to-moderate complexity tasks.

Humanoid social robots guidance offered a balanced alternative: moderate, stable RSME (46.00 learning; 46.50 operation), slightly longer times than video (171.00 s), and equally low errors. Elevated HRV during learning normalized in operation, indicating engaged but manageable cognitive/physiological demand. The interactive, social framing seems to deepen engagement without harming performance, making it suitable where timely feedback and dialogue add value.

VR showed a paradox: low perceived effort during learning (RSME 25.50) but the poorest operational outcomes—slowest times (490.00 s), most errors (8.00), and consistently low HRV ratios—signaling high cognitive/attentional costs once support is removed. Likely drivers include interface novelty, divided attention, and weaker hands-on transfer compared with video and robot. This pattern aligns with habituation and testing-effect perspectives: initial immersive appeal masks later recall and execution challenges when learners must perform independently. Practically, a modality hierarchy emerges: use video for efficient procedural uptake, robots for interactive guidance with preserved performance, and VR selectively, paired with adaptive pacing, repeated practice, and tightly synchronized, just-in-time micro-instructions to curb extraneous load.

4.3 Paper 3

Cognitive ergonomics: Triangulation of physiological, subjective, and performance-based mental workload assessments

4.3.1 Background

Paper 3 developed a multifaceted framework for assessing mental workload in manufacturing, triangulating physiological, subjective, and performance-based measures. Paper 3, while using a similar task and setup to Paper 2, shifts its focus toward identifying correlations among the mental workload measures (HRV, RSME, completion time, and error rate). It also uses a between-subject factorial design, but centers mostly on the operational phase, where participants perform the assembly task without instructional support. The study tests one main hypothesis, that the mental workload measures are interrelated, even if not linearly.

Paper 3 addresses the gap that single measures miss complementary facets in realistic tasks and that cross-class correlations are underreported, while also revealing constraints of short, naturalistic tasks and wearables on physiological sensitivity (Jafari et al., 2020; Matthews, Reinerman-Jones, et al., 2015; Argyle et al., 2021).

4.3.2 Methods

Density plot

Density plots are used in Paper 3 to compare the distributions of mental workload and performance outcomes—such as RSME (subjective workload rating), error rate, completion time, and HRV — across three instructional delivery methods.

Density plots enable us to:

- Visually assess and compare how each modality’s results are distributed (e.g., are completion times more spread out in VR than with a robot?).
- Identify which method yields the highest or lowest mental workload (RSME), the tightest or broadest range of completion times, or the most/least user errors.
- Spot differences in data patterns (e.g., if error rates are bimodal under video but unimodal under VR).
- Present these comparisons intuitively, letting readers immediately see clustering, outliers, or skewness according to instructional condition.

By plotting each group (VR, robot, video) on the same axes for variables like RSME, error rate, completion time, and HRV, the figures provide a clear picture of which instructional method imposes more cognitive or physiological workload and affects user performance. For example, if the VR group’s density for RSME is shifted toward higher values, one can immediately conclude VR elicited a higher workload. Similarly, if the robot condition’s error rate density is sharply peaked at

lower values, it indicates participants made fewer mistakes using that instruction method.

Pearson Corelation In Paper 3, multiple Pearson correlations among completion time, error rate, RSME, and HRV were ran, then plotted in a color-coded matrix. For example, in paper 3, RSME correlated strongly with completion time ($r = 0.70$) and moderately with error rate ($r = 0.51$), while error rate and time were moderately linked ($r = 0.57$). HRV showed very weak associations ($|r| < 0.2$). A prior power analysis (power = 0.283) highlighted that the study was underpowered for detecting physiological relationships. These correlations illustrate which workload measures align and underscore the need for larger samples when using HRV.

4.3.3 Results

RSME correlated strongly with completion time ($r \approx 0.70$, $p < 0.001$) and moderately with error rate ($r \approx 0.51$, $p < 0.002$); time and errors were moderately correlated ($r \approx 0.57$, $p < 0.001$), indicating convergent sensitivity of subjective and performance measures to elevated workload (Matthews, Reinerman-Jones, et al., 2015; DiDomenico and Nussbaum, 2011). HRV showed very weak relationships with RSME, time, and errors ($|r| < 0.2$), with low statistical power (0.283) and high inter-individual variability likely contributing to null findings in short operational windows (Georgiou et al., 2018; Ishaque et al., 2021; Bourdillon et al., 2022). Descriptively, VR produced higher RSME, longer times, and more errors than video and robot in operation (Argyle et al., 2021).

