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Habilitation thesis

Human-centered systems in manufacturing

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For the habilitation title of the University of Pannonia.

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1 Main motivation and goals

For the past five years, I have focused on human-centered manufacturing challenges and solutions. After earning my Ph.D. in a related field, I began formulating the Industry 5.0 laboratory and assembling a team. The human labor-intensive nature of industries in Hungary and across Europe is raising concerns about the aging workforce and the need for change in human resources. The most important aspect within the business area is always performance and return on investment (ROI). As Europe faces a labor shortage, these aspects have become more important in recent years. Understanding the main reasons for the decline in performance of human workers is increasingly important since the market requires more human-centric and enthusiastic workplaces.

Understanding human activities is the first step in creating a supporting system. To this end, we have developed various methods for human-centered performance evaluation, combining traditional Lean methodologies with the latest technologies. I have significant experience with real-time locating systems (RTLS), also known as indoor positioning systems (IPS). We are also working on different solutions for visual-based activity recognition.

To integrate information about our workers into our current system, we need human-centered models and data structures. We developed a Human-Asset Administration Shell (H-AAS) model that includes physiological parameters and calculated human-centered factors, such as cognitive load and stress level. We also proved that human-centered knowledge graphs are useful for modeling human behavior. Overall, I developed the Intelligent Collaborative Manufacturing Space (ICMS) as a human-centric manufacturing framework. I was motivated to lay the groundwork for human-centered systems based on the developed ICMS framework. We conducted several laboratory experiments to demonstrate the applicability of physiological signals in manufacturing using wearable sensors. Since work instructions play a significant role in industry, we developed an evaluation method to assess their effectiveness.

In the following I will shortly introduce the ICMS framework as it is shaped my research in the past 5 years. ICMS is proposed to create a next-level collaborative environment where human workers and automated and semi-automated production assets can work together in the same area to achieve productivity, flexibility, and resilience levels that neither can achieve on their own. To accomplish this, Intelligent Automation Systems are necessary to achieve “Human-Automation Symbiosis”. ICMS aims to create a framework for supporting collaborations based on smart sensor networks and data science techniques. Figure 1.1 shows the elements of the proposed ICMS, which aims to showcase a real-time monitoring-based control for automated and semi-automated production assets to make collaboration between the human workers and the machines more safe and precise. Four main elements or sub-spaces characterize this “Intelligent Workspace”: (i) the Working Space, (ii) the Monitoring Space, (iii) the Modelling Space, and (iv) the Decision Space.

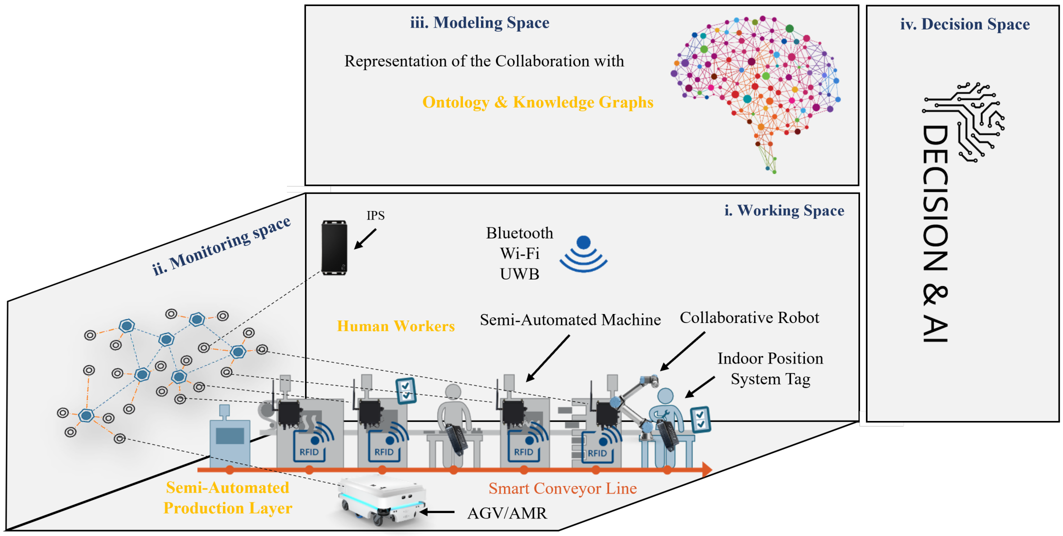

Figure 1.1: The four spaces of Intelligent Collaborative Manufacturing Space

The ICMS is a framework envisioned for supporting the effective collaboration between humans and automated and semi-automated production assets based on activity recognition and prediction paired with machine learning optimization algorithms.

2 Thesis overlook and summary

2.1 Thesis group I.

I developed a set of algorithms and methods to evaluate the human-centered performance indicators based on the real-time locating system (RTLS) information and the visual-based activity recognition. We connected these digital solutions with the traditional Lean techniques to provide real-time and data-based process development.

We proved that RTLS can be use not just for performance evaluation but also to asses the comfort levels of the workers applied in a real-life manufacturing scenario. The results show the indoor positioning data is valuable to not just tracking the human movements and activities but also provide information about the actual environment information (like noise, temperature) to assess the human well-being in space and time.

The traditional skeletal data-based analyses is applied to assess the human performance on a production line to provide valuable information for better task allocation and work schedule. We paired the MS Kinect data with the traditional Lean technique to assess the human performance on a real-life production dataset. The results are shown the applicability of the sceletal data and also proved the usefulness in case of human-centric performance evaluation.

In sum, the thesis group is proven a valuable toolset to track the operator performance within real-life production scenarios and connect these visual- and sensor-based information with the traditional Lean techniques to create more efficient processes.

2.2 Thesis group II.

To handle the real-time performance measurements, I developed a Human-asset administration shell model as a basics of the human digital twin to support the human-factors integration, also I proved the usability of the knowledge graph and developed a human-centered library.

We developed a Human-Asset Administration Shell (HAAS) to handle the operator-related information regarding the task allocation. From the one hand, the model is able to manage the actually perceived cognitive load based on the real-time physiological metrics and in the other hand the model is handling the task requirements also, like the environmental conditions, the worker's characteristics and the task specific information (like routine or nonroutine, cognitive or physical demanding and individual or team required) to pair the assigned tasks with the operator's capabilities. The model is proving a foundation of the cognitive load management with a valuable data schema for task allocation.

A Human-Centric Knowledge Graph (HCKG) is developed to create a knowledge graph for human-related process management with the standard ontologies, data extraction methodologies and the possible applications. The developed graph is a valuable solution for the production management where different assets/actors (robots, operators, sensor and actuators) need to be handled within one system.

