ROBOT-SUPERVISED INTELLIGENT WORKLOAD REALLOCATION BASED ON STRESS-AWARE HUMAN PERFORMANCE MONITORING IN HUMAN-ROBOT TEAMS

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ABSTRACT

Robot-Supervised Intelligent Workload Reallocation Based on Stress-Aware Human Performance Monitoring in Human-Robot Teams

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The integration of humans and artificial intelligence-based robotic systems in collaborative environments is transforming teamwork across domains. These human–robot teams, which include both physically embodied robots and intelligent virtual agents, require careful coordination to ensure effective task performance. A critical factor is the dynamic allocation of workload, which must consider the distinct characteristics of humans and robots. Human performance, influenced by stress and other physiological states, contrasts with the algorithmic and cognitive nature of robotic behavior. This disparity highlights the need for adaptive workload allocation strategies that safeguard human well-being while sustaining overall team efficiency.

This research investigates a robot-supervised, stress-aware workload allocation framework that continuously monitors human stress levels and reallocates tasks in real time to maintain optimal performance. Leveraging advancements in wearable technology and affective computing, the study explores multiple physiological (EEG, f-NIRS, ECG, EDA, EOG) and behavioral (facial expressions, speech, eye movement) indicators to assess stress. It further considers contextual factors such as task complexity, time of day, and individual differences in skills and knowledge.

The central contribution is a stress-sensitive reallocation algorithm that enables robots to adapt task assignments when stress affects human performance. The scope of this thesis is intentionally limited to single-human, single-robot, single-task scenarios to provide a controlled foundation for stress-aware workload redistribution. This focused scope allows a systematic investigation of how human stress influences task execution and how robots can intervene effectively. Within this boundary, the thesis offers a generic stress-sensitive framework and a structured methodological approach validated through simulation.

ACKNOWLEDGEMENTS

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I am sincerely grateful to my supervisors, Prof. Dr. Yong Zeng and Prof. Dr. Ali Akgunduz, for their invaluable guidance and mentorship. Their thoughtful feedback and steady encouragement have helped shape the direction and depth of this work, even during its most difficult phases.

To my beloved spouse, Caner Budakli, thank you for being my anchor. Your constant support, patience, and joy have brought light into my life and balance into every step of this journey. You reminded me to breathe, to laugh, and to keep going.

I also wish to thank all my family members, whose faith in my work and unwavering belief in my potential kept me grounded and inspired. Their support has been a pillar of strength.

As I reach the end of this path, I look forward to the beginning of another. Our baby boy, Baybars Budakli, expected to join our lives in July 2025, has already added unimaginable colour to our world. The anticipation of his arrival has filled these final months with joy, hope, and a renewed sense of purpose. Knowing that one day he may read these words fills this thesis with a meaning far deeper than academic achievement.

To my mentors, family, friends, my spouse, and to Baybars—thank you. In your own unique ways, each of you has played a part in making this achievement a reality.

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1. INTRODUCTION

Humans and intelligently developed computerized systems, commonly known as robots, have recently been forming hybrid teams for collaborative tasks. These robots can either be physically present in human-robot collaborations, such as surgical robots, socially assistive robots, and humanoid robots, or they can be intelligent, software-based programs, such as chatbots, large language models, and virtual AI tools. As humans and AI-assisted robots are expected to collaborate in completing tasks, the careful consideration of their **workload allocation**—and by extension, their **collaborative performance**—is essential.

A key element in this collaboration is **interaction**, which can be viewed as an **evolved form of communication**. Interaction plays a pivotal role in effective teamwork. However, the nature of interaction between humans and robots differs significantly. While human interaction is emotionally driven, influenced by affective states and stress, robot interaction is cognitive, grounded in computer programming, statistical models, and AI algorithms. As such, defining distinct **interaction modes** with unique features is crucial to ensuring that the right tasks are assigned to the appropriate partner. Once these modalities are established, it is essential to assess the suitability of tasks for each partner based on their individual characteristics. This should be followed by an examination of the **dynamics of workload allocation**, leading to the final step of task assignment, taking into account the factors that influence **human-robot collaboration**.

In addition to task allocation, it is vital to continuously monitor **human emotional states** throughout the collaboration, particularly after tasks are assigned. This is necessary because fluctuations in human performance can occur. Should a **human's performance** decline for any reason, the robot partner must investigate the cause and intervene, ensuring that the human remains in optimal conditions for effective collaboration.

According to Yerkes-Dodson’s law (1908), human performance peaks when stress levels are moderate. If stress deviates from this optimal range—either increasing or decreasing beyond predefined thresholds—human performance deteriorates. Therefore, maintaining the human's stress level within its optimal range is critical for sustaining effective performance. However, stress is not the sole factor that may influence performance. Time-related factors such as circadian rhythms, sleep patterns, and the time of day have been shown to significantly impact human performance in human-robot collaborations (Kalanadhabhatta et al., 2021; Razavi et al., 2023). Additionally, the knowledge and skillset of the human assigned to the task can play a crucial role (Nguyen and Zeng, 2017).

Recent developments in technology allow for the assessment of human stress through various physiological measurements. These include the analysis of brain signals using electroencephalography (EEG) (Al-Shargie et al., 2016; Perez-Valero et al., 2021; Katmah et al., 2021; Attar, 2022; Hemakom et al., 2023), the tracking of oxygenated and deoxygenated hemoglobin in brain tissue via functional near-infrared spectroscopy (f-NIRS) (Al-Shargie et al., 2016; Mirbagheri et al., 2019), heart rate evaluation using electrocardiography (ECG) (Behinaein et al., 2021; Hemakom et al., 2023), skin resistance or electrical potential changes through electrodermal activity (EDA) (Awada et al., 2024; Dao et al., 2024; Pop-Jordanova & Pop-Jordanov, 2020; Rahma et al., 2022), and the analysis of cornea-positive potential through electrooculography (EOG) (Mocny-Pachońska et al., 2021; Das et al., 2023; Dao et al., 2024) using skin electrodes near the canthi during horizontal eye movements.

In addition to these physiological measures, behavioral indicators, such as facial expression recognition (Jabon et al., 2010; Zhu et al., 2017), image and speech recognition (Fahn et al., 2022), head pose estimation (Murphy-Chutorian & Trivedi, 2008), and eye movement recognition (Lachance-Tremblay et al., 2025; Gazetta et al., 2023; Mocny-Pachońska et al., 2021), can also provide insights into human emotions.

Given that stress is a dominant emotional factor in human-robot collaboration, this research primarily focuses on monitoring and adjusting **human stress levels** to optimize workload management. As outlined earlier, such adjustments necessitate a well-structured interaction system and **dynamic workload allocation** principles to facilitate **timely and effective interventions**. The following sections will delve into the specific problem addressed in this thesis, explain how the research objectives respond to this issue, identify the basic assumptions and limitations, and provide an overview of the steps that will be covered throughout the thesis.

1.1.Problem Statement

Advancements in artificial intelligence have enabled robots to collaborate with humans in a manner similar to human-to-human collaboration. Recent technological developments allow robots to understand human intentions and behaviors through emotion and stress detection algorithms, establishing feedback-based interaction between both partners. While humans are expected to perform according to predefined standards, their performance can fluctuate over time. Therefore, monitoring human performance plays a critical role in dynamically reallocating tasks between humans and robots to maintain the expected level of human performance. This dynamic task allocation must consider precedence, prioritization, and task compatibility for both humans and robots (Alirezazadeh and Alexandre, 2022).

Although stress recognition and dynamic task allocation have been extensively studied, the development of a human stress-aware task reallocation algorithm designed to maximize the collaborative performance of a human-robot team has not been sufficiently addressed. This research aims to fill this gap by proposing solutions to address fluctuations in human performance within a human-robot team, ultimately enhancing collaborative performance.

1.2.Research Objective

This research aims to enhance the productivity of human–robot teams through a robot-assisted, stress-aware workload allocation algorithm. The underlying hypothesis is that maintaining human stress levels within optimal ranges can maximize individual performance, thereby improving the overall efficiency and effectiveness of the human–robot collaboration. With advancements in technology, robots are now capable of detecting fluctuations in human stress. Accordingly, this study posits that human stress can be quantified, continuously monitored by robots, and used as a basis for timely intervention. Through this approach, workload can be dynamically and adaptively reallocated to optimize team performance in real time.

According to the research objective outlined above, the main research question is first identified, followed by ten sub-research questions developed around it. This structured approach guides the systematic presentation of the proposed model. These questions are listed below.

Main Research Question: How can the collaborative performance of a human-robot team be improved through robot-supervised decision mechanism for workload allocation based on fluctuations in human stress levels?

- **Sub-Research Question 1:** What is the structure of human-robot systems, and how do humans and robots interact within this framework?
- **Sub-Research Question 2:** What are the task zones in human–robot collaboration?
- **Sub-Research Question 3:** What are the interaction channels through which humans and robots collaborate?
- **Sub-Research Question 4:** What are the dynamics of task reallocation when determining the feasible set of tasks?
- **Sub-Research Question 5:** What constitutes the performance of a human–robot team?
- **Sub-Research Question 6:** What are the optimal conditions under which humans perform at their best?
- **Sub-Research Question 7:** What factors influence human stress levels and performance?
- **Sub-Research Question 8:** How can human stress levels be measured, and is there a reliable method to quantify them?
- **Sub-Research Question 9:** How does the robot determine the appropriate moment to intervene in task allocation?
- **Sub-Research Question 10:** How can robots effectively determine when and how to reallocate tasks based on real-time human performance and human stress data?

The following section outlines the key assumptions established for this research.

1.3. Basic Assumptions

- Since this research focuses on human–robot collaboration, it is essential to clearly define the term *robot*. In this study, robots are considered AI-based, intelligent, adaptive, computerized systems.
- Tasks are categorized based on the capability of each partner: some tasks can be performed exclusively by humans, others solely by robots, and some collaboratively. Additionally, certain tasks may be performed by either humans or robots independently, or jointly through human–robot collaboration, forming intersecting task domains.
- Human stress can be measured and quantified using wearable devices that capture physiological biosignals.
- Human stress can serve as a decision checkpoint to support performance optimization.
- Control charts can be utilized to detect irregularities or deviations in human performance over time.
- Task-specific stress levels can be quantified by considering the following parameters:
    - *Perceived workload* (W^p)*:* The workload subjectively experienced by the human at time *t*.
    - *Task complexity* (C)*:* The inherent difficulty level of the assigned task.
    - *Time of day* (T)*:* The temporal context that may affect human cognitive and physical effectiveness.
    - *Actual workload* (W^a)*:* The pre-defined workload assigned to the human at the beginning of the project.
    - *Affective state* (A)*:* The human's emotional or mood-related condition at a given time.
- If the task being pursued lies on the project's critical path and the human's stress level exceeds acceptable thresholds, the task cannot be delayed or paused. In such cases, the task should be reassigned to another human collaborator capable of completing it. If the task is not on the critical path, it may be swapped with another task from the human's to-do list to mitigate the impact of stress.

1.4.Thesis Organization

This thesis presents a comprehensive literature review in Section 2 to illuminate the evolution of human–robot collaboration, the tools and techniques used within this context, the concept of collaborative performance in human–robot teams, the influence of human stress levels on collaboration, and current implementations of robot-supervised human–robot systems. To systematically address these topics, guiding questions are posed for each section and subsection of the literature review. This structured approach is designed to ensure the inclusion of relevant interdisciplinary literature and to support the reader's understanding of the review's flow. The questions used to guide the literature analysis are listed in Table 1.

Table 1: Key Questions Addressed in the Literature

LITERATURE SECTIONS	LITERATURE SUBSECTIONS	QUESTIONS ADDRESSED
2.1 EVOLUTION OF THE HUMAN-ROBOT SYSTEMS	**2.1.1.** System's Evolution: From Human-to-Human Interaction to System-to-System Interaction	• How has human-robot collaboration evolved from human-to-human interaction to system-to-system interaction? • In what ways has the inclusion of systems changed the nature of human work in collaborative environments?
	2.1.2. Evolution of Human-Robot Collaboration: From Coexistence to Proactive Collaboration	I. What are the driving factors behind the evolution of human-robot collaboration from coexistence to active collaboration?
	2.1.3. From Communication/Interaction to Collaboration between Humans and Robots	II. How are communication, interaction, and collaboration defined within human-robot teams? III. What leads human-robot interaction to become collaboration?

		2.1.4. Human Factor in Human-Robot Collaboration	IV.	What are the key human factors influencing the success of human-robot collaboration?
		2.1.5. Robot Factor in Human-Robot Collaboration	V.	What are the defining factors that contribute to a robot's effectiveness in human-robot collaboration?
2.2	**TOOLS AND TECHNIQUES USED IN HUMAN-ROBOT SYSTEMS**	**2.2.1.** Behavioral Measurements in Human-Robot Systems	VI.	What behavioral metrics are used to assess human responses in human-robot collaborations?
		2.2.2. Physiological Measurements in Human-Robot Systems	VII.	What physiological metrics are used to assess human responses in human-robot collaborations?
2.3	**PERFORMANCE, STRESS AND TASK ALLOCATION FACTORS IN HUMAN-ROBOT SYSTEMS**	**2.3.1**. Human-Robot System Performance	VIII.	What factors influence the overall performance of human-robot systems in collaborative tasks?
		2.3.2. The Effect of Human Stress in Human-Robot System Performance	IX.	How does human stress impact the performance and efficiency of human-robot systems?
		2.3.3. Task Allocation in Human-Robot Systems	X. XI.	What factors should be considered when allocating tasks between humans and robots in collaborative systems? How does the human factor influence task allocation in human-robot systems?
2.4	**ROBOT-SUPERVISED HUMAN-ROBOT SYSTEMS**	**2.4.1.** Robots' Decision-Making in Human-Robot Systems	XII.	What are the decision-making algorithms used by robots in collaborative human-robot systems?
		2.4.2. Implementations of Robot-Supervised Human-Robot Systems	XIII.	What are the current real-world applications of robot-supervised human-robot systems, and how do they perform in different industries?

Following the methodology presented in Section 3, the implementation of the proposed model is detailed in Sections 4 through 7. These sections correspond to the sub-research questions outlined in Section 1.2. The mapping of each section to the respective research questions is provided below.

Table 2: Mapping of Thesis Sections to Sub-Research Questions

Thesis Sections	Thesis Subsections	Sub-Research Questions of the Thesis
4. The Human-Robot System Framework in The Proposed Model	**4.1.** System Components in Human-Robot Systems **4.2.** Interactions in Human-Robot Systems	**Question 1:** What is the structure of human-robot systems, and how do humans and robots interact within this framework?
5. Interaction Modalities Across Task Zones in the Proposed Human-Robot Collaboration Model	**5.1.** Definition of Task Zones	**Question 2:** What are the Task zones in human–robot collaboration?
	5.2. Classification of Interaction Modes	**Question 3:** What are the communication channels used in different interaction modes for human-robot collaboration?
	5.3. Integration of Interaction Modes with Task Zones	**Question 2:** What are the task zones in human–robot collaboration? **Question 3:** What are the communication channels used in different interaction modes for human-robot collaboration?
	5.4. Dynamic Task Reallocation Algorithm Based on Task Zones	**Question 4:** What are the dynamics of task reallocation when determining the feasible set of data?
	5.5. Case Study: Dynamic Task Reallocation Management for Optimized Performance in Human-SAP System Collaboration	**Question 2:** What are the task zones in human–robot collaboration? **Question 3:** What are the interaction channels through which humans and robots collaborate? **Question 4:** What are the dynamics of task reallocation when determining the feasible set of data?
6. Performance Evaluation of the Proposed Human-Robot Collaboration Model	**6.1.** Formulating Human-Robot System Performance as a Function of Human Stress	**Question 5:** What constitutes the performance of a human–robot team? **Question 6:** What are the optimal

		conditions under which humans perform at their best?
	6.2. Identification of Parameters Influencing Human Stress and Performance	**Question 7:** What factors influence human stress levels and performance?
	6.3. Measuring Human Stress Levels Using Wearable Devices	**Question 8:** How can human stress levels be measured, and is there a reliable method to quantify them?
	6.4. Quantifying Task-Specific Human Stress: Development of Conceptual Formula	**Question 8:** What methods can be used to quantify task-specific human stress, and how can a conceptual formula be developed to measure it accurately?
7. Robot-Supervised Intelligent Workload Reallocation based on Stress-Aware Human Performance Monitoring in Human-Robot Teams	**7.1.** Process Flow of Robot-Supervised Workload Allocation	**Question 9:** How does the robot determine the appropriate moment to intervene in task allocation?
	7.2. Intervention-Based Task Reallocation Model for Robots	**Question 10:** How can robots effectively determine when and how to reallocate tasks based on real-time human performance and human stress data?
	7.3. Monte Carlo Simulation: Intervention-Based Task Reallocation Model	**Question 9:** How does the robot determine the appropriate moment to intervene in task allocation? **Question 10:** How can robots effectively determine when and how to reallocate tasks based on real-time human performance and human stress data?

Sections 4 through 7 address the core inquiries of this study. The research findings are then discussed in Section 8, followed by a presentation of the study’s limitations in Section 9. Although the thesis offers a significant contribution to the field, certain constraints—outlined in Section 9—limit its applicability in fully replicating the complexity of real-world implementations. Future directions for extending and validating the proposed model are discussed in Section 10. Finally, Section 11 provides the overall conclusion.

2. LITERATURE REVIEW

This section provides a comprehensive examination of the transition from traditional human–human interaction to the development of intelligent, next-generation human–robot systems within collaborative work environments. It begins by tracing the evolution of these systems, emphasizing how technological advancements have transformed interaction dynamics in the workplace. Subsequently, the review explores contemporary tools and techniques used to support and optimize human–robot collaboration. Particular emphasis is placed on the central theme of this research: the relationship between human stress and performance within collaborative systems. Accordingly, this section also examines how these factors have been conceptualized, measured, and addressed in recent studies. Finally, given the thesis's focus on robot-supervised decision-making—especially for workload reallocation—the review investigates current implementations of such systems and the mechanisms they employ to enable task-level intervention.

To structure the review and inform the development of the proposed model, thirteen targeted research questions were formulated. These questions, introduced in the previous section, are systematically addressed in the subsections that follow.

2.1. Evolution of the Human-Robot Systems

This section focuses on the evolution of human-robot systems and the contribution of human and robot partners.

2.1.1. System's Evolution: From Human-to-Human Interaction to System-to-System Interaction

As technology continues to advance, system-to-system interaction has increasingly replaced traditional human-to-human interaction within collaborative work environments. This shift is driven by the promise of faster, more effective, and more efficient automated solutions. The term "systems" here encompasses machines, computerized systems, robots, and Internet of Things (IoT) devices. However, these automated systems cannot operate entirely independently, as many work processes still require human oversight, creativity, and adaptability. As a result, humans must remain an integral part of these systems although their roles have been changed by the CPSs

(Horvath et al., 2017). To address this integration, the concept of Cyber-Physical Systems (CPSs) has emerged. CPSs refer to systems in which physical components—such as humans, machines, robots, and IoT devices—interact with cyber components, including sensors, wireless sensor networks (WSNs), actuators, and software-based programs. These systems operate in a closed-loop manner, enabling real-time monitoring and feedback-based control (Lee, 2008; Marculescu & Bogdan, 2010; Shi et al., 2011; Sanislav et al., 2016). CPSs exhibit cross-domain functionality, distributed control, and heterogeneous components, giving rise to what Liu et al. (2011) describe as organizational intelligence within these systems. Figure 1 illustrates the structure of the CPSs.

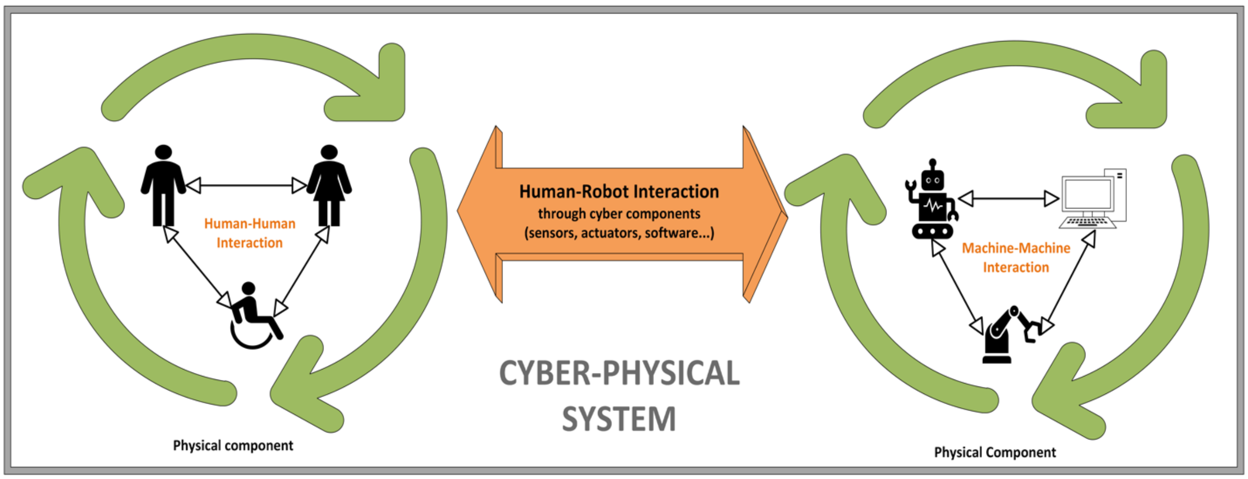

Figure 1: The Structure of Cyber Physical Systems

The evolution toward system-to-system interaction has also been explored through the lens of Machine-to-Machine (M2M**)** communication. Researchers such as Yan et al. (2012) have noted the close relationship among M2M, IoT, WSNs, and CPSs, while Wan et al. (2013) argue that CPSs represent an advanced generation of M2M systems. However, Wan et al. also highlight challenges, including the overwhelming volume of data generated by M2M systems, which places new demands on human operators who must be trained to interpret and manage this information. As Antón-Haro et al. (2013) observe, the M2M research focus has evolved over time—from early studies on access and scheduling algorithms to more recent concerns around energy efficiency and system optimization—reflecting the increasing complexity of human involvement in automated environments.

In addition to advancements in machine technology, Kim et al. (2009) emphasize that the evolution of knowledge within intelligent systems introduces the concept of cooperation as a defining feature of these technologies. As intelligent systems grow more autonomous and context-aware, their ability to collaborate with other agents—both human and machine/robot—becomes increasingly essential. Building on this idea, Marculescu and Bogdan (2010) highlight workload optimization among diverse physical components as a key driver in the development and functioning of cyber-physical systems. This optimization ensures that tasks are dynamically allocated based on the capabilities and current states of each component, contributing to the overall efficiency and adaptability of the system.

Finally, Mois et al. (2016) emphasized that CPSs should not be viewed solely as part of Information and Communication Technology (ICT), despite their connection to it. This distinction arises from the unique demands placed on CPSs, including adaptability, functionality, usability, efficiency, and autonomy. Sanislav et al. (2016) further reinforced these requirements by highlighting additional system attributes such as security, interoperability, predictability, and sustainability. These evolving requirements have undeniably transformed the roles of both humans and robots, a transformation that is further explored in the following subsection.

2.1.2. Evolution of Human-Robot Collaboration: From Coexistence to Proactive Collaboration

As discussed in the previous section, the working environment has progressed from a phase with no systems involved to one characterized by extensive automation, largely due to advancements in Cyber-Physical Systems (CPSs). Within CPSs, Horváth et al. (2017) identify four distinct subsystems that must be considered separately due to their diverse characteristics: human–human interaction, human–system interaction, system–human interaction, and system–system interaction. Given that this thesis focuses on human–robot collaboration, particular attention is paid to the human–system and system–human subsystems. When the term *human–robot systems* is used throughout this work, it specifically refers to these two types of interaction within CPSs.

Horváth et al. (2017) further explain that the level of automation plays a key role in shaping system behavior, ranging from "no system in the loop" to "no human in the loop." This progression—illustrated in Figure 2—demonstrates a central driving factor in the evolution of human–robot collaboration: the increasing automation and intelligence of systems, which gradually shift human roles from coexistence to active collaboration with robotic agents.

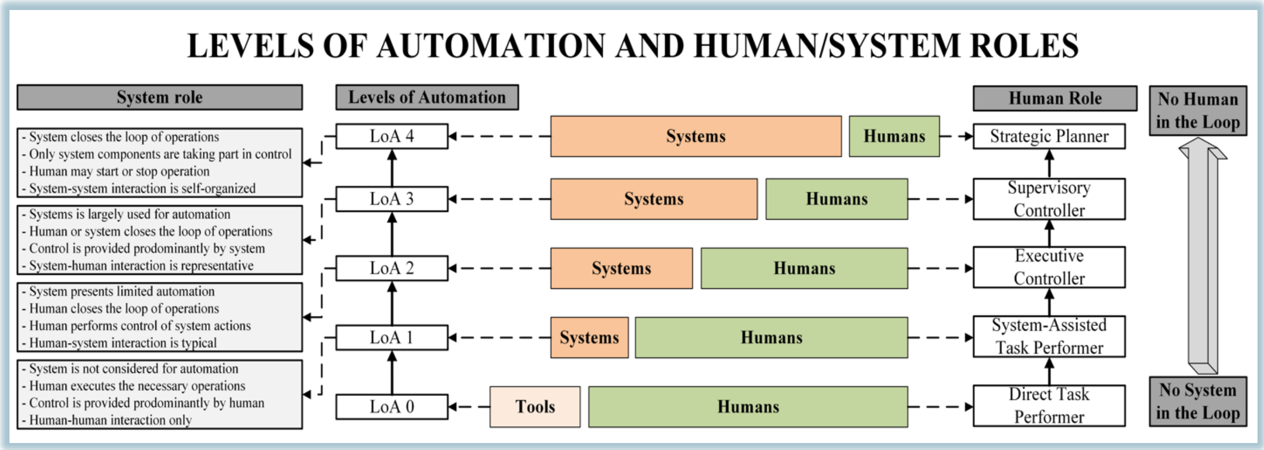

Figure 2: Levels of Automation in Cyber-Physical Systems (adapted from Horvath et al., 2017)

Li et al. (2023) evaluated this system evolution in the context of human–robot relationships by categorizing it into six distinct phases: Human–Robot Coexistence (1979–1985), Human–Robot Interaction (1986–1996), Human–Robot Cooperation (1997–2007), Human–Robot Collaboration (2008–2015), Symbiotic Human–Robot Collaboration (2016–2020), and Proactive Human–Robot Collaboration (2020–present). Initially, robots were merely used as tools. Over time, they began interacting with human operators, then progressed to cooperating—working on related tasks in parallel but not simultaneously on the same task. Eventually, robots became capable of true collaboration, jointly working with humans on common tasks in real time. This collaboration has continued to evolve, shaped by technological advancements, into forms such as standard (or normal), symbiotic (Wang et al., 2021), and proactive collaboration (Li et al., 2021)**.**

Although collaboration represents an advanced form of interaction, this thesis places significant emphasis on interaction as a distinct concept. Interaction establishes the foundation for reciprocal communication between humans and machines, upon which collaboration is built. Therefore, the next subsection explores the definitions and relationships among communication, interaction, and collaboration in greater detail.

2.1.3. From Communication/Interaction to Collaboration between Humans and Robots

Communication plays a crucial role in human life, both in affective socialization and cognitive work. It helps human teams understand each other's intentions, meet each other's requirements, and thereby collaborate toward a shared goal. Given this foundational role, a similar communication method is necessary between humans and robots. Claude Elwood Shannon (1948), a foundational figure in information theory, proposed that communication is essentially a statistical process, where senders offer multiple messages for receivers to select from. Additionally, Shannon and Weaver (1949) identified three levels of communication problems: technical, semantic, and effectiveness. Although originally developed for human-to-human communication, this framework has been extended to various communication forms, including human-robot communication.

Before discussing how communication evolves into collaboration, it is important to clarify the distinctions and overlaps between communication, interaction, and collaboration. McNeil et al. (2000) studied how to facilitate communication, interaction, and collaboration between students and online courses, and thus defined these terms and their boundaries clearly. They described communication as the exchange of ideas regardless of whether the receiver provides feedback, whereas interaction involves reciprocal communication between both parties. Based on this, interaction encapsulates communication, as it requires a reciprocal exchange between agents. On the other hand, collaboration refers to joint work shared by collaborators—such as humans and robots in human-robot systems—toward a common goal.

In terms of communication, Bergman et al. (2019) discussed that current robotics advancements have yet to fully replicate human physical and cognitive communication abilities. Floridi (2020) emphasized that although machines may outperform humans in certain tasks, they do so through fundamentally different mechanisms. Therefore, communication theory needs to adapt to hybrid environments composed of both humans and intelligent computerized systems. Addressing this, McNeese et al. (2021) conducted an experiment comparing collaboration in various team compositions: human-only, human-human-AI, human-AI-AI, and AI-only teams. They observed that team cognition was highest in human-only teams. This demonstrates that, because communication is more structured among humans, their intentions and requirements can be conveyed more effectively than in hybrid or fully automated teams. Nass et al. (1996) also found that humans tend to prefer interacting with other humans. Similarly, Merritt et al. (2011) reported that participants enjoyed collaborating more with partners they believed to be human, even when the partners were AI. These findings suggest that becoming comfortable communicating with robots—comparable to communicating with human partners—takes time, especially until humans feel as fully understood by robots as they do by other humans.

When it comes to interaction, multi-agent learning was studied by Tuyls and Weiss (2012) to develop optimal solutions under dynamically changing conditions, involving many agents with different characteristics. To support this, Maeda et al. (2017) proposed an innovative interaction learning approach based on action recognition and human-robot movement coordination. These learning approaches in human-robot communication support the development of interaction by incorporating partner feedback. In addition, shared control has been proposed as a method to enhance interaction between humans and robots. For instance, Abbink et al. (2018) argued that shared control provides a more comfortable and intuitive way for both human and robotic agents to contribute to a task simultaneously, enabling effective human-robot interaction.

Collaboration, as the final stage of this continuum, requires reciprocal communication, mutual understanding, and joint intention. It represents a coordinated effort between human and robotic partners to achieve a shared objective. Damacharla et al. (2018) conceptualized Human-Machine Teams (HMTs) as collaborative systems that aim to improve overall performance through shared goals, highlighting the importance of mutual contribution. As collaboration has matured over time, proactive methods have been developed to enable both humans and robots to understand each other’s intentions and act accordingly—even before a need or issue arises. For example, Broo (2022) emphasized the necessity of adopting a futuristic mindset in human-robot collaboration within complex and ambiguous smart systems to anticipate unknown unknowns and provide solutions in advance. Moreover, Cruz et al. (2021) developed explainable robotic systems that allow robots to communicate their intentions transparently to human collaborators. Likewise, Li et al. (2021) introduced *Proactive HRC*, a framework based on inter-collaboration cognition that promotes bi-directional empathy between humans and robots.

Based on the literature regarding communication, interaction, and collaboration, Figure 3 below illustrates the conceptual differences and relationships among these terms. According to the logic presented in Figure 3, interaction and communication intersect when there is a reciprocal exchange; however, communication alone does not imply reciprocity and can occur in a one-way manner. On the other hand, interaction does not always include communication, as communication typically involves verbal or non-verbal information exchange. For example, two agents may interact—such as by physically touching—without necessarily engaging in any meaningful communication. Collaboration is represented at the intersection of interaction and communication, where reciprocal exchange and mutual understanding co-occur. Yet, not every interaction involving two-way communication leads to collaboration. For collaboration to emerge, the agents must also share a common goal, which transforms communicative interaction into purposeful joint action.

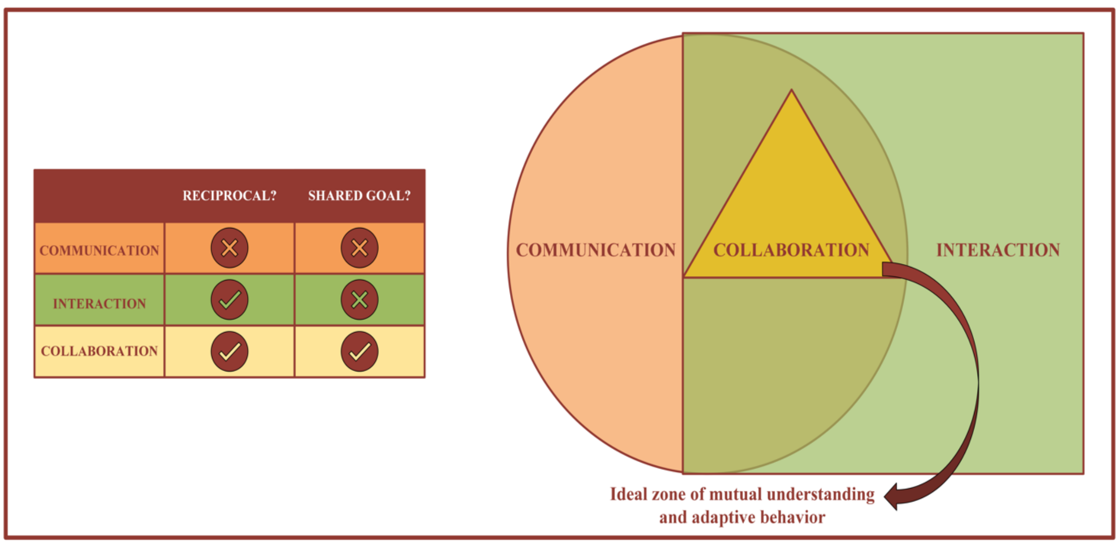

Figure 3: Conceptual Relationship among Communication, Interaction, and Collaboration

2.1.4. *Human Factor in Human-Robot Collaboration*

Human-robot systems have been evolving from supervised models toward more autonomous, unsupervised approaches (Horvath and Wang, 2015). This shift raises concerns about whether humans are being removed from the decision-making loop. However, research strongly emphasizes that human involvement remains essential; the goal is not to eliminate humans from these systems but rather to leverage their cognitive, experiential, and sociocultural contributions (Wang et al., 2010; Liu et al., 2011). Despite the uncertainties inherent in human behavior (Yalçinkaya et al., 2023), humans enrich these technical systems by transforming them into socially embedded and behaviorally adaptive environments through interaction (Horvath, 2014).

Studies have identified several scenarios where human contribution is indispensable. For example, Kosa et al. (2023) explored the application of robots in intensive care units for the elderly, driven by staffing shortages. Their findings confirmed that even in technologically advanced healthcare systems, human involvement remains critical. Similarly, Borges et al. (2021) examined ways to reduce work-related musculoskeletal disorders in industrial settings. Their research demonstrated that when handling small or delicate parts, human input is crucial, as robots may lack the required dexterity or sensitivity.

Beyond direct participation, human feedback plays a critical role in enhancing the performance of human-robot systems. Roveda et al. (2023) proposed a preference-based optimization algorithm that integrates qualitative user input, emphasizing its importance in refining system behavior. In a similar vein, Humann et al. (2023) designed a graphical user interface capable of identifying the optimal configuration and proportion of heterogeneous agent types, tailored to the user's trade-off preferences. Additionally, Kirtay et al. (2023) highlighted the potential of human cognitive strengths—particularly creativity and intuitive judgment—to reduce the computational burden on robotic systems. Collectively, these studies underscore that despite growing automation capabilities, humans continue to be indispensable in the loop, serving as both contributors to and beneficiaries of intelligent systems.

A key consideration for ensuring effective human-robot collaboration is the transparency and intelligibility of robotic capabilities. Boy (2017), for instance, advocated for a human-centered design approach, emphasizing the limited utility of intelligent systems—such as autonomous vehicles—when users are unable to understand their functionalities or resolve system failures. Consequently, although intelligent robotic components provide undeniable support within human-robot teams, they may also function as constraints, particularly when their complexity impedes user comprehension or system transparency (Sha et al., 2008). To address these challenges, researchers have introduced BCI-Augmented Reality (AR) and virtual reality interfaces to facilitate more realistic and comprehensible interactions between humans and robots. These interfaces aim to clarify human expectations in collaborative contexts by enhancing users' understanding of robotic behavior and capabilities (Perrin et al., 2010; Ji et al., 2021; Lei et al., 2023). Complementing these efforts, researchers have also proposed the development of more human-like cognitive models for robots to improve mutual understanding and coordination (Anzalone et al., 2015; He et al., 2021). Also, Gombolay et al. (2017) investigated the role of human situational awareness in collaborative performance, while Nikolaidis et al. (2017) introduced computational frameworks that support mutual adaptation between humans and robotic partners.

This concept of mutual adaptation is foundational for effective collaboration. Rather than imposing rigid task divisions, systems should facilitate bi-directional learning—allowing both humans and robots to adjust to one another's strategies. Yun et al. (2016) distinguished autonomous learning from direct learning, proposing that the former enables humans to generate hypothetical knowledge by integrating insights from multiple experiences. This capacity for abstract and integrative thinking marks a key advantage of human intelligence. In line with this, Rozo et al. (2016) introduced a learning framework demonstrating how humans can teach robots, further enabling adaptive, collaborative behavior.

In conclusion, human-robot collaboration must prioritize the human factor—not only as a practical necessity but as a guiding principle. Since humans are the ultimate beneficiaries and users of these systems, collaboration should be grounded in human cognitive models, enriched by their feedback, and measured by their satisfaction. No matter how advanced robotic technologies become, preserving the human-in-the-loop approach is essential for fostering meaningful, efficient, and ethical collaboration.

2.1.5. Robot Factor in Human-Robot Collaboration

As mentioned in the previous subsection, learning from each other enhances human-robot collaboration. The contribution of robots in collaborative systems largely stems from their ability to learn and adapt based on human input and environmental data. Central to this capability is the Learning from Demonstration (LfD) approach, which enables robots to replicate human actions and develop new skills by observing task execution (Sosa-Ceron, 2022). Building on this, some researchers have proposed more advanced frameworks—such as imitation learning (Hussein et al., 2017), task-parameterized LfD for intelligent robots (Zaatari et al., 2022), and collaborative intelligence-based models incorporating fine-grained human digital twins—to enhance robots' contextual understanding and personalization in task execution (Zheng et al., 2023). Raziei and Moghaddam (2021) further extended robot learning through a hyper-actor model that links lessons learned from past tasks to future operations, thereby creating a knowledge-transfer mechanism that improves robot preparedness. These learning paradigms reflect a broader trend in robotics, where machines are no longer static executors but dynamic participants capable of adapting to changing contexts. In this direction, Parisi et al. (2019) emphasized the importance of lifelong learning frameworks that enable autonomous computational agents to incrementally accumulate knowledge throughout their operational lifetime. As highlighted by di Fiore and Schneider (2017), modern robots refine their cognitive and functional capabilities through continuous analysis of complex datasets, striving to emulate the subtleties of human intelligence. Complementing this view, Soori et al. (2023) provided an extensive overview of artificial intelligence techniques that underpin these learning models, showing the breadth of methods through which robots contribute intelligently and proactively in human-robot collaboration.