4.3.4 Discussion and Conclusion

Triangulating RSME with time/errors provides convergent, practical signals of workload in assembly and supports multidimensional assessment in Industry 5.0 (L. Longo et al., 2022; Van Acker et al., 2018; Tsang and Velazquez, 1996). Current short-duration, PPG-based HRV capture may lack sensitivity and robustness in naturalistic tasks; longer windows, higher-fidelity sensing (e.g., ECG), and larger samples are recommended (Georgiou et al., 2018; Hoover et al., 2012). Practically, use RSME plus time/errors for rapid iteration of instructions and UI, and apply physiology cautiously or with enhanced protocols on the shop floor (Lindblom and P. Thorvald, 2014; Matthews, Reinerman-Jones, et al., 2015).

4.4 Paper 4

Human-centered design of VR interface features to support mental workload and spatial cognition during collaboration tasks in manufacturing

4.4.1 Background

Industry 5.0 calls for human-centric, cognitively efficient VR interfaces that actively support collaboration and reduce unnecessary navigation and attentional demand in industrial contexts (J. Alves, Lima, et al., 2023; E. Loizaga et al., 2023; A. Reiman et al., 2021). While VR is increasingly adopted for layout planning, design reviews, and training, fragmented UI conventions and suboptimal navigation assistance can elevate mental, physical, and temporal demands—particularly in multi-user settings where spatial cognition, layout perception, and coordination are critical (Escallada et al., 2025; Reiners et al., 2021; Thorp et al., 2024). Prior work shows that immersive presence alone does not guarantee better learning or lower workload; design choices around guidance, maps, and interaction framing strongly mediate mental workload and transfer (Makransky et al., 2017; Skulmowski and Xu, 2021; Freina and Ott, 2015). Empirical studies link map and landmark aids, egocentric analytics, and menu design to differences in user performance, workload, and Visuospatial processing in VR (Cheng et al., 2022; Kuo et al., 2022; Sorger et al., 2021). At the same time, workload assessment requires multi-method evidence, with NASA-TLX widely validated alongside physiological and performance measures for sensitivity and comparability across tasks (S. G. Hart and Staveland, 1988; Said et al., 2020; A. Cao et al., 2009). Together, this literature motivates a user-centered, standardizable set of VR interface features—such as portable, cognitively light mini-maps—to reduce extraneous load and improve collaboration, aligning industrial VR with Industry 5.0’s human-centric agenda (H. Cao, S’oderlund, et al., 2024; E. Geurts et al., 2022; Peruzzini, Pellicciari, et al., 2019).

4.4.2 Methods

Paper 4 evaluated five different mini map designs in a collaborative VR manufacturing task to understand how design features—portability, dimensionality, and tangibility—impact mental workload and spatial performance. After identifying mini map types through literature review, five prototypes were developed and integrated into a gamified maintenance task using Unity3D and Photon for a shared VR environment. Participants included 18 students and 12 industry practitioners, divided into pairs. Students tested three random maps; practitioners tested all five, resulting in 114 valid task sessions. Participants used the mini maps to carry out navigation-based tasks, completing surveys and the NASA-TLX mental workload assessment after each session.

The study used mixed-effect ANOVA to analyze how map design and user experience levels affected workload and performance. A thematic analysis of open-ended feedback added qualitative insight, revealing themes like usability, visibility, and collaboration. This hybrid approach combined quantitative and qualitative data to assess the effectiveness of mini map features in VR.

Mixed effect ANOVA test

Mixed-effect ANOVA test is a type of mixed effects modeling, which offers particular advantages for Study C (paper 4). The participants are divided into

two persona profiles, and exposed to unbalanced conditions of trying mini maps (cao-2025).

To examine the impact of mini map design features on mental workload and spatial cognition, Paper 4 employed a mixed-design ANOVA approach that accommodated our unique experimental structure with different participant groups experiencing varying numbers of mini maps. The analysis accounted for our unbalanced design where industrial practitioners ($n = 12$, 6 pairs) experienced all five mini map prototypes (contributing 60 valid data collection sessions), whereas students ($n = 18$, 9 pairs) encountered three randomized mini map prototypes (contributing 54 valid data collection sessions). Although NASA-TLX scores are formally discrete ratings, they were treated as continuous data in accordance with common research practice, enabling the application of parametric tests.