2.3 Thesis group III.

To extend the physical activity performance monitoring with the specific human-centered information, I started to work on the physiological information monitoring within the manufacturing environment to prove more human-centric and personalized solutions according to the performance monitoring, task-allocation and process development. I proved the physiological signals usability and applicability with simple wearable sensors for manufacturing processing integrate the real-time human states and behavior within the systems.

I started the journey of manufacturing related experiments to measure the cognitive load in subjective and objectively with dual-task scenarios where the participants needed to handle a specific secondary task during the primary task execution. In both cases the results are shown some promising correlation between the perceived cognitive load and awareness level and the measured physiological data with industry ready wearable sensors. These open source experiment datasets are valuable information for further research within these areas as a foundation of the applicability of the industry ready sensors usage within the manufacturing processes to assess the cognitive load of the human workers.

The work instruction is one of the most used interface to support the human workers as they are providing all the necessary information to execute the actual tasks. We objectively measured the usability and efficiency of different type of work instruction (like code- and visual-based) during an assembly-like task within a laboratory environment. Both performance and quality metrics are measured paired with the physiological measurements, also with the subjective evaluation of the participants. The results are proved valuable information about the right usage of the code- and visual-based work instruction and also the applicability of the wearable sensors.

3 Thesis Group 1: Human-centered performance evaluation

The importance of monitoring operator performance in human-centric manufacturing is steadily increasing. This trend is driven by the growing shortage of skilled labor, the integration of real-time locating systems, and the rising usability of visual-based activity tracking technologies. These developments enable a more precise, responsive, and worker-oriented approach to managing industrial processes, ensuring both operational efficiency and enhanced human well-being. In this thesis, I demonstrate the applicability of real-time positioning systems and visual observation tools in the recognition of human activities.

3.1 Usability of the real-time locating system for worker well-being and performance evaluation

3.1.1 Background and objective

The evaluation of human workers is a difficult task since we are all different is such way especially within a complex manufacturing process. As a human-centric solution, a human-oriented and personalized evaluation system is needed. For this purpose, I developed different algorithm to explore valuable and human-centered information from the so-called Indoor Positioning System (IPS and also known Real-time Locating System - RTLS) information paired with the traditional Lean techniques.

The powerful combination of lean principles and digital technologies accelerates waste identification and mitigation faster than traditional lean methods. The new Digital Lean (also referred as Lean 4.0) solutions incorporate sensors and digital equipment, yielding innovative solutions that extend the reach of traditional lean tools. The developed algorithms and methods are able to assess not just the performance indicators but also the actual well-being parameters of the human workers.

3.1.2 The developed methods

A framework (see on Figure 3.1) is proposed based on the indoor position data and the Plan–Do–Check–Act (PDCA) cycle for assessing the well-being and the performance of the operators in indoor environments, with the operator comfort level serving as a measurable indicator. It is a detailed guideline about how the information provided by IPS can be utilised in Lean management. The proposed method is embedded into the concept of continuous development. The structured DMAIC (Define-Measure-Analyze-Improve-Control) approach utilised in Six Sigma methodology also follows the concept of the PDCA cycle, which has been proven effective in reducing non-value-added activities in the supply chains and assembly lines.

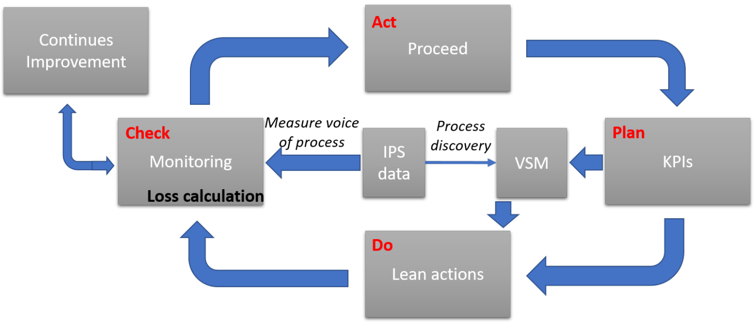

Figure 3.1: IPS data is the key element of the proposed PDCA-based methodology

The core element of the method is the process model (represented as a VSM in the Figure 3.1) that contains all the essential information about the manufacturing process. The proposed improvement cycle continuously updates the model with the help of IPS data. The motivation is to continuously and automatically monitor the production. The developed framework can discover the real process model continuously based on the IPS data with the toolset of process mining. The resulted models are used to update the VSMs, evaluate the performance of the process by calculating the Lean KPIs. We applied Gantt diagrams to analyze the periods of operations. Based on the analysis of positional data additional states of the manufacturing process can be defined and assigned to the product and material flows and states of the resources (e.g. temporal inventories can be defined). The explored states and additional time-stamps provided by the IPS process mining algorithms can be utilised to update VSMs. Thanks to the real-time position of the process flows motion-based anomalies can be detected.

Understanding the specific areas and conditions where workers are exposed to various environmental factors is essential. Distributed information is essential to capture the spatial and contextualized distribution of occupational exposures. Unlike concentrated parameters, this exposure varies between operators and workplaces. To formulate a clear objective, it is necessary to articulate the need for detailed information that encompasses both spatial and temporal dimensions. To achieve this, it is necessary to have position-based information that is contextualized and linked to relevant data. We incorporate indoor positioning data to create location-based sensor information. The application and further development of the IPS serve as a solution to address these motivations. By employing IPS sensors and associated analysis techniques, it becomes possible to gather precise position-based information. The integration of IPS sensors and related technologies offers a promising avenue for advancing workplace monitoring and design, ultimately promoting a safer and more efficient working environment.

The sensor fusion methodology is represented in Figure 3.2. This framework describes the sensor information process, where we have a measurement point that includes humidity (h_t), temperature (w_t), the noise (s_t) and the actual position data ($\mathbf{p}_t$) and the 2D position from the IPS is denoted by $\mathbf{p}_t = [x_t, y_t]$ where t is the actual time point.