After learning the way of handling tasks, robots play a critical role in supporting collaborative work environments, particularly through task sharing and physical assistance. There are many virtual and physical human-robot examples in today's world. Riedelbauch et al. (2023), for instance, investigated novel methods for enabling humans and robots to work side by side, with a focus on handling tasks, collaborative assembly, and broader industrial applications. Their study also emphasized safety concerns, which are essential when integrating robotic systems into shared workspaces. In line with this, numerous studies have examined the physical contribution of collaborative robots in complex and potentially hazardous environments. Many of these works highlight how robots enhance safety and operational efficiency, especially when functioning in close proximity to humans during assembly tasks in smart manufacturing contexts (Merlo et al., 2023; Lopez-de-Ipina et al., 2023; Yonga Chuengwa et al., 2023; Zanchettin et al., 2022; Pereira et al., 2022; Prendergast et al., 2021; Darvish et al., 2021). Beyond task execution, robots also support system reliability and operator awareness. For example, Polenghi et al. (2024) proposed a predictive maintenance framework that enables cobots to detect and respond to anomalous motion patterns, allowing human operators to address issues proactively. Last but not least, Dahl et al. (2021) explored the deployment of two types of robots in collaborative environments: one group focused on mounting tasks, while another was designed for flexible material transportation. These examples demonstrate that robot contributions extend beyond isolated functions, supporting both safety and operational adaptability in dynamic work settings.

In addition to physical assistance and safety functions, robots increasingly contribute to the proactive management of system reliability and human-centered interaction. Park et al. (2021) presented a programmable motion-fault detection method aimed at enhancing predictive maintenance strategies by identifying potential equipment failures before they escalate. This approach enables more efficient upkeep and reduces unexpected downtime in collaborative environments. Complementing this, Dutta and Zielinska (2021) emphasized the need for early detection of two key abnormalities in robotics: information faults and system failures. Their work underscores the importance of anticipating such disruptions and implementing safeguards in advance to maintain system continuity and safety. Beyond technical diagnostics, the role of robots in adapting to human intentions has also gained attention. Lemaignan et al. (2017) explored human-aware task planning through a multi-modal dialogue system supported by a cognitive architecture. Their framework integrates perspective-taking, affordance assessment, situated language interaction, and logical inference to foster more intuitive and responsive collaborations between humans and robots in shared workspaces. These developments illustrate that robotic support is not limited to mechanical functions, but extends into predictive reasoning and socially aware interaction.

Robots are applied in nearly every field, either physically or virtually; therefore, their contribution is extensive and continues to grow—especially in understanding human emotions and intentions in collaborative settings. The following Section 2.2 focuses on how robots perceive and interpret emotional and behavioral signals through physiological and behavioral data analysis.

2.2.Tools and Techniques Used in Human-Robot Systems

Understanding human intentions is a fundamental aspect of effective human-robot collaboration. These intentions can be assessed through two primary sources: behavioral data, which reflects observable actions and expressions, and physiological data, which provides insights into internal states such as stress or cognitive load. Both types of data are captured using a variety of tools and techniques designed to interpret human signals accurately. In this section, the focus begins with an overview of the tools and techniques used to extract behavioral measurements, followed by a discussion of those employed for physiological assessments.

2.2.1. *Behavioral Measurements in Human-Robot Systems*

In human-robot systems, behavioral measurements are essential for understanding human intentions, emotional states, and engagement levels. These measurements rely on external and observable cues collected through various interfaces, sensors, and perceptual systems. The subsections below group the key techniques used for behavioral observation, based on the modality they represent.

2.2.1.1.Mouse and Keyboard Motion

Mouse and keyboard movements are frequently utilized to infer users' behavioral responses in digital environments. Salmeron-Majadas et al. (2014) investigated this method in the context of cyber-physical learning systems and proposed that such inputs could reveal emotional states, though they also noted the importance of combining them with other emotional data sources to improve accuracy. Similarly, Sun et al. (2014) explored the relationship between stress and mouse motion. Their findings suggest that stress can be triggered by users' interactions with unfamiliar or confusing digital interfaces, which manifest as variations in cursor movement or typing behavior.

2.2.1.2.Facial Expression

Facial expressions have long been regarded as valuable indicators of internal emotional states. A widely accepted method in this domain is the **Facial Action Coding System (FACS)**, which identifies emotions based on specific muscle movements (Prkachin & Solomon, 2008). Their study showed strong correlations between physical pain and a set of facial reactions including brow lowering and eye closure. This connection between facial indicators and subjective experience provides a structured approach to interpreting emotional feedback. Building on this, Jabon et al. (2010) focused on detecting accident risk based on facial changes in drivers moments before a collision, proposing systems that can issue warnings or act autonomously. Kaltwang et al. (2012) applied facial recognition to pain detection, though they highlighted challenges in distinguishing subtle variations like eye blinks from true pain signals. In another line of work, McDuff et al. (2014) emphasized the need to differentiate between genuine and posed emotional expressions—particularly smiles—in order to improve recognition accuracy in natural interactions. Zhu et al. (2017) expanded this concept by incorporating gesture recognition into facial analysis, employing LSTM networks to detect meaningful movements. A broader review of technologies for facial expression and gaze recognition was also provided by Fahn et al. (2022), highlighting recent developments in perceptual systems.

2.2.1.3. Image Recognition, Speech and Voice Recognition, and Audiovisual Behavior Descriptors

Multimodal recognition systems that combine visual and auditory cues have gained traction for their ability to detect emotional and psychological states. For example, Malta et al. (2011) integrated facial expression, speech analysis, and behavioral cues like gas and brake pedal usage to detect driver frustration. Their findings suggest that the fusion of multiple inputs strengthens the reliability of affect detection. In contrast, Kim et al. (2013) employed unsupervised learning models to classify audiovisual data, which they found to be effective in situations where clear labeling is not available, such as with unclear speech or ambiguous vocal tones. Further supporting the multimodal approach, Yang et al. (2013) and Scherer et al. (2014) explored how conditions like depression or anxiety manifest through voice prosody and visual signals such as gaze direction, smile behavior, and bodily self-adaptors. Scherer et al. emphasized the challenges in automating the detection of subtle behaviors—like leg fidgeting or voice tension—due to the lack of robust automatic descriptors, hence relying on manual annotations for certain features. Meanwhile, Guo et al. (2018) designed an auditory system for intelligent robots to support emotional interpretation. These efforts are reinforced by Fahn et al. (2022), who reviewed a wide range of recognition technologies, highlighting their expanding role in socially intelligent robotic systems.

2.2.1.4.Head Pose Estimation and Body Position Analysis

Body language, including posture and head orientation, plays a crucial role in decoding human intent during interactions. Murphy-Chutorian and Trivedi (2009) emphasized that head pose estimation can provide insight into social attention and interaction dynamics—for instance, identifying who a person is speaking to in a group setting. They proposed several design principles for future systems, including the need for real-time processing, lighting invariance, and multiperson tracking. Despite progress in this area, they noted that fully capturing nonverbal cues remains an open challenge. Complementing this perspective, Schmitz (2012) pointed out that "self-adaptors"—behaviors like fidgeting or hair twirling—are particularly difficult for machines to interpret due to their subtlety. Recent work by Orsag et al. (2023) demonstrates progress in this domain by analyzing upper-body motion with LSTM networks to infer human intentions in real-time.

2.2.2. Physiological Measurements in Human-Robot Systems

In addition to behavioral observations, physiological data offer an objective and often continuous means to assess human stress levels, cognitive load, and emotional responses in human-robot collaboration. These data are captured through a range of biosensing technologies that measure signals such as heart rate variability, eye movement, brain activity, and skin conductivity. This section outlines key physiological measurement techniques categorized by modality and supported by current research.

2.2.2.1.Heart Rate and Electrocardiography (ECG)

Heart rate monitoring, particularly through electrocardiography (ECG), has been widely used to assess emotional and cognitive states during human-robot interaction. Deep learning approaches have recently been applied to ECG signals for stress recognition, showing robust results across multiple datasets using end-to-end models with minimal manual feature extraction. These advancements have positioned ECG as a reliable tool for real-time affective state recognition. For instance, ECG-based stress detection models have shown promising performance on benchmark datasets.

In another application, heart rate monitoring was employed to track cognitive workload during complex procedures such as endotracheal intubation (ETI) (Gazetta et al., 2023), where participants were exposed to audiovisual stressors. The integration of heart rate sensors with real-time tasks demonstrates the growing relevance of physiological data in high-stress training and evaluation scenarios (Behinaein et al. 2021). Interestingly, non-contact methods for measuring heart rate have also emerged—Poh et al. (2010) showed that specially designed cameras could monitor the heart rates of multiple individuals simultaneously without physical sensors.

2.2.2.2.Eye Tracking and Electrooculography (EOG)

Eye tracking is another widely adopted technique for interpreting users' cognitive and emotional states in human-robot systems. Huang et al. (2015) demonstrated that gaze behavior could be used to infer user intent, employing a support vector machine model trained on eye movement patterns. Other studies have confirmed that eye movements and facial expressions captured through tracking cameras can effectively reflect human performance and engagement in collaborative tasks (Bitkina et al., 2021; Behinaein et al., 2021; Del Carretto Di Ponti E Sessam, 2023; Gazetta et al., 2023; Hemakom et al., 2024; Awada et al., 2024).

Electrooculography (EOG), which captures the eye's corneal-retinal potential via electrodes near the canthi, has also proven useful in detecting horizontal gaze direction (Mocny-Pachońska et al., 2021; Das et al., 2023; Dao et al., 2024). These techniques help identify attention shifts and cognitive workload in real time. In high-pressure environments, such as simulation-based training sessions, metrics derived from eye tracking have been used to distinguish between relaxed and cognitively strained states with high accuracy—up to 83% binary classification between relaxed and stressed conditions during tasks like the Stroop and N-Back tests.

Complementing these findings, wearable technologies like wristbands have gained popularity due to their non-intrusive nature and ability to monitor multiple physiological signals, including heart rate, skin temperature, and electrodermal activity. Their ease of use and reliability make them attractive alternatives to head-mounted systems, especially in applied workplace settings (Gjoreski et al., 2017; Nath & Thapliyal, 2021; Mitro et al., 2023; Bello-Orgaz & Menéndez, 2023; Awada et al., 2024). For instance, Lachance-Tremblay et al. (2025) employed eye-tracking data to manage drivers' workload by redirecting their attention back to critical tasks when distraction was detected.

2.2.2.3. Electroencephalography (EEG) and Functional Near-Infrared Spectroscopy (f-NIRS)

Brain activity provides direct insight into cognitive processes and mental workload. Electroencephalography (EEG) has been extensively applied to capture neural responses during human-robot collaboration (Al-Shargie et al., 2016; Perez-Valero et al., 2021; Katmah et al., 2021; Attar, 2022; Hemakom et al., 2023). For example, Zhao et al. (2024) used EEG to monitor pilots' mental states in a virtual training environment, marking a significant move toward quantitative cognitive measurement. However, EEG sensors often involve intrusive hardware that can limit natural movement during tasks. This concern has been echoed by Sugiono et al. (2022), who noted that while EEG offers precision, it can compromise ergonomics and user comfort.

Functional near-infrared spectroscopy (f-NIRS) presents a less intrusive alternative, capable of tracking hemodynamic responses by measuring the levels of oxygenated and deoxygenated hemoglobin in brain tissue (Al-Shargie et al., 2016; Mirbagheri et al., 2019). Both EEG and f-NIRS have shown promise in advancing cognitive-state recognition in collaborative systems, although each comes with trade-offs related to usability and signal reliability in real-world applications.

2.2.2.4. Electrodermal Activity (EDA)

EDA is a widely used physiological marker for assessing arousal and emotional intensity, particularly in stress detection. It is measured through sensors that detect changes in skin conductance, which are influenced by sweat gland activity. Numerous studies have validated the effectiveness of EDA as a standalone indicator of stress (Pop-Jordanova & Pop-Jordanov, 2020; Rahma et al., 2022; Dao et al., 2024). Awada et al. (2024), through a comparative study of physiological indicators, found that EDA yielded the strongest results in stress classification when compared to other biosignals.

Wearable devices capable of measuring EDA—along with related signals such as blood volume pulse (BVP), skin temperature (ST), and motion acceleration—have proven particularly valuable due to their ergonomic design and suitability for extended monitoring in work environments (Gjoreski et al., 2017; Nath & Thapliyal, 2021; Mitro et al., 2023; Bello-Orgaz & Menéndez, 2023). These tools offer over 90% classification accuracy in stress detection tasks, making them highly reliable for human-robot collaboration studies where user performance and well-being are critical.

These tools and techniques are applied in contexts where human stress levels directly influence both individual and system performance. Section 2.3 explores how the concepts of stress and performance are defined and integrated within human-robot systems.

2.3. Performance, Stress and Task Allocation Factors in Human-Robot Systems

After exploring the evolution of human-robot systems and the tools and techniques used to assess human affective states—such as stress levels and emotional responses—this section shifts the focus to three key factors that shape the success of collaboration: performance, stress, and task allocation. These elements are not only interconnected but also critical for maintaining balance and efficiency within human-robot teams. The following subsections examine these aspects in detail, beginning with an overview of system performance, followed by an analysis of how human stress impacts collaborative outcomes, and concluding with a discussion on task allocation strategies in human-robot environments.

2.3.1. Human-Robot System Performance

Human-robot system performance is shaped by a complex interplay of physiological, cognitive, temporal, and task-related factors. Human performance within these systems is inherently dynamic and subject to fluctuation due to both internal and external influences.

One of the earliest insights into human performance variability comes from Kleitman's (1933, 1938) research on circadian rhythms. His work demonstrated that performance levels rise and fall in alignment with the body's internal biological clock. This rhythm leads to periods of heightened alertness and cognitive capacity, followed by inevitable declines. Building on this, Kalanadhabhatta et al. (2021) examined both circadian and homeostatic components, concluding that human cognitive performance peaks between 09:00–16:00 and diminishes during early morning and late-night hours. Razavi et al. (2023) confirmed that aligning demanding tasks with these peak periods significantly improves overall task efficiency.

In parallel, the Cognitive Load Theory emphasizes the role of knowledge and experience in human performance. Sweller (1988) and Van Merriënboer and Sweller (2010) noted that individuals with greater expertise perceive tasks as less complex, resulting in more efficient execution. Zeitlhofer et al. (2024) experimentally supported this idea by showing that participants performed faster during subsequent attempts at previously complex problems, suggesting that knowledge acquisition plays a critical role in task performance.

Performance variability, however, is not solely a result of time-of-day or knowledge level. Lee and McGreevey (2002) argued that every human task involves inherent variability, distinguishing between natural process variation and deviations that warrant corrective intervention. When performance deviates significantly from expected levels, interventions may be necessary to restore consistency (Caulcutt, 2004). Nguyen and Zeng (2012) synthesized multiple contributing factors—such as ergonomic strain, mental stress, and environmental discomfort—into a conceptual model describing the stress-performance relationship. Their bell-curve representation reflects that optimal performance occurs at moderate stress levels, while both under-stimulation and overload reduce effectiveness. Zhao et al. (2023) adapted this relationship into three performance zones—Laid-back, Capacity, and Fatigue—which can guide intervention strategies based on real-time stress levels.

Project management research adds further depth by linking performance to task structure. According to Wilkinson et al. (2012), Walhout et al. (2017), Guo et al. (2020), and Zhou et al. (2022), estimated task durations often reflect task complexity, especially when skill requirements are comparable. In this way, task duration serves as a proxy for workload and can help optimize individual task distribution. The Project Management Institute (2021) and Mulcahy (2013) emphasize that accurate time estimation during planning is essential for workload balance and schedule reliability.

Several studies have demonstrated the effectiveness of statistical tools in monitoring human performance in both individual and collaborative contexts. Wang et al. (2013) used X-bar control charts to detect performance drops in supermarket cashiers after prolonged working hours. Similarly, Yousefi et al. (2019) introduced the Duration Performance Index (DPI) as a time-efficiency metric in construction projects, using control charts to track performance deviations.

Their findings reinforced that such tools offer valuable insights into when interventions are required to prevent inefficiencies.

In safety-critical contexts such as rail transport, Sugiono et al. (2022) incorporated control charts into their Cognitive Workload Management (CWM) framework. Their system used brain data and train operation logs to assess workload zones (underload, optimal, overload) and recommend rest schedules accordingly. This data-driven approach proved effective in supporting real-time decision-making to maintain operator readiness and safety.

Beyond temporal and cognitive factors, task complexity also plays a crucial role in shaping system performance. Zahmat Doost and Zhang (2023) categorized tasks into skill-based, rule-based, and knowledge-based groups and measured mental workload across different scenarios. Their findings revealed that knowledge-based tasks are the most cognitively demanding, imposing the highest mental workload during uninterrupted performance at 78.2%, followed by rule-based tasks at 50.2%, and skill-based tasks at 40.5%. However, under distraction, the ranking shifted: knowledge-based tasks still led with 58.6%**,** but skill-based tasks (40.4%) slightly exceeded rule-based tasks (36.9%) in terms of perceived mental workload. This nuanced differentiation underscores the importance of considering environmental interruptions when allocating task types in human-robot collaboration settings.

Merlo et al. (2023) approached performance from an ergonomic perspective, emphasizing the need to avoid assigning high-risk or physically demanding tasks to humans under unfavorable ergonomic conditions. Tao et al. (2024) expanded this view by comparing different interaction modalities—such as gesture-based or device-assisted inputs—under varying ergonomic conditions. They concluded that the choice of interaction type can significantly influence user performance and comfort, with mid-air interaction resulting in poorer performance and higher muscle strain, especially in vibration environments.

To ensure consistent and efficient human-robot collaboration, performance should not be treated as a static measure but rather as a dynamic outcome influenced by stress, fatigue, task complexity, and temporal rhythms. As Kalanadhabhatta et al. (2021) and others have shown, aligning human tasks with peak performance windows and continuously monitoring workload conditions can significantly enhance system-wide outcomes. To that end, dynamic task scheduling systems that assess both human capabilities and task demands in real time (Pupa et al., 2021; Alirezazadeh and Alexandre, 2022) are increasingly seen as necessary components of adaptive human-robot systems.

2.3.2. *The Effect of Human Stress in Human-Robot System Performance*

In human-robot collaboration (HRC), human performance is not only influenced by skill or experience but also by fluctuating mental states—especially stress. Stress plays a dual role: while a moderate level can enhance alertness and responsiveness, excessive or insufficient stress can significantly impair human performance. Therefore, understanding and regulating stress levels is a critical factor in optimizing collaborative system outcomes.

The relationship between stress and performance has long been studied, with foundational work by Yerkes and Dodson (1908) showing that performance improves with increasing stress up to a certain point—beyond which it declines. More recently, Awada et al. (2024) reaffirmed this curvilinear relationship and emphasized the need for quantifying stress accurately to improve collaborative system performance. Zhao et al. (2023), though focusing on workload rather than stress, identified a parallel trend: human efficiency increases with workload to a certain threshold before declining—mirroring the stress-performance bell curve. Their classification of performance zones—Laid-back, Capacity, and Fatigue—offers a practical model for identifying when intervention is needed to restore optimal workload levels. Sickles and Zelenyuk (2019) further noted that efficiency is both a key driver of and an outcome of performance, reinforcing the importance of managing human states for improved system outcomes.

The link between stress and performance is further supported by research on creativity and cognitive capacity. Wilke et al. (1985) and Zhao et al. (2018) emphasized that optimal performance—particularly in tasks requiring innovation—occurs when stress is balanced. Low stress may result in disengagement, while high stress can lead to panic or impaired judgment. Similarly, Nguyen and Zeng (2017) offered a stress formulation (Stress = Workload / Mental Capability) to explain how cognitive overload occurs when task demands exceed an individual's internal resources.

One of the challenges in leveraging these models in real-world HRC systems is measuring stress in an accurate yet unobtrusive manner. In this context, Awada et al. (2024) conducted a comparative study of physiological indicators and concluded that Electrodermal Activity (EDA) alone offered the most consistent and interpretable results. Wrist-worn sensors capable of recording EDA, Skin Temperature (ST), Blood Volume Pulse (BVP), and wrist motion have been validated as ergonomically suitable and reliable tools for in-the-field stress detection (Gjoreski et al., 2017; Nath & Thapliyal, 2021; Mitro et al., 2023; Bello-Orgaz & Menéndez, 2023). These technologies enable stress data collection with minimal disruption to the natural flow of human behavior, making them particularly advantageous for use in collaborative settings. Despite the technological advances, however, ergonomic limitations and usability concerns still pose barriers to widespread implementation.

In conclusion, integrating stress-aware task allocation strategies and adopting non-invasive monitoring tools are essential for achieving balanced and efficient human-robot collaboration. Wrist-worn devices and contactless sensors represent viable paths forward, offering accurate stress detection while preserving user comfort. These innovations mark an important step toward more adaptive and intelligent collaborative systems—where human performance is continuously supported through real-time, data-driven stress regulation.

2.3.3. *Task Allocation in Human-Robot Systems*

Humans are efficient elements of human-robot systems, capable of quickly adapting to changing conditions and adjusting themselves when new missions are introduced. For this reason, the human factor is expected to play a role in task allocation. However, as the number of robots increases, the cognitive workload placed on a single human may not be sufficient due to the increased demand of managing multiple robots. To mitigate this issue, the number of humans involved should also be increased accordingly (Jo et al., 2024).

As hybrid teams consisting of both humans and robots become more common, the workload should be allocated by taking the unique characteristics of each into account. Task allocation (Miller et al., 2002; Hardin and Goodrich, 2009; Khamis et al., 2015) and task scheduling (Gutzwiller et al., 2015; Creech et al., 2021; Tokadlı et al., 2021) have been widely discussed in the literature. However, the inclusion of multiple humans in multi-robot systems—particularly when human affective states are considered—has not been studied extensively. A recent study by Jo et al. (2024) addressed this gap by integrating human affective states into workload distribution across multiple humans and robots. This complements earlier research that evaluated human decision-making ability based on task difficulty or performance metrics without explicitly considering cognitive workload (IJtsma et al., 2019; Talebpour and Martinoli, 2019). Still, cognitive workload—which refers to the mental capacity required to complete tasks (Debie et al., 2019)—is one of the key factors influencing human decision-making mechanisms (Harriott et al., 2015; Heard et al., 2018; Roy et al., 2020; Biondi et al., 2021).

Le et al. (2024) emphasized that human participation improves situational awareness and provides flexibility to the team. However, because human affective states—such as emotions and cognitive load—are inconsistent, and human performance can fluctuate due to both internal and external factors (Lyons and Stokes, 2012; Hooey et al., 2017; Kolb et al., 2022), systems need to be aware of and monitor these changes. Accordingly, the allocation of workload should adapt in real time to help maintain humans at their optimal performance level in collaborative environments (Feigh and Pritchett, 2014; Barnes et al., 2015; Dahiya et al., 2023).

Therefore, this thesis focuses on how human performance can be sustained at optimal levels through a robot-supervised intervention algorithm that considers affective states and stress levels. Finally, the following section presents examples of existing robot-supervised systems that support this approach.

2.4.Robot-Supervised Human-Robot Systems

As discussed in the previous chapters, recent technological advancements have enabled robots to take on supervisory roles within human-robot systems. This shift has led to their integration across a wide range of fields, where they monitor, support, and adapt to human behavior. In this section, the focus is placed on how robots make decisions in such systems and how these capabilities are implemented in real-world applications through various examples.

2.4.1. Robots' Decision-Making in Human-Robot Systems

As human-robot collaboration becomes increasingly dynamic and task-oriented, the ability of robots to make context-aware decisions becomes essential for sustaining both efficiency and human well-being. In robot-supervised systems, the robot is not merely a reactive tool but an intelligent agent capable of interpreting human behavior, evaluating task demands, and adapting its responses accordingly.

A foundational approach to robot decision-making lies in the analysis of human behavior across different time scales. Töniges et al. (2017) outlined a human-centered adaptation framework consisting of three behavioral analysis layers. In short-term analysis, robots monitor momentary human actions—such as individual work steps—and detect anomalies or irregularities that may require immediate response. Medium-term analysis focuses on broader task sequences, enabling the robot to evaluate ongoing workload and, if necessary, assume control of specific subtasks to alleviate human strain. Finally, long-term behavioral analysis aims to identify patterns over extended periods, supporting decisions that align with a more holistic understanding of the user's capabilities and working style.

Incorporating human-centered principles into robotic decision-making has also been explored through cognitive and cloud computing integration. Chen et al. (2018) proposed a computing model that leverages real-time cognitive inputs alongside distributed computational resources to enhance the robot's responsiveness and contextual awareness. This approach supports more adaptive decision-making by equipping robots with the capacity to interpret not only what the human is doing but also how and why.

From a health and safety perspective, Borges et al. (2021) introduced a decision-making framework that prioritizes ergonomic considerations. By assessing the physical demands of specific tasks and matching them with the human's ergonomic condition, the system aims to reduce the risk of musculoskeletal disorders while simultaneously optimizing task performance. In this way, robotic decisions are informed by both physiological and operational parameters.

Machine learning techniques, particularly reinforcement learning, are also gaining traction in robotic decision systems. Dromnelle et al. (2022) implemented reinforcement learning models to train robots in dynamic environments where optimal responses are learned through feedback and interaction. This enables robots to adapt their decision-making strategies based on the evolving behavior of their human collaborators and the task context, rather than relying solely on predefined rules.

Together, these approaches reflect a growing emphasis on making robotic systems more intelligent, context-sensitive, and aligned with human needs. By analyzing behavior over time, incorporating ergonomic and cognitive factors, and learning from interaction, robots can make informed decisions that enhance collaboration, reduce human fatigue, and improve overall system resilience.

2.4.2. Implementations of Robot-Supervised Human-Robot Systems

Robot-supervised human-robot systems are no longer confined to industrial manufacturing lines; their applications now span diverse fields—from intelligent tutoring to healthcare, smart mobility, and immersive virtual environments. The core feature across these domains is the robot's capacity to interpret, predict, and respond to human behavior in real time, often underpinned by artificial intelligence, cognitive computing, and adaptive control mechanisms.

In education, intelligent tutoring systems offer a compelling example of robot-supervised implementations. D'Mello et al. (2007) emphasized the importance of integrating affective state recognition into learning environments. Their study proposed that user emotions—such as confusion, boredom, frustration, and engagement—can be detected using multiple data channels including facial expressions, posture sensors, and dialogue cues. They argued that adapting tutoring strategies to these emotional signals can enhance cognitive outcomes. Similarly, Whitehill et al. (2011) investigated how automated systems could emulate human tutors by detecting student emotions to adjust their pedagogical approach. Their findings demonstrated that affect-sensitive systems, powered by data collected through sensor networks, could improve learner engagement and the overall effectiveness of instruction.

In the healthcare domain, brain-computer interfaces (BCIs) represent another significant advancement in robot-supervised interaction. Perrin et al. (2010) designed an intelligent wheelchair system that interprets neural signals to anticipate user needs, enabling the robot to propose supportive actions. Carlson and Demiris (2012) built on this concept by implementing a collaborative control model that allows the robot to detect when users need assistance and step in accordingly. These systems highlight the value of intention recognition in physically supportive environments.

Outside of these cognitive and assistive applications, robot-supervised systems have made strides in industrial settings. Fischer and Pöhler (2018) distinguished between automation and tooling scenarios, pointing out that in modern cyber-physical systems, computer technologies increasingly act as participants rather than passive tools. Wei and Ren (2018) contributed by focusing on dynamic path planning for autonomous adaptation, while Ji et al. (2021) integrated augmented reality to improve situational awareness and human-machine interface clarity in collaborative environments.

More broadly, robot-supervised systems powered by AI, cognitive computing, and operational technologies are now used across numerous sectors. Examples include smart manufacturing systems (Zhang et al., 2023; Johannsmeier and Haddadin, 2016), educational robotics (Sannicandro et al., 2022), surgical and mobile healthcare robots (Chi et al., 2018; Wan et al., 2020), wearable and soft robotics (Lee et al., 2020; Xiong et al., 2021), robotic agriculture (Marinoudi et al., 2019), and robotic systems designed for entertainment or assistive purposes for children (Van Den Heuvel et al., 2022; Mascarenhas et al., 2022). In each of these implementations, robots act not as isolated systems, but as context-aware collaborators capable of adapting their roles based on human needs.

Digital twin modeling further extends the possibilities of robot supervision. Gallala et al. (2022) developed a mixed-reality framework using IoT, collaborative robots, and AI, allowing a virtual counterpart of the human-robot system to simulate and predict behavior. Prasad et al. (2024) and Sreedevi et al. (2022) emphasized the role of cognitive computing and AI in simulating human-like reasoning for robot decision-making. These frameworks not only support predictive maintenance and simulation but also enable real-time decision adjustments based on human activity and context.

In parallel, machine vision and digital twins have been extensively reviewed as key enablers of human-robot collaboration (Yonga et al., 2023; Ramasubramanian et al., 2022). When paired with virtual reality applications, such as those demonstrated by Lei et al. (2023), robot-supervised systems gain immersive capabilities that enhance task planning, situational awareness, and stress-free user interaction.

Despite technological progress, research by Kosa et al. (2023) underscores that full autonomy is not always desirable. Their study on robot support in intensive care units highlights that human involvement remains critical—especially in high-stakes scenarios where empathy, ethical judgment, or contextual interpretation is needed.

Finally, implementation efforts have consistently prioritized safety and ergonomic performance. Numerous studies (e.g., Merlo et al., 2023; Lopez-de-Ipina et al., 2023; Yonga Chuengwa et al., 2023; Zanchettin et al., 2022; Pereira et al., 2022; Prendergast et al., 2021; Darvish et al., 2021) have investigated the physical support provided by collaborative robots in tasks requiring close human-robot proximity, often in environments where ergonomic conditions, safety, and coordination are critical. These implementations have shown that when robot-supervised systems are aligned with human comfort, workload, and task complexity, they significantly enhance both system performance and user satisfaction.

In summary, robot-supervised systems are no longer limited to automation—they are evolving into intelligent, multi-functional collaborators. Whether in education, healthcare, manufacturing, or immersive virtual environments, their implementation is increasingly marked by adaptability, contextual sensitivity, and real-time responsiveness to human needs.

3. METHODOLOGY

Human performance fluctuates based on both implicit conditions, such as stress level, physiological conditions like circadian rhythm (which represents sleep patterns), and knowledge level, as well as explicit conditions such as environmental factors. This thesis proposes that human stress can be controlled by robot partners in human-robot collaboration when human performance is impaired due to changing stress levels. To address fluctuations in human performance and stress level, a robot-supervised intelligent workload reallocation algorithm is introduced. This algorithm tracks human performance through statistical control charts, analyzes human stress via behavioral and physiological data, and intervenes in task allocation between robots and humans. The assumptions underpinning this model are defined in Subsection 1.3. The proposed model executes the following steps:

1. Initially allocates workload according to task characteristics. Some tasks are exclusive to humans, some to robots, and others require human-robot collaboration to utilize both partners' capabilities.
2. The collaborative work is then initiated.
3. The robot begins observing human performance through statistical control charts, alongside its own tasks assigned at the outset.
4. If human performance becomes unstable, the robot checks whether the human's stress level exceeds predefined thresholds to determine if the human is underloaded, overloaded, or stable, using wearable devices such as smartwatches or wristbands. If the stress level is stabilized (within predefined thresholds), the robot assesses that irregularities in human performance may be due to factors such as the human's knowledge, skills, or sleep conditions. While identifying the root causes of unstable human performance is important, investigating this condition is beyond the scope of this thesis. If stress levels are underloaded or overloaded, the algorithm proceeds with the following steps.
5. The robot calculates the task-specific stress level of the current task and possible tasks for the human, based on workload allocation zones that represent potential task distributions according to partners' capabilities.
6. If the wearable device indicates that the human is underloaded, the robot assesses whether task reallocation will increase stress to reach an optimal stress level and enhance

productivity. If the human is overloaded, the robot investigates whether task reallocation will reduce stress, bringing it to the optimal level to boost productivity. This comparison is made using the conceptual formula developed for task-specific human stress, which represents the individual effect of a task on human stress. In this case, the robot subtracts the effect of the current task from the overall stress and adds the potential task's effect, using the task-specific stress values to compare the two different conditions.

7. If the expected condition is achieved, the task is reallocated accordingly. If not, new tasks are tested to determine whether they will achieve the desired condition.
8. The robot continues to monitor human performance after stabilizing human stress, ensuring that performance remains under control in case it fluctuates again.

Although human-robot collaboration occurs in multi-human, multi-robot systems, this thesis tests the proposed algorithm in a one-human, one-robot system to assess whether the model yields the expected results. Following this model logic, subsequent sections provide details of the system, its components, hypotheses for the proposed model, and elaborations on adopted ideas, flowcharts, conceptual formulas, and pseudocodes. A case study and a Monte Carlo simulation model are conducted to evaluate the feasibility of the model.

Section 4 introduces the human-robot system framework, outlining system components and their potential interactions within the human-robot team.

Section 5 presents the interaction modalities across task zones. First, the concept of workload is defined by dividing it into distinct zones using a Venn diagram, representing the ability of collaboration partners to perform tasks. Some tasks require human expertise, others require robot functionality, and some necessitate the complementary capabilities of both. Second, interaction modes are identified using the Axiomatic Theory of Design (Zeng, 2002) to illustrate the diverse communication channels and interactions within the hybrid system. Third, each interaction modality is mapped onto the classified Venn diagram. Fourth, a dynamic task reallocation algorithm, considering task zones and human stress levels, is introduced through pseudocode. Finally, a case study investigates how dynamic task reallocation can optimize performance in human-SAP system collaboration. This study classifies system workload, identifies relevant interaction modes and task zones, and provides data to the supervisory controller (the robot). While dynamic task allocation is discussed as stress-aware in this section, Section 6 explores how human stress levels can be measured and quantified, and Section 7 examines how human stress affects the proposed model in detail. The focus of Section 5 is to identify intervention opportunities based on task zones and interaction modes.

Section 6 evaluates the performance of the proposed human-robot collaboration model, focusing on how human stress influences this performance. First, human-robot system performance as a function of human stress is evaluated mathematically using a disjoint union formula to assess overall system performance, with a focus on human-related factors. Second, the parameters of human performance and stress are analyzed through set theory to identify which factors implicitly and explicitly affect human performance. Third, it is hypothesized, and supported by existing studies, that human stress can be measured through wearable devices. Fourth, a conceptual formula is developed to quantify task-specific human stress and adjust stress levels when they exceed acceptable thresholds. This quantification is crucial because, when stress is monitored through wearable devices, the robot must adjust task assignments and modify the human's workload as needed. Mathematical calculations are performed whenever an intervention is made to verify its effectiveness.

Section 7 introduces the proposed model, building on the foundations established in Sections 4 through 6. First, the process flow of the proposed robot-supervised workload allocation algorithm is outlined using Microsoft Visio, divided into three steps to explain how and when the robot intervenes in workload allocation. These steps are explained in detail within this subsection. The first step focuses on monitoring human performance using statistical process control charts. The second step centers on measuring human stress, as detailed in Subsections 6.3 and 6.4. The third step illustrates the detailed operation of the proposed model, highlighting the need for integration with other systems to ensure proper functionality.

Based on the proposed model's process workflow, as depicted in Subsection 7.1.3, the model's three key phases are discussed in Subsection 7.2. The first phase illustrates a state diagram based on human stress conditions—underloaded, stabilized, and overloaded. The state diagram triggers the robot's intervention in workload reallocation when human stress levels are overloaded or underloaded. The second phase calculates the effect of each task on human stress to determine which task should be exchanged with the current one. This quantification, as mentioned earlier, is explained in Subsection 6.4. The third phase introduces pseudocode that guides the robot in adjusting human stress levels to optimize performance during collaboration, as tested in the simulation study to evaluate the validity of the proposed model. Finally, Subsection 7.3 presents a Monte Carlo simulation to validate the proposed model.

4. THE HUMAN-ROBOT SYSTEM FRAMEWORK IN THE PROPOSED MODEL

Human-robot systems have evolved, as outlined in the literature review, from the use of robots as tools in human-dominated work environments to collaborative interactions within cyber-physical systems, where physical components such as humans and robots interact through cyber components, including sensors, actuators, and software. Since the central theme of this thesis is human-robot collaboration through interaction, this section first visualizes the key system components—humans, robots, and their collaboration. It then explains how interaction is structured within multi-robot, multi-human systems.

4.1. System Components in Human-Robot Systems

In the context of human-robot systems, one system's output serves as the input for another in a collaborative setup. Interactions form the foundation of human-robot collaboration through communication channels. As mentioned in the literature, communication occurs when information is transferred without expecting feedback. In contrast, interaction involves two-way communication, where feedback is expected. When the aim is to achieve a shared goal through this two-way communication, collaboration emerges. Therefore, understanding the interactions and their interrelations within the system concept is crucial.

Human-robot systems consist of multiple humans and robots, which can form various collaborative groups. These groups may include human-human collaborations, where individuals work together to achieve a common goal through human-to-human interactions; robot-robot collaborations, where robots work together toward a shared goal through robot-to-robot interactions; and human-robot collaborations, where humans and robots work together toward the same objective through human-robot interactions.

As each group produces output, these outputs may serve as input for other groups, creating a continuous cycle of interactions and inputs across the system. This exchange of inputs and outputs between groups results in the integration of various system components. This integration mechanism underscores the importance of collaboration among system components. Thus, it is essential to recognize that system components interact to collaborate and generate output, which in turn triggers the operations of other systems. This mechanism is illustrated in Figure 4.