Thematic analysis

In Paper 4, which evaluates VR mini map designs via portable, 2D, 3D, and tangible prototypes, thematic analysis was applied to participants' open-ended feedback collected after each condition. This integration enabled the study to:

1. Capture usability issues (e.g., “easy to bring map into focus” vs. “hard to toggle with controller”) by coding comments on handling and control.
2. Elucidate navigation challenges (e.g., “difficult to orient myself in 3D”) by clustering orientation-related codes.
3. Highlight visibility concerns (e.g., “map too small,” “visual clutter”) through iterative theme review and refinement.
4. Surface collaboration dynamics (e.g., “helpful to see teammate’s location”) by grouping feedback on shared use.

By systematically coding and clustering qualitative insights alongside the quantitative measures (NASA-TLX scores, spatial cognition tasks), thematic analysis in Paper 4 reveals rich, context-sensitive understandings of how design features affect user experience, complementing statistical findings with nuanced explanations of why certain mini map attributes succeed or fail.

4.4.3 Results

We evaluated assisted navigation features for collaborative industrial VR through a mixed-methods, user-centered protocol grounded in Industry 5.0 and HCI principles. Three mini-map attributes—portability (carried vs fixed), tangibility (grabbable/manipulable vs static), and dimensionality (2D vs 3D)—were operationalized across interactive prototypes and tested in a multi-user virtual factory layout scenario. Participants (students and industry practitioners) performed standardized navigation and layout-perception tasks designed to elicit spatial cognition, coordination, and decision-making demands representative of planning workflows in manufacturing (H. Cao, S"oderlund, et al., 2024; Peruzzini, Pellicciari, et al., 2019; A. Reiman et al., 2021).

Quantitative outcomes included task completion time, navigation efficiency (path length, detours), layout perception accuracy (object/zone recall), and error rates.

Subjective workload was captured with the raw NASA-TLX, given its widespread use, sensitivity across varied interaction tasks, and practical software support for collection and postprocessing (S. G. Hart and Staveland, 1988; A. Cao et al., 2009; Said et al., 2020). To complement metrics, post-task interviews and brief open-ended prompts probed clarity, cognitive effort, collaboration fluency, and mini-map usefulness; qualitative data were analyzed using thematic analysis to surface design implications (V. Braun and V. Clarke, 2006). Procedures emphasized comparable task flows and instructions across prototypes to isolate UI effects and reduce extraneous cognitive load (Skulmowski and Xu, 2021; Makransky et al., 2017). Given known impacts of landmarks and map aids on spatial processing in VR, environmental cues were included to enhance ecological validity (Cheng et al., 2022; Kuo et al., 2022). Statistical analysis applied appropriate nonparametric tests and effect sizes common in HCI evaluation; interpretation triangulated performance, workload, and qualitative themes to derive standardizable guidance for cognitively light, portable mini-maps aligned with Industry 5.0’s human-centric agenda (E. Fogelberg et al., 2024; G. Di Leo and F. Sardanelli, 2020; J. Cohen, 1988; J. Alves, Lima, et al., 2023).

4.4.4 Discussion and Conclusion

Findings indicate that assisted navigation design can meaningfully lower cognitive demands in collaborative industrial VR when features are tuned for human-centered use. Portable mini-maps consistently supported quicker, less effortful navigation and more accurate layout perception, suggesting that reducing access cost to spatial aids curbs extraneous load and improves team fluency—an alignment with Industry 5.0’s emphasis on cognitively efficient, worker-supportive interfaces (J. Alves, Lima, et al., 2023; E. Geurts et al., 2022). This complements evidence that presence alone does not ensure learning or performance gains; workload-sensitive guidance and interface scaffolds are decisive (Makransky et al., 2017; Skulmowski and Xu, 2021). The mixed-methods triangulation further underscores that subjective workload (NASA-TLX), task metrics, and qualitative insights converge on a practical principle: navigation aids must be immediately available, easy to manipulate, and visually minimal to avoid attentional tunneling and map–world mismatches (S. G. Hart and Staveland, 1988; Said et al., 2020).