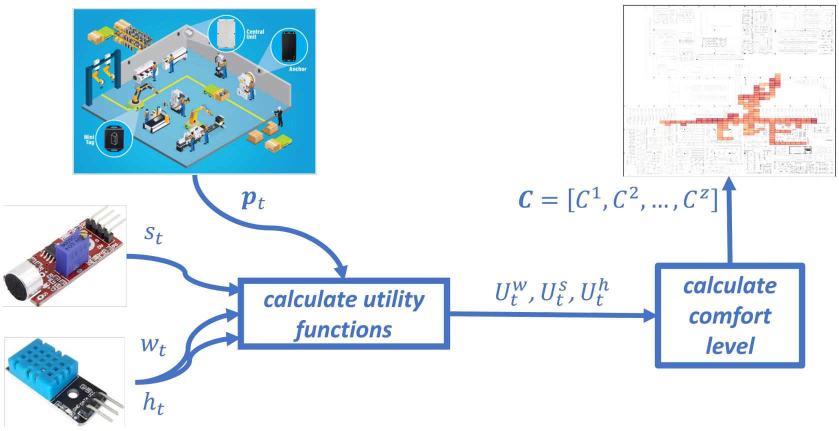

Figure 3.2: The steps of the developed framework for human well-being assessment

For this characterization, we have determined a so-called comfort level. The value represents the extent to which the operator can handle environmental load in each zone of the shop floor and how comfortable they feel in these areas. To measure this new indicator, we have also developed a mobile sensor unit as an extension of the standard IPS tag to make the measurement more cost-effective. With this idea, we can utilize all the moving units on the shop floor, such as AGV (automated guided vehicles) or AMR (autonomous mobile robots), or even the material handler operators equipped with the developed sensor.

As the results are shown the IPS serves as a non-stop monitoring system that contributes to the everyday work of Lean specialists. As a first step, an alarm system can be set up at each workstation to notify if the working or the waiting times in that station exceed their predefined limits; so the line advisor can take required supportive action on time. The integrated application IPS and process mining supports the redesign of the layout thanks to its ability of the detection of hidden stations and states of the process. Also, the results provide valuable insights for identifying potentially hazardous or at-risk areas in the manufacturing layout that can impact the well-being of operators. By analyzing the collected data, we can identify zones that pose potential risks to operator comfort and take appropriate measures to mitigate these risks. Furthermore, by considering the time-aggregated measurements, we can not only evaluate the spatial distribution of exposures but also assess the temporal patterns of exposure over a given period.

3.1.3 Scientific results and novelty

The research resulted in a methodology that enables:

- continuous monitoring of operator performance and well-being using IPS data,
- identification of hidden states in manufacturing processes and updating of Value Stream Maps (VSM),
- introduction of a new comfort level indicator representing the extent to which operators can tolerate environmental load across different shop floor zones.

The developed IPS-based process mining algorithms provided additional states and time stamps that were not captured by the MES, enabling more accurate Gantt diagrams and Lean KPI calculations (e.g., cycle time, waiting time). The methodology also allows for the implementation of alarm systems to notify line advisors if cycle or waiting times exceed predefined limits. Furthermore, the integrated system supports layout redesign and risk identification by highlighting potentially hazardous or comfort-critical areas.

3.1.4 Publication background

- Tran, T. A., Ruppert, T., & Abonyi, J. (2021). Indoor positioning systems can revolutionise digital lean. Applied Sciences, 11(11), 5291., GS citation: 42
- Halász, G., Medvegy, T., Abonyi, J., & Ruppert, T. (2023, September). Indoor positioning-based occupational exposures mapping and operator well-being assessment in manufacturing environment. In IFIP International Conference on Ad-

vances in Production Management Systems (pp. 543-555). Cham: Springer Nature Switzerland., GS citation: 1

3.2 Visual data-based activity recognition

3.2.1 Background and objective

A better understanding of the complexity and uncertainty of worker behavior can be achieved with a closer diagnosis of their movement trajectory. This foundation enhances detailed analysis from ergonomic and productivity improvement aspects. However, traditional initiatives require exhaustive observation and prior knowledge of human workers, while most movement details can not be traced by the naked eyes of experts. There is no development regarding segmentizing camera-captured movement into patterns in the literature.

A Kinect skeleton data is utilised by applying pattern mining and supervised learning algorithms to automatically capture and analyze deeper the movement patterns, thus providing automatic labor performance assessments such as Overall Labor Effectiveness (OLE). Key contributions are the automatic assessment in several aspects (e.g., productivity, ergonomics) and the suggestion of possible human-centric improvements based on assessment results, considering Industry 5.0 objectives. A Python package is developed for post-process the Kinect raw data. A use case is performed on an electrical assembly line, proving that the human performance in each workstation can be assessed, and the manufacturing line can be balanced, with each movement in its workstations optimized. Continuous improvement ideas and long-term Human Resources Development (HRD) plans are suggested. The novelty lies in the innovative usage of Machine Learning (ML) algorithms with a real-time operation model, which can be the core foundation for organizational data-driven improvement in the Industry 5.0 era.

3.2.2 The developed methods

After extracting the raw skeleton data, coordinate transformation, re-sampling, and filtering steps are applied. These steps are mathematical operations based on the camera setup. Supervised learning algorithms are applied to segmentize and recognize working status and movements. Then, motif-searching algorithms are applied to find the similarities between the extracted movements and detect deviation from the standard. The objects of interest are the time series of the joint coordinates, along with their kinematic values. Other work characteristics (e.g., cycle time) can also be recognized.

Every job-unrelated movement should be excluded (i.e., walking, waiting, resting). This approach considers intrinsic characteristics of work movements, such as the position and kinematics of the head and the hands. For instance, the head will be the stationary joint with a very low velocity, and the hands will be the most active joint during the work session. Kinematics values (i.e., velocity) are also utilized as thresholds to identify the movements. Other workstation features, i.e., conveyor geometry and ergonomic working posture, are also considered.

With the recognized work patterns, statistical features can be extracted to build a Human Activity Recognition (HAR) model. The recognized result can be used to predict worker movement for a real-time application. The overall results can be synthesized into the performance assessment of each worker or the line of multiple workers. Based on these assessments, short- and long-term strategies to improve human performance can be elaborated, keeping in mind the objectives of Industry 5.0.