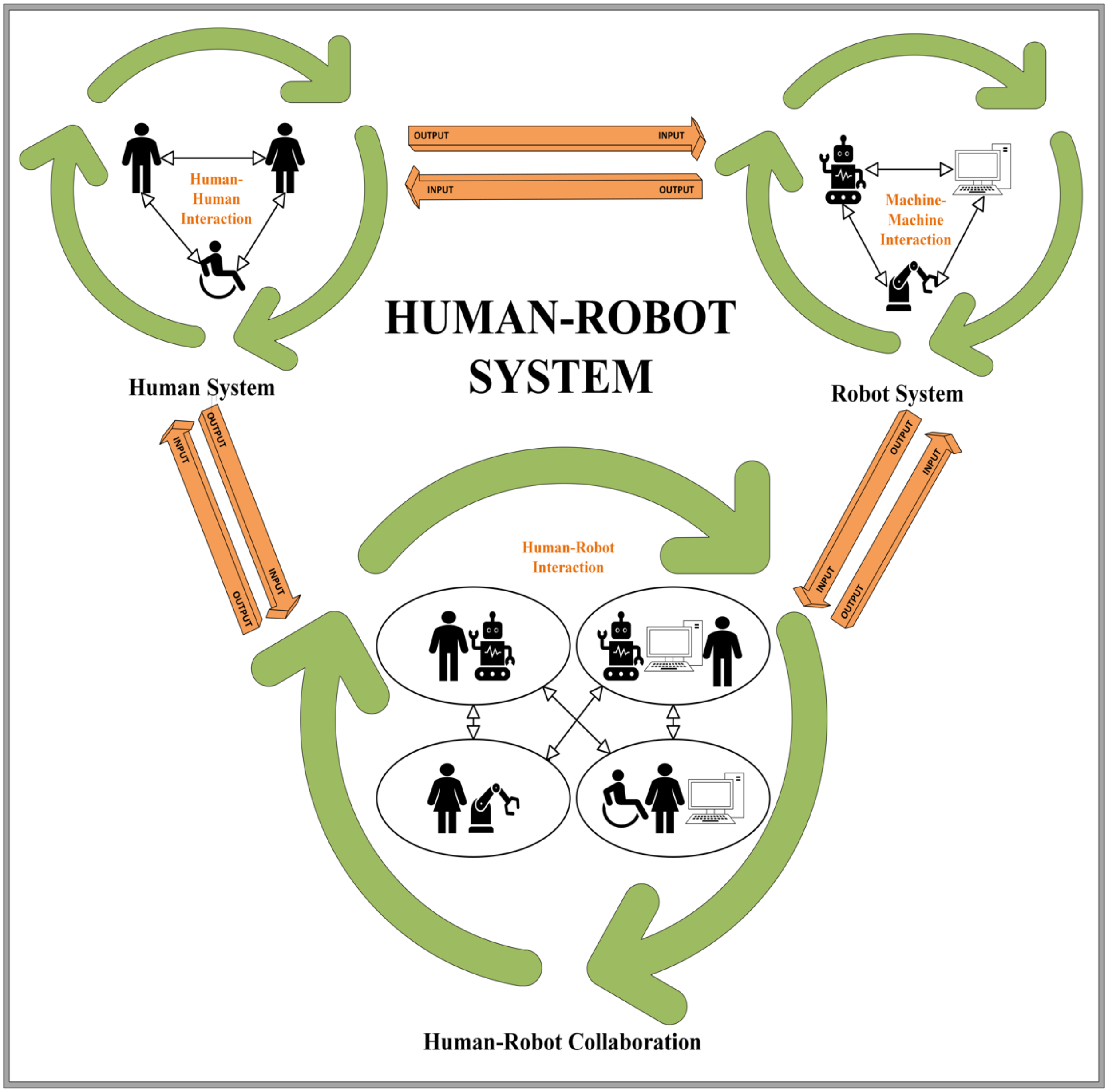

Figure 4: System Components in Human-Robot Systems

4.2.Interactions in Human-Robot Systems

There may be many possible collaboration groups in a human-robot system. The possible collaboration groups in a multi-human, multi-robot system, including human-human interactions, robot-robot interactions, and human-robot interactions, are expressed as follows:

Let n represent the number of humans and m the number of robots. I_H is the number of possible human-human collaboration groups, I_R is the number of possible robot-robot collaboration groups and I_{HR} is the number of possible human-robot collaboration groups in the human-robot systems,

$$I_H = \sum_{x=2}^{n} \binom{n}{x} \text{, where } x \text{ is the number of humans in the collaboration group} \tag{1}$$

$$I_R = \sum_{y=2}^{m} \binom{m}{y} \text{, where } y \text{ is the number of robots in the collaboration group} \tag{2}$$

$$I_{HR} = \sum_{x=1}^{n} \sum_{y=1}^{m} \binom{n}{x} \binom{m}{y} \tag{3}$$

$$\text{where } x \text{ s the number of humans and } y \text{ is the number of robots in the collaboration group}$$

According to the numbers obtained from the Equations (1)-(3), $(I_H * I_R) + (I_H * I_{HR}) + (I_R * I_{HR})$ gives the possible interactions between collaboration groups. These interactions may require integration, as they depend on one group's output to serve as the input for another group within the system.

As illustrated by the multi-human, multi-robot system concept, the system is complex, and the relationships between subsystems are interwoven. Therefore, classifying the communication channels, integration modes, and collaboration groups at the beginning of the project, and distributing the workload based on their characteristics, is crucial for maximizing system performance. The next section explains how such classification can be done, taking into account communication channels, interaction modes, and the characteristics of the workload to be assigned to system components such as humans, robots, or their joint collaborations.

5. INTERACTION MODES ACROSS TASK ZONES IN THE PROPOSED HUMAN-ROBOT COLLABORATION MODEL

Decomposing collaboration into fundamental building blocks facilitates a clearer understanding of hybrid team structures, enabling effective identification and resolution of issues based on the specific needs of each system component. This section outlines how these building blocks are defined and how the overall mechanism operates.

First, *task zones* are introduced to classify task types according to the responsible system component—human, robot, or joint collaboration. This classification supports effective workload allocation by mapping tasks to the most appropriate actors. Second, *interaction modes* are presented, comprising reciprocal communication channels designed to support appropriate feedback-based interactions among system components. Third, the defined interaction modes are integrated into the established task zones to demonstrate their operational alignment within the collaboration framework. Finally, a *dynamic task reallocation algorithm* is proposed, driven by intervention opportunities that arise from the task zone structure. While this algorithm incorporates stress-aware principles, it does not delve into the specifics of stress assessment. A detailed discussion of human stress measurement is provided in Section 6, followed by stress analysis and its integration into the model in Section 7. To elaborate on the practical applicability of the proposed dynamic workload allocation algorithm, a case study on *Dynamic Task Reallocation Management for Optimized Performance in Human-SAP System Collaboration* is presented at the end of this section.

5.1.Definition of Task Zones

In human-robot collaboration, interaction is the key mechanism through which system components coordinate to achieve shared goals. These interactions—whether between humans, robots, or both—directly influence the overall performance of the system. Each collaboration group, defined by its configuration and task responsibility, contributes to system output. *Figure 5* presents the correlation between different types of interactions and their corresponding impact on system performance.

System performance is classified into three categories: human performance, robot performance, and collaboration performance.

- Human performance is influenced by factors such as the human's perceived workload, knowledge, skills, affective states (e.g., emotions and mood), the actual workload assigned to the human, and the time remaining until task deadlines.
- Robot performance is determined by the robot's skills, knowledge, assigned workload, and time to deadline.
- Collaboration performance reflects the integration of both human and robot contributions. It depends on the human's perceived workload and affective states, the joint knowledge and skills of both agents, the collaborative workload assigned, and time to deadline.

The first parameters in the performance formulations shown in Figure 5 reflect the influence of human stress on system performance. Work-associated stress (σ) is defined as a function of perceived workload (W^P), knowledge (K), skills (S), and affective states (A), as shown in Equation 4 below (Nguyen & Zeng, 2017; Yang et al., 2021). When human stress is evaluated using this formula, all parameters— W^P, K, S, and A—are considered human-related. However, when the formula is applied to human-robot collaboration stress, knowledge and skills (K and S) are treated as collaboration-related parameters, while perceived workload and affective states (W^P and A) remain human-related. This distinction arises because the human is the only emotional component in the human-robot team, making W^P and A the emotion-related parameters in the collaborative context.

$$\sigma = \frac{W^P}{(K + S) * A} \tag{4}$$

Stress can arise from a mismatch between the human's capacity and workload or from emotional and cognitive states. Section 6 discusses in detail how different parameters contribute to human stress and how that stress affects both individual and system-wide performance.

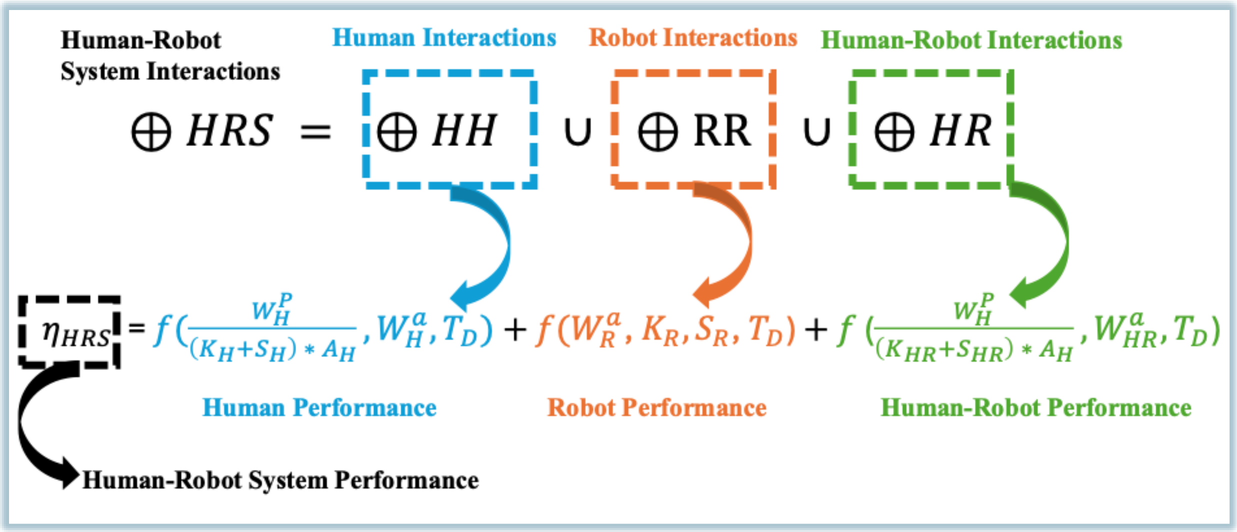

Figure 5: Connection between performance and collaboration

This thesis argues that enhancing human-robot system performance requires optimizing human performance, which is closely linked to the human's stress level. Human stress is primarily influenced by two factors:

1. Affective states (e.g., mood, anxiety, emotional well-being), which are difficult to control directly,
2. Actual workload assigned, which can be adjusted dynamically.

Because affective states are not externally controllable, the actual workload assigned to the human becomes the most practical control variable for managing stress. By adjusting this workload in real time, it is possible to regulate human stress and maintain it within an optimal range that supports high performance.

Therefore, workload management is central to this thesis. Classifying tasks according to the most suitable performer—human, robot, or both—enables the system to allocate workload effectively. This forms the basis of the task zones, which will be used throughout the model to guide task assignment and dynamic reallocation.

Subsequently, two lemmas are presented to formally articulate the problem at hand.

Lemma 1: *Given a set of* N *tasks allocated among humans, robots, or human-robot teams, each task assigned to a human affects their stress level. Some tasks may increase stress, while others may reduce it. If the human stress level falls outside the optimal range, task redistribution among humans and human-robot teams can be employed to bring the stress level back within the desired boundaries.*

Proof: *As shown in Equation 4, assuming a planning period too short for significant changes in knowledge and skills, variations in stress levels can be counterbalanced by modifying the perceived workload.*

Lemma 2*: Perceived workload is a controllable parameter, as defined in Equation 4, and can be regulated through the actual workload.*

Proof: *Perceived workload, shaped by task assignments, previous performance, and time availability, can be actively managed by altering the task composition. Drawing on prior experiences and evaluating the remaining capacity, it is possible to adjust task distribution to regulate perceived workload effectively.*

In a collaborative work environment, tasks are assigned to team members based on their competencies—specifically, their skills, knowledge, and available capacity. As a result, it is known which members (whether human, robot, or human-robot teams) are capable of performing each task. Based on this understanding, tasks can be classified into seven distinct zones, as depicted in Figure 6.

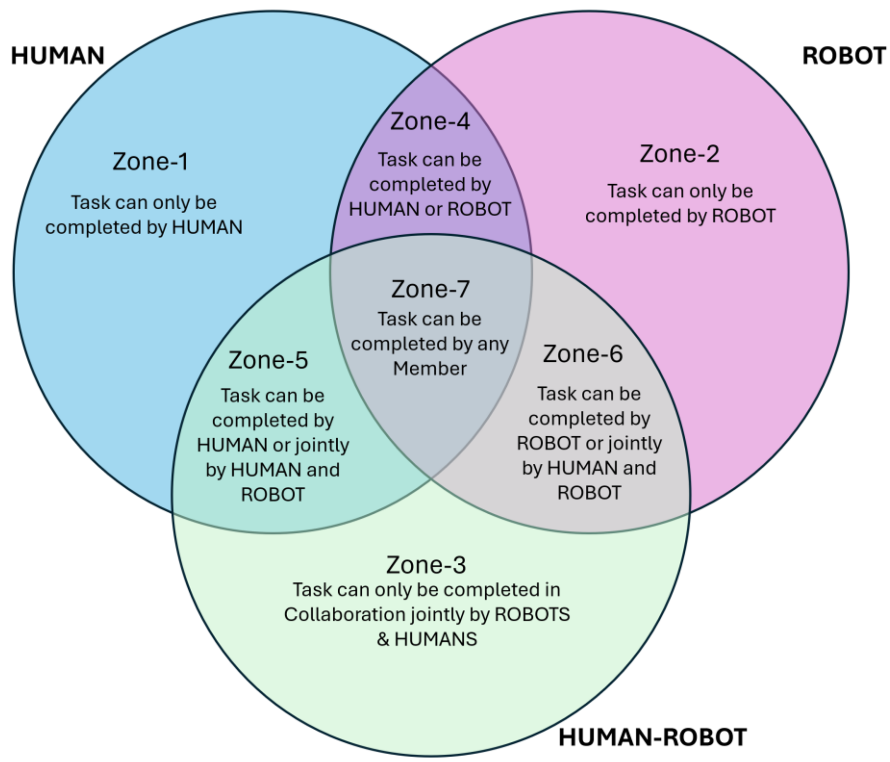

Figure 6: Possible task distribution map among team members

5.2.Classification of Interaction Modes

Building upon the task zone classifications presented in the previous subsection, this section examines the interactions and communication channels within human-robot collaboration. Since collaborators can accomplish tasks through various interaction modes and communication pathways, understanding these dynamics is critical.

Environment-Based Design (EBD) theory (Sun et al., 2011; Zeng, 2011) proposes that the world is shaped by three interconnected environments: the human environment, the natural environment, and the built environment. In the context of human-robot systems, robots represent the built environment. Inspired by the Axiomatic Theory of Design (Zeng, 2002), the relationships among these three environments are interpreted as reciprocal communication channels, which provide a foundational perspective for modeling interactions in collaborative human-robot systems. Based on this theoretical grounding, the communication pathways that constitute a human-robot system are structured into a framework, as shown in Table 3.

Table 3: Communication Channels and their Application Domains

Collaboration Type	Interaction Modality	Communication Channel	Definition	Traditional Application Domains
$\oplus \boldsymbol{HH}$	$(\boldsymbol{H} \otimes \boldsymbol{H})$	$(\boldsymbol{H_i} \rightarrow \boldsymbol{H_j}) \cup (\boldsymbol{H_j} \rightarrow \boldsymbol{H_i})$	Human-Human Interaction composed of communication from H_i to H_j and from H_j to H_i	Education, Psychology, Social Sciences, People Management, Project Management, …
$\oplus \boldsymbol{RR}$	$(\boldsymbol{R} \otimes \boldsymbol{R})$	$(\boldsymbol{R_j} \rightarrow \boldsymbol{R_i}) \cup (\boldsymbol{R_i} \rightarrow \boldsymbol{R_j})$	Robot-Robot Interaction composed of communication from Rj to Ri and from R_i to R_j	Machine-to-Machine Communication Technology, Wireless Sensor Networks, Computer Technology, …
$\oplus \boldsymbol{NN}$	$(\boldsymbol{N} \otimes \boldsymbol{N})$	$(\boldsymbol{N_k} \rightarrow \boldsymbol{N_i}) \cup (\boldsymbol{N_i} \rightarrow \boldsymbol{N_k})$	Human-Human Interaction composed of communication from N_k to N_i and from N_i to N_k	Natural Sciences
$\oplus \boldsymbol{HR}$	$(\boldsymbol{H} \otimes \boldsymbol{R})$	$(\boldsymbol{H_i} \rightarrow \boldsymbol{R_j}) \cup (\boldsymbol{R_j} \rightarrow \boldsymbol{H_i})$	Human-Human Interaction composed of communication from H_i to R_j and from R_j to H_i	Perceptual Processing, Behavioral Processing, Embodied Cognition, Artificial Intelligence, Machine Learning, Natural Language Processing, Voice Recognition, Image Processing,

				Cognitive Psychology, …
$\oplus \boldsymbol{HN}$	$(\boldsymbol{H} \otimes \boldsymbol{N})$	$(\boldsymbol{H_i} \to \boldsymbol{N_k}) \cup (\boldsymbol{N_k} \to \boldsymbol{H_i})$	Human-Nature Interaction composed of communication from H_i to N_k and from N_k to H_i	Applied Science, Economics, Business, …
$\oplus \boldsymbol{RN}$	$(\boldsymbol{R} \otimes \boldsymbol{N})$	$(\boldsymbol{R_j} \to \boldsymbol{N_k}) \cup (\boldsymbol{N_k} \to \boldsymbol{R_j})$	Robot-Nature Communication composed of communication from Rj to N_k and from N_k to R_j	Applied Science, Business, Manufacturing, …
$\oplus\, [(\boldsymbol{H} \otimes \boldsymbol{R})]$	$(\boldsymbol{H} \otimes \boldsymbol{R})$	$(\boldsymbol{H_i} \to \boldsymbol{R_j}) \cap (\boldsymbol{R_j} \to \boldsymbol{H_i})$	Mutual understanding for a shared goal involves communication between H_i, R_j: from H_i to R_j, from R_j to H_i	Applied AI
$\oplus\, [(\boldsymbol{H_i} \otimes \boldsymbol{H_j})]$	$(\boldsymbol{H_i} \otimes \boldsymbol{H_j})$	$(\boldsymbol{H_i} \to \boldsymbol{H_j}) \cap (\boldsymbol{H_j} \to \boldsymbol{H_i})$	Mutual understanding for a shared goal involves communication between H_i, H_j: from H_i to H_j, from H_j to H_i	Human Science
$\oplus\, [(\boldsymbol{R_i} \otimes \boldsymbol{R_j})]$	$(\boldsymbol{R_i} \otimes \boldsymbol{R_j})$	$(\boldsymbol{R_j} \to \boldsymbol{R_i}) \cap (\boldsymbol{R_i} \to \boldsymbol{R_j})$	Mutual understanding for a shared goal involves communication between R_i, R_j: from R_i to R_j, from R_j to R_i	Computer Science, Applied AI

$\oplus[(\boldsymbol{H} \otimes \boldsymbol{R} \otimes \boldsymbol{N})]$	$(\boldsymbol{H} \otimes \boldsymbol{R} \otimes \boldsymbol{N})$	$(\boldsymbol{H_i} \rightarrow \boldsymbol{R_j}) \cap (\boldsymbol{R_j} \rightarrow \boldsymbol{H_i}) \cap (\boldsymbol{H_i} \rightarrow \boldsymbol{N_k}) \cap (\boldsymbol{N_k} \rightarrow \boldsymbol{H_i}) \cap (\boldsymbol{R_j} \rightarrow \boldsymbol{N_k}) \cap (\boldsymbol{N_k} \rightarrow \boldsymbol{R_j})$	Mutual understanding for a shared goal involves communication between H_i, R_j, and N_k: from H_i to R_j, from R_j to H_i, from H_i to N_k from N_k to H_i, from Rj to N_k and from N_k to R_j	Applied AI

According to Table 1, communication channels are denoted by the symbol "→", interactions by "⊗", and collaborations by "⊕". As discussed in the Literature Review section, communication channels constitute interactions when they are bidirectional, and interactions lead to collaborations when the system components share a common goal. The shared goal is expressed as "⊕[(H⊗R⊗N)]", indicating that it must involve the intersection of all interaction modes within the system. This representation reflects the mutual understanding of each component's requirements, achievements, capabilities, and limitations, allowing them to compensate for one another in order to achieve the collective objective. The communication channels outlined in Table 1 provide the foundation for formulating Human-Robot-Nature System Collaboration (⊕HRNS) as a function of these interlinked communication pathways:

$$\begin{aligned}
\oplus \boldsymbol{HRNS} = \; & [(\boldsymbol{H_i} \rightarrow \boldsymbol{H_j}) \cup (\boldsymbol{H_j} \rightarrow \boldsymbol{H_i})] \cup [(\boldsymbol{H_i} \rightarrow \boldsymbol{H_j}) \cap (\boldsymbol{H_j} \rightarrow \boldsymbol{H_i})] \cup \\
& [(\boldsymbol{R_j} \rightarrow \boldsymbol{R_i}) \cup (\boldsymbol{R_i} \rightarrow \boldsymbol{R_j})] \cup [(\boldsymbol{R_j} \rightarrow \boldsymbol{R_i}) \cap (\boldsymbol{R_i} \rightarrow \boldsymbol{R_j})] \cup \\
& [(\boldsymbol{N_k} \rightarrow \boldsymbol{N_i}) \cup (\boldsymbol{N_i} \rightarrow \boldsymbol{N_k})] \cup [(\boldsymbol{N_k} \rightarrow \boldsymbol{N_i}) \cap (\boldsymbol{N_i} \rightarrow \boldsymbol{N_k})] \cup \\
& [(\boldsymbol{H_i} \rightarrow \boldsymbol{R_j}) \cup (\boldsymbol{R_j} \rightarrow \boldsymbol{H_i})] \cup [(\boldsymbol{H_i} \rightarrow \boldsymbol{R_j}) \cap (\boldsymbol{R_j} \rightarrow \boldsymbol{H_i})] \cup \\
& [(\boldsymbol{H_i} \rightarrow \boldsymbol{N_k}) \cup [(\boldsymbol{N_k} \rightarrow \boldsymbol{H_i})] \cup [(\boldsymbol{H_i} \rightarrow \boldsymbol{N_k}) \cap [(\boldsymbol{N_k} \rightarrow \boldsymbol{H_i})] \cup \\
& [(\boldsymbol{R_j} \rightarrow \boldsymbol{N_k}) \cup (\boldsymbol{N_k} \rightarrow \boldsymbol{R_j})] \cup (\boldsymbol{R_j} \rightarrow \boldsymbol{N_k}) \cap (\boldsymbol{N_k} \rightarrow \boldsymbol{R_j})] \cup \\
& [(\boldsymbol{H_i} \rightarrow \boldsymbol{R_j}) \cap (\boldsymbol{R_j} \rightarrow \boldsymbol{H_i}) \cap (\boldsymbol{H_i} \rightarrow \boldsymbol{N_k}) \cap (\boldsymbol{N_k} \rightarrow \boldsymbol{H_i}) \cap
\end{aligned} \tag{5}$$

$$(R_j \rightarrow N_k) \cap (N_k \rightarrow R_j)]$$

$$\begin{aligned} \oplus \boldsymbol{HRNS} = \; & (H \otimes H) \cup [(H_i \rightarrow H_j) \cap (H_j \rightarrow H_i)] \cup (R \otimes R) \cup [(R_j \rightarrow R_i) \cap \\ & (R_i \rightarrow R_j)] \cup (N \otimes N) \cup [(N_k \rightarrow N_i) \cap (N_i \rightarrow N_k)] \cup (H \otimes R) \cup \\ & [(H_i \rightarrow R_j) \cap (R_j \rightarrow H_i)] \cup (H \otimes N) \cup [(H_i \rightarrow N_k) \cap [(N_k \rightarrow H_i)] \cup \\ & [(R \otimes N) \cup (R_j \rightarrow N_k) \cap (N_k \rightarrow R_j)] \cup [(H \otimes R) \cap (H \otimes N) \cap \\ & (R \otimes N)] \end{aligned} \tag{6}$$

The HRNS formula can be simplified when individual collaborative interactions are organized as illustrated below:

$$\begin{aligned} \oplus \boldsymbol{HRNS} = & \oplus HH \cup \oplus (H \otimes H) \cup \oplus RR \cup \oplus (R \otimes R) \cup \oplus NN \cup \oplus (N \otimes N) \cup \\ & \oplus HR \cup \oplus (H \otimes R) \cup \oplus HN \cup \oplus RN \cup \oplus (R \otimes N) \cup \oplus [(H \otimes R \otimes N)] \end{aligned} \tag{7}$$

While the influence of nature on a human-robot system (HRS) is indisputable, its inherent complexity leads to its exclusion from the HRS formulation. Therefore, the HRS system examined in this thesis is defined as follows:

$$\oplus \boldsymbol{HRS} = \oplus HH \cup \oplus (H \otimes H) \cup \oplus RR \cup \oplus (R \otimes R) \cup \oplus HR \cup \oplus (H \otimes R) \tag{8}$$

As demonstrated in Equation 8, multi-human–multi-robot system collaboration comprises human–human interaction ($\oplus HH$), robot–robot interaction ($\oplus RR$), human–robot interaction ($\oplus HR$), and their shared understanding of a common objective. Therefore, humans must not only understand their human partners' requirements, capabilities, and limitations ($\oplus (H \otimes H)$) but also those of their robot partners ($\oplus (H \otimes R)$). Similarly, robots must comprehend the needs, abilities, and limitations of both their robotic counterparts ($\oplus (R \otimes R)$)—via automated integration—and their human collaborators ($\oplus (H \otimes R)$)—through physiological and behavioral analysis.

However, mutual understanding is not meaningful unless it leads to action that compensates for each other's limitations. At this point, the intersection of human-robot interactions, denoted as "$\oplus (H \otimes R)$" plays a crucial role. It represents mutual understanding directed toward a shared goal within the human–robot system and captures the decision-making process of system components—human or robot—when they detect performance-degrading limitations in their partners.

This interaction can be evaluated in two directions: how humans respond to a robot's inability or constraint in task execution, and vice versa. This thesis proposes a decision-making algorithm that enables robots to recognize such limitations and take appropriate action. Consequently, the thesis centers on the "$\oplus\,(\boldsymbol{H} \otimes \boldsymbol{R})$" component of the collaboration tree defined in Equation 8.

5.3. Integration of Interaction Modes with Task Zones

After understanding task zones and interaction modes, this section matches these terms to show relationship. This relationship facilitates assigning right tasks to the right task owners while deploying system components in the human-robot collaboration.

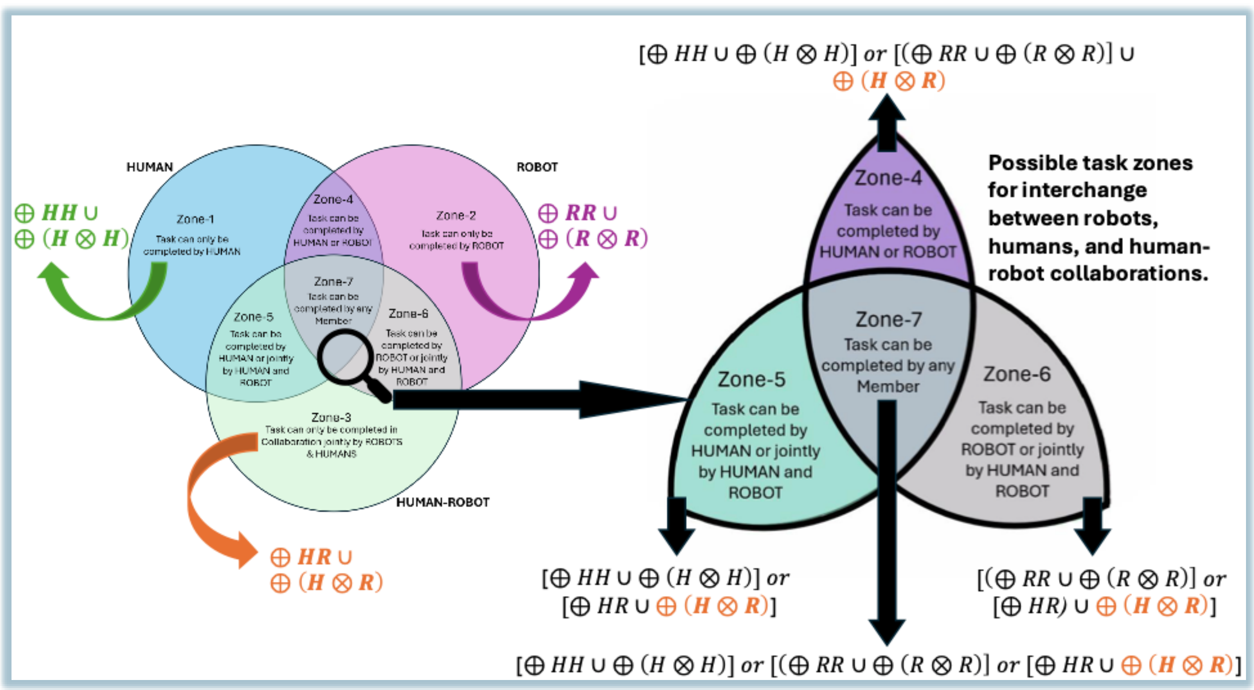

Figure 7: Possible task zones for interchange

Figure 7 emphasizes that Zone 4, Zone 5, Zone 6, and Zone 7 are the only zones where robots can either change tasks assigned to humans or assign new tasks to them. In these zones, mutual understanding for a shared goal must be maintained throughout the collaboration, regardless of whether the task is performed by a human or a robot. The main objective of conducting task reallocation in these zones is to optimize human working conditions and enhance their performance while both human and robot partners work toward a common goal.

Therefore, each member should be aware of their partner's individual abilities and limitations, aiming to compensate for each other's weaknesses during collaboration. When a decrease in a partner's performance is detected, an appropriate action should be taken. This behavior represents the essence of effective and efficient collaboration. This logic is symbolized by the notation "$\oplus$[(H$\otimes$R)]" introduced in the previous subsection, which denotes the need to understand a collaborator's state and respond accordingly.

Additionally, identifying the correct interaction modes plays a crucial role in recognizing the active communication channels based on the task at hand. For example, tasks in Zone 6 can be executed either by robots alone or through human-robot collaboration. In this case, both (R$\otimes$R) and (H$\otimes$R) interaction channels should remain active when a task from Zone 6 is undertaken. The robot continuously monitors the human channel during joint tasks. If the human is overloaded while performing the task, the robot can take over the task entirely to reduce the human's workload. Conversely, if a robot is independently handling a Zone 6 task and observes that the human partner is underloaded, the task assignment can shift from the (R$\otimes$R) channel to the (H$\otimes$R) channel.

Such adaptive task exchange mechanisms serve as a foundational component in modeling intelligent human-robot systems that are responsive to real-time variations in partner performance and workload.

5.4.Dynamic Task Reallocation Algorithm Based on Task Zones

Effective collaboration depends on establishing a shared cognitive framework among all participants, which promotes mutual understanding. In human-robot collaboration, this shared understanding hinges on the robot's ability to exhibit decision-making capabilities that are compatible with human reasoning. A key enabler of such intelligent and coordinated behavior is the implementation of an advanced supervisory control system. In this thesis, the supervisory controller is embedded directly into the robot systems, enabling them to autonomously monitor, interpret, and respond to dynamic task environments. This intelligent controller ensures a continuous and synchronized exchange of information, drawing from both human performance data and collaborative task dynamics. Within this adaptive communication environment, the controller evaluates whether task reallocation is necessary using embedded decision-making algorithms. When reallocation is required, it efficiently redistributes tasks—either by assigning responsibilities to human collaborators or autonomously taking over certain tasks—ensuring a balanced and responsive workload distribution. The structure of this mechanism is presented in Figure 8 below.

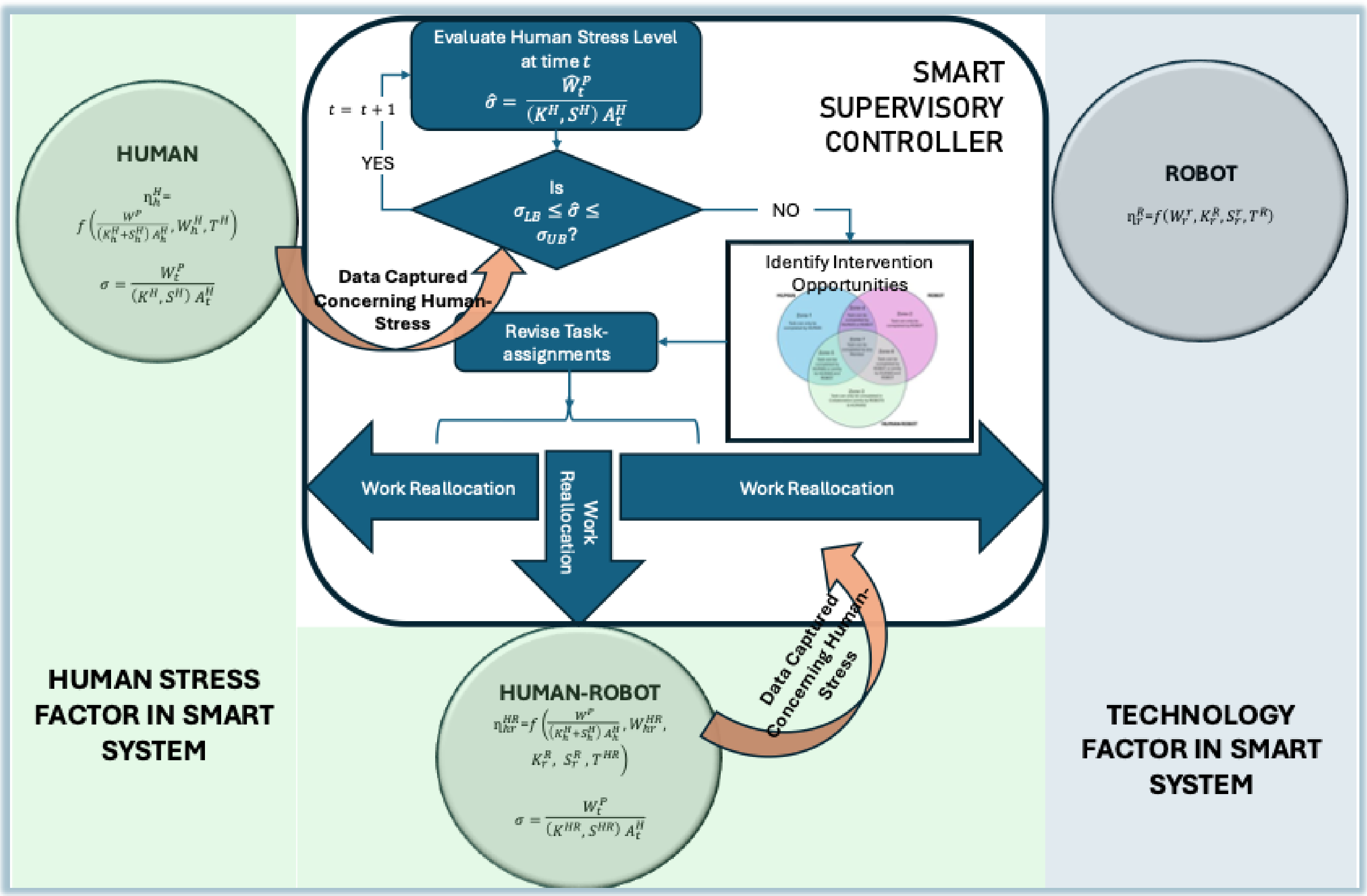

Figure 8: Workload reallocation between humans, robots and their collaborations in smart systems

The intelligent human-robot system utilizes its interaction modes to dynamically manage task allocation across defined zones, as illustrated in Figure 7, with the primary goal of maintaining human stress levels within an optimal range. To support this objective, this thesis introduces an eight-step methodology designed to regulate human stress and enhance human performance in collaborative settings. Stress monitoring—explained in detail in Section 6—combined with the implementation of the algorithm outlined in the pseudo-code below, serves as the foundation of this approach. For the human-robot system to effectively reallocate tasks, it is essential to identify communication pathways, foster collaborative interactions, and promptly detect stress in human partners to enable timely interventions.

An Eight-Step Algorithm for Performance Optimization through Stress Regulation in Smart Robot-Governed Systems:

1. Apply the Axiomatic Theory of Design to analyze complex interaction structures within the system.
2. Identify distinct interaction modes: $\boldsymbol{H} \otimes \boldsymbol{H}$ (human-human), $\boldsymbol{R} \otimes \boldsymbol{R}$ (robot-robot), and $\boldsymbol{H} \otimes \boldsymbol{R}$ (human-robot).
3. Address each interaction mode within the smart system and associate relevant tasks.
4. Define the roles of each system component—humans, robots, and human-robot collaborations.
5. Determine which roles may be executed by multiple system components, where applicable.
6. Highlight human-involved tasks to prioritize stress monitoring.
7. Develop an algorithm for robots to detect, assess, and respond to human stress by redistributing workload accordingly. Implement the algorithm via a smart supervisory controller, which may be embedded within robot systems—as proposed in this thesis—or supported externally, depending on system capabilities.

The detailed pseudo-code implementing this logic follows below.

Task Reallocation Algorithm:

Inputs:

i. *Resources: Set of Human* $(h \in H)$*; Set of Robots/Machines* $(r \in R)$

ii. *Set of tasks* $(\boldsymbol{w} \in \boldsymbol{W})$

iii. *Capabilities of Human, Robot and Human-Robot team: Distribute tasks according to resource capabilities as illustrated in Figure 5.*

Step 0: $t = 0$ *distribute tasks among Human, Robot, and Human-Robot jointly*

$W_0^H \in \{w^{Z1}, w^{Z4}, w^{Z5}, w^{Z7}\}$

$W_0^R \in \{w^{Z2}, w^{Z4}, w^{Z6}, w^{Z7}\}$

$W_0^{HR} \in \{w^{Z3}, w^{Z5}, w^{Z6}, w^{Z7}\}$

Step 1: $t = t + 1$, *assess human stress* $\left(\sigma = \frac{W_t^P}{(K^H, S^H)\, A_t^H}\right)$

Step 2: *Task reallocation:*

if $(\sigma \geq \sigma_{UB})$*:*

<u>*Human is over-stressed:*</u> *Transfer tasks from Human to Robot or Human to Human-Robot team*

If W_t^H *includes tasks belong to Zone 4* ➔ *Transfer tasks to Robot*

elseif W_t^H *includes tasks belong to Zone 5* ➔ *Transfer tasks to Human-Robot team*

elseif W_t^H *includes tasks belong to Zone 7* ➔ *Transfer tasks to Robot or Human-Robot team*

elseif if $(\sigma \leq \sigma_{LB})$*:*

<u>*Human is under-stressed*</u>*: Transfer tasks from Robot or Human-Robot team to Human*

If W_t^R *includes tasks belong to Zone 4* ➔ *Transfer tasks to Human*

elseif W_t^{HR} *includes tasks belong to Zone 5* ➔ *Transfer tasks to Human*

elseif W_t^R *or* W_t^{HR} *includes tasks belong to Zone 7* ➔ *Transfer tasks to Human*

Subject to following constraints

$$\sum_{k \in W_t^H} t_k^H + \sum_{k \in W_t^{HR}} t_k^{HR} \leq T^H \quad (9)$$

$$\sum_{k\in W_t^R} t_k^R + \sum_{k\in W_t^{HR}} t_k^{HR} \leq T^R \tag{10}$$

$$\widehat{W}_t^P = f\left(\left(\sum_{k\in W_t^H} f(t_k^H,\, K_k^H, S_k^H) + \sum_{k\in W_t^{HR}} f(t_k^{HR},\, K_k^H, S_k^H,\, K_k^R, S_k^R)\right),\, \beta_{t-1}^H,\, T^H\right) \tag{11}$$

$$\hat{\sigma} = \frac{\widehat{W}_t^P}{(K^H,\, S^H)\, A_t^H} \tag{12}$$

$$\sigma_{LB} \leq \hat{\sigma} \leq \sigma_{UB} \tag{13}$$

Where:

t_k^H *is the estimated completion time when task k is completed by a Human alone*

t_k^R *is the estimated completion time when task k is completed by a Robot alone*

t_k^{HR} *is the estimated task completion time when handled by Human-Robot jointly.*

T^H *is the available time (remaining capacity) and the* t *is the current period.*

$\widehat{W}_t^P$ *is the estimated perceived workload at period t*

β_{t-1}^H *is the performance of human (percentage of successful completion of tasks) at the t-1*

K^H, S^H *and* A_t^H *are knowledge, skill and the affective state of human at time* t_i.

$\hat{\sigma}$ *is the estimated stress level at period* t_i

σ_{LB} *is the lower bound for desired stress level*

σ_{UB} *is the upper bound for desired stress level*

else

Continue with the current task assignment

Step 3: Has the job completed?