For standardization, the results extend earlier calls to codify user-centered VR components for industrial planning and reviews—positioning portable mini-maps as a transferable pattern for multi-user workflows (H. Cao, Söderlund, et al., 2024; Peruzzini, Pellicciari, et al., 2019). Practically, teams should: (i) prefer portable over fixed maps for continuous access, (ii) keep interaction manipulable but low-friction, and (iii) tailor visual density to task complexity. Future studies should quantify effects across expertise levels and disturbances (e.g., time pressure), integrate physiological load indicators, and explore interoperability with digital twins to sustain human-centricity at scale (A. Reiman et al., 2021; Escallada et al., 2025; Reinert et al., 2021).

CHAPTER 5

Discussion

The research is led by two research questions:

RQ1 *How do cognitive augmentation technologies influence shop floor workers during the learning and operational phase in the Industry 5.0 manufacturing context?*

Cognitive augmentation technologies significantly influence shop floor workers during both the learning and operational phases within the Industry 5.0 manufacturing context, primarily by aiming to enhance human capabilities while managing the associated mental workload (H. Cao, Rivera, et al., 2025; Emmie Fogelberg, Huizhong Cao, et al., 2025; Nitish Singh Jangwan et al., 2022; Lucchese et al., 2025). Industry 5.0 marks a shift from the automation-focused Industry 4.0 towards a human-centric, sustainable, and resilient manufacturing paradigm, where human creativity, ingenuity, and innovation are enhanced by technology, rather than replaced (Breque et al., 2021; Lihui Wang, 2021).

A central concept for understanding this influence is mental workload, defined as the amount of mental resources and cognitive effort required to complete a task (L. Longo et al., 2022). Mental workload is a crucial indicator for monitoring stress, maintaining mental health, and objectively assessing factors linked to productivity, error reduction, and overall performance in technology adoption (Galy, 2018; Young et al., 2015). Both excessive mental workload, which can lead to errors and slower response times, and underload from monotonous tasks can negatively impact performance (Xie and Salvendy, 2000).

This thesis focuses on the following three cognitive augmentation technologies: VR, humanoid social robots (HSR), and video as shown in Table 5.1.

Table 5.1: Cognitive augmentation technologies and mental workload optimization metrics

Technology	Use case	Productivity and mental workload	Design guidelines	Comparison results	Significance
VR	Training	Test effect, habituation theory	Avoid too much guidance, encourage active information recalling, analysis, and hands-on experience	Contrast results during learning and operational phase: RSME and learning outcome	RSME operational phase, completion time and error rates
VR	Layout planning and design reviews	Cognitive ergonomics enhance productivity	Portability can mediate the mental workload	Portability is more impactful compared to tangibility and dimensionality	$p < 0.05$
Humanoid social robots	Training	Over-reliance on AI reduce productivity, moderate	Critical reflection on AI instructions, more personalized interaction	Moderate in the triangulation modalities, HRV learning is higher than the other types without significance ($p > 0.5$)	Completion time and error rate, significantly lower than VR

Continued on next page

Table 5.1: Cognitive augmentation technologies and mental workload optimization metrics (continued)

Technology	Use case	Productivity and mental workload	Design guidelines	Comparison results	Significance
Video	Training	Simplified and cognitive efficient	Segmented sessions	Relatively lowest mental workload	RSME operational, completion time and error rate, significantly lower than VR

- VR:
 - VR provides immersive and interactive training at a lower cost, reducing travel and waste as documented in Paper 1. However, it also imposes a substantially higher workload compared to the other modalities, which negatively affects task efficiency once instructional support is removed (Papers 2 and 3).
 - Interestingly, while VR appears less effortful during the learning phase, this initial ease does not translate into operational effectiveness. The paradox suggests that the true cognitive load emerges when users need to perform tasks independently, underscoring potential issues in transfer from guided to autonomous performance.
 - Elevated workload in VR has been linked to the novelty of interaction schemes, lack of haptic feedback, and interface complexity (Paper 4; (Y.-T. Huang et al., 2025; Han et al., 2021)). Navigation challenges and rich visual environments can amplify cognitive demands, occasionally causing disorientation (H. Cao, Rivera, et al., 2025; Han et al., 2021; Parsons et al., 2023). These findings align with the "test effect," which suggests that excessive guidance in learning phases may create an illusion of mastery but hinder recall and long-term learning (Oden et al., 2024).
- Humanoid social robots (HSRs):
 - HSR-based instruction represents a middle ground between video and VR, balancing engagement with moderate cognitive demands (Papers 2 and 3).
 - Unlike VR, workload in HSR-based instruction appears stable across both learning and operational phases, indicating sustained but manageable engagement. Learners also maintain high accuracy, albeit at slightly slower speeds compared to video-based instruction. Additional physiological signals suggest that robots might evoke deeper engagement without tipping into cognitive overload.
 - Nevertheless, over-reliance on interactive robotic guidance could increase task dependency and cognitive strain, as hinted by qualitative feedback from Study B.
- Video-based instruction:
 - Video consistently supports the most efficient task performance with low mental workload (Paper 2). Compared to HSR and VR, it results in faster task execution and fewer errors, making it particularly effective for procedural or low-complexity tasks.
 - Its effectiveness stems from simplicity, visual clarity, and alignment with hands-on practice. However, it is not without drawbacks, as segmented clip formats or requirements for physical mockups may slow down learning in more complex scenarios.