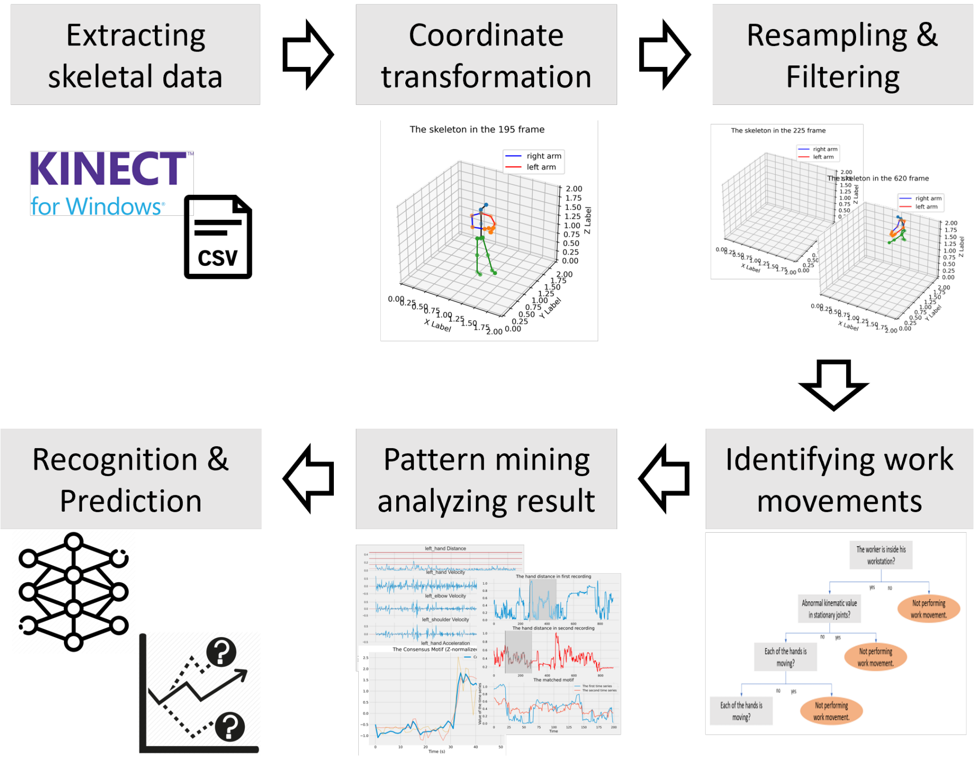

Figure 3.3: The proposed flowchart to process Kinect sensor skeleton data.

The processing flowchart is described in Figure 3.3. After extracting the raw skeleton data, coordinate transformation, re-sampling, and filtering steps are applied. These steps are mathematical operations based on the camera setup. Supervised learning algorithms are applied to segmentize and recognize working status and movements. The developed steps can be described as:

- Whether the workers are in their workstation: The standing zone can be defined by applying kNN clustering on the position data of the head and the hand joints, and can be confirmed by the position of the head and its low velocity (see on Figure 3.4.
- Whether the worker is performing the work: If the worker is working, the head should be moving slowly within the standing zone. If the worker is walking, the velocity is much higher than the working state.
- Whether the hand of the worker is moving or not: Based on the kinematic characteristics of each hand such as moving distance, velocity, and acceleration, the frames in which the worker is performing work and not standing idle can be recognized. After this step, the timeline of the working state can be created.
- After the aforementioned steps, we can define the relevant frames in which the worker is performing work movement. Ergonomics assessment can be applied during these periods. The given work instruction can be utilized to identify the movement, and the motif searching techniques are performed to find the movement pattern.

3.2.3 Scientific results and novelty

The developed method enables:

- automatic assessment of labor performance across multiple dimensions (e.g., productivity, ergonomics),
- recognition and classification of work-related movements at both individual and line-level scales,
- identification of improvement opportunities for balancing manufacturing lines and optimizing workstations.

The proposed workflow (Figure 3.3) provides an automated pipeline for HAR and OLE calculation. The novelty lies in combining supervised learning and motif-searching algorithms with real-time movement tracking to create a continuous and objective assessment system. The methodology supports both short-term improvement actions and long-term HRD strategies within the Industry 5.0 paradigm.

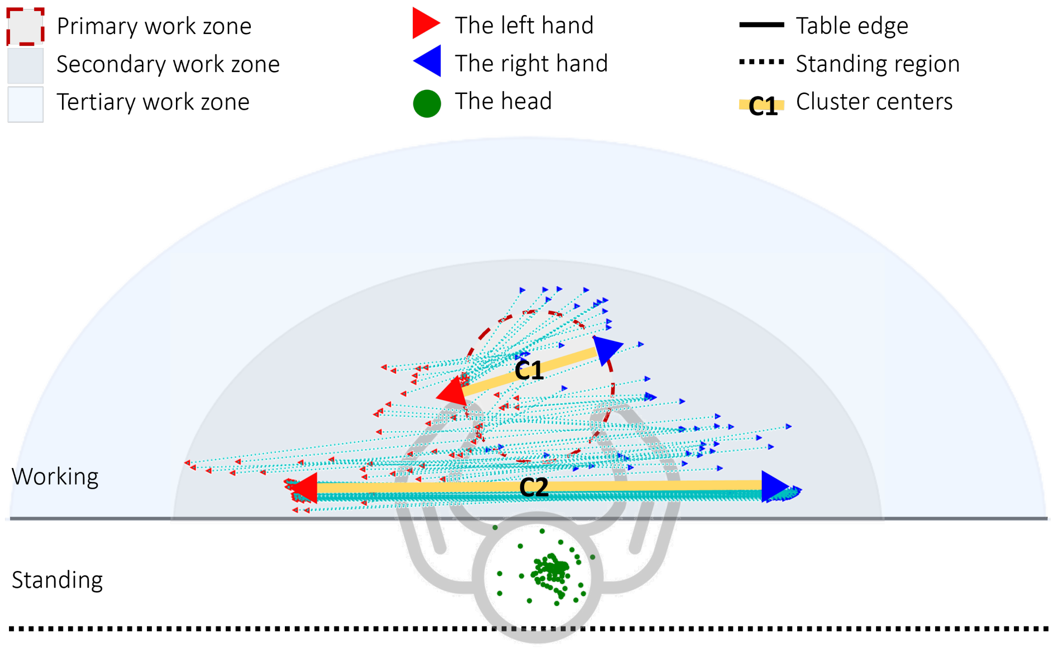

Figure 3.4: The schema of the head and hand positions in working posture. Example data from one workstation.

3.2.4 Publication background

- Tran, T. A., Ruppert, T., Eigner, G., & Abonyi, J. (2023). Assessing human worker performance by pattern mining of Kinect sensor skeleton data. Journal of Manufacturing Systems, 70, 538-556., GS citation: 14
- Jeskó, Z., Tran, T. A., Halász, G., Abonyi, J., & Ruppert, T. (2024, September). Enriching Scene-Graph Generation with Prior Knowledge from Work Instruction. In IFIP International Conference on Advances in Production Management Systems (pp. 290-302). Cham: Springer Nature Switzerland. GS citation: 0

4 Thesis Group 2: Human-centered digital models

The importance of highly monitored and analysed processes, linked by information systems such as knowledge graphs, is growing. In addition, the integration of operators has become urgent due to their high costs and from a social point of view. An appropriate framework for implementing the Industry 5.0 approach requires effective data exchange in a highly complex manufacturing network, to utilise resources and information. Furthermore, the continuous development of collaboration between human and machine actors is fundamental for industrial cyber-physical systems, as the workforce is one of the most agile and flexible manufacturing resources. The necessity of the Human Digital Twin is arising this year but to achieve this we need to carefully develop the data models which can consider the human factors is a human-centric way within the industrial environment. The asset administration shell (AAS) is a well designed approach for the digital twin development which highlighting the needs of the Human AAS.