NO: Go to Step 1

YES: Go to step 4

Step 4: End intervention

Outputs:

i. *Updated* W_t^H, W_t^R *and* W_t^{HR}

ii. *Optimized Human stress* ($\sigma_{LB} \leq \sigma \leq \sigma_{UB}$)

8. Optimize human stress levels to achieve overall enhancement of smart system performance.

The objective of the outlined steps is to maximize the effective use of human and robotic capabilities, as well as their collaborative synergy. Managing this interaction through well-established interaction modes (reciprocal communication channels) enables collaborators to maintain human stress within an optimal range, thereby supporting the attainment of targeted system productivity.

5.5. Case Study: Dynamic Task Reallocation Management for Optimized Performance in Human-SAP System Collaboration

This subsection demonstrates how the proposed algorithm, introduced throughout Section 5, can be applied in a real-world context. The case study focuses on the interaction between humans and SAP systems within an organizational setting, where the human-robot collaboration control model is evaluated through the lens of SAP integration.

The implementation of SAP Transportation Management (TM) software is examined by comparing task allocations and operational outcomes before and after its adoption. Task assignments across different zones (see Figure 6) are determined based on SAP's functional capabilities. Although SAP's integrated architecture supports smooth coordination with other enterprise systems, communication conflicts during collaboration may still occur, leading to reduced efficiency in human-SAP interaction.

This case study aims to identify both the timing and nature of these conflicts and explores how they can be addressed through the dynamic task reallocation method presented earlier and visualized in Figure 8.

5.5.1. Introduction of the System Structure

SAP is a multifaceted system consisting of numerous IT components that support a wide range of business processes. This study focuses on eight key SAP modules: S/4 HANA (Cloud ERP), Transportation Management, Event Management, Extended Warehouse Management, Business Network Global Track and Trace, Business Network for Logistics, External Geographic Information Systems, and the VSR (Vehicle and Routing) Optimizer. These modules are interconnected through a variety of integration technologies, including IDOC, SOAP, REST, RFC, Proxy, File, EDI, JDBC, and BAPI. Additionally, SAP Process Integration serves as a dedicated integrator system, specifically designed to facilitate seamless communication across different platforms.

The primary emphasis is placed on the SAP Transportation Management (TM) module and its interactions with both direct and indirect collaborators that impact its operational performance. Evaluating the system's overall efficiency requires an understanding of how these collaborators contribute to SAP TM's functionality. Smooth operation of TM processes depends heavily on input from surrounding systems, which deliver critical data needed to execute logistics tasks effectively.

To illustrate this, a scenario involving an S/4 HANA side-car configuration is presented, highlighting the integration of SAP TM with external systems. Lauterbach et al. (2019) offer a detailed representation of these continuous integrations in the context of such a setup (see Figure 9). Although the case study centers on the adaptation process of logistics service providers to the SAP Business Network for Logistics (LBN), SAP TM remains the core element—functioning as the central hub for operational data flow. Figure 10 provides a visual overview of the information exchange within a SAP TM-centric system.

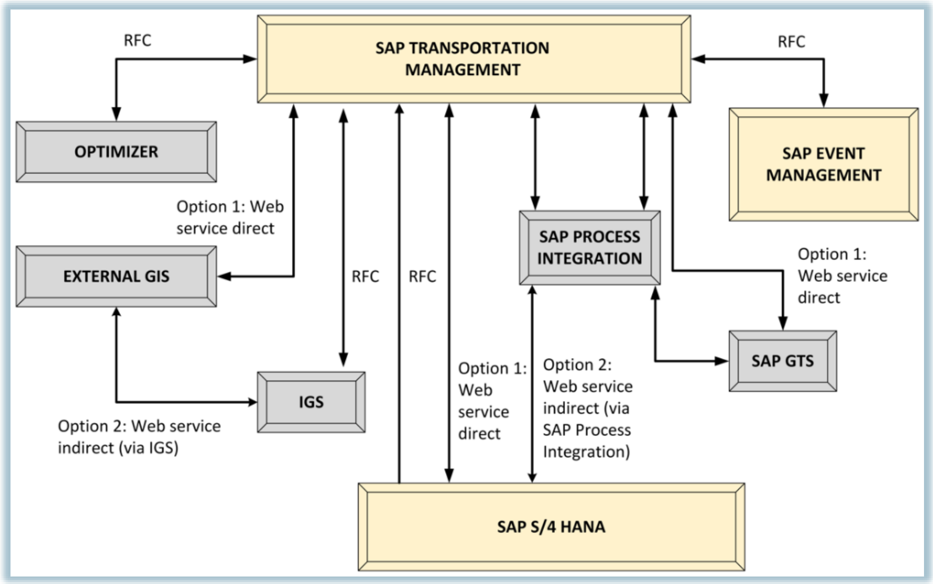

Figure 9: Overview of SAP TM Integration When Not Embedded in SAP S/4 HANA (Lauterbach et al., 2019)

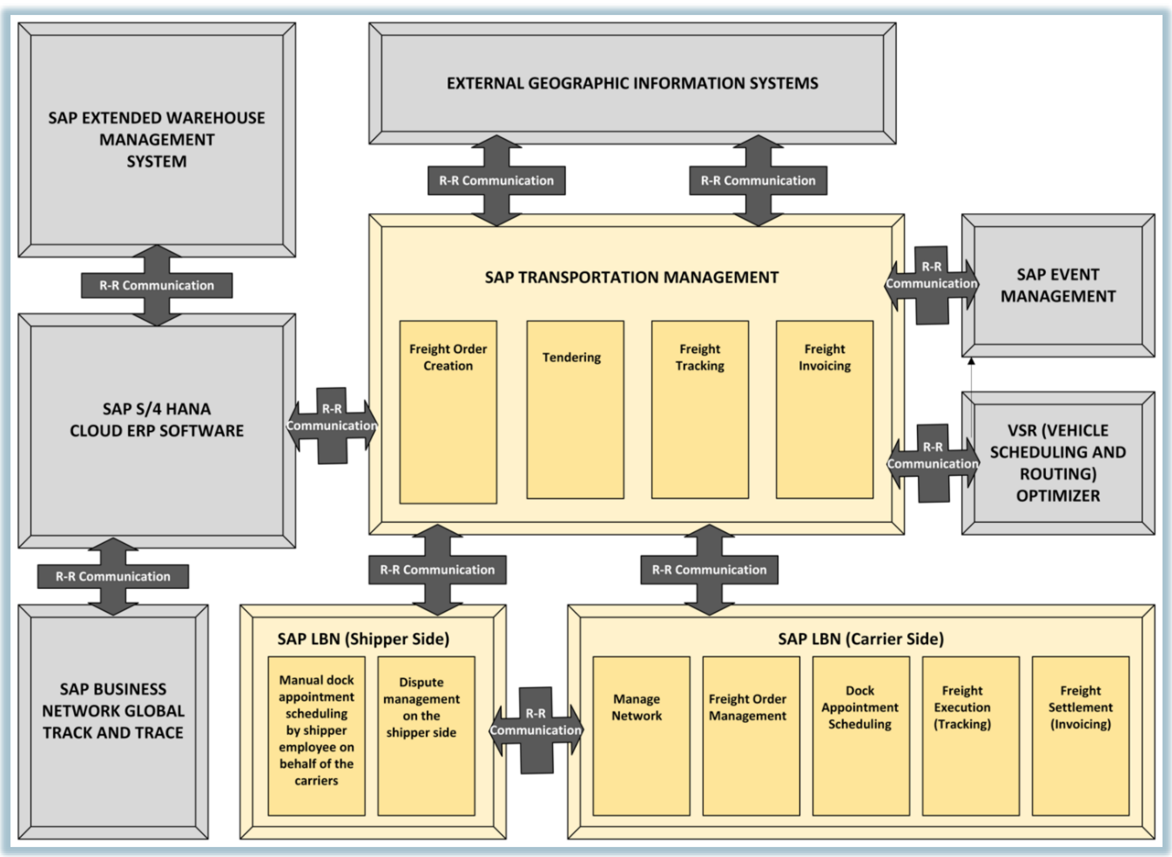

Figure 10: Illustration of Robot-Robot Communication; Systems integration in SAP S/4 HANA Side-Car Scenario (Robots are systems such as SAP LBN and SAP S/4 HANA)

To ensure a clear distinction and understanding of roles within the system, robotic components are labeled as 'R' followed by numerical identifiers (e.g., R1, R2, R3), while human personas—such as users, developers, analysts, consultants, and managers—are represented as 'H' with corresponding numbers (e.g., H1, H2, H3). While existing SAP systems do not yet exhibit autonomous intelligence or engage in dynamic interaction with human collaborators, it is anticipated that future advancements will transform these systems into intelligent robotic entities capable of ongoing cooperation with humans.

Integration technologies form the foundation for communication among robotic systems. In this context, integration components are also referred to as robots, as they actively facilitate system-level interactions. Additionally, human contributors responsible for managing these integrations—particularly through SAP Process Integration (PI)—are recognized as SAP PI consultants.

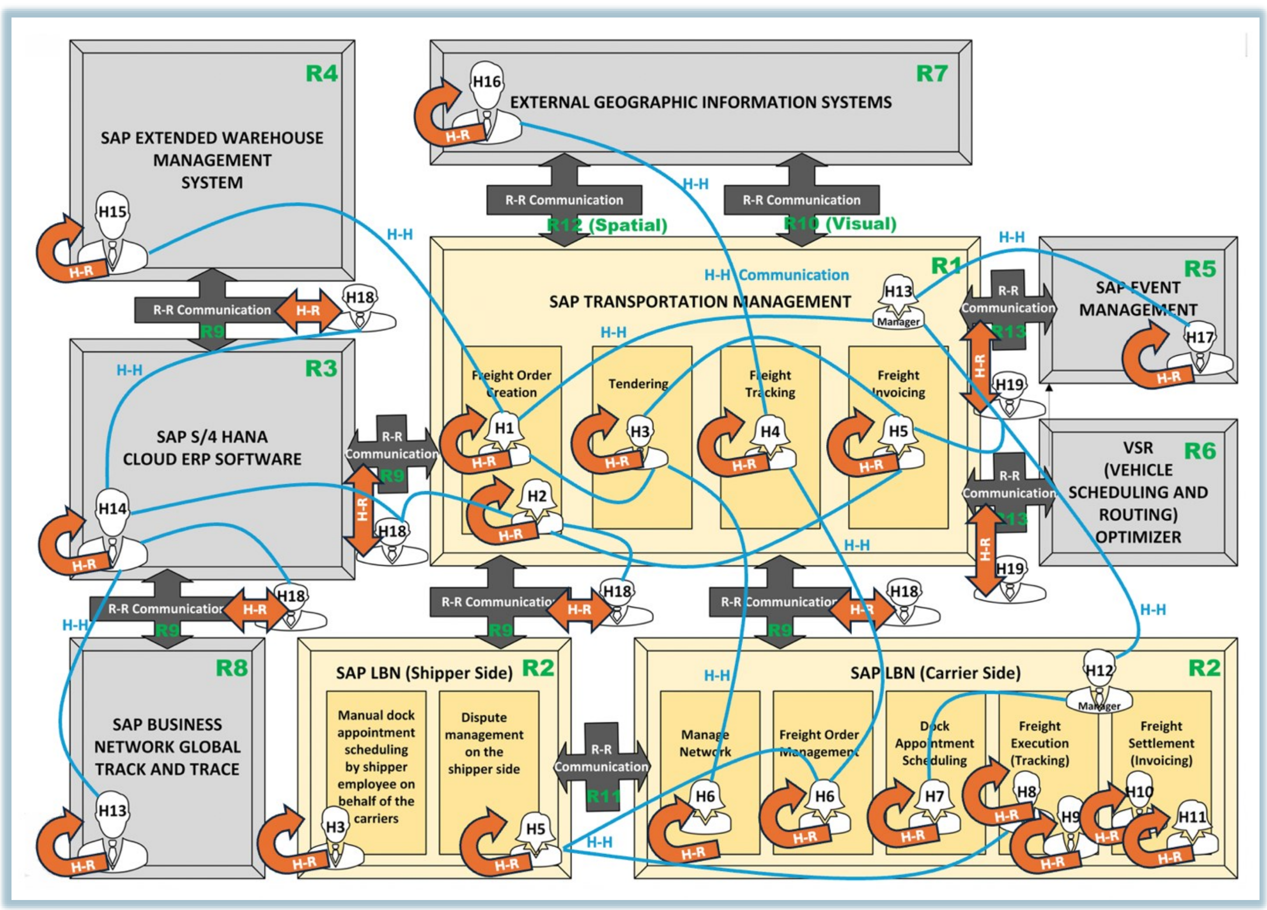

Figure 11: Dynamic Collaboration between Human-SAP systems (robots): Navigating the Smart SAP S/4 HANA Side-Car Ecosystem with human in the loop

Given this structure, robotic systems communicate with one another via an intermediary robot that serves as an integrator, forming the R⨂R interaction channel. These exchanges are supervised and coordinated by human collaborators through the H⨂R channel. Each robotic system also interfaces with its human users to support their interactions, which also take place through the H⨂R pathway. Meanwhile, human-to-human communication occurs through the H⨂H channel. The envisioned collaborative ecosystem for a future smart SAP system—where both robots and humans work together dynamically—is illustrated in Figure 11.

5.5.2. *Identifying Tasks and Their Corresponding Zones*

To conduct a comprehensive analysis of human-robot collaboration, the first essential step is to clearly define and map out the communication channels involved, as discussed earlier. Grounded in the Axiomatic Theory of Design (Zeng, 2011), this approach requires recognizing three core relational dynamics: human-human, robot-robot, and the crucial bidirectional interactions that define human-robot collaboration. Based on this framework, tasks within the SAP system are identified, along with their potential executors—classified into designated zones. As illustrated in Figure 6, tasks are grouped into seven distinct zones depending on the capabilities of the collaborators (H, R, or H-R). Table 4 presents the identified tasks alongside their corresponding zones.

Table 4: Possible Tasks Available for Human, Robot, Human-Robot in the LBN (Business Network for Logistics) System of SAP S/4 HANA Side-Car Scenario

Task number	Task details	Channel	Tasks that can by			Task Zone
			H	R	HRC	
T01	H18 initiates integration between different systems.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T02	H19 designs the RFC (Remote Function Call) interface.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T1	H4 creates deliveries on R3.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T2	Deliveries are sent from R3 to R4 and from R3 to R1.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**

T3	Transportation units are automatically created on R4. (Together with the delivery information, those form the basis for warehouse planning and execution.)	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T4	Freight orders are created by H1 or H2 in collaboration with R1.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T5	The information regarding planned freight orders is sent from R1 to R2 and R1 to R4.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T6	H6 confirms the freight orders through R2 on the Freight Order Management section, or this process can be automated.	$(\boldsymbol{R} \otimes \boldsymbol{R})$ ***or*** $(\boldsymbol{H} \otimes \boldsymbol{R})$		X	X	**6**
T7	Information regarding freight orders is sent from R2 to R1.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T8	H15 creates the picking warehouse on R4, or this process can be automated.	$(\boldsymbol{R} \otimes \boldsymbol{R})$ ***or*** $(\boldsymbol{H} \otimes \boldsymbol{R})$		X	X	**6**
T9	Information regarding warehouse task creation is sent from R4 to R3 and then R3 to R1. (R1 and R3 can be directly integrated. In this case, information is sent directly from R4 to R1.)	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T10	When the freight orders are confirmed on the Freight Order Management section of R2, they appear on Dock Appointment Scheduling and Freight Execution sections of R2.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T11	H7 books appointments for the assigned freight orders.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T12	The driver(s) pick up the freight(s) from the warehouse and transportation(s) start.	$(\boldsymbol{H} \otimes \boldsymbol{H})$	X			**1**
T13	When the driver(s) pick up the freight(s) from the warehouse and transportation(s) start, H8 or H9 should report each stop's arrival and departure time on the Freight Execution section of R2.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T14	When reporting is completed on the Freight Execution section of R2, invoicing information is visible on the Freight Settlement section of R2.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**

T15	If there is a dispute that should be created for the invoice, H10 or H11 creates dispute(s) on the Freight Settlement section of R2.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T16	Information regarding dispute(s) is sent from R2 carrier tenant to R2 shipper tenant.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T17	H5 resolves the dispute indicated by the carrier on the shipper tenant of R2.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T18	Information regarding dispute resolution is sent from the shipper tenant of R2 to the carrier tenant of R2.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T19	H10 or H11 confirms the invoices finalized on the carrier tenant of R2 (Freight Settlement section).	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T20	Confirmed invoices are sent from R2 to R1.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T21	Confirmed invoices are sent from R1 to R3.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T22	R1 users (H1, H2, H3, H4, H5, H13) meet to allocate tasks.	$(\boldsymbol{H} \otimes \boldsymbol{H})$	X			**1**
T23	R2 users (H6, H7, H8, H9, H10, H11, H12) meet to allocate tasks.	$(\boldsymbol{H} \otimes \boldsymbol{H})$	X			**1**
T24	R1 users and R2 users meet to resolve the problems occurred on R2 that lead to setbacks on R1.	$(\boldsymbol{H} \otimes \boldsymbol{H})$ ***or*** $(\boldsymbol{H} \otimes \boldsymbol{R})$	X		X	**5**
T25	H13 meets managers of the other systems to address the problem(s) occurred on R1, whether it is because of integration incompatibilities or not.	$(\boldsymbol{H} \otimes \boldsymbol{H})$ ***or*** $(\boldsymbol{H} \otimes \boldsymbol{R})$	X		X	**5**
T26	Other systems' managers meet the consultants, specialists, and developers to find the root cause of the problem(s).	$(\boldsymbol{H} \otimes \boldsymbol{H})$ ***or*** $(\boldsymbol{R} \otimes \boldsymbol{R})$ ***or*** $(\boldsymbol{H} \otimes \boldsymbol{R})$	X	X	X	**7**
T27	The people in charge of the problematic point(s) of the system work on the system components in collaboration.	$(\boldsymbol{H} \otimes \boldsymbol{H})$ ***or*** $(\boldsymbol{H} \otimes \boldsymbol{R})$	X		X	**5**
T_{AD1}	H17 reports transportation events in collaboration with R5.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T_{AD2}	Reported events are sent from R5 to R1 (and R1 to R2 if needed).	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**

T_{AD3}	R6 constantly runs while H1, H2, H3, H4, H5, H13 run the optimizer on R2.	$(\boldsymbol{R} \otimes \boldsymbol{R})$ ***or*** $(\boldsymbol{H} \otimes \boldsymbol{R})$		X	X	**6**
T_{AD4}	H13 reports events regarding orders and shipments on R8.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T_{AD5}	Reported events are sent from R8 to R3 and then from R3 to R1 if needed.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**
T_{AD6}	H16 creates a company-specific geographic information system structure.	$(\boldsymbol{H} \otimes \boldsymbol{R})$			X	**3**
T_{AD7}	The information regarding the GIS structure is sent from R7 to R1.	$(\boldsymbol{R} \otimes \boldsymbol{R})$		X		**2**

The next step involves systematically navigating through each task assigned within the respective zones outlined in Figure 12. This deliberate navigation enables the collaborative robot—or smart supervisory controller—to detect and intervene where necessary. According to the proposed framework, the robot's intervention is limited to the overlapping areas within its designated operational zones. These intersecting regions represent key opportunities for reallocating tasks, as they allow transitions between robots, humans, or joint execution depending on situational needs.

Within this shared responsibility structure, the robot or smart supervisory controller can dynamically adjust task assignments to enhance overall efficiency—either by delegating specific responsibilities to human collaborators or by taking over certain tasks itself. However, it is important to highlight that tasks assigned to Zones 1, 2, and 3 are not eligible for cross-component reassignment; instead, they can only be redistributed internally—for example, transferring tasks from one human to another in order to mitigate individual stress levels.

The overarching goal is to optimize human stress conditions, beginning with robotic support and followed by internal reallocation within the same system category. In this context, tasks T6, T8, T24, T25, T26, T27, and T_AD3 are identified as flexible and dynamic elements that can influence workload distribution, based on the algorithm introduced earlier in the pseudocode.

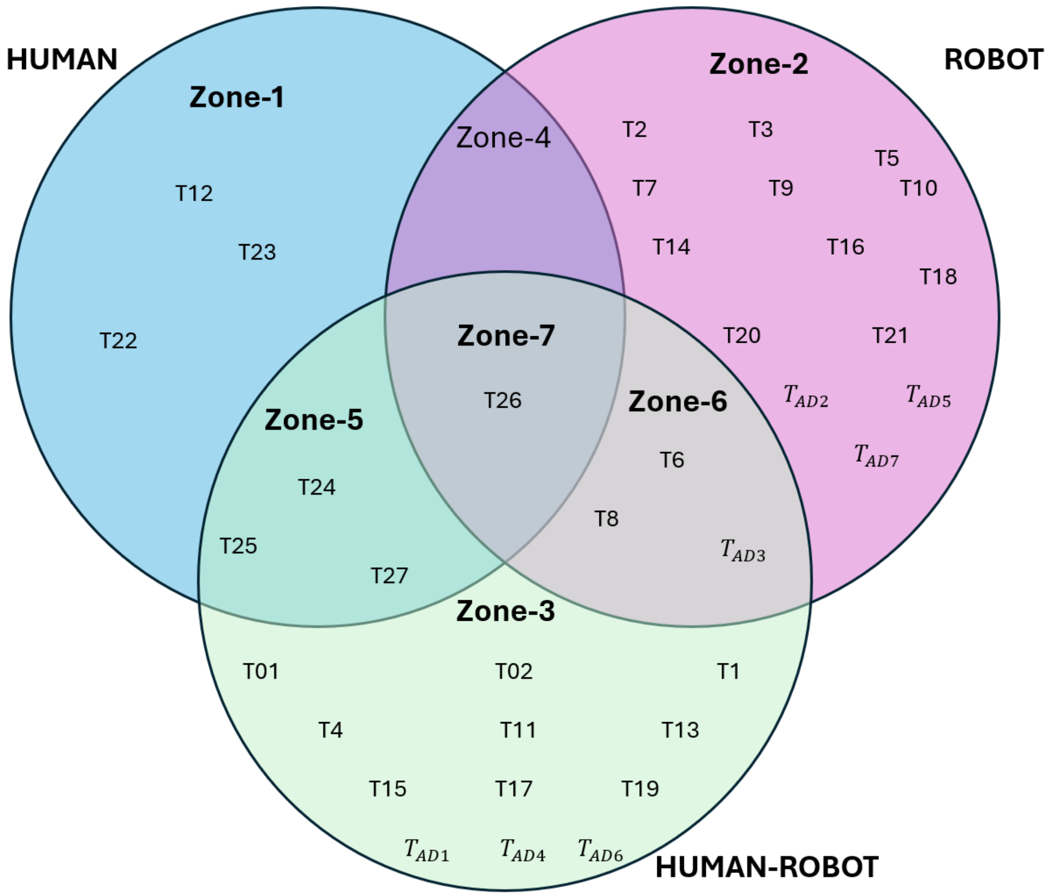

Figure 12: Generating Task Zones for Human, Robot, Human-Robot in the LBN System of SAP S/4 HANA Side-Car Scenario

The first six steps of the proposed procedure have been carefully implemented up to this point. The next part of the case study focuses on the detailed process of identifying human stress levels and enhancing system performance by keeping individuals within optimal emotional ranges. This section offers an in-depth exploration of methods aimed at fostering emotionally supportive environments for human collaborators—ultimately contributing to improved efficiency and stability across the entire system.

5.5.3. *Task Reallocation Based on Stress/Workload*

As the assigned workload (W_t^H) steadily increases, there is a natural escalation in the perceived workload (W_t^P) experienced by individuals, compounded by the current stressors (σ_t^H) they face. The rise in perceived workload, assuming the task completion time or time-to-deadline (T_D) remains constant, inevitably leads to a decline in human performance (η^H). This decrement in performance not only impacts the ongoing emotional and psychological states of individuals (A_t^H), but also serves as a precursor for the level of stress (σ_{t+1}^H) in the next period. Consequently, this evolving stress level influences how individuals perceive and respond to the forthcoming workload assigned to them.

Smart supervisory system's (robot) primary function within this context is to monitor human stress levels and correlate them with performance output. Should the estimated stress level deviates from predetermined thresholds, both below or above the acceptable range ($\sigma_{LB} \leq \hat{\sigma} \leq \sigma_{UB}$), the robots are tasked with dynamically adjusting workload allocation. This intervention mechanism is crucial for maintaining human stress within an optimal range conducive to efficient performance. In our detailed case study, aforementioned task reallocation algorithm is applied on the case study as:

Task Reallocation Algorithm for SAP S/4HANA Side-Car Scenario (Mathematical Representation)

$if\ \hat{\sigma} \geq \sigma_{UB}$:

$\quad if\ \{T25\ \vee\ T24\ \vee\ T27\} \in W_t^H$:

$\quad\quad TRANSFER\ \{T25\ \vee\ T24\ \vee\ T27\}\ from\ W_t^H\ to\ W_t^{HR}$

$\quad if\ T26\ \in\ W_t^H$:

$\quad\quad TRANSFER\ T26\ from\ W_t^H\ to\ \{W_t^{HR}\ \vee\ W_t^R\}$

$\quad elseif\ T26\ \in\ W_t^{HR}$:

$\quad\quad TRANSFER\ T26\ from\ W_t^{HR}\ to\ W_t^R$

$\quad if\ \{T6\ \vee\ T8\ \vee\ T_{AD3}\}\ \in\ W_t^{HR}$:

$\quad\quad TRANSFER\ \{T6\ \vee\ T8\ \vee\ T_{AD3}\}\ from\ W_t^{HR}\ to\ W_t^R$

$elseif\ \hat{\sigma} \leq \sigma_{LB}$:

$\quad if\ \{T24\ \vee\ T25\ \vee\ T27\} \in W_t^{HR}$:

$\quad\quad TRANSFER\ \{T24\ \vee\ T25\ \vee\ T27\}\ from\ W_t^{HR}\ to\ W_t^H$

$\quad if\ T26\ \in\ W_t^R$:

$\quad\quad TRANSFER\ T26\ from\ W_t^R\ to\ \{W_t^H\ \vee\ W_t^{HR}\}$

$\quad elseif\ T26\ \in\ W_t^{HR}$:

$\quad\quad TRANSFER\ T26\ from\ W_t^{HR}\ to\ W_t^H$

$\quad if\ \{T6\ \vee\ T8\ \vee\ T_{AD3}\}\ \in\ W_t^R$:

$\quad\quad TRANSFER\ \{T6\ \vee\ T8\ \vee\ T_{AD3}\}\ from\ W_t^R\ to\ W_t^{HR}$

$Repeat\ while\ \sigma_{LB} \leq \hat{\sigma} \leq \sigma_{UB}\ not\ TRUE$

The algorithm outlined above for the case study provides a mathematical representation of the proposed logic, inspired by common problems encountered during system implementation in IT projects. Below, the details are evaluated and explained verbally:

Task Reallocation Verbal Assessment for SAP S/4HANA Side-Car Scenario:

<u>Inputs:</u>

i. *<u>Resources: Set of Human ($h \in H$); Set of Robots/Machines ($r \in R$)</u>*

Assuming the presented case study involves 19 humans, 13 robots, and 22 human-robot (H-R) teams, representing the collaboration between systems and their users.

H: *{H1, H2, H3, H4, H5, H6, H7, H8, H9, H10, H11, H12, H13, H13, H14, H15, H16, H17, H18, H19}*

R: *{R1, R2, R3, R4, R5, R6, R7, R8, R9, R10, R11, R12, R13}*

HR: *{H1-R1, H2-R1, H3-R1, H4-R1, H5-R1, H13-R1, H6-R2, H7-R2, H8-R2, H9-R2, H10-R2, H11-R2, H12-R2, H3-R2, H5-R2, H13-R8, H14-R3, H15-R4, H16-R7, H17-R5, H18-R9, H19-R13}*

ii. *<u>Set of tasks ($\boldsymbol{w} \in \boldsymbol{W}$)</u>*

At the start of the project, the work breakdown structure should be clearly defined for each communication channel. In other words, each task should be specified along with the corresponding system component capable of undertaking it. This approach allows robots to first evaluate which communication channels can facilitate the assigned tasks and map these onto task zones using a Venn diagram. Once the re-allocatable tasks on the Venn diagram are identified, the robots can then analyze these tasks to determine alternative communication channels for possible reassignment. The tasks to be completed using the SAP LBN system are outlined below:

T: *{T1, T2, T3, T4, T5, T6, T7, T8, T9, T10, T11, T12, T13, T14, T15, T16, T17, T18, T19, T20, T21, T22, T23, T24, T25, T26, T27,* T_{AD1}, T_{AD2}, T_{AD3}, T_{AD4}, T_{AD5}, T_{AD6}, T_{AD7}*}*

iii. *Capabilities of Human, Robot and Human-Robot team: Distribute tasks according to resource capabilities as illustrated in Figure 2.*

Systems comprising software-based programs and their users must ensure seamless collaboration. Users should be adequately trained on the system's operation and equipped with strategies to resolve potential blockages effectively. Moreover, computerized systems must be fully integrated with other digital systems, functioning smoothly even when users are actively involved in the workflow.

Step 0: $t = 0$ *distribute tasks among Human, Robot, and Human-Robot jointly:*

Initially, the tasks were allocated as follows:

$W_0^H \in \{w^{Z1}, w^{Z4}, w^{Z5}, w^{Z7}\}$

$W_0^H: \{T12\ (Z1), T13(Z1), T22(Z1), T24(Z5), T25(Z5), \boldsymbol{T26(Z7)}, \boldsymbol{T27(Z5)}\}$

$W_0^R \in \{w^{Z2}, w^{Z4}, w^{Z6}, w^{Z7}\}$

$W_0^R: \{T2\ (Z2), T3(Z2), T5(Z2), T7(Z2), T9(Z2), T10(Z2), T14(Z2), T16(Z2), T18(Z2), T20(Z2), T21(Z2), TADD2(Z2), TADD3(Z6), TADD5(Z2), TADD7(Z2)\}$

$W_0^{HR} \in \{w^{Z3}, w^{Z5}, w^{Z6}, w^{Z7}\}$

$W_0^{HR}: \{T01\ (Z3), T02(Z3), T1(Z3), T4(Z3), \boldsymbol{T6(Z6)}, \boldsymbol{T8(Z6)}, T11(Z3), T13(Z3), T15(Z3), T17(Z3), T19(Z3), TADD1(Z3), TADD4(Z3), TADD6(Z3)\}$

Step 1: $t = t + 1$, *assess human stress* $\left(\sigma = \frac{W_t^P}{(K^H, S^H)A_t^H}\right)$*:*

After assessing human stress levels, the robot (assumed to be an intelligent SAP system in our case) determines that human stress is higher than expected. It also double-checks human performance outputs, such as whether tasks are completed within the given time frame, to identify any irregularities. Consequently, the robot reviews the tasks assigned to the human and analyzes how the workload is distributed, aiming to reduce stress and optimize performance.

Step 2: *Task reallocation:*

When the human stress level exceeds the upper limit $(\sigma \geq \sigma_{UB})$ *, the robot should take over some tasks from the human. Since performance is calculated based on group outputs using the disjoint union formula, the overall performance of the group must be considered when evaluating an individual human's performance. Therefore, communication channels are emphasized here rather than focusing solely on humans, robots, or human-robot teams.*

Following the stress analysis and performance check, the robot detects a blockage caused by systems communication (R⨂R) that is hindering human performance. While humans attempt to resolve the encountered issues, they lack sufficient knowledge to overcome them, leading to increased stress levels and higher perceived workload.

The robot identifies that tasks T26(Z7) and T27(Z5), which belong to zone 7 (representing tasks that can be undertaken by humans, robots, or through collaboration) and zone 5 (representing tasks that can be undertaken by humans or through collaboration), were initially assigned to the (H⨂H) communication channel. Since human involvement remains necessary to address the issues encountered while collaborating with the robot systems, these tasks will be reassigned from the (H⨂H) channel to the (H⨂R) channel to reduce human stress.

However, during the second iteration, the robot determines that this reassignment alone may not sufficiently lower human stress levels, as humans still retain partial responsibility for these tasks despite robot involvement. Consequently, the robot further detects that tasks T6(Z6) and T8(Z6), currently assigned to the (H⨂R) channel, can be fully automated and reassigned to the (R⨂R) channel. As a result, T6(Z6) and T8(Z6) will be moved from the (H⨂R) channel to the (R⨂R) channel to further alleviate human workload and stress.

Step 3: *Has the job completed?*

NO: Go to Step 1

YES: Go to step 4

Step 4: *End intervention*

<u>Outputs:</u>

i. *Updated* W_t^H, W_t^R *and* W_t^{HR}*:*

W_{t+1}^H: $\{T12\ (Z1), T13(Z1), T22(Z1), T24(Z5), T25(Z5), \cancel{\boldsymbol{T26(Z7), T27(Z5)}}\}$

W_{t+1}^R: $\{T2\ (Z2), T3(Z2), T5(Z2), \boldsymbol{T6(Z6)}, T7(Z2), \boldsymbol{T8(Z6)}, T9(Z2), T10(Z2), T14(Z2), T16(Z2), T18(Z2), T20(Z2), T21(Z2), TADD2(Z2), TADD3(Z6), TADD5(Z2), TADD7(Z2)\}$

W_{t+1}^{HR}: $\{\ T01\ (Z3), T02(Z3), T1(Z3), T4(Z3), \cancel{\boldsymbol{T6(Z6), T8(Z6)}}, T11(Z3), T13(Z3), T15(Z3), T17(Z3), T19(Z3), \boldsymbol{T26(Z7), T27(Z5)}, TADD1(Z3), TADD4(Z3), TADD6(Z3)\ \}$

ii. *Optimized Human stress* ($\sigma_{LB} \leq \sigma \leq \sigma_{UB}$)*:*

Ultimately, human stress levels are effectively minimized, leading to enhanced overall performance and productivity.

Upon completion of the robot's intervention process—where the system workload is reallocated across both humans and robots—the aim is to maintain human stress levels within a range that enables peak performance. This approach not only supports the full utilization of human capacity but also recognizes the value of human input within the collaboration, even in the presence of the robot's virtually boundless capabilities.

6. PERFORMANCE EVALUATION OF THE PROPOSED HUMAN-ROBOT COLLABORATION MODEL

System performance has been emphasized throughout the thesis, although the core focus remains on adjusting human stress levels and understanding their relationship within the dynamic workload allocation algorithm. As consistently highlighted across the sections and subsections, the aim of robotic intervention in dynamic workload reallocation is to enhance human performance by addressing and managing stress levels. Given the significance of this relationship, a detailed evaluation of both performance and stress is essential. Therefore, these concepts are further examined through conceptual formulations and supporting analysis in the following subsections: Subsection 6.1 presents the performance formulation of the human-robot system; Subsection 6.2 explores the relationship between human stress and performance by examining the parameters that influence stress; Subsection 6.3 reviews existing studies on human stress measurement methods; and finally, Subsection 6.4 introduces a conceptual formula to express the effect of task-specific stress on overall human performance.

6.1. Formulating Human-Robot System Performance as a Function of Human Stress

In collaborative environments where humans and robots work toward shared objectives, effective use of communication tools is essential for sustaining optimal collaboration. However, while robots rely on structured communication mechanisms, these tools are not yet capable of fully interpreting the emotional needs of their human partners—who remain the emotional actors in such systems. This limitation underscores the importance of examining how human emotional states, particularly stress, relate to performance in human-robot systems.

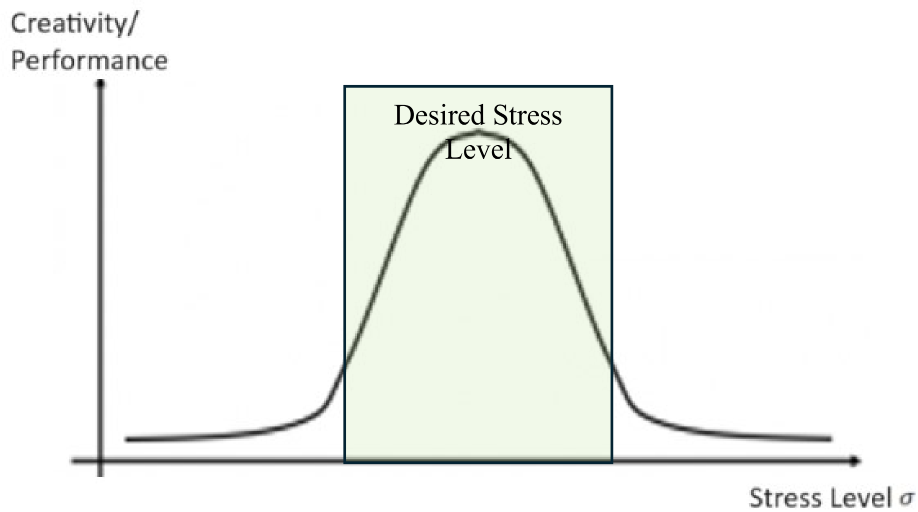

Figure 13: Relationship between Stress and Creativity/Performance

Several studies have explored this connection. Building on the Yerkes-Dodson law, Nguyen and Zeng (2017) demonstrate that human performance is strongly influenced by stress levels, with the highest levels of performance occurring under moderate stress. Both insufficient and excessive stress levels have been shown to reduce human performance and creativity as illustrated in Figure 13.

A conceptual model describing this relationship was introduced earlier in Equation 4 (see Subsection 5.1). In this model, work-associated stress (σ) is defined as a function of perceived workload *(*W^P*)*, knowledge *(K)*, skills *(S)*, and affective states *(A)*, as proposed by Nguyen and Zeng (2017) and supported by Yang et al. (2021). The model suggests that stress is directly proportional to perceived workload, while it is inversely proportional to an individual's knowledge, skills, and affective states.

Since affective states fluctuate in response to changing environmental conditions—even when knowledge and skill levels remain constant—human stress is inherently variable. When stress levels move outside the desired range, human performance tends to decline. Within a smart human-robot collaboration system, it becomes essential for robots to monitor these stress levels and intervene when necessary to restore balance.

Before establishing mechanisms to manage human stress within such systems, the human-robot system performance (η) should be formally defined. It is composed of three main elements: human performance (η^{H}), robot performance (η^{R}) and their collective performance (η^{HR}). This relationship is expressed as:

$$\eta = \eta^{H} + \eta^{R} + \eta^{HR} \tag{14}$$

Each of these components is a function of specific variables. Human performance (η^{H}) depends on the human's stress level (σ_H), assigned workload (W^{H}), and time allocated for task completion (T^{H}). Robot performance (η^{R}) is influenced by its knowledge (K^{R}), skillset (S^{R}), assigned workload (W^{R}), and available execution time (T^{R}). Collaborative performance (η^{HR}) is shaped by human stress (σ_H), collective knowledge and skills (K^{HR}, S^{HR}), shared workload (W^{HR}), and the time allotted for collaborative tasks (T^{HR}):

$$\eta^{H} = f(\sigma^{H}, W^{H}, T^{H});\ \eta^{R} = f(K^{R}, S^{R}, W^{R}, T^{R});\ \text{and}\ \eta^{HR} = f(\sigma^{H}, K^{R}, S^{R}, W^{HR}, T^{HR}) \tag{15}$$

Assuming robots operate under stable conditions—without significant variations in knowledge or skill and without encountering mechanical or computational issues—their performance can be considered steady and predictable during a given planning period. In contrast, human performance is more variable, as stress levels influence not only task completion times but also the quality of outputs, particularly for tasks assigned to humans (W^{H}) or jointly shared (W^{HR}).