***RQ2** How can quantification of mental workload be utilized for improvement of cognitive augmentation technologies?*

Assessing mental workload typically involves a triangular combination of subjective, physiological, and performance-based measures because such assessment is much stronger than the single instruments, but it is not necessary in all cases, and it is definitely not widely done (Emmie Fogelberg, Peter Thorvald, et al., 2024). The correlation of the triangulation combination of metrics is tested in Paper 3, and from the study, it seems the physiological data requires accurate and high-fidelity equipment for a longer testing period to get a strong and significant correlation with the other two metrics.

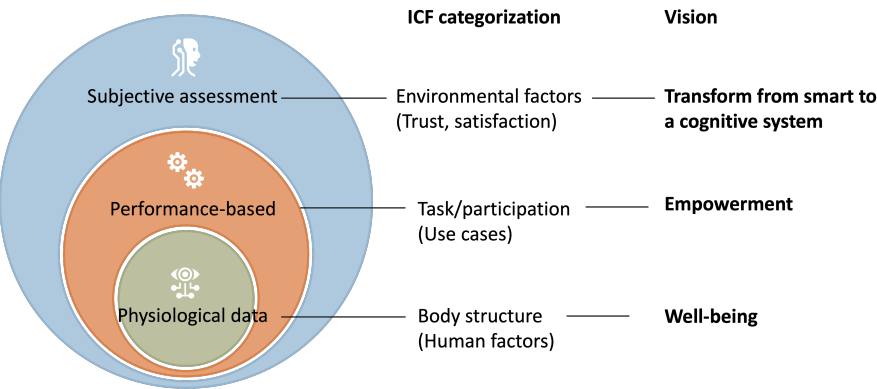


Figure 5.1: Vision and the multi-model triangulation of mental workload metrics

The triangulation observed across multi-modal mental workload metrics in Figure 5.1 aligns with the ICF’s biopsychosocial model, where functioning emerges from interactions among body functions/structures, activities/participation, and environmental factors (WHO, 2001; Battistella and De Brito, 2002). Physiological indicators (e.g., HRV) index body functions/structures and capture cognitive functions from a human-factors perspective, supporting the thesis vision of well-being through measurable changes in mental functioning. Performance-based outcomes correspond to Activities/Participation by expressing capacity and performance in realistic work tasks; selecting or designing suitable digitalization tools thereby enhances task execution and perceived empowerment on the shop floor. Subjective assessments reflect Environmental Factors by evaluating facilitation, trust, and satisfaction as perceived barriers or facilitators, which in turn motivate the progression from “smart” toward cognitive systems in practice.

Quantifying mental workload provides direct, actionable insights to improve these technologies for Industry 5.0. As shown in Paper 3, RSME (subjective assessment), error rate, and completion time (performance-based) statistically significantly correlate during the same phase, either in learning or operation. Previous literature has stressed that a multi-dimensional tool to detect multiple mental

workload signals is needed to cover the complexity of the phenomenon. As from study B (papers 2 and 3), the HRV did not show statistical significance result due to the ultra-short phase and equipment accuracy, but it does show the concept of real-time monitoring in a longer phase as indicated in the literature (Shao et al., 2020).