4.1 Human-Asset Administration Shell

4.1.1 Background and objective

The rapid advancement of technology related to Industry 4.0 has brought about a paradigm shift in the way we interact with assets across various domains. This progress has led to the emergence of the concept of a Human Digital Twin (HDT), a virtual representation of an individual's cognitive, psychological, and behavioral characteristics. The HDT has demonstrated potential as a strategic tool for enhancing productivity, safety, and collaboration within the framework of Industry 5.0. My research is centered on addressing two primary areas of concern that arise during the transition toward industrial digitization and suggesting solutions for them: “What is the cognitive load level that a specific task may induce on an operator, and what is the limit of cognition that the operator should not exceed to tackle that task's load with the best performance?", factoring in the individual skills and “Based on the outcomes of the first question, is there a need to control the cognitive load of that task, and if so, how?”.

4.1.2 Applied methods

We identified seven main modules: the task, worker skills, environmental conditions, psychological state, kinematic parameters, anthropometric parameters, and physiological metrics. My research novelty is depending on four of these modules: the physiological metrics (GSR and HRV) to evaluate the worker’s cognitive load and classify it as low, medium, or high, while the other three modules, the task, the worker’s skills, and the environmental conditions surrounding the worker, will be used to estimate the required cognitive load and also classify it as low, medium, or high to compare it with the evaluated cognitive load of the worker.

The developed model provides a process for tracking human cognitive load using the GSR as a physiological marker and proposes a novel method for managing cognitive load based on the extended Human Asset Administration Shell (HAAS). The proposed HAAS framework integrates real-time data streams from wearable sensors, user skills, contextual information, task specifics, and environmental and surrounding conditions to deliver a comprehensive understanding of an individual’s cognitive state, physical wellness, and skill set. Through the incorporation of skills set, physical, physiological, and psychological variables, and task parameters, the developed HAAS framework enables the identification, management, and development of individual capabilities, thereby facilitating individualized training and knowledge exchange.

The HAAS model we proposed is built around four fundamental modules that serve as the basis for its structure and operation. These modules include physiological parameters, workers’ characteristics, task type and level, and environmental conditions. As seen in Figure 4.1 located on the right side, the physiological metrics focus on the GSR and HRV data, which are acquired using sensors placed on the individuals doing the tasks. This crucial module records these parameters and subsequently evaluates and categorizes the cognitive load into three noticeable categories: low, medium, and high, as shown on the upper right side under the "Evaluated Cognitive load".

On the left side of Figure 4.1 are three modules, the workers’ characteristics module, which is designed to effectively capture the distinct skills and proficiencies possessed by each worker and recognizes that individual capabilities can vary widely. This module is updated based on a preliminary assessment of each worker’s abilities prior to engaging in specific tasks. Task type and level is the other module in the developed model. It takes into account not just the categorical nature of a task but also integrates the worker’s

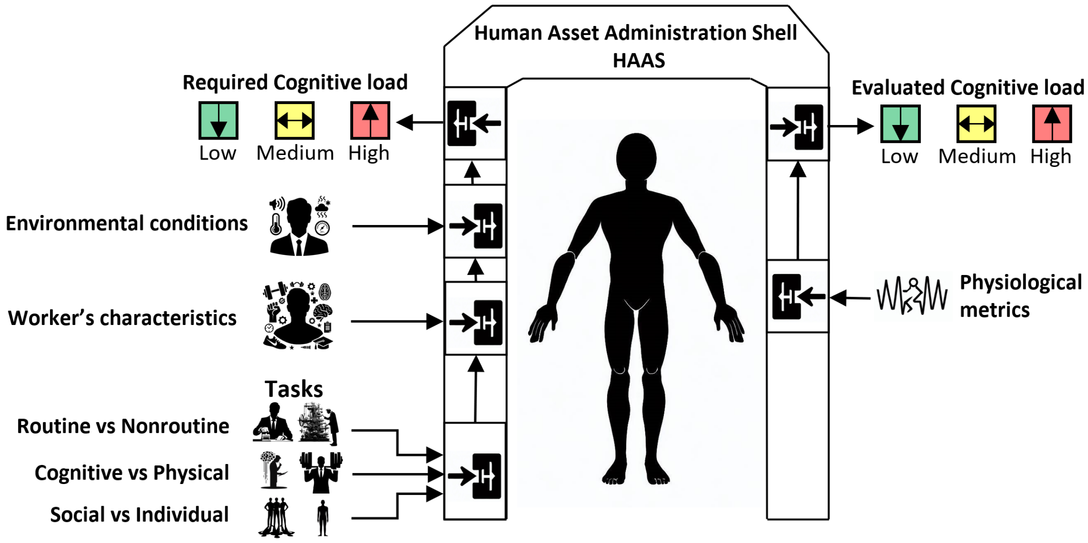

Figure 4.1: Extended HAAS proposed diagram

innate skills and capacities into its analysis. As an example, a task with cognitive demands might be perceived differently by two workers of varying physical strengths, illustrating that the complexity of a task is multifaceted. The final module in our model is the environmental condition, which acknowledges that external factors play a crucial role in determining cognitive load. This module continuously monitors and adjusts the changes in the environment, such as noise, temperature, etc. These modules on the left side will estimate the required cognitive load based on their inputs into three levels: low, medium, and high, as shown on the upper left side under "Required Cognitive load". With these four modules in place, the extended HAAS model establishes a dynamic interplay. By comparing the evaluated and required cognitive loads, it aims to modulate tasks and surrounding conditions, ensuring a balance between optimal worker comfort and heightened productivity.

4.1.3 Scientific results and novelty

The developed HAAS model:

- enables real-time evaluation of operator cognitive load based on physiological and contextual data,
- estimates task-related cognitive demands and compares them to individual cognitive states,

- dynamically suggests task and environmental adjustments to maintain optimal cognitive load levels.

The novelty lies in extending the conventional AAS concept beyond interoperability between assets toward active manipulation of task parameters and environmental conditions, enabling human-centric optimization in Industry 5.0. By integrating cognitive, physiological, and contextual dimensions, the model supports individualized training, knowledge exchange, and continuous development of human capabilities.