In collaborative projects, the interplay between humans and robots complicates dynamics, underscoring the importance of cohesive team performance. Robots are required not only to interact with individual human partners but also to assess the collective stress level of the team. This enables them to take appropriate actions—such as reallocating tasks—to enhance performance and ensure smooth collaboration. Effectively managing such interactions calls for nuanced, context-aware adjustments. Disjoint union logic is employed to represent the complexity of these interactions across diverse system components. Through this formulation, the performance metrics of humans, robots, and their collaborative efforts are expressed, leading to a comprehensive evaluation of system performance in scenarios involving multiple humans and robots working toward a common goal.

Let η_h^H, η_r^R and η_{hr}^{HR} be performances of h^{th} human, r^{th} robot and h^{th} human and r^{th} robot interaction respectively. Accordingly:

$$\eta_h^H = \left\{ f\left(\frac{W_h^P}{(K_h^H + S_h^H) * A_h^H}, W_h^H, T^H\right) \middle| \begin{matrix} W_h^P, K_h^H, S_h^H, A_h^H, W_h^H, T^H \ are \\ humans' performance \ parameters \\ when \ they \ work \ in \ (\boldsymbol{H} \otimes \boldsymbol{H}) \ collaboration \end{matrix} \right\} \quad (16)$$

$$\eta_r^R = \left\{ f(W_r^R, K_r^R, S_r^r, T^R) \middle| \begin{matrix} W_r^R, K_r^R, S_r^R, T^R \ are \ robots' \ performance \ parameters \\ when \ they \ work \ in \ (\boldsymbol{R} \otimes \boldsymbol{R}) \ collaboration \end{matrix} \right\} \quad (17)$$

$$\eta_{hr}^{HR} = \left\{ f\left(\frac{W_h^P}{(K_h^H + S_h^H) * A_h^H}, W_{hr}^{HR}, \ K_r^R, \ S_r^R \ , T^{HR}\right) \middle| \begin{matrix} W_h^P, \ K_h^H, \ S_h^H, \ A_h^H, W_{hr}^{HR}, \ K_r^R, \ S_r^R \ , T^{HR} \ are \\ performance \ parameters \ of \ H - R \ teams \\ when \ they \ work \ in \\ (\boldsymbol{H} \otimes \boldsymbol{R}) \cup (\boldsymbol{R} \otimes \boldsymbol{H}) \ Collaboration \end{matrix} \right\} \quad (18)$$

The disjoint union formula for individual sets delineates the performance levels of overall human, robot, and collaboration group performances as follows

$$\eta^H = \coprod_{h \in H} \eta_h^H = \bigcup_{h \in H} \left\{ \left(f\left(\frac{W_h^P}{(K_h^H + S_h^H) * A_h^H}, W_h^H, T^H\right), h \right) \middle| W_h^P, K_h^H, S_h^H, A_h^H, W_h^H, T^H \in H \right\} \quad (19)$$

$$\eta^R = \coprod_{r \in R} \eta_r^R = \bigcup_{r \in R} \{ (f(W_r^R, K_r^R, S_r^r, T^R), r) | W_r^R, K_r^R, S_r^R, T^R \in R \} \quad (20)$$

$$\eta^{HR} = \coprod_{h \in H;\, r \in R} \eta_{hr}^{HR} = \bigcup_{r \in R} \bigcup_{h \in H} \left\{ \left(f\left(\frac{W_h^P}{(K_h^H + S_h^H) * A_h^H}, W_{hr}^{HR}, \ K_r^R, \ S_r^R \ , T^{HR}\right), h, r \right) \middle| \begin{matrix} W_h^P, \ K_h^H, \ S_h^H, \ A_h^H \in H \\ K_r^R, \ S_r^R \in R \\ W_{hr}^{HR}, \ T^{HR} \in H \cup R \end{matrix} \right\} \quad (21)$$

This thesis adopts a comprehensive approach to measuring performance, defining it as the ratio of completed tasks to the total number of tasks assigned to each system component. This definition encompasses multiple performance indicators, including the monetary value generated by the smart system, the number of clients effectively served, and the completion rate of allocated tasks. Within this framework, the collective performance of a human group is derived from the combined contributions of individual members, while the performance of a group of robots is calculated as the sum of each robot's individual output. Similarly, the contribution of collaborative efforts between humans and robots is evaluated as the cumulative effect of their joint task completions, reflecting the effectiveness of shared responsibilities within the system.

To accurately assess the level of success, it is essential to normalize performance values by dividing them by the total number of tasks assigned across all system components—humans, robots, and collaborative groups. This normalization process enables equitable comparison and offers meaningful insights into the efficiency and effectiveness of each entity within the system (see Equation 22). The complete logic described above is now formalized through the following mathematical expression:

$$\eta = \frac{\coprod_{h\in H} \eta_h^H + \coprod_{r\in R} \eta_r^R + \coprod_{h\in H, r\in R} \eta_{hr}^{HR}}{\sum_h W_h^H + \sum_r W_r^R + \sum_{h,r} W_{hr}^{HR}} \tag{22}$$

Under current conditions, evaluating system performance requires a holistic approach that integrates the average proficiency of humans, the average capability of robots, and the collective effectiveness of collaborative efforts. At the core of this evaluation lies human stress, which serves as a key indicator for robots to assess and maintain balance within the system. Since human performance is closely tied to stress levels, robots are assigned the critical role of continuously monitoring and adjusting human performance as needed. The previously introduced formula captures this qualitative dimension of smart system performance, highlighting the dual responsibility of robots to regulate human stress while enhancing both individual and collaborative performance outcomes.

Following the clarification of system performance, the next subsection turns to an in-depth analysis of the parameters that impact human affective responses, workload perception, and performance—highlighting stress as the core element influencing human efficiency.

6.2. Identification of Parameters Influencing Human Stress and Performance

In preceding sections, we delved into the pivotal role of interaction modes and communication channels in effectively navigating diverse collaboration types. Additionally, we dissected various collaboration models, shedding light on their intricate dynamics. This discourse underscores the profound impact of human stress levels on the efficacy of these collaborations. Consequently, this section endeavors to formulate qualitative metrics crucial for assessing and quantifying human stress levels. The precision of these metrics is of paramount importance, as they hold the key to comprehending and potentially shaping the overarching dynamics of collaborative smart systems. This formulation operates along three pivotal dimensions: firstly, by measuring human affective states, which exert a direct influence on human stress levels; secondly, through the assessment of perceived human workload, intricately intertwined with both the assigned workload and human stress; and thirdly, by evaluating human performance, which is shaped by factors such as task completion time and the perceived workload burden.

To establish the parameters governing human stress and performance, Cantor's (1895) Set Theory is employed, elucidating the intricate relationships within the realm of human performance parameters. Assumptions are carefully crafted to enhance the clarity of the proposed model. It is noteworthy that the parameters in the subsequent formulations are designed to represent an individual human being. However, when considering a scenario involving a collaborative effort between a human group and a robot group, the collective human-robot system performance formula introduced earlier becomes paramount. This collective formula should be utilized to gauge the collective stress performance levels of the entire group. Hereafter, each of these levels, accompanied by their respective assumptions, is meticulously examined.

6.2.1. Formula Generation: Human Affective States

The first step in comprehending human performance within the realm of their emotions involves the measurement of their stress levels. The underlying assumptions guiding the assessment of human stress levels are elucidated below:

- Human's ***initial affective states*** (A_H^0) are influenced by input parameters of human performance such as knowledge (K_H) and skills (S_H), which are evaluated under the human capability class.
- ***Human initial stress*** is a function of human capability and initial environmental conditions (E_0).
- Human's ***ongoing affective states*** at time *t* (A_H^t) are influenced by output parameters of human performance such as human's previous performance (η_H^{t-1}) and available human time (T_H^t) at time *t*, which are evaluated under the human achievement class.

- ***Human stress over time*** is a function of human achievement and environmental conditions over time (E_t).

During human interaction with a smart system, two distinct affective states emerge: initial affective states and affective states over time. The former is influenced by the combination of human capabilities, such as skills (S_H) and knowledge (K_H), along with the current environmental conditions (E_0), while the latter is determined by past performance (η_H^{t-1}) and the amount of available human time (T_H^t), in addition to the affective states that evolve over time (E_t). Leveraging Cantor's Set theory (1895), we can articulate the initial affective states of a human within this context through the following formulation (Equations 23-26) illustrated in Figure 14:

$$A_H^0 = f_1(S_H \cup K_H) \cup f_2(E_0) \tag{23}$$

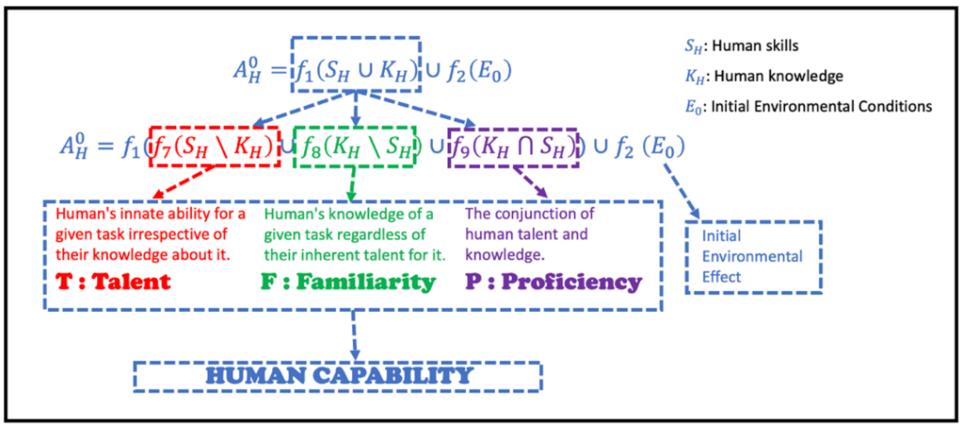

Figure 14: Decomposition of Initial Human Affective States

Expanding on the conceptual foundation of set operations, particularly the union of two sets, it is expressed as the union of the intersection of those sets and the symmetric difference between them. This extension of the formula is articulated as follows:

$$A_H^0 = f_1(\,f_7(S_H \setminus K_H) \cup f_8(K_H \setminus S_H) \cup f_9(K_H \cap S_H)) \cup f_2(E_0) \tag{24}$$

In the expanded formula, $f_7(S_H \setminus K_H)$ denotes human talent for the assigned task, $f_8(K_H \setminus S_H)$ represents human familiarity with the task, and $f_9(K_H \cap S_H)$ signifies human proficiency in executing the task. The combined influence of these three parameters defines ***human capability***, which in turn impacts human affective states. Additionally, it's important to note that initial environmental conditions also play a significant role in shaping an individual's initial affective states.

$$A_H^0 = f_1(Talent \cup Familiarity \cup Proficiency) \cup f_2(E_0) \tag{25}$$

$$A_H^0 = Human\ Capability\ Effect \cup Initial\ Environmental\ Effect \tag{26}$$

The experience of initial human stress can be seen as intricately connected to the initial states of human affectivity, underscoring the profound impact of our emotional well-being on the manifestation and modulation of stressors. In that case, initial human stress is a function of initial affective states (Equations 27-30).

$$\sigma_H^0 = f_3(A_H^0) \tag{27}$$

In that case, the expanded formula is as follows:

$$\sigma_H^0 = f_3(f_1(f_7(S_H \setminus K_H) \cup f_8(K_H \setminus S_H) \cup f_9(K_H \cap S_H)) \cup f_2(E_0)) \tag{28}$$

$$\sigma_H^0 = f_3(f_1(Talent \cup Familiarity \cup Proficiency) \cup f_2(Initial\ Environmental\ Conditions)) \tag{29}$$

$$\sigma_H^0 = f_3(Human\ Capability\ Effect \cup Initial\ Environmental\ Effect) \tag{30}$$

The second influential factor affecting overall stress encompasses the ongoing affective states of individuals. This intricate interplay involves a fusion of previous time's human performance (η_H^{t-1}) and the availability of human time (T_H^t), and a function of ever-changing environmental conditions (E_t). The amalgamation of these elements creates a dynamic landscape that significantly contributes to the overall emotional and psychological well-being of individuals, ultimately shaping their stress levels (Equations 31-34) illustrated in Figure 15:

$$A_H^t = f_4(\eta_H^{t-1} \cup T_H^t) \cup f_5(E_t) \tag{31}$$

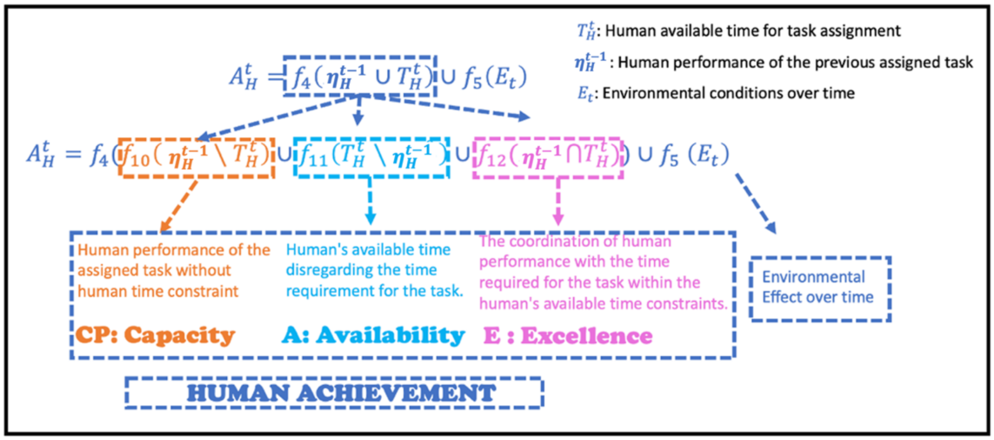

Figure 15: Decomposition of Ongoing Human Affective States

Again, the combination of the intersection of those sets and the symmetric difference between them is employed to demonstrate the union of two sets.

$$A_H^t = f_4(f_{10}(\eta_H^{t-1} \setminus T_H^t) \cup f_{11}(T_H^t \setminus \eta_H^{t-1}) \cup f_{12}(\eta_H^{t-1} \cap T_H^t)) \cup f_5(E_t) \tag{32}$$

In the expanded formula, $f_{10}(\eta_H^{t-1} \setminus T_H^t)$ represents human capacity, $f_{11}(T_H^t \setminus \eta_H^{t-1})$ denotes human availability, and $f_{12}(\eta_H^{t-1} \cap T_H^t)$ signifies human excellence. These parameters collectively contribute to the human achievement effect, which, when combined with environmental conditions over time, delineates the dynamic affective states.

$$A_H^t = f_4(Capacity \cup Availability \cup Excellence) \cup f_5(E_t) \tag{33}$$

$$A_H^t = Human\ Achievement\ Effect\ \cup \text{Environmental Effect over time} \tag{34}$$

The ongoing human stress is closely tied to the evolving affective states, highlighting the crucial role of emotional landscapes in determining stress levels (Equations 35-38).

$$\sigma_H^t = f_6(A_H^t) \tag{35}$$

The subsequent passage delves into the intricacies of the ongoing stress formula.

$$\sigma_H^t = f_6(f_4(f_{10}(\eta_H^{t-1} \setminus T_H^t) \cup f_{11}(T_H^t \setminus \eta_H^{t-1}) \cup f_{12}(\eta_H^{t-1} \cap T_H^t)) \cup f_5(E_t) \tag{36}$$

$$\sigma_H^t = f_6(f_4(Capacity \cup Availability \cup Excellence) \cup f_5(Environmental\ Conditions\ over\ time)) \tag{37}$$

$$\sigma_H^t = f_6(Human\ Achievement\ Effect \cup Environmental\ Effect\ over\ time) \tag{38}$$

Unquestionably, the cumulative human stress (σ_H) comprises both the inherent initial stress (σ_H^0) and the persisting ongoing stress (σ_H^t) (Equation 39).

$$\sigma_H = \sigma_H^0 \cup \sigma_H^t = f_3(A_H^0) \cup f_6(A_H^t) \tag{39}$$

Upon expanding this formula as outlined in Equation 40, each factor contributing to the overall human stress becomes apparent:

$$\sigma_H = f_3(f_1(f_7(S_H \setminus K_H) \cup f_8(K_H \setminus S_H) \cup f_9(K_H \cap S_H)) \cup f_2(E_0)) \cup f_6(f_4((f_{10}(\eta_H \setminus T_H) \cup f_{11}(T_H \setminus \eta_H) \cup f_{12}(\eta_H \cap T_H)) \cup f_5(E_t)) \tag{40}$$

This formula indicates that the human stress level depends on human talent, familiarity with the work, proficiency, capacity, availability, excellence, as well as initial and ongoing environmental conditions. The relationship between the features and the formula is illustrated in Figure 14 and Figure 15.

$$\sigma_H = f_3(f_1(Talent \cup Familiarity \cup Proficiency) \cup f_2(E_i - \text{Initial Environmental Conditions})) \cup f_6(f_4(Capacity \cup Availability \cup Excellence) \cup f_5(E_t - Environmental\ Conditions\ over\ time)) \tag{41}$$

$$\sigma_H = f_3(Human\ Capability\ Effect \cup Initial\ Environmental\ Effect) \cup f_6(Human\ Achievement\ Effect \cup \text{Environmental Effect over time}) \tag{42}$$

In summary, human stress levels comprise the function of the combined human capability and initial environmental conditions, as well as the function of human achievement and ongoing environmental conditions.

6.2.2. Formula Generation: Perceived Human Workload

Tasks are commonly assigned to humans, robots, and their collaborative efforts within smart systems, yet often, implicit influencing factors such as human affective states and stress levels are overlooked. Consequently, the workload allocated to a human may differ significantly from the workload they subjectively perceive. In this context, the perceived workload is evaluated as a dynamic function, accounting for both the assigned workload and the individual's stress level. This implies that humans gauge the workload imposed on them in relation to their current stress levels. To further elucidate, the following assumptions are outlined below to formulate the perceived workload of an individual.

- Assigned workload (W_H^a) and perceived workload (W_H^p) are not equal.
- Perceived workload (W_H^p) is a union of assigned workload (W_H^a) and human stress (σ_H).

Equation 43 outlines the methodology for measuring perceived workload:

$$W_H^p = f_{13}(W_H^a \cup \sigma_H) \tag{43}$$

$$W_H^p = f_{13}(f_{14}(W_H^a \setminus \sigma_H) \cup f_{15}(\sigma_H \setminus W_H^a) \cup f_{16}(W_H^a \cap \sigma_H)) \tag{44}$$

In the expanded formula, $f_{14}(W_H^a \setminus \sigma_H)$ stands for the initial workload, $f_{15}(\sigma_H \setminus W_H^a)$ indicates the level of human stress prior to workload allocation, and $f_{16}(W_H^a \cap \sigma_H)$ represents the human stress following workload allocation.

$$W_H^p = f_{13}(Raw\ Workload \cup Stress\ before\ workload\ assignment \cup Stress\ after\ workload\ assignment) \tag{45}$$

In the exploration of Set Theory-driven expansions within the formula, the perceived workload emerges as intricately linked to the unalloyed task volume delegated to individuals. Notably, this connection extends beyond the mere quantitative assessment of raw workload, delving into the profound impact of stress levels. The holistic framework encompasses stress both preceding and succeeding workload assignment, unraveling a complex interplay that significantly shapes the perception of workload. This nuanced relationship finds its visual representation in the elucidating Figure 16 below, where the dynamic dynamics of workload, coupled with antecedent and subsequent stress factors, are graphically showcased for clarity and comprehension.

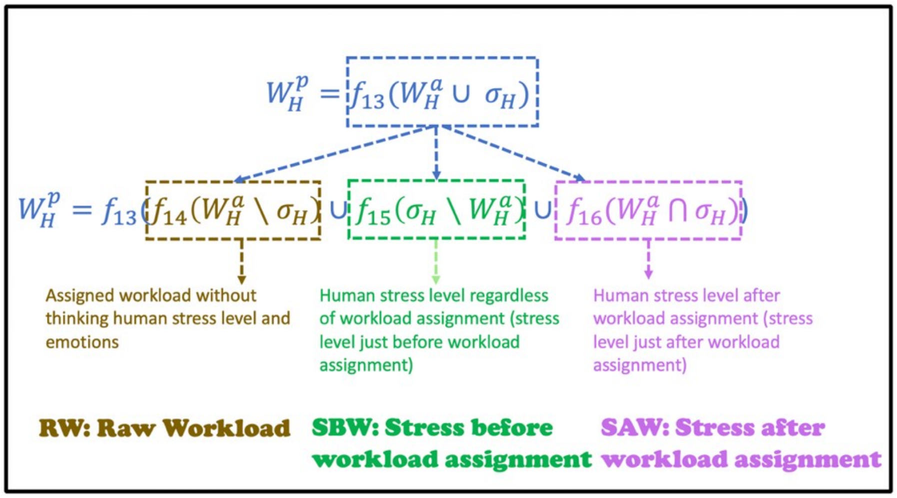

Figure 16: Formulation of human workload

6.2.3. *Formula Generation: Human Performance*

In the realm of human performance evaluation, Set Theory serves as the cornerstone for formulating a comprehensive understanding. The intricate web of human capabilities is intricately woven into an assessment that intricately considers perceived human workload and task completion time as pivotal variables. This formulation operates on certain foundational assumptions, elucidated below to lend clarity and coherence to the evaluative process.

- Performance is affected by task completion time T_D (Time to deadline)
- Performance is based on human's perceived workload W_H^p
- Performance is a union of T_D and W_H^p

In accordance with this data, human performance is articulated below through Equations 46-48:

$$\eta = f_{17}(W_H^p \cup T_D) \tag{46}$$

$$\eta = f_{17}(f_{18}(W_H^p \setminus T_D) \cup f_{19}(T_D \setminus W_H^p) \cup f_{20}(W_H^p \cap T_D)) \tag{47}$$

In the expanded formula, $f_{18}(W_H^p \setminus T_D)$ symbolizes the workload perception without time constraints, $f_{19}(T_D \setminus W_H^p)$ describes the deadline devoid of workload assignments, and $f_{20}(W_H^p \cap T_D)$ denotes the ideal deadline considering the human's perceived workload.

$$\eta = f_{17}(Time - free\ Perceived\ Workload \cup Assignment - free\ Deadline \cup Optimum\ Deadline\ with\ Human's\ Perceived\ Workload) \tag{48}$$

Following an exhaustive performance analysis, three specific factors that directly impact human performance were identified:

- <u>Time-Free Perceived Workload (TFPW):</u> This refers to the workload perceived by the individual without taking into account time-to-deadline constraints.
- <u>Assignment-Free Deadline (AFD):</u> This parameter indicates the deadline irrespective of the individual's perceived workload.
- <u>Optimum Deadline with Human's Perceived Workload (ODW):</u> This signifies the synchronization between the individual's perceived workload and the deadline necessary for optimal performance.

These key factors are visually depicted in Figure 17:

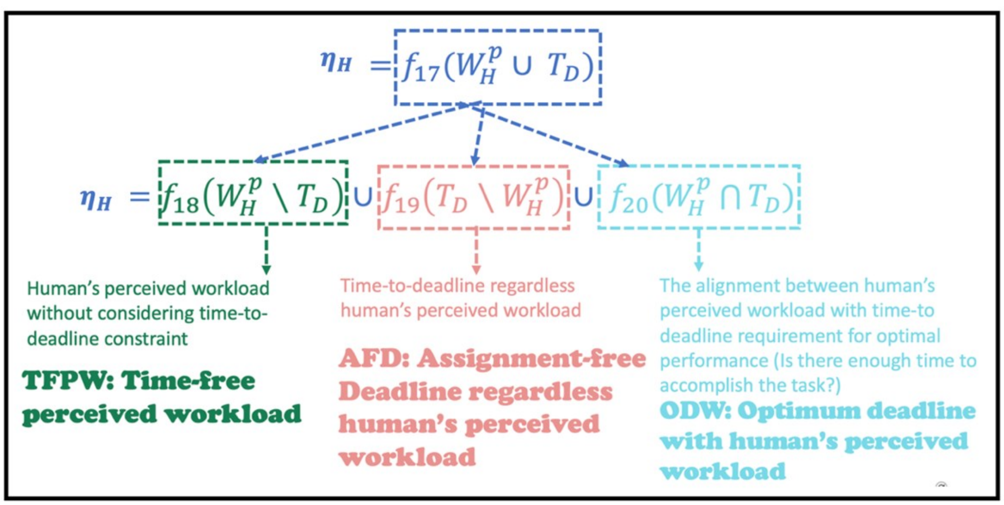

Figure 17: Formulation of human performance

On the flip side, a myriad of indirect factors intricately shape human performance, exerting a significant influence on stress levels, perceived workload, and overall efficiency. The following catalog elucidates these subtle yet impactful parameters of human performance:

- Raw Workload (RW): The workload assigned without considering human stress levels and emotions.
- Stress before Workload Assignment (SBW): The level of human stress regardless of workload assignment, representing stress just before task allocation.
- Stress after Workload Assignment (SAW): Human stress level following workload assignment, indicating stress levels immediately after task allocation.
- Capacity (CP): Human performance on the assigned task without any time constraints, reflecting inherent ability.
- Availability (AV): The time available for the human without task engagement.
- Excellence (EX): The alignment between human performance and task time requirements within the limited available time, indicating exceptional execution.
- Talent (T): The situation where a human is not knowledgeable about the assigned workload but possesses the skills required to accomplish the task.
- Familiarity (F): The scenario where a human is knowledgeable about the assigned workload but lacks practical skills, possessing theoretical understanding.
- Proficiency (P): The state where a human is either knowledgeable or skilled regarding the assigned workload.

In Figure 18, a comprehensive overview of all the introduced formulas is presented. This visual representation underscores the intricate interplay of various elements in the dynamics of human experience. The demonstration reveals a fascinating cascade of events, where affective states become the genesis of human stress, forming the foundation for the perceived human workload when individuals are engaged in a task.

Subsequently, the perceived human workload becomes a pivotal factor influencing human performance, its efficacy inherently constrained by the task completion time. What adds an intriguing layer to this process is the cyclical nature of the system dynamics — human performance, the tangible output of this intricate dance, serves as the input for subsequent affective states in the following timeframe.

This recursive relationship establishes an undeniable truth: the system dynamically generates a loop, perpetually feeding into itself. This holistic understanding sheds light on the complex and dynamic nature of the human experience within the context of assigned tasks and their temporal constraints.

$$A_H^t = f_1(S_H \cup K_H) \cup f_2(E_t)$$
$$\sigma_H^t = f_3(A_H^t)$$

$$A_H^0 = f_4(\eta_H \cup T_H) \cup f_5(E_o)$$
$$\sigma_H^0 = f_6(A_H^0)$$

$$\sigma_H = \sigma_H^t \cup \sigma_H^0 = f_3\,(A_H^t) \cup f_6(A_H^0)$$

$$W_H^p = f_{13}(W_H^a \cup \sigma_H)$$

$$\eta_H = f_{17}(W_H^p \cup T_D)$$

Figure 18: Overview of the introduced formulas

In summary, smart systems are intricately woven from the threads of human intellect, robots and the collaborative interplay between them. These system components manifest as communication channels with distinctive characteristics, dynamically shaping their features during interactions and collaborations. Collaborative endeavors unfold across these communication channels, each channel encapsulating diverse attributes.

Consider the ebb and flow of the human-human interaction mode, susceptible to dynamic shifts influenced by human emotions. In contrast, the robot-robot interaction mode adheres to a stringent model, devoid of the adaptability inherent in human interactions. Yet, there exists another interaction mode that facilitates collaborative efforts among system components, allowing them to converge towards a shared goal. This channel fosters a profound understanding, mutual support, and adaptive adjustments, transforming robots into collaborative entities and, consequently, rendering smart systems collaborative.

Precise definitions for each interaction mode form the bedrock for comprehending the unique needs of each collaborator, enabling the judicious allocation of tasks within smart system projects. A heightened awareness of the environment begets greater wisdom in executing tasks. Following the initial task allocation, robots, functioning as the artificial smart controllers of the system, shift their focus to discerning human stress dynamics. This acute understanding enables the reallocation of tasks as needed, given that human emotions constitute dynamic facets within human-robot teams.

While robots diligently carry out their assigned tasks in support of their human partners and manage their workload, the smart system undergoes a continuous optimization process. The anticipation of challenges, coupled with a responsive approach to human emotions, underscores the adaptability and efficiency intrinsic to these intelligent systems.

In light of the influencing factors of human stress and its effect on performance discussed in this subsection, the next subsection explores how human stress can be measured using current technologies in order to quantitatively assess stress levels, enabling robots to observe their human partners and determine appropriate moments for intervention in their working processes.

6.3. Measuring Human Stress Levels Using Wearable Devices

To support the Yerkes-Dodson law adopted in this thesis for illustrating fluctuations in human performance, this subsection draws on the findings of Awada et al. (2024) to examine how human stress levels can be measured using current wearable technologies. Their study involved two experimental conditions designed to simulate low-stress and high-stress environments. In the low-stress condition, participants were given 40 minutes to prepare a PowerPoint presentation on a familiar topic, with no recordings involved. Conversely, the high-stress condition required participants to prepare a presentation on an unfamiliar topic within 30 minutes, while being recorded by a university professor using live video, audio, and screen sharing tools.

Forty-eight participants were equipped with the tools listed in Table 5. The researchers identified 83 measurable features and recorded data every 30 seconds, resulting in a total of 6,720 data points.

Table 5: Tools for Measuring Human Stress (Awada et al., 2024)

Tools used	Data Collected
Empatica E4 Wristband	Electrodermal Activity (EDA), Skin Temperature (ST), Blood Volume Pulse (BVP), and x,y,z wrist acceleration
H10 Polar Chestwrap	Heart Rate (HR)
Microsoft Azure Kinect DK Camera	Facial expressions
Mini Mouse Macro Logging Application	Participants' activities involving the computer's mouse and keyboard

Participants were prompted with pop-up screens asking them to rate their perceived stress, mood, and productivity on a scale from 0 to 100. They were also asked to classify their stress as either a source of pressure or as an opportunity/challenge. To enhance the depth of their analysis, the researchers used box plots to compare participants' self-assessments across these different stress interpretations. The findings supported the Yerkes-Dodson law (1908), demonstrating that performance peaks at moderate levels of stress arousal, while both low and high extremes are associated with diminished outcomes.

Drawing on the responses from the subjective questionnaires, the researchers utilized the Valencia Eustress-Distress Appraisal Scale (VEDAS) to categorize participants' stress perceptions. This framework allowed them to distinguish among different stress appraisals, including boredom, eustress (positive stress), distress (negative stress), and the coexistence of both eustress and distress. The researchers noted that previous studies had largely concentrated on stress arousal indicators—such as physiological measurements—to assess stress levels. However, appraisal types like boredom, eustress, and their coexistence with distress had received limited attention in earlier work. Addressing this gap, their study incorporated these appraisal categories to enable a more refined and comprehensive assessment of human stress.

This methodology aligns closely with the research objective of this thesis, which seeks to maintain human stress within the eustress range to enhance productivity. The classification of stress into four distinct categories—boredom, eustress, eustress-distress coexistence, and distress—alongside the principles of the Yerkes-Dodson law, offers valuable direction for refining the approach taken in this study. Furthermore, the application of the XGBoost machine learning algorithm in their research demonstrates the potential of wearable and facial data for stress detection, achieving an accuracy rate of 81.08% when both wristband and facial expression inputs are used, and 73.43% accuracy when relying solely on wristband data. These results suggest the viability of a comparable system in which a robot continuously monitors stress levels in a human partner by analyzing data from a wristband or smartwatch—especially in scenarios where control charts signal an out-of-control condition. Overall, their findings reinforce the feasibility and practicality of the stress quantification model proposed in this thesis.

In addition to Awada et al. (2024), Zhao et al. (2023) simulated various human workload conditions to explore their effect on efficiency. They categorized human affective states into three workload-based zones: laidback, capacity, and fatigue. Their findings align with this thesis's objective of maintaining human stress within the eustress zone—by ensuring workload remains within the capacity zone—thereby maximizing performance, as illustrated in Figure 19.

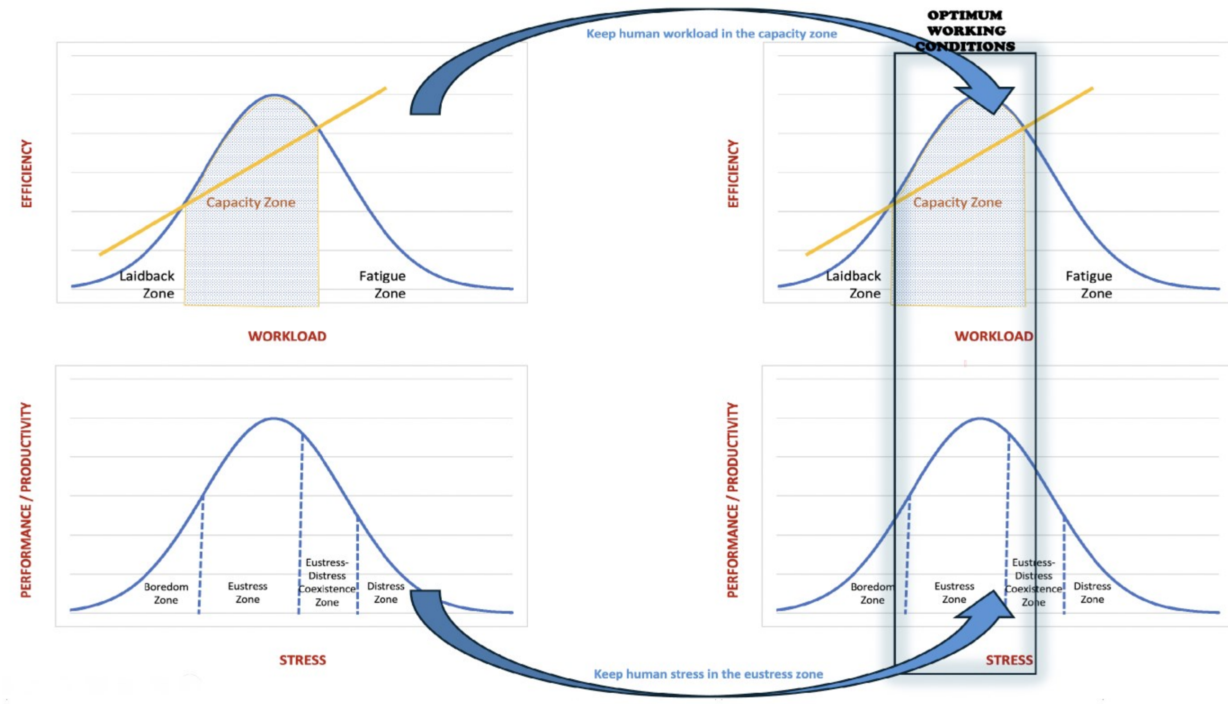

Figure 19: Robot's Intervention on Human-Robot Workload Allocation to maintain optimum human stress by keeping human workload in their capacity zone

As illustrated in Figure 19, efficiency is modeled as a function of workload (Zhao et al., 2023), while stress is represented as a function of performance (Yerkes–Dodson, 1908; Awada et al., 2024). Since this thesis focuses on the relationship between workload and stress in the context of system performance, the findings of Sickles and Zelenyuk (2019) offer valuable insight. Although their research centers on productivity, they highlight that efficiency acts both as a driver and an outcome of productivity. Interpreted within the scope of this study, where system performance is the key concern, this relationship suggests that performance and efficiency are closely intertwined. Based on this understanding, it is assumed that stress can be modeled as a function of workload, and that stress levels may be modulated through workload adjustment to optimize human performance.

$$[Performance = f_{21}(Stress)] \wedge [Efficiency = f_{22}(Workload)] \wedge [Efficiency = f_{23}(Performance)] \Rightarrow [Stress = f_{24}(Workload)] \tag{49}$$

Building on this theoretical framework, the practical measurement and validation of stress are further explored. In this context, Awada et al. (2024) demonstrated that wearable technologies can reliably estimate stress levels by analyzing physiological signals. This finding underscores the importance of physiological monitoring tools for effective stress detection and regulation within human–robot collaboration systems. Accordingly, stress can be monitored through wearable devices and modulated by reallocating human workload whenever a deviation from the optimal stress range is detected. This process is further examined in Subsection 7.1.2, where the stress analysis is discussed in detail, followed by the presentation of the task reallocation algorithm.

To enable a comparison between stress levels detected by wearable devices and the impact of individual tasks on overall human stress, it is also necessary to quantify task-specific stress. This denotes the incremental stress induced by a task when it is allocated to a human. Therefore, the next section introduces a conceptual formula designed to measure the influence of each task on human stress levels.

6.4. Quantifying Task-Specific Human Stress: Development of Conceptual Formula

Once the robot determines the appropriate intervention to regulate human stress—guided by the human state diagram—it must select the most suitable task from a set of feasible options generated by an external support system. This system provides a dynamic task pool based on various allocation algorithms, including those that incorporate precedence constraints, critical path analysis, or the method proposed in Subsection 5.4 of this thesis. Within this framework, the feasible task set represents a collection of alternative actions the robot may choose from when anomalies in human performance or deviations in stress levels are detected.

Because the influence of specific tasks on human stress plays a critical role in deciding whether tasks should be assigned or exchanged, the relationship between task type and stress must be evaluated through multiple interacting parameters. These include the weighted effect of task complexity, time of day, individual skills and knowledge, initial task assignments made at the project's onset, perceived workload, and mood-related affective states. These factors are inherently interdependent and collectively shape how a task impacts human stress. Among them, task complexity is examined in particular detail in Subsection 6.4.1 to clarify its role within this network of influencing variables and to lay the groundwork for the development of a conceptual formula that quantifies task-specific human stress.

6.4.1. Task Complexity and Human Workload

In the context of task complexity, Zahmat Doost and Zhang (2023) investigated how different task types influence human workload and developed a detailed classification system. Their framework distinguishes among three types of tasks: skill-based tasks, which depend on routine knowledge retrieved from long-term memory; rule-based tasks, which involve goal-directed behavior guided by stored propositions and if-then logic; and knowledge-based tasks, which require problem-solving in unfamiliar contexts lacking predefined solutions. The study also examined how environmental interruptions—such as hedonic, social, or cognitive distractions—affect mental workload. Under uninterrupted conditions, knowledge-based tasks resulted in the highest mental workload (78.2%), followed by rule-based tasks (50.2%) and skill-based tasks (40.5%). However, in interrupted scenarios, the pattern shifted: knowledge-based tasks remained the most demanding (58.6%), while skill-based tasks (40.4%) slightly surpassed rule-based tasks (36.9%) in terms of mental workload.

Despite offering a foundational classification, Zahmat Doost and Zhang's (2023) model does not account for other important variables that influence task complexity—namely, human capability (encompassing knowledge and skills), time of day, and the actual task requirements initially assigned. Therefore, the subsequent sections expand on these variables, exploring their roles in shaping task complexity from a human-centered perspective and contributing to the development of a conceptual formula.