As shown in Study B (papers 2 and 3), the parallel comparison of the mental workload imposed by the cognitive augmentation technologies—VR, humanoid social robots, and video instruction—helps to understand the relation between the functioning of humans and the technology and builds a new way of interpreting human-computer interaction. Measuring mental workload can help create adaptive learning environments that customize experiences, provide a more just-in-time instruction design, and optimize cognitive resource allocation. Though the HRV did not show a strong statistically significant correlation to the other metrics, it shows the potential in a longer testing phase with higher accuracy, or using other physiological metrics like eye tracking or ECG (Emmie Fogelberg, Huizhong Cao, et al., 2025), the real-time monitoring to match modality to task and learners' need is potential. Real-time monitoring of the mental load imposed by the digital technologies, and provide sensitive feedback to accelerate design iteration. Focus on designing user-friendly and intuitive interfaces, particularly in VR, to avoid unnecessary complexity, as shown in Paper 4. For example, portable mini-maps in VR significantly reduce mental, physical, and temporal demands and frustration, while improving navigation and layout perception (H. Cao, Söderlund, et al., 2024). This suggests that user-controlled interfaces that offer immediate availability, low friction, and minimal visual density are crucial (H. Cao, Söderlund, et al., 2024).

Findings suggest that 3D maps, as opposed to 2D, improved layout perception and reduced completion time, indicating that appropriate contextual representation might be more critical than absolute visual simplicity, as shown in Paper 4. Through the subjective assessment (NASA-TLX, spatial navigation metrics) and performance-based assessment (completion time, error rate) in Paper 4, we could see the positive correlation between the user experience and productivity while they navigate and collaborate in the virtual environment. By identifying portability as the design feature that could lower the mental workload, the design of the user interface is thus optimized and aimed at a better user experience. By measuring mental workload, designers can identify and adjust overwhelming information presentation to better reduce the burden on limited-capacity working memory (Paas et al., 2016).

The purpose of quantifying mental workload is to provide a comprehensive understanding of the cognitive aspects of human factors. The goal is not necessarily to reduce mental workload, but rather to align individuals' capabilities with appropriate technologies and minimize unnecessary extraneous demands. Moreover, integrating real-time monitoring into the human digital twin within factory planning can generate valuable insights to support truly human-centric production.

In conclusion, the systematic quantification and evaluation of mental workload, through a multi-modal assessment approach, is fundamental for iteratively improving cognitive augmentation technologies. This data-driven approach allows for the creation of systems that are not only technologically advanced but also truly human-centric, ensuring efficiency, effectiveness, and user well-being in the evolving industrial and learning landscapes of Industry 5.0.

5.1 Contributions of This Thesis

The thesis advances a human-centric, cognitively efficient approach to industrial training and collaboration aligned with Industry 5.0, operationalizing “augment, not overload” across Papers 1–4 through validated measurement, comparative modality analysis, and actionable design patterns.

Academic contribution:

- Quantifies mental workload via triangulated measures (physiology, performance, and subjectives) and models its relationship to learning transfer, error rates, and task efficiency across training and collaborative planning tasks.
- Compares instructional modalities (video, VR, humanoid social robots) under matched objectives to derive modality–task fit rules of thumb and boundary conditions, informing selection and sequencing for skill acquisition and retention.
- Translates cognitive ergonomics into reusable VR interface and workflow patterns for collaborative planning, with principles for reducing extraneous load, scaffolding germane load, and preserving situation awareness in multi-user contexts.
- Demonstrates an ICF-informed mapping from mental functions to activities/participation and contextual factors, providing a theoretically grounded lens that links cognitive workload to real-world performance and well-being outcomes.

Industrial contribution:

- Provides a practical playbook for selecting and configuring digitalization tools (video, VR, humanoid social robots) to accelerate onboarding and upskilling while controlling cognitive load, including readiness checks, modality selection criteria, and roll-out steps.
- Delivers shop-floor–tested VR interface patterns and collaboration workflows that reduce time-to-competence and rework, with guidelines for task chunking, feedback timing, and attention management in constrained environments.
- Establishes a lightweight measurement toolkit (HRV, performance telemetry, brief subjective scales) that production teams can deploy to monitor cognitive strain during training and continuous improvement activities.

- Supplies decision support for human–technology allocation in Industry 5.0 initiatives, clarifying when to automate, augment, or re-sequence work so operators remain empowered, safe, and in control.
- Codifies change-management and adoption guidance—stakeholder mapping, trust-building through transparent feedback, and iterative pilots—so interventions scale from pilot cells to lines without overload.

Overall, the mission was met to a strong degree: the work provides evidence-based design principles, validated measures and protocols, and concrete implications for deployment in real industrial contexts. Research questions were addressed through controlled experiments, mixed-method evaluations, and design-science contributions. Sustainability is supported indirectly by improving training efficiency, reducing rework and errors, and enabling remote collaboration.