4.1.4 Publication background

- Eesee, A. K., Jaskó, S., Eigner, G., Abonyi, J., & Ruppert, T. (2024). Extension of haas for the management of cognitive load. IEEE Access, 12, 16559-16572. GS citation: 7

- Cutrona, V., Bonomi, N., Montini, E., Ruppert, T., Delinavelli, G., & Pedrazzoli, P. (2024). Extending factory digital Twins through human characterisation in Asset Administration Shell. International Journal of Computer Integrated Manufacturing, 37(10-11), 1214-1231. GS citation: 25

4.2 Knowledge graphs for human-centered manufacturing

4.2.1 Background and objective

The integration of collaborative robots into manufacturing processes, known as human-robot collaboration (HRC), represents a significant advancement in Industry 4.0. Unlike traditional industrial robots that are confined to isolated cells, collaborative robots are designed to work alongside humans, using embedded interaction, sensing, and safety technologies. This enables a hybrid production environment where human and robot resources are dynamically allocated to optimize productivity, flexibility, and reconfigurability. HRC environments aim to overcome the limitations of manual and robotic assembly lines by providing a novel approach to task allocation and execution that improves overall manufacturing efficiency and adaptability.

Semantic networks and graph-based analytics are recommended to handle process information using linked data features. Knowledge graph techniques are capable of extracting data from structured, semi-structured or unstructured sources and then incorporating this information into a graph-based knowledge representation. To improve operator working conditions, various monitoring systems, such as sensor networks, can be utilized to monitor operator movements and physical states, enabling the assessment of performance metrics.

4.2.2 Applied methods

We developed a Human-Centric Knowledge Graph (HCKG) framework by adapting ontologies and standards to model the operator-related factors such as monitoring movements, working conditions, or collaborating with robots. It also presents graph-based data querying, visualisation, and analysis through an industrial case study. The main contribution of this work is a knowledge graph-based framework that focuses on the work performed by the operator, including the evaluation of movements, collaboration with machines, ergonomics, and other conditions. In addition, the use of the framework is demonstrated in a complex use case based on an assembly line, with examples of resource allocation and comprehensive support in terms of collaboration aspect between shop-floor workers.

The primary contribution is the introduction of a framework known as HCKG, which models elements related to the human operator, such as monitoring movement, work environment, and collaboration with robots, using ontology and standards. The framework is exemplified through an industrial case study and incorporates graph-based data querying, visualization, and analysis. An instance involving a complex wire harness assembly process illustrates instances of resource allocation and comprehensive support for human-machine collaboration.

The objective of the HCKG design concept is to establish a framework to monitor and control human-machine collaboration, improve resilience, agility, and improve working conditions for operators. The Knowledge Graph incorporates monitored data concerning the operator's activities, the environment, as well as all robots and equipment within the manufacturing space. Through the analysis of the collected Knowledge Graph data, collaboration can be enhanced, work instructions can be customized for the operator, and any modifications can be adaptively managed. Figure 4.2 illustrates the integration approach of the HCKG concept.

A detailed case study is developed thoroughly considers the tasks performed by operators, encompassing movement assessment, collaboration with machines, work sequences, and ergonomic aspects. It is also emphasized that the integration of activity recognition technologies can enrich the valuable data within a Knowledge Graph in a smart factory setting. Our objective was to summarize current methods and tools for semantic development and to introduce a concept for creating standard models of human-centered

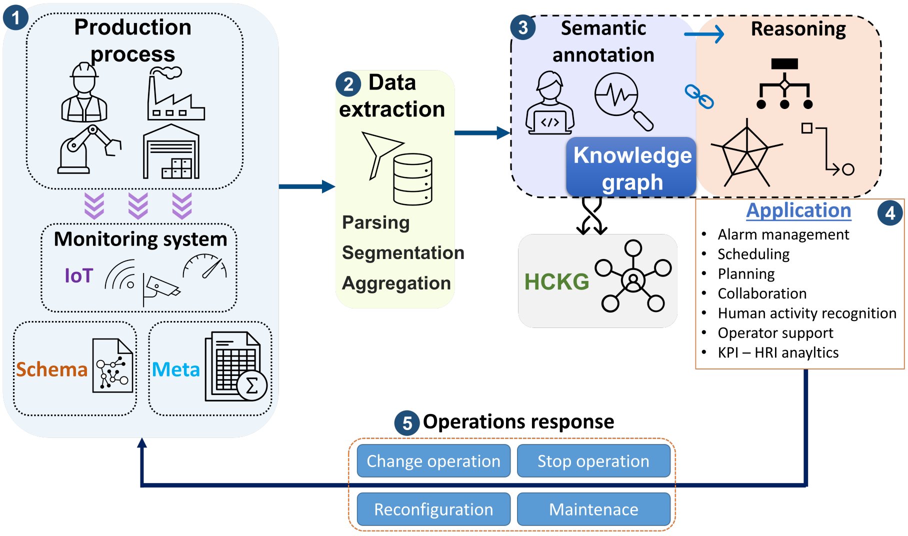

Figure 4.2: Integration of the HCKG design concept connect to the production process, using five segments

collaboration, illustrated through an industrial case study.

4.2.3 Scientific results and novelty

The key contributions were as follows:

- Emphasized the importance of incorporating human factors into cyber-physical systems.
- Proposed an expansion of automation standards (ISA-95, AutomationML, B2MML) to include human-related processes and demonstrated the use of semantic technologies.
- The concept was validated through a replicable industrial case study. Various graph-based analyses were conducted using different types of graphs such as normal, directed, or hypergraphs, including resource allocation analysis, KPI evaluation, and the integration of a DAS.
- The application based on HCKG facilitated the identification of various forms of collaboration between human and machine actors in the assembly process.
- Furthermore, a conceptual design was put forward for a human-centric manufacturing dashboard.

4.2.4 Publication background

- Nagy, L., Abonyi, J., & Ruppert, T. (2024). Knowledge Graph-Based Framework to Support Human-Centered Collaborative Manufacturing in Industry 5.0. Applied Sciences, 14(8), 3398. GS citation: 8
- Tóth, A., Nagy, L., Kennedy, R., Bohuš, B., Abonyi, J., & Ruppert, T. (2023). The human-centric Industry 5.0 collaboration architecture. MethodsX, 11, 102260. GS citation: 72
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- Nagy, L., Ruppert, T., Löcklin, A., & Abonyi, J. (2022). Hypergraph-based analysis and design of intelligent collaborative manufacturing space. Journal of Manufacturing Systems, 65, 88-103. GS citation: 23

5 Thesis Group 3: Human-centered indicators and physiological parameters

Research on physiological data within manufacturing environments remains limited, with a notable lack of reliable ground truth and comprehensive databases. To address this gap, I collaborated with cognitive psychologists to design and execute multiple controlled experiments in our laboratory, simulating manufacturing-related scenarios. These studies aimed to establish a solid foundation for integrating physiological measurements into human-centric industrial research.