This formula is constructed using mathematical relationships of direct and inverse proportionality; however, it is not designed to calculate an exact stress level. Rather, its purpose is to provide directional insight—indicating whether stress is likely to increase or decrease depending on the combination of influencing parameters. To this end, values inspired by prior research are assigned to each variable, resulting in an estimated stress level for the task assigned. By normalizing these values and incorporating stress measurements obtained from wearable devices, the estimated and actual stress levels can be compared to assess whether task reallocation leads to a rise or fall in stress.

Building on the classification proposed by Zahmat Doost and Zhang (2023), this study adopts the following categorization of task complexity: knowledge-based tasks are considered high-complexity, skill-based tasks are moderate-complexity, and rule-based tasks are low-complexity. Given that interruptions are inherent in real-world work environments, the findings under interrupted conditions are considered more representative. Accordingly, task complexity weights are assigned—based on the interrupted-condition data—as shown in Table 6.

Table 6: The Weighted Impact of Task Complexity on Human Stress (Zahmat Doost and Zhang, 2023)

Complexity Class	Type	Weighted Impact of Task Complexity on Human Stress (C_i)
High-Compexity	Knowledge-Based Tasks	5.9
Moderate-Complexity	Skill-Based Tasks	4.0
Low-Complexity	Rule-Based Tasks	3.7

The next subsection explores the parameters that influence the perception of task complexity from a human-centered perspective. These factors form the foundation of the task-specific conceptual formula and help clarify the interrelationships among them.

6.4.2. The Influence of Other Parameters on Task Complexity

As human cognitive and affective states fluctuate in response to various implicit and explicit factors, their perception of task complexity can vary depending on the context. This subsection examines three key parameters—time of day, human capability (including knowledge and skills), and actual task requirements—to support the development of a conceptual formula for estimating task-specific stress.

Time of Day: The time at which a task is performed significantly influences how complex it is perceived to be. Kalanadhabhatta et al. (2021) studied the relationship between human cognitive performance and biobehavioral rhythms, focusing on two major regulatory mechanisms:

- the circadian rhythm, which governs the body's internal biological clock
- the homeostatic process, which regulates sleep pressure based on the need for and quality of sleep

Their findings showed that cognitive performance peaks between 09:00–12:00 and 12:00–16:00, decreases slightly between 16:00–20:00, and drops to its lowest between 04:00–08:00 and 20:00–24:00. Razavi et al. (2023) confirmed that assigning demanding tasks during high-performance time windows enhances outcomes, especially for cognitively complex activities.

Drawing on Kalanadhabhatta et al.'s (2021) study, this thesis adopts a weighted impact scale for time-of-day effects, based on relative response time and the number of additions attempted in their experiment. These weights are presented in Table 7.

Table 7: The Weighted Impact of Time of the Day extracted from Kalanadhabhatta et al. (2021)

Time of the Day	Weighted Impact of Time of the Day on Task Complexity Perception (T_i)
04:00-08:00	0.23
08:00-12:00	2.63
12:00-16:00	2.53
16:00-20:00	1.33
20:00-24:00	0.11

This weighted scale reflects the expected level of human cognitive performance at different times of day. Higher weights indicate periods of peak performance, while lower weights reflect decreased performance levels. Consequently, tasks assigned during high-performance windows are likely to be perceived as less complex, whereas those assigned during lower-performance periods may feel more demanding.

Human Capability: An individual's perception of task complexity is closely tied to their level of knowledge and skill. According to Cognitive Load Theory, individuals with greater expertise experience reduced cognitive load when engaging in a task, thereby perceiving it as less complex. Conversely, insufficient knowledge or skill increases the perceived difficulty of the same task (Sweller, 1988; Van Merriënboer & Sweller, 2010). This is further supported by Zeitlhofer et al. (2024), who found that participants performed more efficiently when reattempting previously encountered complex tasks, indicating that experience improved their capability and reduced perceived complexity.

Actual Task Requirement: In project environments, large tasks are broken down to distribute work effectively among team members. As emphasized in project management guidelines, the estimated duration of each task must be accurately assessed during the planning phase (Mulcahy, 2013; Project Management Institute, 2021). When tasks require comparable levels of knowledge and skills, those with longer durations are typically regarded as more complex and demanding (Wilkinson et al., 2012; Walhout et al., 2017; Guo et al., 2020; Zhou et al., 2022). In this study, task duration is used as a proxy for actual time-based workload, offering a measurable indicator to assess and balance complexity across task assignments.

These parameters—time of day, human capability, and actual task requirements—form the foundation for modeling task complexity from the human perspective. Their integration into a conceptual formula explained in Subsection 6.4.3 allows for the estimation of task-specific stress when allocating tasks in human–robot collaboration systems.

6.4.3. *Conceptual Formula for Task-Specific Human Stress*

Based on the foundations identified so far, *Complexity (C)* is a function of:

1. *Actual Task Requirement (W^a)* – Time-based workload assigned to human
2. *Human Capability (S+K)* – consisting of *skills and knowledge*

3. *Time of the Day (T)*

In this function, it is proposed that the perception of task complexity is directly proportional to the Actual Task Requirement (W^a), while human capability (S+K) and time of the day (T) are inversely proportional to the perceived task complexity. Accordingly, a conceptual formula is established to represent the complexity of each task from the perspective of an individual human as follows:

Let

$$C_i = f(W_i^a, (S_i + K_i), T_i) \quad \forall i \in \mathbb{N}, where\ 1 \leq i \leq N \tag{50}$$

be the function that defines the task-related estimated cognitive complexity level for the i^{th} task, where:

- W_i^a is the **actual workload assigned for task *i***,
- S_i represents the **human skill level for task *i***,
- K_i represents the **human knowledge level for task *i***,
- the sum $(S_i + K_i)$ models the **human capability for task *i*,**
- T_i is a **time-of-day coefficient** accounting for temporal cognitive fluctuations,
- and N is the **total number of tasks**.

Accordingly, the estimated cognitive complexity level for a given task i can be formulated as follows:

$$C_i = \frac{W_i^a}{(S_i + K_i).T_i} \tag{51}$$

In addition to this, Nguyen and Zeng (2017) defined stress (σ_i) as a function of perceived workload, human capability, and affective states. Therefore, for a given task i, its contribution to human stress can be formulated as shown in Equation 52. Considering that each task has a unique contribution to perceived workload (W_i^p) and that each individual possesses a unique combination of knowledge and skills (S_i + K_i) in response to task i, the specific contribution of that task to human stress can be further expressed as shown in Equation 53.

$$\sigma_i = f\,(W_i^p, (S_i + K_i), A_i), \forall i \in \mathbb{N}, 1 \leq i \leq N \qquad (52)$$

Where:

- W_i^P is the **perceived workload for task *i***
- A is the individual's **affective (emotional) state**.

$$\sigma_i = \frac{W_i^p}{(S_i + K_i).A_i} \qquad (53)$$

Given that capability ($S_i + K_i$) appears in both the complexity (Equation 51) and stress functions (Equation 53) presented in Table 8, the task-specific stress can be derived as shown in Equation 54:

$$\frac{W_i^a}{C_i\,T} = \frac{W_i^P}{\sigma_i\ A} \Rightarrow \sigma_i = \frac{W_i^P\ C_i\,T}{W_i^a\ A} = DPI_i\frac{C_i\,T}{A} \qquad (54)$$

Where, according to Yousefi et al. (2019), *Duration-Based Performance Indicator*: DPI $= \frac{W_i^P}{W_i^a}$

Table 8: The Combination of Task Complexity and Stress Formulas

Proposed Conceptual Formula	**Conceptual Stress Formula** **(Nguyen and Zeng, 2017)**
$C_i = \frac{W_i^a}{(S_i + K_i).T_i}$	$\sigma_i = \frac{W_i^p}{(S_i + K_i).A_i}$

$$(S_i + K_i) = \frac{W_i^{a}}{C_i \,.\, T_i}$$	$$(S_i + K_i) = \frac{W_i^{p}}{\sigma_i \,.\, A_i}$$

Affective State: In this integrated formula, the variable (*A*) represents a human's affective state, encompassing mood-related conditions categorized into five distinct types, as outlined in Table 9. This classification is adapted from the work of Cittadini et al. (2023) on *Affective State Estimation*. As the Yerkes-Dodson law is adopted in this thesis to explain the relationship between stress and performance, and the affective states defined in their study align with the stress–performance bell curve, the same mood categories are incorporated into the formula to evaluate their impact on human stress. Each category is assigned a corresponding weighted impact score, calculated using the Analytical Hierarchy Process (AHP) method (Saaty, 1977; Saaty, 1980).

Table 9: Weighted Impact of Affective States Estimated Based on Cittadini et al. (2023)

Mood	Affective State	Weighted Impact of Affective State on Human Stress (A_i)	Example Emotions
High Arousal – High Valence (HAHV)	"Positive and involved state of the person"	4.59	pleasure, joy and excitement
Low Arousal – High Valence (LAHV)	"Positive and uninvolved state of the person"	2.99	calm, relaxed, peaceful
Neutral	Neutral	1	emotionally balanced, flat

Low Arousal – Low Valence (LALV)	"Negative and uninvolved state of the person"	0.56	boredom, sleep
High Arousal – Low Valence (HALV)	"Negative and involved state of the person"	0.42	anger, fear, anxiety

Equation 54 is developed in this study to support the adjustment of stress levels detected through wristband data by reallocating feasible tasks. To enable this, it is necessary to quantify the stress impact associated with each individual task. This allows for the evaluation of changes in human stress levels when a task is either assigned (i.e., current stress + task-induced impact) or removed (i.e., current stress − task-induced impact). However, the stress measurements obtained from wearable devices and the task-specific stress values derived from the conceptual model are based on different numerical scales. To ensure meaningful comparison and integration, both datasets must be normalized. Once normalized, they can be combined—for instance, by adding a task's impact to the current stress level or subtracting it to simulate the effect of task removal.

After presenting the structure of the human-robot system, outlining the communication channels, interaction modes, and collaboration types, detailing the logic behind the dynamic workload allocation model, and explaining the factors influencing human stress along with their interrelationships, Section 7 provides a step-by-step, phase-by-phase explanation of the dynamics of the proposed model.

7. ROBOT-SUPERVISED INTELLIGENT WORKLOAD REALLOCATION BASED ON STRESS-AWARE HUMAN PERFORMANCE MONITORING IN HUMAN-ROBOT TEAMS

This thesis proposes a human-robot collaboration framework in which robots monitor human performance by analyzing physiological and behavioral signals, enabling them to manage and reallocate human workload accordingly—a concept reiterated throughout the study. This section outlines the step-by-step execution of the proposed model. To assess its feasibility, the section concludes with a Monte Carlo simulation that validates the model's effectiveness in dynamic, stress-aware workload reallocation.

7.1. Process Flow of Robot-Supervised Workload Allocation

The algorithm outlined so far presents an innovative framework for dynamic workload allocation within human-robot or human-computer collaborative systems. Building on previously established goals, its primary focus is to manage human stress levels to support optimal performance. This objective is implemented through a systematic, three-step process:

- **i.** Monitoring human performance using control charts
- **ii.** Analyzing stress and performance correlations using physiological and behavioral data
- **iii.** Reallocating workload to balance stress levels utilizing state diagrams

Figure 20 illustrates the overall structure of the proposed approach. At its core, this framework relies on the robot's capacity to monitor the human collaborator through both quantitative metrics and qualitative observations, and to actively intervene in the work environment—for instance, by supporting task redistribution. The primary goal is to maintain human stress within an optimal range—avoiding both underload and overload—to maximize human contribution to system performance and foster more balanced and efficient human-robot collaboration, a goal reiterated in earlier sections.

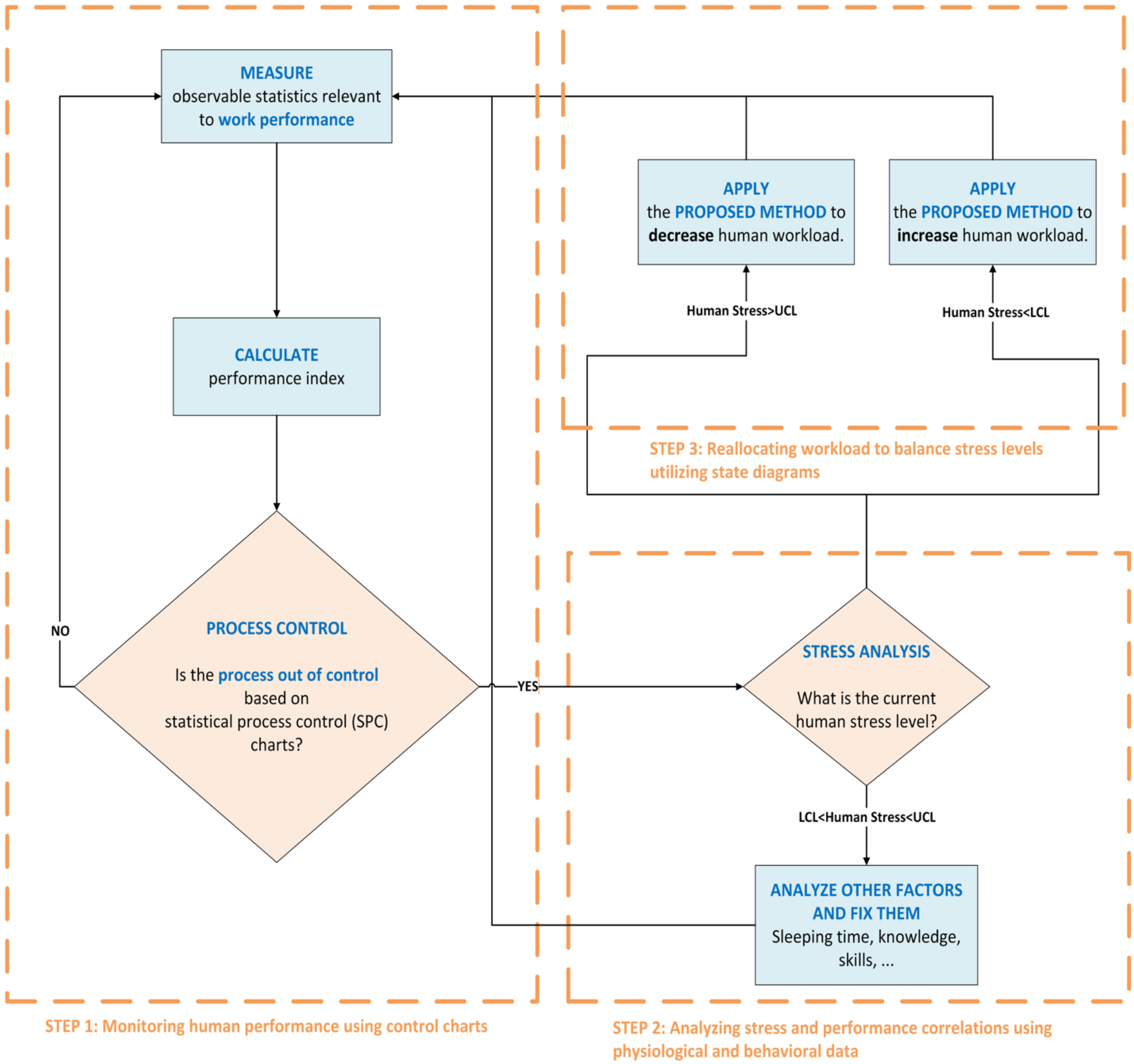

Figure 20: Role of Robot: Controlling Human Stress through Workload Reallocation

The subsequent third-level subsections provide a detailed explanation of each individual step within the proposed process. Each step is examined separately to highlight its specific role, underlying logic, and contribution to the overall framework.

7.1.1. ***Step 1****: Monitoring Human Performance Using Control Charts*

Human performance in collaborative systems naturally fluctuates throughout the workday due to changes in physical and mental states. While some of these fluctuations are minor and transient, others may indicate deeper issues that require corrective action (Lee & McGreevey, 2002; Caulcutt, 2004). As the first step in the proposed supervisory control strategy, this framework positions the robot as an intelligent observer capable of distinguishing between normal performance variability and deviations caused by specific stress-related factors.

To facilitate this capability, the robot is equipped with the tools of Statistical Process Control (SPC), particularly control chart construction and interpretation (Lee & McGreevey, 2002; Montgomery, 2007; Tague, 2023). Control charts offer a robust method for real-time monitoring by comparing performance indicators—such as task duration or error rate—against statistically defined control limits. When these metrics exceed threshold values, the robot is alerted to potential anomalies and can initiate data-driven interventions (Yousefi et al., 2019). This approach not only improves process stability but also contributes to enhanced productivity, cost efficiency, and overall system predictability (Lee & McGreevey, 2002).

In this context, the robot continuously monitors the human partner's performance for signs of statistical irregularity. When a deviation is detected, it analyzes whether the observed change stems from normal variability or indicates an abnormal condition. At this stage, no direct intervention occurs. Instead, the robot functions solely as a diagnostic observer, aiming to determine whether the deviation may be attributed to fluctuating stress levels or to other underlying factors.

This distinction informs the next phase of the framework, where the source of the deviation—if linked to stress—is examined in detail and appropriate actions are taken. Accordingly, the following hypothesis frames Step 1 of the supervisory control strategy:

- **H_0**: The robot can accurately detect when human performance exceeds statistical control thresholds.
- **H_1**: The robot cannot reliably detect such deviations.

The effectiveness of control charts in monitoring human performance has been validated across several domains. For instance, Wang et al. (2013) used X-bar control charts to track cashier scanning durations in supermarkets. When scan times exceeded upper control limits after four hours, fatigue was inferred, demonstrating the chart's effectiveness in identifying time-induced inefficiencies.

Yousefi et al. (2019) proposed the Duration Performance Index (DPI)—calculated as the ratio of earned duration to actual duration—as a metric for assessing task efficiency in construction projects. A DPI value of 1 indicates adherence to the planned schedule, while values below 1 suggest inefficiency and those above 1 reflect superior performance. Their application of control charts to monitor DPI variations yielded meaningful insights into temporal performance patterns.

Similarly, Sugiono et al. (2022) integrated control charts into their Cognitive Workload Management (CWM) framework for train operators. By combining brain simulation models with data from On-Train Data Recorders (OTDR), they continuously assessed drivers' cognitive workload and categorized it into underload, optimal load, and overload states. Control charts were instrumental in identifying instances where cognitive stress exceeded acceptable thresholds, thereby supporting the development of rest schedules and the reallocation of tasks. Their findings underscore the value of statistical monitoring in bridging subjective workload evaluations with objective performance data.

Collectively, these studies demonstrate the effectiveness of statistical control charts in identifying performance deviations, uncovering their underlying causes, and informing appropriate interventions. Within the proposed framework, this analytical function is delegated to the robot supervisor, which continuously monitors human performance, detects anomalies, and initiates further diagnostic steps to ensure that performance remains within safe and efficient operational thresholds.

Given this capability, the hypothesis that the robot can detect when human performance is statistically out of control is accepted (H_0). With this confirmation, the robot can proceed to the next stage—Step 2: Analyzing Stress and Performance Correlations Using Physiological and Behavioral Data—to determine whether the detected performance deviation stems from elevated or reduced stress levels.

7.1.2. ***Step 2: Analyzing Stress and Performance Correlations Using Physiological and Behavioral Data***

While Statistical Process Control (SPC) charts allow robots to detect when human performance exceeds defined control limits, such detections alone do not provide insight into the root causes of these deviations. To address this limitation, SPC data must be supplemented with indicators of human stress. Generally, low stress levels are associated with a state of boredom, whereas high stress may indicate cognitive overload or task-related chaos. Therefore, in cases where performance anomalies are identified, the robot—as a supervisory controller—must evaluate the human's stress condition in real time to determine whether stress is the underlying cause.

To support this decision-making process, the robot must be equipped with non-intrusive sensing capabilities for continuous monitoring of human stress. In this step, a stress assessment method is introduced that enables the robot to estimate human stress levels precisely at the point when performance deviates from defined thresholds. This estimation is based on physiological and behavioral data collected through minimally invasive sensing technologies.

Extensive research has demonstrated that such physiological and behavioral signals can effectively indicate human emotions and associated stress levels. For example, Zhao et al. (2024) employed EEG signals to monitor pilots' cognitive states during virtual simulation exercises. Their study marked a significant advancement by enabling the quantitative measurement of cognitive activity and its association with stress, surpassing the limitations of traditional qualitative approaches. However, the use of EEG hardware during active task execution presents notable ergonomic challenges. This concern is echoed by Sugiono et al. (2022), who emphasized that while such intrusive technologies are effective for measuring cognitive states, they can hinder natural movement and negatively impact task performance.

Given these limitations, it is essential that any data acquisition tools used in robotic supervision rely on non-intrusive technologies. Wearable devices such as wrist-worn fitness trackers and smartwatches, as well as contactless behavioral monitoring tools (e.g., cameras), offer viable alternatives (Gjoreski et al., 2017; Nath and Thapliyal, 2021; Mitro et al., 2023; Bello-Orgaz and Menéndez; Awada et al., 2024; Jo et al., 2025). For instance, Awada et al. (2024) demonstrated a

73.43% accuracy in stress detection using wristband data, highlighting the potential of such technologies for continuous stress assessment.

Building on this body of research, the proposed framework assumes that robots can effectively estimate human stress using wearable sensing devices. Once a robot detects that human performance has exceeded control limits, it evaluates whether the anomaly is stress-induced. If elevated stress is identified, the robot prepares for an appropriate intervention. However, if stress levels remain within the optimal range, the robot will consider alternative explanations—though such diagnostic exploration falls outside the scope of this study.

To formalize this component of the framework, the following hypothesis is adapted from the work of Awada et al. (2024):

- **H_0**: Human stress levels can be estimated with high accuracy using wearable devices (e.g., wristbands, smartwatches).
- **H_1**: Human stress levels cannot be accurately estimated using wearable devices (e.g., wristbands, smartwatches).

Quantitatively linking stress and performance has long been studied, with the Yerkes–Dodson law (1908) establishing one of the earliest models to describe an inverted-U relationship between arousal and performance. In more recent work, Awada et al. (2024) further quantified this relationship by incorporating biosignals and task performance metrics. While these studies center on the stress–performance interaction, it is proposed here that workload also plays a significant role in shaping stress levels. For this reason, the workload-related findings of Zhao et al. (2023) are considered alongside the Yerkes–Dodson principle and Awada et al.'s results. Despite their different scopes, all studies converge on a similar bell-shaped pattern, often modeled using Gaussian distributions, reflecting an optimal zone of stress known as eustress.

Given that Step 1 confirms the robot's ability to detect when human performance falls outside control limits, and Step 2 establishes that human stress can be reliably estimated using wearable technology, these components can be integrated into a unified control strategy. In this model, SPC charts are used for anomaly detection, followed by real-time stress evaluation to determine the need for corrective action. The objective is to maintain emotional states within the eustress zone—

where productivity and cognitive function are optimized—through adaptive workload management.

By interpreting biosignals from wearable devices, the robot can detect shifts away from the optimal zone and implement timely interventions, such as task redistribution or workload adjustment. This proactive stress management strategy not only supports individual well-being but also enhances the overall efficiency of the human-robot system. Embedding this capability into the proposed framework creates a data-driven mechanism for regulating stress, thereby strengthening the system's adaptive and collaborative potential.

Given the supporting evidence and demonstrated feasibility—particularly the findings of Awada et al. (2024), whose study was discussed in detail in Subsection 6.3—the hypothesis H_0 (that human stress levels can be estimated with high accuracy using wearable devices such as wristbands or smartwatches) is accepted. With this confirmation, the robot is now equipped to proceed to the next phase. In Step 3: Balance Stress Levels Using Robot-Supervised Task Reallocation, the system leverages real-time stress assessments to initiate adaptive workload adjustments aimed at restoring and maintaining human performance within the optimal stress range.

7.1.3. Step 3: Balance Stress Levels Using Robot-Supervised Task-Reallocation

This section introduces the intervention algorithm that governs the task reallocation process when irregularities in human performance are accompanied by deviations in stress levels—whether elevated or reduced beyond acceptable thresholds. Upon identifying such deviations, the robot evaluates current stress indicators and proceeds to review individualized task assignments. This evaluation considers a range of contextual and systemic factors that influence task distribution, rendering the human-robot collaboration process both dynamic and adaptive.

As discussed previously in Section 5, multiple modes of collaboration exist within human-robot teams, including human-human, robot-robot, and human-robot interactions. Although the algorithm proposed here primarily operates within a human-robot framework—where the robot supervises and responds to human states—it is important to recognize the role of other collaboration types in shaping decision-making. In particular, robot-robot collaboration at the system level is crucial for accessing and integrating data from distributed subsystems, enabling the robot to make informed decisions about task reallocation. This integrated interaction is depicted in Figure 21.

This third step constitutes the core contribution of the study. Accordingly, a detailed, phase-by-phase explanation of the proposed intervention mechanism is provided in Subsection 7.2.

7.2. Intervention-Based Task Reallocation Model for Robots

With the advancement of human-robot systems through machine-to-machine (M2M) communication, wireless sensor networks, and intelligent AI-driven algorithms, these systems have evolved into complex, highly integrated frameworks. In such settings, the outputs of certain systems function as critical inputs for others, enabling a continuous exchange of data and inter-system coordination.

To accurately interpret implicit human conditions—such as cognitive workload, domain knowledge, emotional states, stress levels, and sleep quality—the robot responsible for executing the proposed intervention model (System 1 in Figure 21) must rely on input from complementary systems, including other robotic agents within a smart integration architecture. Incorporating wearable technologies further augments the model's capability by supplying real-time physiological indicators of stress, which are essential for monitoring performance and ensuring stress levels remain within optimal thresholds (System 2 in Figure 21) (Gjoreski et al., 2017; Nath & Thapliyal, 2021; Mitro et al., 2023; Bello-Orgaz & Menéndez, 2023; Awada et al., 2024).

Additionally, temporally dependent variables—such as circadian rhythms, sleep cycles, and time-of-day effects—play a pivotal role in modulating human performance during collaborative tasks (System 3 in Figure 21) (Kalanadhabhatta et al., 2021; Razavi et al., 2023). To accommodate these fluctuations and execute task transitions effectively, a responsive dynamic task scheduling mechanism is essential (System 4 in Figure 21). This system must continuously assess task availability and human functional capacity to enable real-time adjustments as needed (Pupa et al., 2021; Alirezazadeh & Alexandre, 2022).

Moreover, an analytical evaluation unit should be incorporated to assess task complexity, offering critical insights into how individual task demands influence human stress and perceived workload

(Zahmat Doost & Zhang, 2023). This layered integration of systems forms the foundation for intelligent, context-aware task reallocation in robot-supervised environments.

In cases where performance irregularities are observed but stress levels remain within acceptable thresholds, it suggests that stress is not the primary factor impairing performance. In such scenarios, an alternative diagnostic system should be activated to identify other potential causes. For instance, a human capacity analysis module can be employed to evaluate the alignment between the individual's current knowledge, skills, and the demands of the assigned task (Nguyen & Zeng, 2017). If a discrepancy is identified, the system should propose suitable interventions—ranging from immediate support mechanisms to longer-term upskilling strategies—to address the misalignment (System 5 in Figure 21).

The architecture of the proposed framework allows for the integration of additional subsystems as required to increase adaptability and contextual awareness. Figure 12 provides an overview of the core reallocation algorithm and its interaction with the broader set of supporting systems. Although the literature supports expanding the model by incorporating further modules, the primary emphasis of this thesis remains on the development and implementation of the task reallocation algorithm itself (System 1 in Figure 21).

Overall, Figure 21 presents a comprehensive overview of the integrated system architecture, highlighting how various subsystems interact to support adaptive task management in human-robot collaboration. While the primary focus remains on the task reallocation algorithm (System 1), the figure also illustrates the interconnected roles of complementary systems—such as physiological monitoring, capacity analysis, and dynamic scheduling—that collectively contribute to informed, real-time decision-making. This visual representation underscores the complexity and modularity of the proposed framework, reinforcing the importance of multi-system integration for effective workload distribution.

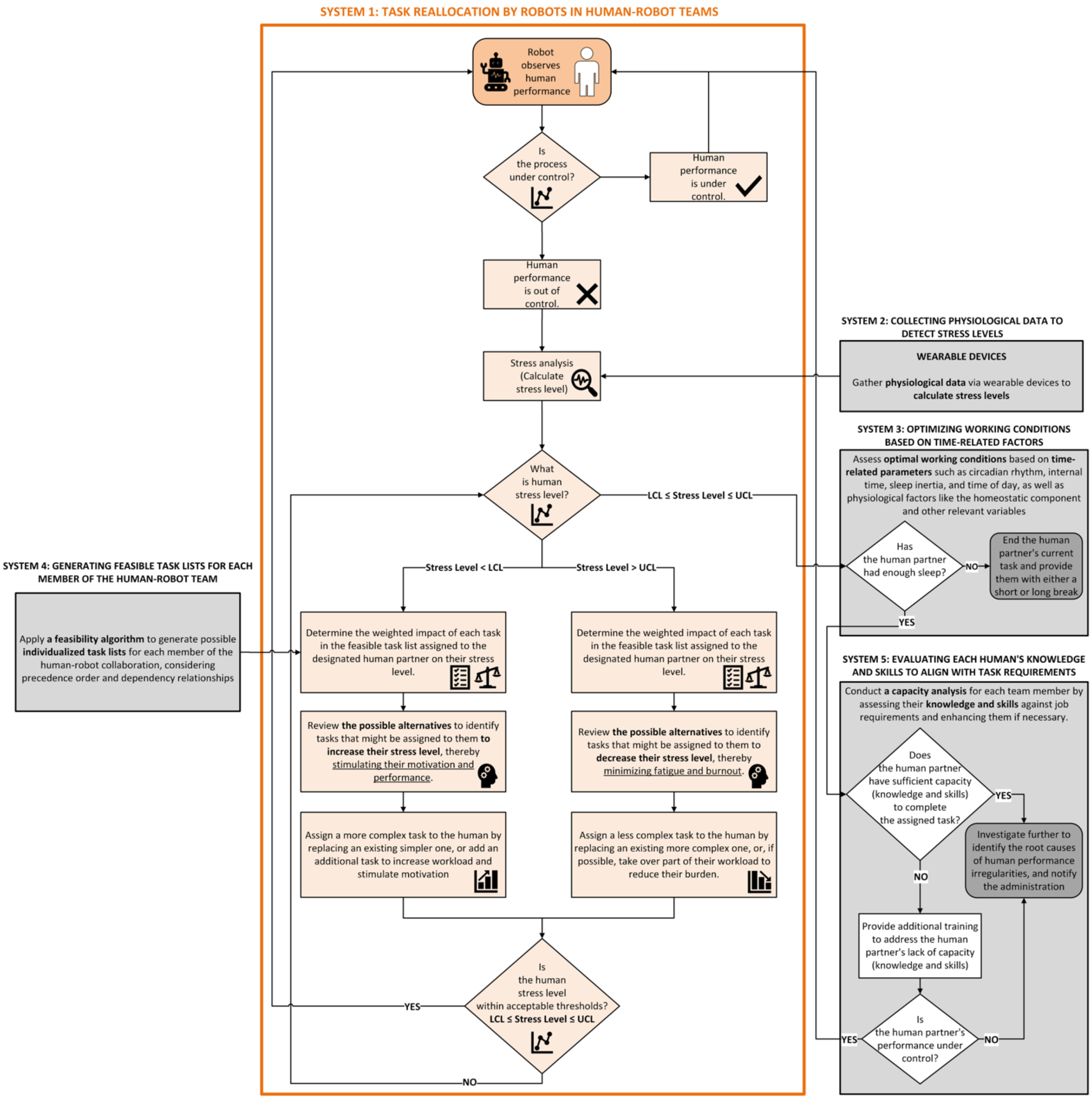

Figure 21: Intervention-Based Task Reallocation Model for Human-Robot Systems

According to the intervention-based task reallocation logic illustrated in Figure 21, the robot's decision-making follows these phases:

1. Utilizing a State Diagram for Adjusting Human Stress Levels

2. Quantitative Evaluation of the Impact of Task Complexity and the Formulation of Stress Induced by the Assigned Task
3. Deciding on the Suitable Task for Optimal Performance

The robot's intervention strategy unfolds through a structured sequence of decision points, each addressing a distinct aspect of task reallocation. The following subsections delve into these phases, outlining how stress regulation, task complexity analysis, and final task selection are systematically integrated to support informed and adaptive collaboration.

7.2.1. Phase 1: Utilizing a State Diagram for Adjusting Human Stress Levels

When stress-related input is received from an external supporting system (referred to as System 2 in Figure 21), the robot processes the incoming biophysical data—following the methodology described by Awada et al. (2024)—to assess the individual's current stress state. This value is then positioned along a bell-curve representation (Figure 22), classifying the state as "underloaded" (-1), "stabilized" (0), or "overloaded" (1).

If the detected stress level falls into either the underloaded or overloaded category, the system activates a Moore State Diagram–based control mechanism (Giantamidis et al., 2021) to trigger task reallocation, aiming to return the individual to a stabilized state. According to the logic of the state diagram, when a transition occurs from the stabilized state to either overload or underload—or when the system remains in a non-optimal state—the robot intervenes by modifying the workload. Specifically, it reduces the workload **(**Wp−**)** to mitigate high stress or increases it **(**Wp+**)** to counteract low stress. In contrast, if the stress level remains within the stabilized zone, no immediate intervention is initiated. The robot continues to observe and monitor performance and stress levels to detect any future deviations.

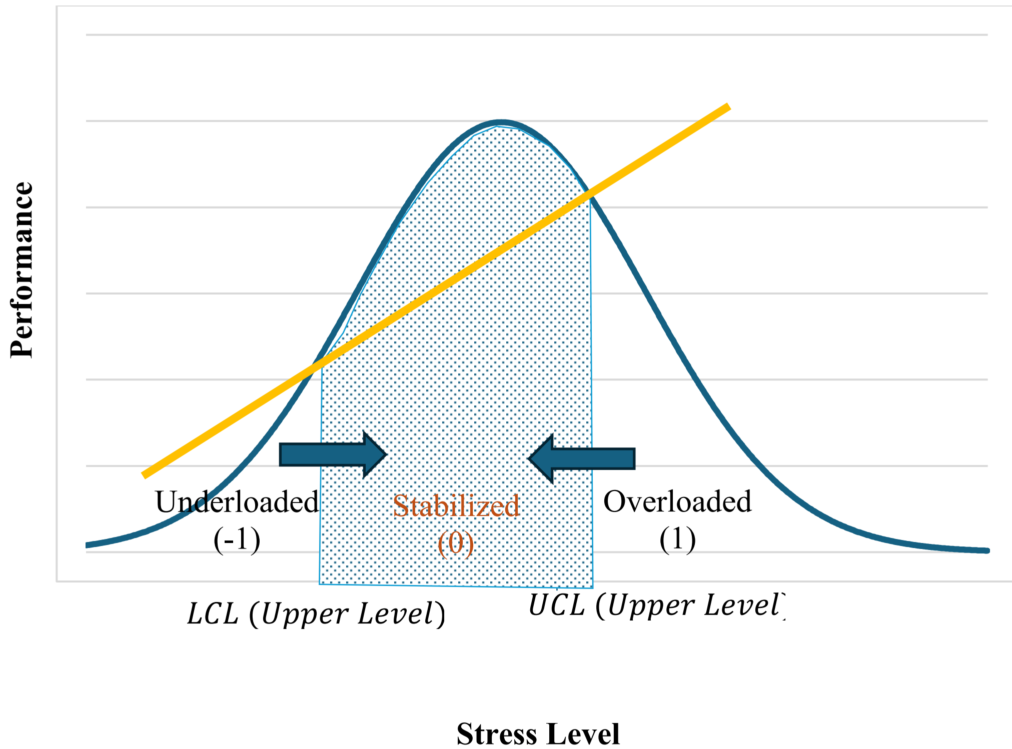

Figure 22: Mapping of Human Stress Levels on a Bell Curve

At this stage, specific input conditions determine whether the robot should intervene in workload allocation. If any of the following transitions are observed, the system output is defined as "No", indicating that the robot does not intervene (denoted as W^{p0}) and continues monitoring human performance and stress levels:

- [-1, 0]: Transition from an underloaded state to a stabilized state
- [+1, 0]: Transition from an overloaded state to a stabilized state
- [0, 0]: The human state remains stabilized

In contrast, intervention is required when any of the following state transitions occur:

- [0, -1] or [0, +1]: Transition from the stabilized state to either underload or overload
- [-1, +1] or [+1, -1]: Cross-transitions between underload and overload
- [-1, -1] or [+1, +1]: The human state remains underloaded or overloaded, respectively

In these cases, the output is "Yes", prompting the robot to initiate workload reallocation. The overarching aim of the state diagram is to restore the human to a stabilized stress level and maintain this condition. A summary of this algorithmic logic is presented in Table 10. Based on this decision-making framework, the robot operates using the state diagram illustrated in Figure 23, which classifies the human state as stabilized, underloaded, or overloaded, and guides whether workload intervention is warranted.

Table 10: Summary of the State Diagram Algorithm

Input	Output	Action
[-1 , 0]	**No**	**W^{p0} (Not intervene in workload allocation)**
[+1 , 0]	**No**	**W^{p0} (Not intervene in workload allocation)**
[0 , 0]	**No**	**W^{p0} (Not intervene in workload allocation)**
[0 , -1]	**Yes**	**W^{p+}** (Increase human workload)
[0 , +1]	**Yes**	**W^{p-}** (Decrease human workload)
[-1 , +1]	**Yes**	**W^{p-}** (Decrease human workload)
[+1 , -1]	**Yes**	**W^{p+}** (Increase human workload)
[-1 , -1]	**Yes**	**W^{p+}** (Increase human workload)
[+1 , +1]	**Yes**	**W^{p-}** (Decrease human workload)

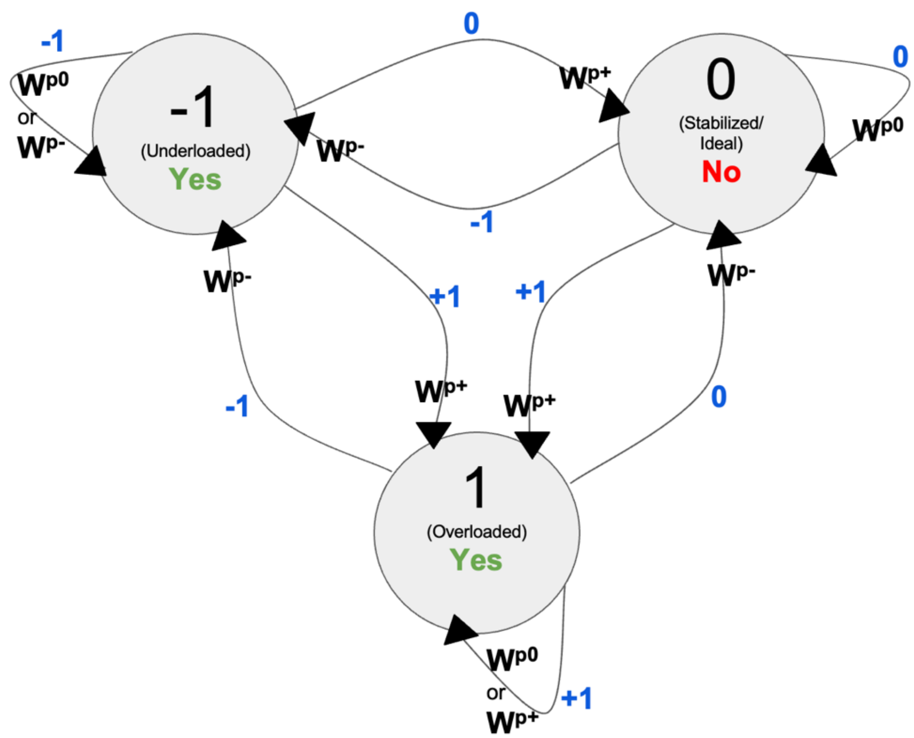

Figure 23: The State Diagram for Robot's Decision-Making in Reallocation Interventions

Human-centric evaluations, as embedded in the proposed algorithm, enhance the robot's ability to interpret and respond to human states, thereby fostering more effective and adaptive collaboration. In the current framework, these human conditions are classified into two categories: stabilized and non-stabilized stress states. In a similar vein, Merlo et al. (2023) investigated dynamic human-robot task collaboration by allocating tasks based on a comparison between an individual's current physical condition and the ergonomic requirements of the task. Their findings indicated that withholding high-risk tasks when ergonomic conditions were suboptimal significantly reduced human fatigue and frustration during interaction.