5.2 Reflection on methodology

This work stems from a long-standing fascination with the rules, regularities, and underlying simplicity that mathematics reveals, and with the aesthetic of scientific, universal methods that make such structure visible. This orientation has consistently shaped the research stance adopted here: a commitment to clear hypothesis formation grounded in real-world norms, and to rigorous sampling and comparative experimentation capable of identifying meaningful, statistically and practically significant differences. The trajectory of the project—and the development of the researcher—has been guided by these principles, for which there is strong cause for gratitude and reflection.

The central contribution of this thesis lies less in any single domain-specific result than in the methodology itself. The research demonstrates that a carefully integrated, multidisciplinary approach can be made operational in manufacturing contexts, bringing together cognitive science, architecture, human–computer interaction (HCI), and software engineering within the emerging paradigm of Industry 5.0. In doing so, it reframes manufacturing not merely as a site of production optimization, but as a design space where human cognition, spatial and material constraints, interaction modalities, and software-intensive systems co-evolve.

Methodologically, the study shows how quantitative and qualitative strands can be productively intertwined to reveal regularities that neither approach alone would surface. Quantitative methods—through controlled comparisons, sampling strategies, and inferential analyses—yielded measurable effects and patterns (Pruzan, 2016), while qualitative inquiry—through observation, elicitation, and interpretive synthesis—contextualized those patterns, explained outliers, and uncovered latent mechanisms (V. Braun and V. Clarke, 2006). The result is a mixed-methods framework capable of formulating and testing hypotheses that are both empirically robust and experientially grounded.

Two implications follow:

First, for Industry 5.0, which emphasizes human-centricity, resilience, and sustainability (Breque et al., 2021), the integration of cognitive science and HCI into manufacturing research is not optional but necessary. It supports the design of systems that are not only efficient but also learnable, error-tolerant, and aligned with human decision-making and perceptual limits (Lihui Wang, 2021). Architecture contributes by situating these systems in spatial and organizational configurations that afford safe, intelligible, and adaptable workflows. Software engineering connects these human and spatial insights to implementable, maintainable, and scalable solutions.

Second, for universal design, the findings indicate that mixed-methods inquiry can accelerate the articulation of cross-context “rules” and design regularities. By iterating between numerical evidence of effect and qualitative accounts of experience and use, the research identifies design constraints and affordances that travel across settings and user groups, thereby advancing generalizable design principles without erasing contextual nuance.

Taken together, these results suggest a pathway toward a methodology-driven science of manufacturing for Industry 5.0: one that treats methodological rigor and integrative design as mutually reinforcing. The thesis argues that this approach—rooted in hypothesis discipline, comparative experimentation, and mixed-methods triangulation—constitutes its primary contribution. It demonstrates that a universalist aspiration in design need not conflict with local specificity; rather, it can emerge from systematic, transparent integration of quantitative regularities with qualitative understanding. This integration yields not only better explanations of current systems but also a principled basis for guiding future interventions in human-centric, software-intensive, and spatially situated manufacturing environments.

The experiments could be further improved by adopting the following strategies:

- Increasing practitioner diversity and sample size; balancing gender representation.
- Expanding task complexity, incorporating disturbances, and adding team-based trials.
- Running within-subject or longitudinal designs to capture habituation, retention, and transfer.
- Augmenting **workload batteries** with additional *physiological* (where feasible and privacy-preserving), *behavioral* (micro-interactions), and *secondary-task probes*; preregistering analyses when appropriate.

5.3 Reflections on Research Quality and Ethics

The research followed core principles of informed, voluntary, and documented consent; participants received clear information on aims, procedures, risks, data handling, and withdrawal rights before any activity. Recruitment targeted adult

volunteers without known contraindications for immersive or sensor-based studies, and participation could be discontinued at any time without penalty. Procedures minimized burden by using short sessions, familiarization where appropriate, and debriefing. Personal data were collected only to the extent necessary for research objectives and handled according to institutional guidance, with anonymization in analysis and reporting. Future work should further scrutinize privacy and data protection in sensor-rich settings (e.g., video, voice, physiological signals), clarify secondary use, retention, and cross-border data processing, and strengthen processes for participant comprehension across languages and accessibility needs.