5.1 Cognitive load during task executions

5.1.1 Background and objective

We investigate the feasibility of attentional multitasking in collaborative human-robot assembly. We performed an exploratory study in which participants carried out a wire harnessing task with a cobot, while simultaneously engaging in parallel attention-demanding task through a Go/No-Go test. To evaluate the effects of multitasking, we designed the Go/No-Go test with two levels of difficulty in terms of their attentional demands. We conducted a user study with 16 participants and gathered quantitative metrics on task performance and response rates and qualitative feedback to evaluate the ability of engaging in secondary attentional tasks.

To observe the effect of multitasking, we varied the difficulty of the secondary task across two levels and analysed its impacts on work performance and workload. Our results confirm threaded cognition theory, suggesting that human-robot collaboration could reduce cognitive capacity by extend attentional resources, leading to higher errors and cycle times during multitasking. This underscores the importance of a detailed understanding of attentional factors in human-robot collaboration.

5.1.2 Design of Experiment

The experiment was designed to divide participants' attention, providing a realistic assembly scenario where the participant must balance the attentional load of the main task while also responding to the demands of the secondary task to simulate multitasking. The main task involved working on a wire harnesses in collaboration with a UR5e cobot, while the secondary task involved a Go/No-Go test to impose increased attentional demands. The experimental study was carried out at the Industry 5.0 laboratory at the University of Pannonia. Figure 5.1 illustrates the experimental setup used in this research.

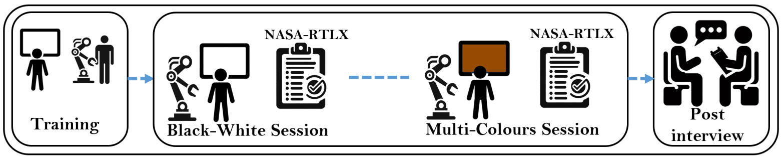

Figure 5.1: Overview of the setup and the procedure of the study. The task order was counterbalanced, with 8 participants starting with the black-white condition, and 8 starting with the multi-colour session.

5.1.3 Scientific results and novelty

Our experiment suggests that multitasking scenarios may lead to higher cycle times and potentially even increased errors, and operators might be prompted to adapt to the attentional load by prioritising only one of the tasks. Although we view multitasking in HRC as feasible, we raise concerns about potential effects on productivity and call for future research on designing HRC applications that don't deplete attentional resources.

Our results also show that, when multitasking in HRC settings, participants may adapt their strategy and prioritise one task over another, leading to more errors in the respective task. We speculate that this can be either due to the inability to split attention between multiple tasks, or simply because of the preference to maximising the efficiency in one task while sacrificing efficiency in another.

5.1.4 Publication background

- Eesee, A. K., Kostolani, D., Kang, T., Schlund, S., Medvegy, T., Abonyi, J., & Ruppert, T. (2024). May I Have Your Attention?! Exploring Multitasking in Human-Robot Collaboration. IFAC-PapersOnLine, 58(19), 241-246. GS citation: 2

- Eesee, A. K., Kostolani, D., Varga, V., Kang, T., Schlund, S., & Ruppert, T. (2025, June). Studying Dual-Task Awareness in Industrial Settings Through Reaction Times and Physiological Signals. In 2025 IEEE Conference on Cognitive and Computational Aspects of Situation Management (CogSIMA) (pp. 151-156). IEEE. GS citation: 0

5.2 Work instruction evaluation

5.2.1 Background and objective

In the industrial setting, poorly designed instructions can significantly undermine productivity, increase the likelihood of errors, and lower overall job satisfaction. Moreover, the detrimental economic and social consequences of poor instruction have been extensively documented, resulting in reduced levels of customer satisfaction, increased operational costs, and inefficient decision-making processes. Although numerous studies have explored the benefits of simplified or digital work instructions—such as textual guides or augmented reality (AR)-based solutions—these approaches often do not systematically validate the objective metrics with the subjective experience of workers based on the utilized instructions. Furthermore, research that integrates subjective questionnaires and objective physiological metrics to comprehensively evaluate worker cognitive load and efficiency based on work instructions remains limited. This gap is particularly pressing in modern assembly environments, where rising task complexity calls for instruction designs that are both cognitively considerate and operationally effective.

5.2.2 The developed methods and Design of Experiment

We systematically compared two distinct instructional approaches—code-based and visual-based—within an assembly-like scenario. Specifically, we hypothesize that code-based instructions, which rely on alphanumeric codes to guide the assembly process, impose a higher subjective cognitive load due to the increased mental effort required to decode the codes. By contrast, visual-based instructions are expected to reduce cognitive load by offering more intuitive, graphical representations of the same tasks. However, this simplified approach may induce more frequent hand movements and repeated task cycles—potentially resulting in more pronounced changes in physiological signals (Galvanic Skin Response GSR and Photoplethysmogram PPG) due to increased physical activity. In evaluating these hypotheses, we measure both subjective cognitive load (using the NASA Task Load Index 'NASA_TLX' and short Dundee Stress State Questionnaire 'short DSSQ') and objective indicators (physiological signals and task performance metrics) to capture a comprehensive view of how work instructions influence operator well-being and efficiency. We therefore pose the central question: *How do subjective perceptions of cognitive load and performance align with objectively measured changes in cognitive load and performance when different instructional methods are employed?*

Given the gap identified in the literature, we designed a controlled experiment in which participants assembled “Make 'N' Break Extreme” blocks using two instructional methods: code-based and visual-based instructions. This protocol was chosen specifically to isolate extraneous load while maintaining consistent intrinsic load across tasks. The present study aims to investigate the impact of work instructions on operator cognitive load and performance within a controlled, assembly-like scenario.

The study involved the use of two instructional approaches for two distinct sessions: *Visual-based* instructions for the low cognitive load session and *Code-based* instructions for the high cognitive load session. In the visual-based session, the participants see a series of step-by-step images depicting exactly how each pair of blocks should connect. In other words, each image clearly shows which sides of the pieces should touch, allowing participants to visually align the blocks until they match the illustrated pattern. The visual instructions presented in this context are characterized by their clarity as they provide a straightforward and unambiguous representation of the final goal. This approach aims to minimize the need for interpretive effort from the participants.

On the other hand, we utilized a color-based coding system for the assembly instructions to increase the difficulty level in the code-based hard session. A code, usually consisting of the first two letters of its color, references each piece. For example, 'Re' signifies the red piece and appears in red text, while 'Gr' signifies the green piece and appears in green text. The instructional material provides participants with these codes, which they must use to determine the position and contact points between pieces. The representation of spatial relationships between pieces is denoted by 'A' for Above, 'B' for Below, 'L' for Left of, and 'R' for Right of. We denote the degree of contact between two adjacent pieces as 'T1' for a single contact region and progressively increase it to 'T4' for four contact regions. The codes require participants to translate abstract instructions into the concrete task of assembling the blocks, reflecting a cognitive challenge often encountered in real-life situations where such instructions can be difficult to interpret. Figure 5.2 shows the setup of the experiment in this study.