Tao et al. (2024) further examined how various forms of human-robot interaction—including touchless mid-air gesture-based systems and device-assisted methods—influence human performance under differing ergonomic constraints. Collectively, these studies, along with the proposed model, underscore the importance of continuously monitoring human physiological and behavioral states in collaborative environments.

By integrating real-time assessments of human condition, robots can make informed decisions about task assignment and interaction modalities. This not only optimizes task performance but also ensures that human collaborators remain within an ergonomic, cognitive, and emotional comfort zone. In essence, the robot's ability to monitor and respond to human conditions supports efficient, responsive, and sustainable collaboration in dynamic human-robot teams.

7.2.2. Phase 2: Quantitative Evaluation of the Impact of Task Complexity and the Formulation of Stress Induced by the Assigned Task

Following the detection of human stress levels, the robot must initiate appropriate adjustments by either assigning new tasks, modifying the human's current role, or removing ongoing tasks. To make informed decisions, it is essential to quantify the stress-inducing potential of each task—both current and prospective—in terms of its impact on human performance. This task-specific stress value enables the robot to compare multiple task options and select the one that aligns best with the human's current stress condition, thereby facilitating optimal performance. The methodology for quantifying these stress effects is described in detail in Subsection 6.4.

7.2.3. Phase 3: Deciding on the Suitable Task for Optimal Performance

In human-robot collaboration, ongoing monitoring enables robots to identify inconsistencies in human task execution. This process begins with the detection of anomalies—such as prolonged task completion times and increased error frequencies—as discussed in Section 7.1.1. Following the detection of such performance issues, the robot assesses the human's stress levels using physiological signals captured by wearable devices, as detailed in Section 7.1.2. If the assessment indicates that task reallocation is required, the robot selects and assigns tasks more appropriately aligned with the human's current cognitive and physical state, with the goal of sustaining or enhancing performance, as explained in Section 7.1.3.

The reallocation mechanism unfolds over three consecutive phases. Section 7.2.1 outlines a state diagram that assists in determining when task reassignment should be initiated. Section 7.2.2 introduces a mathematical model that quantifies the potential stress induced by each task. This quantification is not limited to task complexity alone; it also incorporates factors such as task-specific perceived workload, the time of day the task is performed, time constraints representing actual workload demands, and the human's affective state during task execution. Building on these foundations, the current section (7.2.3) focuses on the final phase: selecting the most suitable task by taking into account the human's current condition as well as broader system constraints.

To support implementation, Table 11 introduces a pseudocode framework that brings together the model's key assumptions, visual tools, and mathematical foundations. Figure 20 provides an illustrative overview of the three main stages of the intervention process, while Figure 21 offers a more detailed depiction of the integrated, human-centered task reallocation architecture.

Table 11: Decision Algorithm for Intervention-Based Task Reallocation in Robots

BEGIN (at time t)

1. Is human performance within the control limits?

   YES: Continue monitoring human performance: $t = t + 1$

   NO: Verify if the stress is the main reason human performance is reduced

   Go to step 2:

2. Observe and record the human's stress level (σ_w^t) from the wearable device at time *t*.

3. Normalize σ_w^t as

$$\hat{\sigma}_w^t = \frac{\sigma_w^t - \sigma_w^{min}}{\sigma_w^{max} - \sigma_w^{min}}$$

   Where minimum $\left(\sigma_w^{min}\right)$ and maximum (σ_w^{max}) stress values are obtained from previous observations

4. Use the state diagram introduced in Figure 5 to determine whether the robot should intervene in task reallocation.

   IF intervention is required:

   Proceed to Step 5.

   ELSE:

   $t = t + 1$

Return to Step 1

5. Perform task reallocation:

5.1 Evaluate currently handled task's ($task\ i$) contribution on human stress (σ_i)

5.1.1 Calculate actual workload for the currently assigned $task\ i$:

Let ε be time spent on task i so far.

$W^{a}{}_{i}^{t} = W^{a}{}_{i}^{t'} - \varepsilon$, where t' is the time when $task\ i$ is assigned to human

5.1.2 Identify the human's perceived workload for task *i* at time *t*, $W^{p}{}_{i}^{t}$:

- *For controlled experiments*: ask the human partner via subjective questionnaires.
- *For real-time applications*: estimate via facial expression analysis and/or physiological data using inference algorithms.

5.1.3 Determine Duration-Based Performance Indicator:

$$\mathrm{DPI}_i^t = \frac{W^{p}{}_{i}^{t}}{W^{a}{}_{i}^{t}}$$

5.1.4 Determine current task's contribution on human stress (σ_i^t).

$$\sigma_i^t = \frac{W_i^{p^t} C_i T}{W_i^a A^t} = \mathrm{DPI}_i^t \frac{C_i T}{A^t}$$

Where:

$$C_i = \begin{Bmatrix} \text{Knowledge} - \text{based tasks} & 5.9 \\ \text{Skill} - \text{based tasks} & 4.0 \\ Rule - based\ tasks & 3.7 \end{Bmatrix}$$

$$T = \begin{Bmatrix} 04{:}00 < Time\ of\ Day < 08{:}00 & 0.23 \\ 08{:}00 < Time\ of\ Day < 12{:}00 & 2.63 \\ 12{:}00 < Time\ of\ Day < 16{:}00 & 2.53 \\ 16{:}00 < Time\ of\ Day < 20{:}00 & 1.33 \\ 20{:}00 < Time\ of\ Day < 24{:}00 & 0.11 \end{Bmatrix}$$

$$A^t = \begin{Bmatrix} \text{HAHV: High Arousal} - \text{High Valence} & 4.59 \\ \text{LAHV: Low Arousal} - \text{High Valence} & 2.99 \\ Neutral & 1 \\ LALV: Low\ Arousal - Low\ Valence & 0.56 \\ HALV: High\ Arousal - Low\ Valence & 0.42 \end{Bmatrix}$$

5.1.5 *Normalize* σ_i^t as:

$$\hat{\sigma}_i^t = \frac{\sigma_i^t - \sigma_i^{min}}{\sigma_i^{max} - \sigma_i^{min}}$$

Where σ_i^{min} and σ_i^{max} values are obtained from previous observations

5.2 Determine the contribution of task considered to be assigned on human stress

5.2.1 Identify feasible task which is possible to assign to human at time t

5.2.2 Determine candidate task's contribution on human stress (σ_j^t).

$$\sigma_j^t = \frac{W_j^{p^t} C_j T}{W_j^a A^t} = \mathrm{DPI}_j^t \frac{C_j T}{A^t}$$

Where C_j, T and A^t are determined similar to Step 5.1.4.

5.2.3 Normalize σ_j^t as:

$$\hat{\sigma}_j^t = \frac{\sigma_j^t - \sigma_j^{min}}{\sigma_j^{max} - \sigma_j^{min}}$$

Where σ_j^{min} and σ_j^{max} values are obtained from previous observations

6. Evaluate reassignment of tasks:

6.1 Case 1: $\hat{\sigma}_w^t \leq LCL$ → Human is in boredom state. Add new *task j* without removing the current *task i*

$$\hat{\sigma}_w^{t+1} = \hat{\sigma}_w^t + \hat{\sigma}_i^t + \hat{\sigma}_j^t$$

IF $LCL \leq \hat{\sigma}_w^{t+1} \leq UCL$:

Accept the new assignment

Update time $t = t + 1$

Go to step 1 and verify the stress level using wearable device data.

ELSE consider adding more task and repeat Step 6.1

6.2 Case 2: $\sigma_w^t \leq LCL$ → Human is in boredom state. Replace *task i* with more complex *task j*

$$\hat{\sigma}_w^{t+1} = \hat{\sigma}_w^t - \hat{\sigma}_i^t + \hat{\sigma}_j^t$$

IF $LCL \leq \hat{\sigma}_w^{t+1} \leq UCL$:

Accept the reassignment

Update time $t = t + 1$

Go to Step 1 and verify the stress level using wearable device data.

ELSE consider replacing *task i* with a more challenging task and repeat Step 6.2

6.3 Case 3: $\sigma_w^t \geq UCL$ → Human is in chaos state. Replace *task i* with a simpler *task j*

$$\hat{\sigma}_w^{t+1} = \hat{\sigma}_w^t - \hat{\sigma}_i^t + \hat{\sigma}_j^t$$

IF $LCL \leq \hat{\sigma}_w^{t+1} \leq UCL$:

Accept the reassignment

Update time $t = t + 1$

Go to Step 1 and verify the stress level using wearable device data.

ELSE consider replacing *task i* with a less challenging task and repeat Step 6.3

END

7.3. Monte Carlo Simulation: Intervention-Based Task Reallocation Model

To evaluate the validity of the proposed human-centered dynamic workload reallocation model, a Monte Carlo simulation study was conducted. This simulation aims to offer empirical insights that can guide the design of future controlled experiments and support the adaptation of the proposed model for real-time applications.

The simulation follows a structured sequence of steps:

i. *Parameter Initialization:*

In accordance with Section 2.3.2, key variables were established: actual workload (W^a), perceived workload (W^p), task complexity (C), time-of-day impact (T), and affective state (A).

- W^a and W^p were randomly sampled from a *uniform distribution*, as this distribution is suitable for modeling bounded variables, consistent with project management estimates.
- C, T, and A were generated using *multinomial distributions*, reflecting predefined weighted categories for these variables.

ii. *Task-Specific Stress Computation:*

The stress level associated with each task (σ_i) was calculated using Equation 54 and normalized for comparison.

iii. *Wearable-Based Stress Generation:*

A general stress level (σ_W), mimicking data from wearable sensors, was generated using a *normal distribution* and normalized. This allowed for direct comparison with the task-induced stress values.

iv. *Performance Evaluation:*

Human performance was quantified using Equation 55, which is based on the "Duration-Based Performance Indicator (DPI)" proposed by Yousefi et al. (2019). The DPI was then normalized to reflect a performance percentage.

$$Performance \Rightarrow DPI = \frac{1}{W^p/_{W^a}} = \frac{W^a}{W^p} \tag{55}$$

A DPI approaching zero does not imply zero performance; rather, it indicates extremely low task-related motivation at that specific time and context.

v. *Checkpoint Analysis:*

Two critical checkpoints were assessed:

- *Control Chart Monitoring:* DPI values were monitored to determine if performance remained within control. DPI ≥ 1 indicated that performance was acceptable.
- *Stress Validation:* If performance was out of control, the system checked whether stress was the underlying factor:
    - *Case 1:* If stress was within acceptable bounds, the issue was attributed to other variables (refer to Figure 3: Systems 3 and 5). No intervention occurred.
    - *Case 2:* If stress was beyond thresholds, the individual's state was reclassified. Based on Zhao et al. (2023), the following conditions applied:

$$\mu - 1.5\sigma \leq \sigma_w \leq \mu + 1.2\sigma \tag{56}$$

- $\sigma_w < LCL$: Underload (State = -1)
- $\sigma_w > UCL$: Overload (State = 1)
- $LCL \leq \sigma_w \leq UCL$: Stabilized (State = 0)

If overload or underload was detected, robot intervention was initiated.

vi. *Robot Intervention and Task Reallocation:*

When necessary, the robot reallocated tasks to stabilize the human's stress level. Task-specific stress contributions were recalculated using Equation 54. The updated overall stress at time *t* was determined using Equation 57 below:

$$\sigma_w^t = \sigma_w^{t-1} - \sigma_i^t + \sigma_j^t \tag{57}$$

Here, σ_i^t represents the stress contribution of the removed task, and σ_j^t that of the newly assigned task. If the resulting stress σ_w^t fell within predefined thresholds ($LCL \leq \sigma_w^t \leq UCL$), the new task assignment was confirmed.

7.3.1. Simulation Design and Parameters

In this simulation study, synthetic data were generated to assess the validity of the proposed human-centered task reallocation model. The study setup was as follows:

- *Participants:* 10 individuals
- *Task pool:* Each individual was assigned 20 potential tasks
- *Evaluation frequency:* Performance was assessed at 10 distinct time points throughout the day
- Assumption: None of the tasks were on the project's critical path

This configuration resulted in 2,000 unique data points (10 individuals × 20 tasks × 10 time points), forming the foundation for the simulation analysis.

To account for time-dependent variation in performance, simulation times were distributed across five time slots, as outlined in Table 7:

- 04:00–08:00 → 3%
- 08:00–12:00 → 25%
- 12:00–16:00 → 51%
- 16:00–20:00 → 20%
- 20:00–24:00 → 1%

The *time-of-day selection* was modeled using a *normal distribution*, centered around peak cognitive performance periods (08:00–16:00), based on findings by Kalanadhabhatta et al. (2021), which indicate enhanced mental performance during standard working hours. This approach ensured that data points were predominantly concentrated around these high-performance windows.

7.3.2. Simulation Results and Insights

As summarized in Table 12, only 9% of cases required intervention—triggered when wearable-derived stress measurements diverged significantly from the expected stress levels calculated through task-based parameters.

Table 12: The Distribution of Data in the Monte Carlo Simulation of the Proposed Model: **I**=Intervene; **NI**=Not intervene

Simulated Personas	**Time of the Day**									
	04:00-08:00		**08:00-12:00**		**12:00-16:00**		**16:00-20:00**		**20:00-24:00**	
	I	**NI**	**I**	**NI**	**I**	**NI**	**I**	**NI**	**I**	**NI**
Person 1	0	0	3	37	6	134	2	18	0	0
Person 2	0	20	6	54	13	67	3	37	0	0
Person 3	0	0	4	56	14	126	0	0	0	0
Person 4	0	0	8	72	10	90	1	19	0	0
Person 5	0	0	0	0	14	126	4	56	0	0
Person 6	0	0	7	93	1	79	2	18	0	0
Person 7	0	0	1	39	8	92	8	52	0	0
Person 8	1	19	6	34	7	53	8	52	1	19
Person 9	0	0	3	57	10	50	9	71	0	0
Person 10	2	18	0	20	13	107	5	35	0	0
Total number of simulations	3	57	38	462	96	924	42	358	1	19
% of total Simulation cases	0.15	2.85	1.9	23.1	4.8	46.2	2.1	17.9	0.05	0.95

Table 13: Monte Carlo Simulation Results for the Proposed Model

Simulated Personas	**t: The time irregularity is observed**	**Task i**			**Task j**			**Expected Improvement through intervention (%)**
		σ_w^t **with** $Task\ i$	**Human State with** $Task\ i$ **{-1, 0, 1}**	**Task-Specific** DPI_i **(%)**	σ_w^t **with** $Task\ j$	**Human State with** $Task\ j$ **{-1, 0, 1}**	**Task-Specific** DPI_j **(%)**	
Person 1	11:59:00 AM	0.28	-1	9	0.74	0	25	16
Person 2	1:53:00 PM	0.80	1	2	0.68	0	37	35
Person 3	3:15:00 PM	0.18	-1	19	0.38	0	54	34
Person 4	4:05:00 PM	0.22	-1	0	0.59	0	66	66
Person 5	4:00:00 PM	0.77	1	8	0.58	0	28	19
Person 6	8:52:00 AM	0.76	1	14	0.41	0	95	81
Person 7	12:29:00 PM	0.20	-1	1	0.69	0	48	47
Person 8	8:12:00 PM	0.13	-1	1	0.67	0	74	73
Person 9	6:58:00 PM	0.93	1	2	0.63	0	79	77
Person 10	7:16:00 AM	0.86	1	9	0.39	0	93	84
Average				**7**			**60**	**53**

Table 13 presents a detailed comparison of ten simulation points across ten individuals. Each case documents Task i (initial assignment) and Task j (reallocated alternative), with corresponding stress levels measured using wearable devices. These cases demonstrate how robot-assisted reallocation adjusts task assignments to bring the individual's emotional and physiological state closer to a stable condition.

It is important to note that, due to the randomized input structure, the precise numerical effect of task substitution on stress (as described by Equation 8) cannot be validated deterministically. However, the aggregate outcomes were encouraging. Average performance without intervention was only 7%, whereas robot-assisted task reallocation led to an improvement up to 60%—an increase of 53%. Additionally, participants' emotional states shifted from overloaded or underloaded conditions (± 1) to a stabilized state (0), indicating successful stress regulation through intelligent intervention.

8. DISCUSSIONS

This thesis focuses on robots' capabilities to observe their human partners, interpret their performance along with corresponding emotional and stress states, and act accordingly within human-robot collaboration to make smart systems more symbiotic and proactive. To this end, the literature was thoroughly reviewed to identify current technologies capable of recognizing both covert and overt human intentions. It was found that recent advancements are sufficient to assess human behaviors, cognitive states, and emotional conditions.

This finding led to the formulation of the central research question: *"How can the collaborative performance of a human-robot team be improved through a robot-supervised decision mechanism for workload allocation based on fluctuations in human stress levels?"* This question formed the foundation and objective of the thesis.

To address this question, the structure of human-robot systems was first analyzed. Particular attention was given to the communication channels and interaction modes through which collaboration occurs. The differences between these terms were clarified, and their roles in task execution were investigated. In addition, performance factors influencing these channels and modes were examined, leading to the identification of task zones that facilitate robots' role in task allocation. These zones were defined according to the distinct characteristics of system members—namely, humans, robots, or their joint activities.

Once the foundational components of communication and collaboration were established, a stress-aware dynamic task allocation algorithm was proposed for robots to apply when intervention becomes necessary. The algorithm was conceptually implemented within the context of the SAP system architecture, which integrates numerous subsystems and provides visibility into various communication channels during operational processes. Although current SAP systems are not equipped with the necessary capabilities to detect users' affective or cognitive states, it is assumed that future systems will possess the intelligence required to collaborate with users in the proposed manner.

Following this, the regulation of human stress became a central focus. It was hypothesized that certain performance signals could trigger robot intervention. According to the literature, human performance often reflects underlying emotional or affective states. Thus, human performance was chosen as the entry point for the proposed model: *"Robot-supervised intelligent workload reallocation based on stress-aware human performance monitoring in human-robot teams."*

Accordingly, after reviewing the stress–performance relationship, performance parameters for each member in a multi-human, multi-robot system were analyzed in detail to understand their collective impact on team output. Furthermore, the individual parameters influencing human stress and performance were examined, leading to the identification of a self-feeding loop—a dynamic cycle in which output parameters from one stage serve as input parameters for the next. This feedback structure highlights the temporal dependencies within the system.

The next step was to evaluate how other researchers measure human stress levels. A comprehensive review of stress detection methods was conducted to identify effective techniques, drawing on validated approaches. Based on this analysis, wristbands were selected as the most efficient, accurate, and non-intrusive solution for monitoring stress in real-time.

However, measuring overall human stress alone was not sufficient for the scope of this study. Since human stress may fluctuate for various reasons, this thesis focused specifically on how task-induced stress contributes to general stress levels. This is critical, as the aim is to regulate human stress through task reallocation. Consequently, the quantification of task-specific stress contribution became essential.

To address this, a conceptual formula was developed to calculate the stress induced by individual tasks. This formula incorporates parameters such as perceived workload, task complexity, time of day, actual workload, and mood-related affective states. According to this formulation, the task-specific effect on human stress can be estimated, enabling more informed task allocation decisions.

Finally, the process flow of the proposed model was visualized and tested using a Monte Carlo simulation. Although there was insufficient time to conduct controlled experiments for real-world implementation, the simulation study yielded promising results. The objective was to sustain optimal performance by maintaining human stress within an ideal range. The results showed that the proposed system successfully maintains stress at manageable levels while simultaneously enhancing performance.

8.1. Practical Applications of Stress-Aware Human-Robot Collaborations

Even though the proposed framework introduces a generic algorithm for human-robot collaboration—where a robot can represent any computerized smart system—it is evident that the framework is applicable to various domains sensitive to workload fluctuations in human performance, such as manufacturing and assembly lines, healthcare and assistive robotics, transportation and logistics, and military and emergency response. However, since the concrete measurement of stress remains the primary challenge in this study, the numerical values within the proposed model cannot be generalized. In other words, no universally accepted quantitative method has yet been introduced to measure human stress levels; therefore, generic thresholds cannot be defined across all application areas. Moreover, different fields may require distinct optimal values to successfully accomplish their corresponding tasks. Consequently, this study generalizes that neither low nor high stress levels support optimal human performance, but rather a moderate level of stress enables maximum human efficiency. Building on this principle, the proposed model formalizes human-robot teaming by allocating workload according to stress levels.

8.2. Ethical Considerations in Stress-Aware Human-Robot Collaboration

Ethical concerns inevitably arise in team collaborations where humans are involved. As Paul et al. (2022) note, embedding ethics into technology is challenging, yet it remains essential to account for human perceptions of collaboration's ethical dynamics. These dynamics include **fairness** (justice, non-discrimination, equity), **trust and transparency** (explainability, reliability), **accountability** (responsibility, liability), and **well-being** (safety, cognitive load).

Ali et al. (2022) examined role allocation between humans and robots, suggesting that robots should assume task-allocation responsibilities to reduce human workload and allow humans to concentrate on execution. However, in high-risk domains such as healthcare or military operations, human judgment remains indispensable. Where applicable, research supports automation-driven allocation as a means of facilitating effective collaboration.

Kim and Phillips (2021) hypothesized that maintaining fairness in human-robot collaboration enhances motivation and fosters acceptance of robot decisions. Ali et al. (2022) similarly emphasized fairness in shaping team relationships and performance, while also highlighting the importance of negotiation. In this vein, Roncone et al. (2017) proposed a method that allows humans to either accept or reject a robot's decision regarding task execution. Such negotiation ensures fairness and strengthens trust within the collaboration.

When considering task reallocation, **trust** becomes the pivotal factor influencing both individual and team performance. Lee and See (2004) classified trust into three categories: *undertrust, overtrust,* and *calibrated trust*. Undertrust results in the disuse of robotic capacity, while overtrust can lead to misuse through inflated expectations of robot capability. Both disuse and misuse hinder team performance, as highlighted by Azevedo-Sa et al. (2020). Only calibrated trust—where robot capacity aligns with human expectations—supports effective collaboration.

Ali et al. (2022) further linked trust to task allocation, noting that undertrust may cause humans to underestimate the benefits of robot decision-making, while overtrust may lead them to accept decisions without sufficient scrutiny. Calibrated trust, on the other hand, fosters **shared understanding**, which introduces another ethical dimension: **shared situational awareness.** This alignment of team members' mental models toward a common goal is critical, as Hagos et al. (2024) argue, for effective decision-making in collaborative systems.

Although ethical considerations lie beyond the primary scope of this thesis, their influence on human perception is undeniable. Ethical dynamics directly shape stress levels, trust, and ultimately human performance—factors that are central to the success of human-robot collaboration.

9. LIMITATIONS

While this study presents a novel framework for stress-aware human-robot collaboration, several limitations should be acknowledged.

First, the framework is currently limited to a single-human, single-robot, single-task scenario. Real-world applications often involve multiple humans, robots, and tasks interacting dynamically. The lack of simulation or experimentation in complex n-human–n-robot–n-task environments constrains the generalizability of the findings. Additionally, although the system attends to the task actively pursued by a human at a given moment, it does not fully account for the background influence of other pending tasks, which may still affect stress levels. These indirect effects are assumed to be partially captured through affective state parameters, as outlined in Equation 4, but further empirical validation is required.

Second, the current model does not address situations that require simultaneous task reallocations, as it assumes a human can only manage one task at any given time. In such cases, a more complex multi-agent environment should be considered. This simplification underscores the need for future research involving adaptive strategies for dynamic, multi-task settings.

Third, although a simulation study was conducted, the system lacks validation through quantitative performance metrics such as task completion time, error rates, or productivity indices. Moreover, the framework has not yet been tested across robots with varying levels of intelligence or integrated with different systems. As a result, its ability to function effectively in diverse real-world applications—where such variability is common—remains uncertain.

Fourth, long-term changes in human capability and stress levels were not examined due to the absence of longitudinal experiments. As such, the model's capacity to adapt to evolving human states over time remains an open question for future investigation.

Despite these limitations, this work contributes a foundational model for robot-supervised decision-making under uncertain human performance. The framework demonstrates how robots can monitor human activity, estimate task-induced stress, and intelligently intervene to optimize collaboration. Although full-scale experimental validation remains a future goal, the simulation results provide promising preliminary evidence that targeted interventions can stabilize human stress levels and improve overall team performance.

10. FUTURE WORK

As noted in the Discussion and Limitations sections, this study could not be validated through controlled experiments, which limits the assessment of its effectiveness in real-world applications. Future research should therefore focus on conducting such experiments—particularly within multi-human, multi-robot systems—to evaluate the impact of the proposed model under complex and dynamic collaboration conditions.

Additionally, this study highlights the importance of quantifying task-specific stress contributions to overall human stress in order to guide accurate task allocation. While a conceptual formula was proposed and demonstrated promising results in simulation, it lacks empirical validation and mathematical rigor. Future work should include controlled experimental studies to evaluate the formula's effectiveness and determine its success rate in practical settings.

To enhance the reliability of this quantification, the development of a mathematical model is recommended alongside the existing conceptual framework. In this context, the logic of electrical circuits—particularly the self-feeding loop structure discussed in the thesis—may offer a useful analogy. Applying Kirchhoff's Current and Voltage Laws could provide a systematic approach for modeling stress flow and feedback within the task allocation process, leading to a more concrete and testable mathematical representation.

11. CONCLUSIONS

This thesis has explored the integration of stress-aware decision-making into human-robot collaboration, focusing on how robots can adaptively manage workload in response to fluctuations in human performance. The study contributes to the broader field of intelligent systems by framing collaboration not only in terms of efficiency but also in relation to human cognitive and emotional well-being.

Rather than treating robots as passive executors of predefined tasks, the proposed framework positions them as active observers and adaptive decision-makers—capable of interpreting human states and responding accordingly. This human-centered approach aligns with emerging trends in proactive and symbiotic robotics, where the goal is to foster sustainable, responsive, and psychologically supportive collaboration environments.

Although implemented and evaluated within a simplified context, the framework opens several pathways for future research. Extending this work to multi-agent systems, integrating long-term learning mechanisms, and validating real-time performance through field experiments will be essential steps toward operationalizing stress-responsive robotic systems in practical settings.

The findings highlight the importance of incorporating affective understanding into collaborative technologies. As the boundaries between human and robot capabilities continue to blur, designing systems that can perceive, interpret, and respond to human needs in real time will be critical for advancing the next generation of human-robot partnerships.

REFERENCES

Abbink, D. A., Carlson, T., Mulder, M., De Winter, J. C., Aminravan, F., Gibo, T. L., & Boer, E. R. (2018). A topology of shared control systems—Finding common ground in diversity. *IEEE Transactions on Human-Machine Systems, 48*(5), 509–525. https://doi.org/10.1109/THMS.2018.2791570

Ali, A., Tilbury, D. M., & Robert Jr, L. P. (2022). Considerations for task allocation in human-robot teams. arXiv preprint arXiv:2210.03259.

Alirezazadeh, S., & Alexandre, L. A. (2022). Dynamic task scheduling for human–robot collaboration. *IEEE Robotics and Automation Letters, 7*(4), 8699–8704. https://doi.org/10.1109/LRA.2022.3188906

Al-Shargie, F., Kiguchi, M., Badruddin, N., Dass, S. C., Hani, A. F. M., & Tang, T. B. (2016). Mental stress assessment using simultaneous measurement of EEG and fNIRS. *Biomedical Optics Express, 7*(10), 3882–3898. https://doi.org/10.1364/BOE.7.003882

Antón-Haro, C., Lestable, T., Lin, Y., Nikaein, N., Watteyne, T., & Alonso-Zarate, J. (2013). Machine-to-machine: An emerging communication paradigm. *Transactions on Emerging Telecommunications Technologies, 24*(4), 353–354. https://doi.org/10.1002/ett.2668

Anzalone, S. M., Boucenna, S., Ivaldi, S., & Chetouani, M. (2015). Evaluating the engagement with social robots. *International Journal of Social Robotics, 7*(4), 465–478. https://doi.org/10.1007/s12369-015-0298-7

Attar, E. T. (2022). Review of electroencephalography signals approaches for mental stress assessment. *Neurosciences*, *27*(4), 209–215. https://doi.org/10.17712/nsj.2022.4.20220025

Awada, M., Becerik-Gerber, B., Lucas, G. M., & Roll, S. C. (2024). Stress appraisal in the workplace and its associations with productivity and mood: Insights from a multimodal machine learning analysis. *PLOS ONE, 19*(1), e0296468. https://doi.org/10.1371/journal.pone.0296468

Azevedo-Sa, H., Jayaraman, S. K., Yang, X. J., Robert, L. P., & Tilbury, D. M. (2020). Context-adaptive management of drivers' trust in automated vehicles. IEEE Robotics and Automation Letters, 5(4), 6908-6915.

Barnes, M. J., Chen, J. Y., & Jentsch, F. (2015, October). Designing for mixed-initiative interactions between human and autonomous systems in complex environments. *In 2015 IEEE International Conference on Systems, Man, and Cybernetics* (pp. 1386–1390). IEEE. https://doi.org/10.1109/SMC.2015.246

Behinaein, B., Bhatti, A., Rodenburg, D., Hungler, P., & Etemad, A. (2021, September). A transformer architecture for stress detection from ECG. In *Proceedings of the 2021 ACM International Symposium on Wearable Computers* (pp. 132–134). https://doi.org/10.1145/3460421.3480427

Bello-Orgaz, G., & Menéndez, H. D. (2023, April). *Smartphones and wristbands detect stress as good as intrusive physiological devices*. In *WorldCist '23 – 11th World Conference on Information Systems and Technologies* (pp. 308–319). Springer. https://doi.org/10.1007/978-3-031-45642-8_31

Bergman, M., de Joode, E., de Geus, M., & Sturm, J. (2019). Human-cobot teams: Exploring design principles and behaviour models to facilitate the understanding of non-verbal communication from cobots. *Proceedings of the 3rd International Conference on Computer-Human Interaction Research and Applications*, 191–198. https://doi.org/10.5220/0008363201910198

Biondi, F. N., Cacanindin, A., Douglas, C., & Cort, J. (2021). Overloaded and at work: Investigating the effect of cognitive workload on assembly task performance. *Human Factors, 63*(5), 813–820. https://doi.org/10.1177/0018720820929928

Bitkina, O. V., Park, J., & Kim, H. K. (2021). The ability of eye-tracking metrics to classify and predict the perceived driving workload. *International Journal of Industrial Ergonomics, 86*, 103193. https://doi.org/10.1016/j.ergon.2021.103193

Borges, G. D., Reis, A. M., Ariente Neto, R., Mattos, D. L. D., Cardoso, A., Gonçalves, H., ... & Arezes, P. (2021). Decision-making framework for implementing safer human-robot collaboration workstations: System dynamics modeling. *Safety, 7*(4), 75. https://doi.org/10.3390/safety7040075

Boy, G. A. (Ed.). (2017). *The handbook of human-machine interaction: A human-centered design approach*. CRC Press.

Broo, D. G. (2022). Transdisciplinarity and three mindsets for sustainability in the age of cyber-physical systems. *Journal of Industrial Information Integration, 27*, 100290. https://doi.org/10.1016/j.jii.2021.100290

Caulcutt, R. (2004). Control charts in practice. *Significance, 1*(2), 81–84. https://doi.org/10.1111/j.1740-9713.2004.024.x

Carlson, T., & Demiris, Y. (2012). Collaborative control for a robotic wheelchair: Evaluation of performance, attention, and workload. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 42*(3), 876–888. https://doi.org/10.1109/TSMCB.2011.2181833

Chen, M., Herrera, F., & Hwang, K. (2018). Cognitive computing: Architecture, technologies and intelligent applications. *IEEE Access, 6*, 19774–19783. https://doi.org/10.1109/ACCESS.2018.2791469

Chi, C., Sun, X., Xue, N., Li, T., & Liu, C. (2018). Recent progress in technologies for tactile sensors. *Sensors*, *18*(4), 948. https://doi.org/10.3390/s18040948

Cittadini, R., Tamantini, C., Scotto di Luzio, F., Lauretti, C., Zollo, L., & Cordella, F. (2023). Affective state estimation based on Russell's model and physiological measurements. *Scientific Reports, 13*, 9786. https://doi.org/10.1038/s41598-023-36915-6

Creech, N., Pacheco, N. C., & Miles, S. (2021). Resource allocation in dynamic multiagent systems. *arXiv*. https://doi.org/10.48550/arXiv.2102.08317

Cruz, F., Dazeley, R., Vamplew, P., & Moreira, I. (2021). Explainable robotic systems: Understanding goal-driven actions in a reinforcement learning scenario. *Neural Computing and Applications, 35*(25), 18113–18130. https://doi.org/10.1007/s00521-021-06425-5

Dahiya, A., Aroyo, A. M., Dautenhahn, K., & Smith, S. L. (2023). A survey of multi-agent human–robot interaction systems. *Robotics and Autonomous Systems, 161*, 104335. https://doi.org/10.1016/j.robot.2022.104335

Dahl, M., Bengtsson, K., & Falkman, P. (2021). Application of the sequence planner control framework to an intelligent automation system with a focus on error handling. *Machines, 9*(3), 59. https://doi.org/10.3390/machines9030059

Damacharla, P., Javaid, A. Y., Gallimore, J. J., & Devabhaktuni, V. K. (2018). Common metrics to benchmark human-machine teams (HMT): A review. *IEEE Access, 6*, 38637–38655. https://doi.org/10.1109/ACCESS.2018.2853560

Dao, J., Liu, R., & Solomon, S. (2024). State anxiety biomarker discovery: Electrooculography and electrodermal activity in stress monitoring. *arXiv preprint* arXiv:2411.17935. https://arxiv.org/abs/2411.17935

Darvish, K., Simetti, E., Mastrogiovanni, F., & Casalino, G. (2021). A hierarchical architecture for human–robot cooperation processes. *IEEE Transactions on Robotics, 7*(2), 567–586. C:\Users\rukiyekirgilbudakli\Downloads\10.1109\TRO.2020.3033715

Das, A. K., Kumar, P., & Halder, S. (2023). Complexity analysis of ocular signal for detection of human fatigue using small datasets. *Procedia Computer Science, 218*, 858–866. https://doi.org/10.1016/j.procs.2023.01.066Get rights and content

Debie, E., Rojas, R. F., Fidock, J., Barlow, M., Kasmarik, K., Anavatti, S., ... & Abbass, H. A. (2019). Multimodal fusion for objective assessment of cognitive workload: A review. *IEEE Transactions on Cybernetics, 51*(3), 1542–1555. https://doi.org/10.1109/TCYB.2019.2939399

Del Carretto Di Ponti E Sessam, E. (2023). *Exploring the impact of stress and cognitive workload on eye movements: A preliminary study* (Doctoral dissertation, Politecnico di Torino). http://webthesis.biblio.polito.it/id/eprint/29968

di Fiore, A., & Schneider, S. (2017). *Crowd-scanning: The future of open innovation and artificial intelligence*. LSE Business Review. Retrieved from https://blogs.lse.ac.uk/businessreview/2017/10/30/crowd-scanning-the-future-of-open-innovation-and-artificial-intelligence/

D'Mello, S., Picard, R. W., & Graesser, A. (2007). Toward an affect-sensitive AutoTutor. *IEEE Intelligent Systems, 22*(4), 53–61. https://doi.org/10.1109/MIS.2007.79

Dromnelle, R., Renaudo, E., Chetouani, M., Maragos, P., Chatila, R., Girard, B., & Khamassi, M. (2023). Reducing computational cost during robot navigation and human–robot interaction with a human-inspired reinforcement learning architecture. *International Journal of Social Robotics, 15*(8), 1297–1323. https://doi.org/10.1007/s12369-022-00942-6

Dutta, V., & Zielińska, T. (2021). Cybersecurity of robotic systems: Leading challenges and robotic system design methodology. *Electronics, 10*(22), 2850. https://doi.org/10.3390/electronics10222850

Fahn, C. S., Chen, S. C., Wu, P. Y., Chu, T. L., Li, C. H., Hsu, D. Q., ... & Tsai, H. M. (2022, November). Image and speech recognition technology in the development of an elderly care robot: Practical issues review and improvement strategies. *Healthcare, 10*(11), 2252. https://doi.org/10.3390/healthcare10112252

Feigh, K. M., & Pritchett, A. R. (2014). Requirements for effective function allocation: A critical review. *Journal of Cognitive Engineering and Decision Making, 8*(1), 23–32. https://doi.org/10.1177/1555343413490945

Fischer, C., & Pöhler, A. (2018). Supporting the change to digitalized production environments through learning organization development. In C. Harteis (Ed.), *The Impact of Digitalization in* *the Workplace: An Educational View* (Professional and Practice-Based Learning, Vol. 21, pp. 141–160). Springer, Cham. https://doi.org/10.1007/978-3-319-63257-5_10

Floridi, L. (2020). What the near future of artificial intelligence could be. In C. L. Floridi (Ed.), *2019 Yearbook of the Digital Ethics Lab* (pp. 127–142). Springer. https://doi.org/10.1007/s13347-019-00345-y

Gallala, A., Kumar, A. A., Hichri, B., & Plapper, P. (2022). Digital twin for human–robot interactions by means of Industry 4.0 enabling technologies. *Sensors, 22*(13), 4950. https://doi.org/10.3390/s22134950

Gazetta, G., Miller, C., Clemency, B., Tanaka, K., Hackett, M., Norfleet, J., ... & Cavuoto, L. (2023, September). Evaluating workload indicators for learning during stress exposure training of endotracheal intubation. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 67*(1), 574–578. https://doi.org/10.1177/21695067231199681

Giantamidis, G., Tripakis, S., & Basagiannis, S. (2021). Learning Moore machines from input–output traces. *International Journal on Software Tools for Technology Transfer, 23*(1), 1–29. https://doi.org/10.1007/s10009-019-00544-0

Gjoreski, M., Luštrek, M., Gams, M., & Gjoreski, H. (2017). Monitoring stress with a wrist device using context. *Journal of Biomedical Informatics, 73*, 159–170. https://doi.org/10.1016/j.jbi.2017.08.006

Gombolay, M., Bair, A., Huang, C., & Shah, J. (2017). Computational design of mixed-initiative human–robot teaming that considers human factors: Situational awareness, workload, and workflow preferences. *The International Journal of Robotics Research, 36*(5–7), 597–617. https://doi.org/10.1177/0278364916688255

Guo, H., Pu, X., Chen, J., Meng, Y., Yeh, M. H., Liu, G., ... & Wang, Z. L. (2018). A highly sensitive, self-powered triboelectric auditory sensor for social robotics and hearing aids. *Science Robotics, 3*(20), eaat2516. https://doi.org/10.1126/scirobotics.aat2516

Guo, J., Tao, D., & Yang, C. (2020). The effects of continuous conversation and task complexity on usability of an AI-based conversational agent in smart home environments. *In* S. Long & B. S. Dhillon (Eds.), *Man–Machine–Environment System Engineering: Proceedings of the 19th International Conference on MMESE* (Lecture Notes in Electrical Engineering, Vol. 576, pp. 695–703). Springer, Singapore. https://doi.org/10.1007/978-981-13-8779-1_79

Gutzwiller, R. S., Lange, D. S., Reeder, J., Morris, R. L., & Rodas, O. (2015). Human-computer collaboration in adaptive supervisory control and function allocation of autonomous system teams. In R. Shumaker & S. Lackey (Eds.), *Virtual, Augmented and Mixed Reality – 7th International Conference, VAMR 2015, Held as Part of HCI International 2015, Proceedings, Part II* (Lecture Notes in Computer Science, Vol. 9179, pp. 447–456). Springer. https://doi.org/10.1007/978-3-319-21067-4_46

Hardin, B., & Goodrich, M. A. (2009, March). On using mixed-initiative control: A perspective for managing large-scale robotic teams. *In Proceedings of the 4th ACM/IEEE International Conference on Human-Robot Interaction* (pp. 165–172). https://doi.org/10.1145/1514095.1514126

Harriott, C. E., Buford, G. L., Adams, J. A., & Zhang, T. (2015). Mental workload and task performance in peer-based human-robot teams. *Journal of Human-Robot Interaction, 4*(2), 61–96. https://doi.org/10.5898/JHRI.4.2.Harriott

He, H., Gray, J., Cangelosi, A., Meng, Q., McGinnity, T. M., & Mehnen, J. (2021). The challenges and opportunities of human-centered AI for trustworthy robots and autonomous systems. *IEEE Transactions on Cognitive and Developmental Systems, 14*(4), 1398–1412. https://doi.org/10.1109/TCDS.2021.3132282

Heard, J., Harriott, C. E., & Adams, J. A. (2018). A survey of workload assessment algorithms. *IEEE Transactions on Human-Machine Systems, 48*(5), 434–451. https://doi.org/10.1109/THMS.2017.2782483

Hemakom, A., Atiwiwat, D., & Israsena, P. (2023). ECG and EEG-based detection and multilevel classification of stress using machine learning for specified genders: A preliminary study. *PLOS ONE, 18*(9), e0291070. https://doi.org/10.1371/journal.pone.0291070

Hooey, B. L., Kaber, D. B., Adams, J. A., Fong, T. W., & Gore, B. F. (2017). The underpinnings of workload in unmanned vehicle systems. *IEEE Transactions on Human-Machine Systems, 48*(5), 452–467. https://doi.org/10.1109/THMS.2017.2759758

Horváth, I., Rusák, Z., Hou, Y., & Ji, L. (2014). On some theoretical issues of interaction with socialized and personalized cyber-physical systems. In *Informatik 2014*.