Research quality and usefulness: The work answers well-defined questions with convergent evidence, yields actionable design guidance (e.g., just-in-time, cognitively light interfaces; portable navigation aids), and contributes to VR HCI and industrial ergonomics by connecting measurable workload effects to concrete interface features. The results are useful for practitioners who must balance cognitive demands, clarity, and efficiency in digital work instructions and collaborative VR.

Future directions: Address ethical and privacy issues around sensing in operational contexts; develop robust, real-time workload inference models across tasks and populations; evaluate hybrid instruction ecosystems (video, social robots, VR) in varied industrial applications; and integrate IoT and smart manufacturing data streams for adaptive, human-centric systems.

5.4 Future Research

The study further addresses accessibility issues and regards it as a future direction: individuals with hearing impairments may struggle with audio-based instructions from social robots, making VR a more suitable alternative for them; in contrast, social robots may be preferable for users with vision impairments. Overall, video instruction emerges as the most universally accessible digital tool, yet the research emphasizes the importance of improving user experience and accessibility in both AI-driven social robots and VR by applying universal design principles. For future work, the study will be extended to universal design and the prototyping development of more cognitive augmentation technologies for prescriptive studies:

- Consider personal factors, including disabled and aging people's special demand for universal design of cognitive augmentation technologies.
- Understand the vulnerable groups' needs, such as disabled, aging, or novice workers, and provide guidelines for different cognitive augmentation technologies' development.
- Prototype development for a humanoid social robots, with more interaction techniques like facial expression, dialect, information density in instruction, and camera feed for better engagement.
- Real-time workload inference and closed-loop adaptation. Explore a more accurate HRV method, and use it as the dynamic input to manage the mental workload of a digital system.
- Broader industrial applications, integration with IoT/DT pipelines, and sustainability metrics (e.g., rework, travel, and material waste reductions).
- Longitudinal and within-subject studies to capture habituation, retention, and transfer.

In sum, the thesis fulfills its vision and mission to a high degree: it connects rigorous workload evidence to actionable design choices for human-centric digitalization, providing a practical roadmap for Industry 5.0 training and collaborative cognitive system.

CHAPTER 6

Conclusion

This thesis investigated the role of cognitive augmentation technologies on the Industry 5.0 shop floor with a dual focus on human-centric value and measurable cognitive impact.

The results show that these technologies can meaningfully augment rather than replace human capabilities—improving learning effectiveness, operational performance, and inclusion—when they are designed and deployed with attention to ethics, accessibility, and well-being. Across modalities, human-centered user interface design emerges as a primary lever to reduce unnecessary complexity, accommodate diverse worker needs, and sustain motivation and satisfaction in daily operations. Properly configured, adaptive, natural, and cognitive systems can empower vulnerable groups, support lifelong learning, and improve job quality.

Furthermore, the research demonstrates that a mixed-measures approach integrating subjective ratings, physiological signals, and performance metrics—provides a reliable basis for quantifying workload and guiding design decisions. In practice, triangulating instruments (e.g., NASA-TLX, HRV, RSME, error rates, and completion time) enables detection of overload or underload, comparison between modalities, and iterative tuning of interfaces and training protocols. This evidence can be operationalized through adaptive interventions: adjusting information density and pacing with segments, simplifying interaction flows, or switching the assistance modality, like proper UI, to keep workload within an optimal band. Such closed-loop, data-informed adjustments improve learning efficiency, reduce errors, and enhance operational satisfaction.

The key findings of the licentiate are as follows:

- VR provides immersion and ecological validity but imposes the highest mental workload, reducing effectiveness during operational tasks.
- Humanoid social robots achieve a middle ground, offering interactive engagement with moderate and stable workload.
- Video instruction supports the fastest, most accurate, and cognitively efficient task execution, making it the most reliable modality for procedural training.
- Triangulated workload measurement (subjective, physiological, performance-based) strengthens evaluation but requires careful implementation, especially with physiological signals.
- Applying workload metrics enables actionable design refinements, such as portable VR mini-maps and user-controlled interaction features.
- The thesis operationalizes the principle of “augment, not overload” by linking workload assessment directly to instructional design guidelines.

Taken together, the thesis concludes that cognitive augmentation for Industry 5.0 is most effective when it (i) centers human agency for inclusion, empowerment, symbiosis, and augmentation, (ii) matches modality to task and user profile, and (iii) uses validated, multimodal workload assessment to drive continuous refinement. These principles offer a practical pathway to productivity gains and digital proficiency that also protect dignity, well-being, and long-term resilience on the shop floor.

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