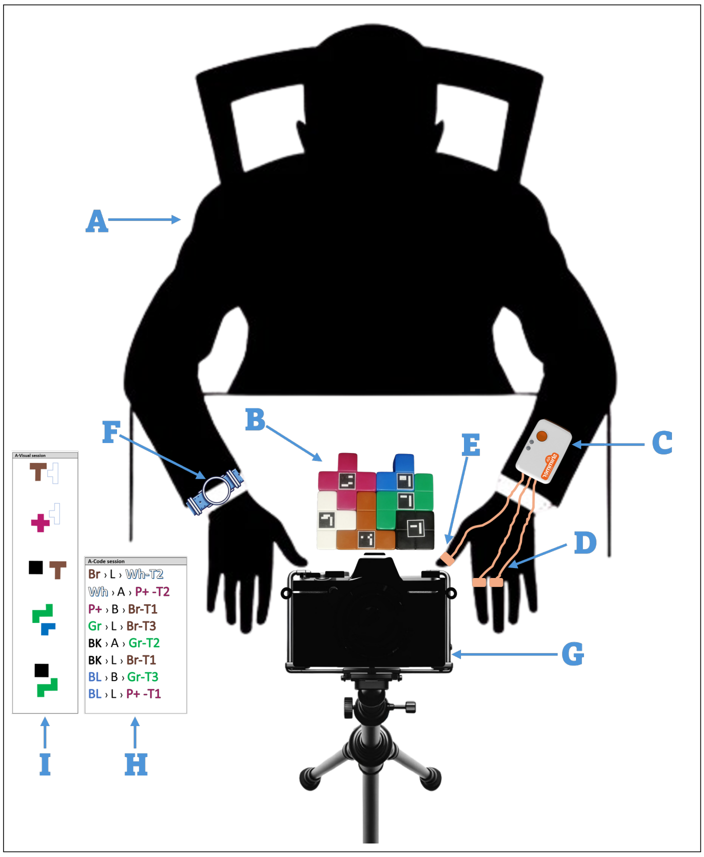

Figure 5.2: This figure illustrates the comprehensive setup used in our experiment.

5.2.3 Scientific results and novelty

This study provides new insights into the relationship between work instruction design and operator cognitive load in industrial-like assembly scenarios. The key scientific contributions and novel aspects are as follows:

1. **Integrated evaluation approach:** We systematically combined subjective workload assessment tools (NASA-TLX and short DSSQ) with objective physiological measures (Galvanic Skin Response and Photoplethysmogram) and task performance indicators to obtain a comprehensive understanding of cognitive load during assembly tasks.

2. **Experimental evidence on instruction modalities:** We designed and executed a controlled experiment to compare two distinct instruction modalities: visual-based and code-based. Our results show that visual-based instructions substantially reduce subjective cognitive load, while code-based instructions impose

higher mental demands due to the need for decoding and translation of abstract codes into concrete actions.

3. **Revealing trade-offs between cognitive and physical load:** Although visual-based instructions lowered cognitive load, they were associated with increased hand movements and repeated task cycles, which were reflected in physiological signals. This highlights a trade-off between cognitive and physical dimensions of workload not sufficiently addressed in the existing literature.

4. **Practical implications for instruction design:** Our findings provide actionable evidence for the development of cognitively considerate and operationally effective work instructions in modern industrial environments, particularly where task complexity is increasing.

The novelty of this work lies in its holistic methodological approach, its empirical validation of instruction-induced workload differences, and the identification of interaction effects between subjective and objective indicators of cognitive load.

5.2.4 Publication background

- Eesee, A. K., Varga, V., Eigner, G., & Ruppert, T. (2025). Impact of work instruction difficulty on cognitive load and operational efficiency. Scientific Reports, 15(1), 11028. GS citation: 0

- Gugolya, M., Varga, V., Medvegy, T., & Ruppert, T. (2025, August). The Impact of Work Instruction Simplification on Operator Performance and Learning Curve Efficiency. In IFIP International Conference on Advances in Production Management Systems (pp. 148-162). Cham: Springer Nature Switzerland. GS citation: 0

6 Appendix: Original Articles of the Habilitation

The following original articles are been discussed within this habilitation thesis:

- Tran, T. A., Ruppert, T., & Abonyi, J. (2021). Indoor positioning systems can revolutionise digital lean. Applied Sciences, 11(11), 5291., GS citation: 42
- Halász, G., Medvegy, T., Abonyi, J., & Ruppert, T. (2023, September). Indoor positioning-based occupational exposures mapping and operator well-being assessment in manufacturing environment. In IFIP International Conference on Advances in Production Management Systems (pp. 543-555). Cham: Springer Nature Switzerland., GS citation: 1
- Tran, T. A., Ruppert, T., Eigner, G., & Abonyi, J. (2023). Assessing human worker performance by pattern mining of Kinect sensor skeleton data. Journal of Manufacturing Systems, 70, 538-556., GS citation: 14
- Eesee, A. K., Jaskó, S., Eigner, G., Abonyi, J., & Ruppert, T. (2024). Extension of haas for the management of cognitive load. IEEE Access, 12, 16559-16572. GS citation: 7
- Nagy, L., Abonyi, J., & Ruppert, T. (2024). Knowledge Graph-Based Framework to Support Human-Centered Collaborative Manufacturing in Industry 5.0. Applied Sciences, 14(8), 3398. GS citation: 8
- Eesee, A. K., Kostolani, D., Kang, T., Schlund, S., Medvegy, T., Abonyi, J., & Ruppert, T. (2024). May I Have Your Attention?! Exploring Multitasking in Human-Robot Collaboration. IFAC-PapersOnLine, 58(19), 241-246. GS citation: 2
- Eesee, A. K., Kostolani, D., Varga, V., Kang, T., Schlund, S., & Ruppert, T. (2025, June). Studying Dual-Task Awareness in Industrial Settings Through Reaction Times and Physiological Signals. In 2025 IEEE Conference on Cognitive

and Computational Aspects of Situation Management (CogSIMA) (pp. 151-156). IEEE. GS citation: 0

- Eesee, A. K., Varga, V., Eigner, G., & Ruppert, T. (2025). Impact of work instruction difficulty on cognitive load and operational efficiency. Scientific Reports, 15(1), 11028. GS citation: 0

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