Horváth, I., Rusák, Z., & Li, Y. (2017, August). Order beyond chaos: Introducing the notion of generation to characterize the continuously evolving implementations of cyber-physical systems. In *ASME 2017 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. American Society of Mechanical Engineers. https://doi.org/10.1115/DETC2017-67082

Horváth, I., & Wang, J. (2015, August). Towards a comprehensive theory of multi-aspect interaction with cyber physical systems. In *ASME 2015 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*. American Society of Mechanical Engineers. https://doi.org/10.1115/DETC2015-47243

Huang, C. M., Andrist, S., Sauppé, A., & Mutlu, B. (2015). Using gaze patterns to predict task intent in collaboration. *Frontiers in Psychology, 6*, 1049. https://doi.org/10.3389/fpsyg.2015.01049

Humann, J., Fletcher, T., & Gerdes, J. (2023). Modeling, simulation, and trade-off analysis for multirobot, multioperator surveillance. *Systems Engineering*. https://doi.org/10.1002/sys.21685

Hussein, A., Gaber, M. M., Elyan, E., & Jayne, C. (2017). Imitation learning: A survey of learning methods. *ACM Computing Surveys (CSUR), 50*(2), 1–35. https://doi.org/10.1145/3054912

IJtsma, M., Ma, L. M., Pritchett, A. R., & Feigh, K. M. (2019). Computational methodology for the allocation of work and interaction in human-robot teams. *Journal of Cognitive Engineering and Decision Making, 13*(4), 221–241. https://doi.org/10.1177/1555343419869484

Jabon, M., Bailenson, J., Pontikakis, E., Takayama, L., & Nass, C. (2010). Facial expression analysis for predicting unsafe driving behavior. *IEEE Pervasive Computing, 10*(4), 84–95. https://doi.org/10.1109/MPRV.2010.46

Ji, Z., Liu, Q., Xu, W., Yao, B., Liu, J., & Zhou, Z. (2021). A closed-loop brain-computer interface with augmented reality feedback for industrial human-robot collaboration. *The International Journal of Advanced Manufacturing Technology*, 1–16. https://doi-org.lib-ezproxy.concordia.ca/10.1007/s00170-021-07937-z

Jo, W., Wang, R., Yang, B., Foti, D., Rastgaar, M., & Min, B. C. (2024). Cognitive load-based affective workload allocation for multihuman multirobot teams. *IEEE Transactions on Human-Machine Systems.* Advance online publication. https://doi.org/10.1109/THMS.2024.3509223

Johannsmeier, L., & Haddadin, S. (2016). A hierarchical human–robot interaction-planning framework for task allocation in collaborative industrial assembly processes. *IEEE Robotics and Automation Letters, 2*(1), 41–48. https://doi.org/10.1109/LRA.2016.2535907

Kalanadhabhatta, M., Rahman, T., & Ganesan, D. (2021). Effect of sleep and biobehavioral patterns on multidimensional cognitive performance: Longitudinal, in-the-wild study. *Journal of Medical Internet Research, 23*(2), e23936. https://doi.org/10.2196/23936

Kaltwang, S., Rudovic, O., & Pantic, M. (2012, July). Continuous pain intensity estimation from facial expressions. *In Advances in Visual Computing: International Symposium on Visual Computing* (Lecture Notes in Computer Science, Vol. 7432, pp. 368–377). Springer. https://doi.org/10.1007/978-3-642-33191-6_36

Katmah, R., Al-Shargie, F., Tariq, U., Babiloni, F., Al-Mughairbi, F., & Al-Nashash, H. (2021). A review on mental stress assessment methods using EEG signals. *Sensors, 21*(15), 5043. https://doi.org/10.3390/s21155043

Khamis, A., Hussein, A., & Elmogy, A. (2015). Multi-robot task allocation: A review of the state-of-the-art. *Cooperative Robots and Sensor Networks 2015*, 31–51. https://doi.org/10.1007/978-3-319-18299-5_2

Kim, B., & Phillips, E. (2021). Humans' assessment of robots as moral regulators: Importance of perceived fairness and legitimacy. arXiv preprint arXiv:2110.04729.

Kim, D. H., Song, J. Y., Lee, J. H., & Cha, S. K. (2009). Development and evaluation of intelligent machine tools based on knowledge evolution in M2M environment. *Journal of Mechanical Science and Technology, 23*(10), 2807–2813. https://doi.org/10.1007/s12206-009-0725-5

Kim, Y., Lee, H., & Provost, E. M. (2013, May). Deep learning for robust feature generation in audiovisual emotion recognition. In *2013 IEEE International Conference on Acoustics, Speech and Signal Processing* (pp. 3687–3691). IEEE.

Kirtay, M., Hafner, V. V., Asada, M., & Oztop, E. (2023). Trust in robot-robot scaffolding. *IEEE Transactions on Cognitive and Developmental Systems, 15*(4), 1841–1852. https://doi.org/10.1109/TCDS.2023.3235974

Kleitman, N. (1933). Studies on the physiology of sleep: VIII. Diurnal variation in performance. *American Journal of Physiology-Legacy Content, 104*(2), 449–456. https://doi.org/10.1152/ajplegacy.1933.104.2.449

Kolb, J., Ravichandar, H., & Chernova, S. (2022, August). Leveraging cognitive states in human-robot teaming. *In 2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)* (pp. 792–799). IEEE. https://doi.org/10.1109/RO-MAN53752.2022.9900794

Kosa, G., Morozov, O., Lehmann, A., Pargger, H., Marsch, S., & Hunziker, P. (2023). Robots and intelligent medical devices in the intensive care unit: Vision, state of the art and economic analysis. *IEEE Transactions on Medical Robotics and Bionics*. https://doi.org/10.1109/TMRB.2023.3240537

Lachance-Tremblay, J., Tkiouat, Z., Léger, P. M., Cameron, A. F., Titah, R., Coursaris, C. K., & Sénécal, S. (2025). A gaze-based driver distraction countermeasure: Comparing effects of multimodal alerts on driver's behavior and visual attention. *International Journal of Human-Computer Studies, 193*, 103366. https://doi.org/10.1016/j.ijhcs.2024.103366

Lauterbach, B., Sauer, S., Gottlieb, J., Sürie, C., & Benz, U. (2019). *Transportation management with SAP* (3rd ed.). Rheinwerk Publishing, Inc. Retrieved from https://www.perlego.com/book/2826166/transportation-management-with-sap-pdf

Le, K. B. Q., Sajtos, L., Kunz, W. H., & Fernandez, K. V. (2024). The future of work: Understanding the effectiveness of collaboration between human and digital employees in service. *Journal of Service Research, 28*(1), 1–20. https://doi.org/10.1177/10946705241229419

Lee, E. A. (2008, May). Cyber physical systems: Design challenges. *In 2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC)* (pp. 363–369). IEEE. https://doi.org/10.1109/ISORC.2008.25

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. Human factors, 46(1), 50-80.

Lee, K., & McGreevey, C. (2002). Using control charts to assess performance measurement data. *The Joint Commission Journal on Quality Improvement, 28*(2), 90–101. https://doi.org/10.1016/S1070-3241(02)28009-8

Lei, Y., Su, Z., & Cheng, C. (2023). Virtual reality in human–robot interaction: Challenges and benefits. *Electronic Research Archive, 31*(5), 2374–2408. https://doi.org/10.3934/era.2023121

Lee, Y., Song, W. J., & Sun, J. Y. (2020). Hydrogel soft robotics. *Materials Today Physics, 15*, 100258. https://doi.org/10.1016/j.mtphys.2020.100258

Lemaignan, S., Warnier, M., Sisbot, E. A., Clodic, A., & Alami, R. (2017). Artificial cognition for social human–robot interaction: An implementation. *Artificial Intelligence, 247*, 45–69. https://doi.org/10.1016/j.artint.2016.07.002

Li, S., Wang, R., Zheng, P., & Wang, L. (2021). Towards proactive human–robot collaboration: A foreseeable cognitive manufacturing paradigm. *Journal of Manufacturing Systems, 60*, 547–552. https://doi.org/10.1016/j.jmsy.2021.07.017

Li, S., Zheng, P., Liu, S., Wang, Z., Wang, X. V., Zheng, L., & Wang, L. (2023). Proactive human–robot collaboration: Mutual-cognitive, predictable, and self-organising perspectives. *Robotics and Computer-Integrated Manufacturing, 81*, 102510. https://doi.org/10.1016/j.rcim.2022.102510

Liu, Z., Yang, D. S., Wen, D., Zhang, W. M., & Mao, W. (2011). Cyber-physical-social systems for command and control. *IEEE Intelligent Systems, 26*(4), 92–96. https://doi.org/10.1109/MIS.2011.69

Lopez-de-Ipina, K., Iradi, J., Fernandez, E., Calvo, P. M., Salle, D., Poologaindran, A., Villaverde, I., Daelman, P., Sanchez, E., Requejo, C., & Suckling, J. (2023). HUMANISE: Human-inspired smart management, towards a healthy and safe industrial collaborative robotics. *Sensors, 23*(3), Article 1170. https://doi.org/10.3390/s23031170

Lyons, J. B., & Stokes, C. K. (2012). Human–human reliance in the context of automation. *Human Factors, 54*(1), 112–121. https://doi.org/10.1177/0018720811427034

Maeda, G., Neumann, G., Ewerton, M., Lioutikov, R., Kroemer, O., & Peters, J. (2017). Probabilistic movement primitives for coordination of multiple human–robot collaborative tasks. *Autonomous Robots, 41*(3), 593–612. https://doi.org/10.1007/s10514-016-9556-2

Malta, L., Miyajima, C., Kitaoka, N., & Takeda, K. (2011). Analysis of real-world driver's frustration. *IEEE Transactions on Intelligent Transportation Systems, 12*(1), 109–118. https://doi.org/10.1109/TITS.2010.2070839

Marculescu, R., & Bogdan, P. (2010). Cyberphysical systems: Workload modeling and design optimization. *IEEE Design & Test of Computers, 28*(4), 78–87. https://doi.org/10.1109/MDT.2010.142

Marinoudi, V., Sørensen, C. G., Pearson, S., & Bochtis, D. (2019). Robotics and labour in agriculture: A context consideration. *Biosystems Engineering, 184*, 111–121. https://doi.org/10.1016/j.biosystemseng.2019.06.013

Mascarenhas, S., Guimarães, M., Prada, R., Santos, P. A., Dias, J., & Paiva, A. (2022). Fatima toolkit: Toward an accessible tool for the development of socio-emotional agents. *ACM Transactions on Interactive Intelligent Systems (TiiS), 12*(1), 1–30. https://doi.org/10.1145/3510822

McDuff, D., El Kaliouby, R., Senechal, T., Demirdjian, D., & Picard, R. (2014). Automatic measurement of ad preferences from facial responses gathered over the Internet. *Image and Vision Computing, 32*(10), 630–640. https://doi.org/10.1016/j.imavis.2014.01.004

McNeese, N. J., Schelble, B. G., Canonico, L. B., & Demir, M. (2021). Who/what is my teammate? Team composition considerations in human–AI teaming. *IEEE Transactions on Human–Machine Systems, 51*(4), 288–299. https://doi.org/10.1109/THMS.2021.3086018

McNeil, S. G., Robin, B. R., & Miller, R. M. (2000). Facilitating interaction, communication and collaboration in online courses. *Computers & Geosciences, 26*(6), 699–708. https://doi.org/10.1016/S0098-3004(99)00106-5

Merlo, E., Lamon, E., Fusaro, F., Lorenzini, M., Carfì, A., Mastrogiovanni, F., & Ajoudani, A. (2023). An ergonomic role allocation framework for dynamic human–robot collaborative tasks. *Journal of Manufacturing Systems, 67*, 111–121. https://doi.org/10.1016/j.jmsy.2022.12.011

Merritt, T., McGee, K., Chuah, T. L., & Ong, C. (2011, June). Choosing human team-mates: Perceived identity as a moderator of player preference and enjoyment. *Proceedings of the 6th International Conference on the Foundations of Digital Games (FDG 2011)*, 196–203. https://doi.org/10.1145/2159365.2159392

Miller, C. A., Funk, H. B., Dorneich, M., & Whitlow, S. D. (2002, October). A playbook interface for mixed-initiative control of multiple unmanned vehicle teams. *Proceedings of the 21st Digital Avionics Systems Conference*, Vol. 2, 7E4–7E4. https://doi.org/10.1109/DASC.2002.1052935

Mirbagheri, M., Jodeiri, A., Hakimi, N., Zakeri, V., & Setarehdan, S. K. (2019, November). Accurate stress assessment based on functional near infrared spectroscopy using deep learning approach. *Proceedings of the 2019 26th National and 4th International Iranian Conference on Biomedical Engineering (ICBME)*, 4–10. https://doi.org/10.1109/ICBME49163.2019.9030394

Mitro, N., Argyri, K., Pavlopoulos, L., Kosyvas, D., Karagiannidis, L., Kostovasili, M., … Amditis, A. (2023). AI-enabled smart wristband providing real-time vital signs and stress monitoring. *Sensors, 23*(5), 2821. https://doi.org/10.3390/s23052821

Mocny-Pachońska, K., Doniec, R. J., Sieciński, S., Piaseczna, N. J., Pachoński, M., & Tkacz, E. J. (2021). The relationship between stress levels measured by a questionnaire and the data obtained by smart glasses and finger pulse oximeters among Polish dental students. *Applied Sciences, 11*(18), 8648. https://doi.org/10.3390/app11188648

Mois, G., Sanislav, T., & Folea, S. C. (2016). A cyber-physical system for environmental monitoring. *IEEE Transactions on Instrumentation and Measurement, 65*(6), 1463–1471. https://doi.org/10.1109/TIM.2016.2526669

Montgomery, D. C. (2007). *Introduction to statistical quality control*. John Wiley & Sons.

Mulcahy, R. (2015). *PMP exam prep: Rita's course in a book for passing the PMP exam* (8th ed.). RMC Publications, Inc.

Murphy-Chutorian, E., & Trivedi, M. M. (2008). Head pose estimation in computer vision: A survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 31*(4), 607–626. https://doi.org/10.1109/TPAMI.2008.106

Nass, C., Fogg, B. J., & Moon, Y. (1996). Can computers be teammates? *International Journal of Human-Computer Studies, 45*(6), 669–678. https://doi.org/10.1006/ijhc.1996.0073

Nath, R. K., & Thapliyal, H. (2021). Smart wristband-based stress detection framework for older adults with cortisol as stress biomarker. *IEEE Transactions on Consumer Electronics, 67*(1), 30–39. https://doi.org/10.1109/TCE.2021.3057806

Nguyen, T. A., & Zeng, Y. (2012). A theoretical model of design creativity: Nonlinear design dynamics and mental stress-creativity relation. *Journal of Integrated Design and Process Science, 16*(3), 65–88. https://doi.org/10.3233/JID-2012-0007

Nguyen, T. A., & Zeng, Y. (2017). Effects of stress and effort on self-rated reports in experimental study of design activities. *Journal of Intelligent Manufacturing, 28*(7), 1609–1622. https://doi.org/10.1007/s10845-016-1196-z

Nikolaidis, S., Hsu, D., & Srinivasa, S. (2017). Human-robot mutual adaptation in collaborative tasks: Models and experiments. *The International Journal of Robotics Research, 36*(5–7), 618–634. https://doi.org/10.1177/0278364917690593

Orsag, L., Stipancic, T., & Koren, L. (2023). Towards a Safe Human–Robot Collaboration Using Information on Human Worker Activity. *Sensors, 23*(3), 1283. https://doi.org/10.3390/s23031283

Parisi, G. I., Kemker, R., Part, J. L., Kanan, C., & Wermter, S. (2019). Continual lifelong learning with neural networks: A review. *Neural Networks, 113*, 54–71. https://doi.org/10.1016/j.neunet.2019.01.012

Park, Y. S., Yoo, D. Y., & Lee, J. W. (2021). Programmable motion-fault detection for a collaborative robot. *IEEE Access, 9*, 133123–133142. https://doi.org/10.1109/ACCESS.2021.3114505

Paul, S., Yuan, L., Jain, H. K., Robert Jr, L. P., Spohrer, J., & Lifshitz-Assaf, H. (2022). Intelligence augmentation: Human factors in ai and future of work. AIS Transactions on Human-Computer Interaction, 14(3), 426-445.

Pereira, D., Bozzato, A., Dario, P., & Ciuti, G. (2022). Towards foodservice robotics: A taxonomy of actions of foodservice workers and a critical review of supportive technology. *IEEE Transactions on Automation Science and Engineering, 19*(3), 1820–1858. https://doi.org/10.1109/TASE.2021.3129077

Perez-Valero, E., Vaquero-Blasco, M. A., López-Gordo, M. A., & Morillas, C. (2021). Quantitative assessment of stress through EEG during a virtual reality stress-relax session.

Frontiers in Computational Neuroscience, 15, Article 684423. https://doi.org/10.3389/fncom.2021.684423

Perrin, X., Chavarriaga, R., Colas, F., Siegwart, R., & Millán, J. d. R. (2010). Brain-coupled interaction for semi-autonomous navigation of an assistive robot. *Robotics and Autonomous Systems, 58*(12), 1246–1255. https://doi.org/10.1016/j.robot.2010.05.010

Poh, M. Z., McDuff, D. J., & Picard, R. W. (2010). Non-contact, automated cardiac pulse measurements using video imaging and blind source separation. *Optics Express, 18*(10), 10762–10774. https://doi.org/10.1364/OE.18.010762

Polenghi, A., Cattaneo, L., & Macchi, M. (2024). A framework for fault detection and diagnostics of articulated collaborative robots based on hybrid series modelling of Artificial Intelligence algorithms. *Journal of Intelligent Manufacturing, 35*(5), 1929–1947. https://doi.org/10.1007/s10845-023-02076-6

Pop-Jordanova, N., & Pop-Jordanov, J. (2020). Electrodermal activity and stress assessment. *Prilozi, 41*(2), 5–15. https://doi.org/10.2478/prilozi-2020-0028

Prasad, A., Kumar, A., & Prasad, P. (2024). Conceptualizing a digital twin model for natural gas retailing in a geographic area in India. *SPAST Reports, 1*(1). https://doi.org/10.69848/sreports.v1i1.4791

Prendergast, J. M., Balvert, S., Driessen, T., Seth, A., & Peternel, L. (2021). Biomechanics aware collaborative robot system for delivery of safe physical therapy in shoulder rehabilitation. *IEEE Robotics and Automation Letters, 6*(4), 7177–7184. https://doi.org/10.1109/LRA.2021.3097375

Prkachin, K. M., & Solomon, P. E. (2008). The structure, reliability and validity of pain expression: Evidence from patients with shoulder pain. *Pain, 139*(2), 267–274. https://doi.org/10.1016/j.pain.2008.04.010

Project Management Institute. (2021). *A guide to the project management body of knowledge (PMBOK® guide) – Seventh edition and the standard for project management*. Project Management Institute.

Pupa, A., Van Dijk, W., & Secchi, C. (2021). A human-centered dynamic scheduling architecture for collaborative application. *IEEE Robotics and Automation Letters, 6*(3), 4736–4743. https://doi.org/10.1109/LRA.2021.3068888

Rahma, O. N., Putra, A. P., Rahmatillah, A., Putri, Y. S. A. K. A., Fajriaty, N. D., Ain, K., & Chai, R. (2022). Electrodermal activity for measuring cognitive and emotional stress level. *Journal of Medical Signals & Sensors, 12*(2), 155–162. https://doi.org/10.4103/jmss.JMSS_78_20

Ramasubramanian, A. K., Mathew, R., Kelly, M., Hargaden, V., & Papakostas, N. (2022). Digital twin for human–robot collaboration in manufacturing: Review and outlook. *Applied Sciences, 12*(10), 4811. https://doi.org/10.3390/app12104811

Razavi, S. R., Akgunduz, A., & Zeng, Y. (2023). Impact of course timetabling on learning quality: sustaining an optimized stress level to stimulate enhanced comprehension. *Journal of Integrated Design and Process Science, 26*(1), 25–44. https://doi.org/10.3233/JID-220019

Raziei, Z., & Moghaddam, M. (2021). Adaptable automation with modular deep reinforcement learning and policy transfer. *Engineering Applications of Artificial Intelligence, 103*, 104296. https://doi.org/10.1016/j.engappai.2021.104296

Riedelbauch, D., Höllerich, N., & Henrich, D. (2023). Benchmarking teamwork of humans and cobots: An overview of metrics, strategies, and tasks. *IEEE Access, 11*, 43648–43674. https://doi.org/10.1109/ACCESS.2023.3271602

Roncone, A., Mangin, O., & Scassellati, B. (2017, May). Transparent role assignment and task allocation in human robot collaboration. In 2017 IEEE International Conference on Robotics and Automation (ICRA) (pp. 1014-1021). IEEE.

Roveda, L., Veerappan, P., Maccarini, M., Bucca, G., Ajoudani, A., & Piga, D. (2023). A human-centric framework for robotic task learning and optimization. *Journal of Manufacturing Systems, 67*, 68–79. https://doi.org/10.1016/j.jmsy.2023.01.003

Roy, R. N., Drougard, N., Gateau, T., Dehais, F., & Chanel, C. P. C. (2020). How can physiological computing benefit human-robot interaction? *Robotics, 9*(4), Article 100. https://doi.org/10.3390/robotics9040100

Rozo, L., Calinon, S., Caldwell, D. G., Jimenez, P., & Torras, C. (2016). Learning physical collaborative robot behaviors from human demonstrations. *IEEE Transactions on Robotics, 32*(3), 513–527. https://doi.org/10.1109/TRO.2016.2540623

Saaty, T. L. (1977). A scaling method for priorities in hierarchical structures. *Journal of Mathematical Psychology, 15*(3), 234–281. https://doi.org/10.1016/0022-2496(77)90033-5

Saaty, T. L. (1980). *The analytic hierarchy process: Planning, priority setting, resource allocation*. New York, NY: McGraw-Hill.

Salmeron-Majadas, S., Santos, O. C., & Boticario, J. G. (2014). An evaluation of mouse and keyboard interaction indicators towards non-intrusive and low-cost affective modeling in an educational context. *Procedia Computer Science, 35*, 691–700. https://doi.org/10.1016/j.procs.2014.08.151

Sanislav, T., Mois, G., & Miclea, L. (2016). An approach to model dependability of cyber-physical systems. *Microprocessors and Microsystems, 41*, 67–76. https://doi.org/10.1016/j.micpro.2015.11.021

Sannicandro, K., De Santis, A., Bellini, C., & Minerva, T. (2022). A scoping review on the relationship between robotics in educational contexts and e-health. *Frontiers in Education, 7*, 955572. https://doi.org/10.3389/feduc.2022.955572

Scherer, S., Stratou, G., Lucas, G., Mahmoud, M., Boberg, J., Gratch, J., & Morency, L. P. (2014). Automatic audiovisual behavior descriptors for psychological disorder analysis. *Image and Vision Computing, 32*(10), 648–658. https://doi.org/10.1016/j.imavis.2014.06.001

Schmitz, A. (2012). *A primer on communication studies*. Retrieved September 19, 2016, from https://2012books.lardbucket.org/books/a-primer-on-communication-studies/

Sha, L., Gopalakrishnan, S., Liu, X., & Wang, Q. (2008, June). Cyber-physical systems: A new frontier. In *Proceedings of the 2008 IEEE International Conference on Sensor Networks, Ubiquitous, and Trustworthy Computing (SUTC 2008)* (pp. 1–9). IEEE. https://doi.org/10.1109/SUTC.2008.85

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal, 27*(3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x

Shannon, C. E., & Weaver, W. (1949). *The mathematical theory of communication*. University of Illinois Press.

Shi, J., Wan, J., Yan, H., & Suo, H. (2011, November). A survey of cyber-physical systems. *Proceedings of the 2011 International Conference on Wireless Communications and Signal Processing (WCSP)*, 1–6. https://doi.org/10.1109/WCSP.2011.6096958

Sickles, R. C., & Zelenyuk, V. (2019). Envelopment-type estimators. In R. C. Sickles & V. Zelenyuk (Eds.), *Measurement of productivity and efficiency: Theory and practice* (pp. 243–285). Cambridge University Press. https://doi.org/10.1017/9781139565981.010

Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics: A review. *Cognitive Robotics, 3*, 54–70. https://doi.org/10.1016/j.cogr.2023.04.001

Sosa-Ceron, A. D., Gonzalez-Hernandez, H. G., & Reyes-Avendaño, J. A. (2022). Learning from demonstrations in human–robot collaborative scenarios: A survey. *Robotics, 11*(6), 126. https://doi.org/10.3390/robotics11060126

Sreedevi, A. G., Harshitha, T. N., Sugumaran, V., & Shankar, P. (2022). Application of cognitive computing in healthcare, cybersecurity, big data, and IoT: A literature review. *Information Processing & Management, 59*(2), Article 102888. https://doi.org/10.1016/j.ipm.2022.102888

Sugiono, S., Nugroho, W. S., Rahayudi, B., Lintangsari, A., & Lustyana, A. (2022). Train driver cognitive workload management framework based on neuronal dynamics principle to maintain train driver's health and railway safety. *SSRN*. https://doi.org/10.21303/2461-4262.2023.002652

Sun, D., Paredes, P., & Canny, J. (2014). MouStress: detecting stress from mouse motion. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI 2014)*, 61–70. https://doi.org/10.1145/2556288.2557243

Sun, X., Zeng, Y., & Zhou, F. (2011). Environment-based design (EBD) approach to developing quality management systems: A case study. *Journal of Integrated Design and Process Science, 15*(2), 53–70. https://doi.org/10.3233/JID-2011-15204

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Tague, N. R. (2023). *The quality toolbox* (3rd ed.). ASQ Quality Press.

Talebpour, Z., & Martinoli, A. (2019). Adaptive risk-based replanning for human-aware multi-robot task allocation with local perception. *IEEE Robotics and Automation Letters, 4*(4), 3790–3797. https://doi.org/10.1109/LRA.2019.2926966

Tao, D., Luo, W., Wu, Y., Yang, K., Wang, H., & Qu, X. (2024). Ergonomic assessment of mid-air interaction and device-assisted interactions under vibration environments based on task performance, muscle activity and user perceptions. *International Journal of Human-Computer Studies, 192*, 103364. https://doi.org/10.1016/j.ijhcs.2024.103364

Tokadlı, G., Dorneich, M. C., & Matessa, M. (2021). Evaluation of Playbook delegation approach in human-autonomy teaming for single pilot operations. *International Journal of Human–Computer Interaction, 37*(7), 703–716. https://doi.org/10.1080/10447318.2021.1890485

Töniges, T., Ötting, S. K., Wrede, B., Maier, G. W., & Sagerer, G. (2017). An emerging decision authority: Adaptive cyber-physical system design for fair human-machine interaction and decision processes. In H. Song, D. B. Rawat, S. Jeschke, & C. Brecher (Eds.), *Cyber-physical systems: Foundations, principles, and applications* (pp. 419–430). Academic Press. https://doi.org/10.1016/B978-0-12-803801-7.00026-2

Tuyls, K., & Weiss, G. (2012). Multiagent learning: Basics, challenges, and prospects. *AI Magazine, 33*(3), 41–52. https://doi.org/10.1609/aimag.v33i3.2426

Van den Heuvel, R., Jansens, R., Littler, B., Huijnen, C., Di Nuovo, A., Bonarini, A., … & De Witte, L. (2022). The potential of robotics for the development and wellbeing of children with disabilities as we see it. *Technology and Disability, 34*(1), 25–33. https://doi.org/10.3233/TAD-210346

Van Merriënboer, J. J. G., & Sweller, J. (2010). Cognitive load theory in health professional education: Design principles and strategies. *Medical Education, 44*(1), 85–93. https://doi.org/10.1111/j.1365-2923.2009.03498.x

Walhout, J., Oomen, P., Jarodzka, H., & Brand-Gruwel, S. (2017). *Effects of task complexity on online search behavior of adolescents.* Journal of the Association for Information Science and Technology, 68(6), 1449–1461. https://doi.org/10.1002/asi.23782

Wan, J., Chen, M., Xia, F., Di, L., & Zhou, K. (2013). From machine-to-machine communications towards cyber-physical systems. *Computer Science and Information Systems, 10*(3), 1105–1128. https://doi.org/10.2298/CSIS120326018W

Wan, S., Gu, Z., & Ni, Q. (2020). Cognitive computing and wireless communications on the edge for healthcare service robots. *Computer Communications*, *149*, 99–106. https://doi.org/10.1016/j.comcom.2019.10.012

Wang, F. Y. (2010). The emergence of intelligent enterprises: From CPS to CPSS. *IEEE Intelligent Systems, 25*(4), 85–88. https://doi.org/10.1109/MIS.2010.104

Wang, Y., Karray, F., Kwong, S., Plataniotis, K. N., Leung, H., Hou, M., ... & Patel, S. (2021). On the philosophical, cognitive and mathematical foundations of symbiotic autonomous systems. *Philosophical Transactions of the Royal Society A, 379*(2207), 20200362. https://doi.org/10.1098/rsta.2020.0362

Wang, Y., Sun, G. Q., Zhong, J., & Shen, W. L. (2013). The determining method of cashiers working fatigue point based on performance measurement. In M. Qi, Y. Yang, & J. Gao (Eds.), *International Asia Conference on Industrial Engineering and Management Innovation (IEMI2012) Proceedings: Core Areas of Industrial Engineering* (pp. 97–105). Springer.https://doi.org/10.1007/978-3-642-38445-5

Wei, K., & Ren, B. (2018). A method on dynamic path planning for robotic manipulator autonomous obstacle avoidance based on an improved RRT algorithm. *Sensors, 18*(2), 571. https://doi.org/10.3390/s18020571

Whitehill, J., Serpell, Z., Foster, A., Lin, Y. C., Pearson, B., Bartlett, M., & Movellan, J. (2011, June). Towards an optimal affect-sensitive instructional system of cognitive skills. In *CVPR 2011 Workshops* (pp. 20–25). IEEE. https://doi.org/10.1109/CVPRW.2011.5981778

Wilke, P. K., Gmelch, W. H., & Lovrich, N. P. (1985). Stress and productivity: Evidence of the inverted U function. Public Productivity Review, 9, 342–356. https://www.jstor.org/stable/3379944

Wilkinson, S. C., Reader, W., & Payne, S. J. (2012). Adaptive browsing: Sensitivity to time pressure and task difficulty. *International Journal of Human-Computer Studies, 70*(1), 14–25. https://doi.org/10.1016/j.ijhcs.2011.08.003

Xiong, J., Chen, J., & Lee, P. S. (2021). Functional fibers and fabrics for soft robotics, wearables, and human–robot interface. *Advanced Materials, 33*(19), 2002640. https://doi.org/10.1002/adma.202002640

Yalçinkaya, B., Couceiro, M. S., Soares, S. P., & Valente, A. (2023). Human-aware collaborative robots in the wild: Coping with uncertainty in activity recognition. *Sensors, 23*(7), 3388. https://doi.org/10.3390/s23073388

Yan, H. H., Wan, J. F., & Suo, H. (2012). Adaptive resource management for cyber-physical systems. *Applied Mechanics and Materials, 157–158*, 747–751. https://doi.org/10.4028/www.scientific.net/AMM.157-158.747

Yang, Y., Fairbairn, C., & Cohn, J. F. (2013). Detecting depression severity from vocal prosody. *IEEE Transactions on Affective Computing, 4*(2), 142–150. https://doi.org/10.1109/T-AFFC.2012.38

Yang, J., Yang, L., Quan, H., & Zeng, Y. (2021). Implementation barriers: A TASKS framework. *Journal of Integrated Design and Process Science, 25*(3–4), 134–147. https://doi.org/10.3233/JID-210011

Yerkes, R. M., & Dodson, J. D. (1908). The relation of strength of stimulus to rapidity of habit-formation. *Journal of Comparative Neurology and Psychology, 18*(5), 459–482. https://doi.org/10.1002/cne.920180503

Yonga Chuengwa, T., Swanepoel, J. A., Kurien, A. M., Kanakana-Katumba, M. G., & Djouani, K. (2023). Research perspectives in collaborative assembly: A review. *Robotics, 12*(2), 37. https://doi.org/10.3390/robotics12020037

Yousefi, N., Sobhani, A., Moslemi Naeni, L., & Currie, K. R. (2019). Using statistical control charts to monitor duration-based performance of project. *arXiv preprint arXiv:1902.02270*. https://arxiv.org/abs/1902.02270

Yun, J. J., Lee, D., Ahn, H., Park, K., & Yigitcanlar, T. (2016). Not deep learning but autonomous learning of open innovation for sustainable artificial intelligence. *Sustainability, 8*(8), 797. https://doi.org/10.3390/su8080797

Zaatari, S. E., Wang, Y., Hu, Y., & Li, W. (2022). An improved approach of task-parameterized learning from demonstrations for cobots in dynamic manufacturing. *Journal of Intelligent Manufacturing*. https://doi.org/10.1007/s10845-021-01743-w

Zahmat Doost, E., & Zhang, W. (2023). Mental workload variations during different cognitive office tasks with social media interruptions. *Ergonomics, 66*(5), 592–608. https://doi.org/10.1080/00140139.2022.2104381

Zanchettin, A. M., Messeri, C., Cristantielli, D., & Rocco, P. (2022). Trajectory optimisation in collaborative robotics based on simulations and genetic algorithms. *International Journal of Intelligent Robotics and Applications, 6*(4), 707–723. https://doi.org/10.1007/s41315-022-00240-4

Zeitlhofer, I., Zumbach, J., & Schweppe, J. (2024). Complexity affects performance, cognitive load, and awareness. *Learning and Instruction, 94*, Article 102001. https://doi.org/10.1016/j.learninstruc.2024.102001

Zeng, Y. (2002). Axiomatic theory of design modeling. *Journal of Integrated Design and Process Science, 6*(3), 1–28. https://doi.org/10.3233/JID-2002-6301

Zeng, Y. (2011). Environment-based design (EBD). *In International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (Vol. 54860, pp. 237–250). https://doi.org/10.1115/DETC2011-48263

Zhang, R., Lv, J., Bao, J., & Zheng, Y. (2023). A digital twin-driven flexible scheduling method in a human–machine collaborative workshop based on hierarchical reinforcement learning. *Flexible Services and Manufacturing Journal, 35*(4), 1116–1138. https://doi.org/10.1007/s10696-023-09498-7

Zhao, M., Jia, W., Jennings, S., Law, A., Bourgon, A., Su, C., Larose, M.-H., Grenier, H., Bowness, D., & Zeng, Y. (2024). Monitoring pilot trainees' cognitive control under a simulator-based training process with EEG microstate analysis. *Scientific Reports, 14*, 24632. https://doi.org/10.1038/s41598-024-76046-0

Zhao, M., Qiu, D., & Zeng, Y. (2023). How much workload is a 'good' workload for human beings to meet the deadline: Human capacity zone and workload equilibrium. *Journal of Engineering Design, 34*(8), 644–673. https://doi.org/10.1080/09544828.2023.2249216

Zhao, M., Yang, D., Liu, S., & Zeng, Y. (2018). Mental stress-performance model in emotional engineering. In *Emotional Engineering* (Vol. 6, pp. 119–139). Springer. https://doi.org/10.1007/978-3-319-70802-7_9

Zheng, P., Li, S., Fan, J., Li, C., & Wang, L. (2023). A collaborative intelligence-based approach for handling human–robot collaboration uncertainties. *CIRP Annals, 72*(1), 1–4. https://doi.org/10.1016/j.cirp.2023.04.057

Zhou, X., Wang, X., & Liu, X. (2022). The impact of task complexity and translating self-efficacy belief on students' translation performance: Evidence from process and product data. *Frontiers in Psychology, 13*, Article 911850. https://doi.org/10.3389/fpsyg.2022.911850

Zhu, G., Zhang, L., Shen, P., & Song, J. (2017). Multimodal gesture recognition using 3-D convolution and convolutional LSTM. *IEEE Access, 5*, 4517–4524. https://doi.org/10.1109/ACCESS.2017.2684186