Óbuda University

PhD Dissertation

Sensor technology and data science to facilitate
Lean 4.0 and Operator 4.0

by

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List of Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
AWCRS	Acute Work-Content-Related Stress
CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System
DT	Digital Twin
EU	European Union
GDPR	General Data Protection Regulation
HAR	Human Activity Recognition
H-CPS	Human-Cyber-Physical System
HDT	Human Digital Twin
HR	Heart Rate
HRV	Heart Rate Variability
I4.0	Industry 4.0
I5.0	Industry 5.0
IIoT	Industrial Internet of Things
IoT	Internet of Things
IPS	Indoor Positioning System
IT	Information Technology
JITAI	Just-in-the-Moment Adaptive Interventions
KPI	Key Performance Indicator
LM	Lean Manufacturing
ML	Machine Learning
MLOps	Machine Learning Model Operationalization Management
NASA-TLX	NASA Task Load Index
O4.0	Operator 4.0
O5.0	Operator 5.0
OLE	Overall Labor Effectiveness
PDCA	Plan-Do-Check-Act
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
RTLS	Real-time Location System
VSM	Value Stream Mapping
WEBA	Work-content Effect on a BArista
WHO	World Health Organization

Acknowledgements

My long-held dream of pursuing a Ph.D. sparked a long time ago, but I did not expect it to be such an immersive, vivid, and joyful adventure, which fueled me in the world of academia and fantasia alike. This transformative journey has fundamentally shaped me as a researcher and as an individual with a new set of knowledge and skills. At the finish line, I would like to express my deepest gratitude to the people who have supported and guided me throughout this long and winding journey, enabling me to obtain my doctorate successfully.

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1

Introduction

> The message of the Kaizen strategy is that not a day should go by without some kind of improvement being made somewhere in the company.
>
> *Masaaki Imai (1930-2023)*
> *Japanese management consultant*
> *Father of Continuous Improvement*

Industry 4.0 (I4.0) was coined as an umbrella for modernizing smart automation, data exchange/processing, and manufacturing technologies [R1]. The connectivity of equipment, machines, and various supporting devices to the Industrial Internet of Things (IIoT) within a manufacturing facility is a critical player in I4.0 [R2], that enables the communication between humans and machines, and offers data-driven insights and solutions. An intelligent manufacturing system can be monitored efficiently with optimized resources regarding human labor [R3], production time [R4], energy [R5], and operational cost [R6]. Modern machines come with various ways of transmitting data and communicating with each other, creating a connected Cyber-Physical Production System (CPPS) [R7], enabling the automatic deployment of management principles [R8].

1.1 Current development of Lean 4.0 and Operator 4.0

Lean Manufacturing (LM) is a production management doctrine stemmed from Toyota Motor Company [R9] and widely accepted in various industries, e.g., logistics [R10], automotive assembly [R11], carton production [R12], electrical and electronics [R13], handicraft [R14, R15], and maintenance [R16]. LM focuses on cutting waste and improving operation performance [R17], with the core concepts are:

- identifying wastes in production processes to eliminate them [R18]
- shortening the lead time of production [R19]
- reducing inventory and stock levels [R19]
- standardizing tasks and motion to stabilize the output quality [R20]
- developing a continuous flow of information and materials [R18, R11]
- balancing the manufacturing line to avoid bottleneck [R21]

- employing a comprehensive scheme to maintain productivity [R22].

Continuous improvement is an essential initiative in maintaining the efficiency of LM system [R23], with kaizen activities conducted by a group of employees to solve an organizational problem [R24]. Lean 4.0 is a new generation of LM with the implementation of I4.0 technologies [R25, J1], creating a unique effect for LM deployment designing, operating, monitoring, and optimizing manufacturing systems [R26, R27], enhancing the flexibility and reconfigurability [R28].

I4.0 technologies enabled the integration of human operators with manufacturing processes and equipment into Human-Cyber-Physical Systems (H-CPSs) [R29, R30, R31] as a new generation of workers/operators (i.e., Operator 4.0 (O4.0) [R32]), with O4.0 types corresponding to different I4.0 technology gadgets [R33, R34]. Not only giving a tool-set to support human workers, the O4.0 concept puts them back at the center of manufacturing, as well-stated by Rosenbrock [R35]: Humans should never be subservient to machines and automation, but machines and automation should be subservient to humans.

The current development of O4.0 is scattered and intermittent [J2], despite a growing research interest in human factors within industries. The O4.0 concept was only considered the main interest in a few theoretical and statistical studies. Within experimental studies, the O4.0 types experienced an imbalanced development due to different readiness levels and customization possibilities of the respective core technologies. O4.0 pillars need more time for the core technologies to be elaborated and circulated in the market, with more practical studies required to materialize the current concepts and proposals.

1.2 The motivation toward Industry 5.0

The Industry 5.0 (I5.0) formulated by the European Commission (EC) calls for a sustainable, human-centric, and resilient industry [R36], by utilizing rapid developments of sensors, wearables, actuators, and communication technologies [R37, R38]. Fostering the transition toward the I5.0 will be the key objective of every modern economy. From organizational contribution, the EU is the first player in the field with tremendous corporate efforts to establish and facilitate the transition. One such activity is the direct inclusion of the I5.0 paradigm into Horizon Europe calls, which reorients previous focus (mainly technological and economic sustainability) to include human-centrism, resilience, and a holistic sustainability approach.

However, other stakeholders welcome this initiative with scattered and unbalanced efforts. They were primarily focused on augmented workforce initiative, collaborative, social, and resilient aspects [R39, R40, R41]. The German industry generally focuses more on the virtual, healthy, smart, and resilient aspects [R42]. Other aspects were design principles, ethics, and regulations that linked to team robotics and the Human Digital Twin (HDT), and the development of mobile work approaches [R42, R43]. The O5.0 approach gained little practical relevance in the United States, as the human operators are rarely addressed in employed activities [R44, R45], except the application of augmented reality (AR) headsets for worker support [R45]. The 14th Five-Year Plan on Intelligent Manufacturing in China essentially promoted the application of AR, virtual reality (VR), and mixed reality (MR) for supporting the work of operators [R46].

Answering the call of I5.0, the ideal symbiosis work system consisting of H-CPS and adaptive automation is proposed as Operator 5.0 (O5.0) [R47, R33], which aims at a socially sustainable manufacturing workforce, proposing resilience requirements for human operators and human-machine systems. Incorporating Lean 4.0 can further improve sustainable operation, while O4.0 and O5.0 contribute directly to human centricity and the self-resilience of a system [J2]. The benefits from the organizational, system, and operator viewpoints when adopting Lean 4.0 along with O4.0/O5.0 solutions can be categorized into four types as illustrated in Fig. 1.1:

- Sustainable operation: efficient organization and supply chain operations.
- Human-system collaboration: enhanced the efficiency and convenience.
- Human-centric consideration: bringing benefits for workers based on their needs.
- Social resilience: larger-scale benefits for the workforce and society.

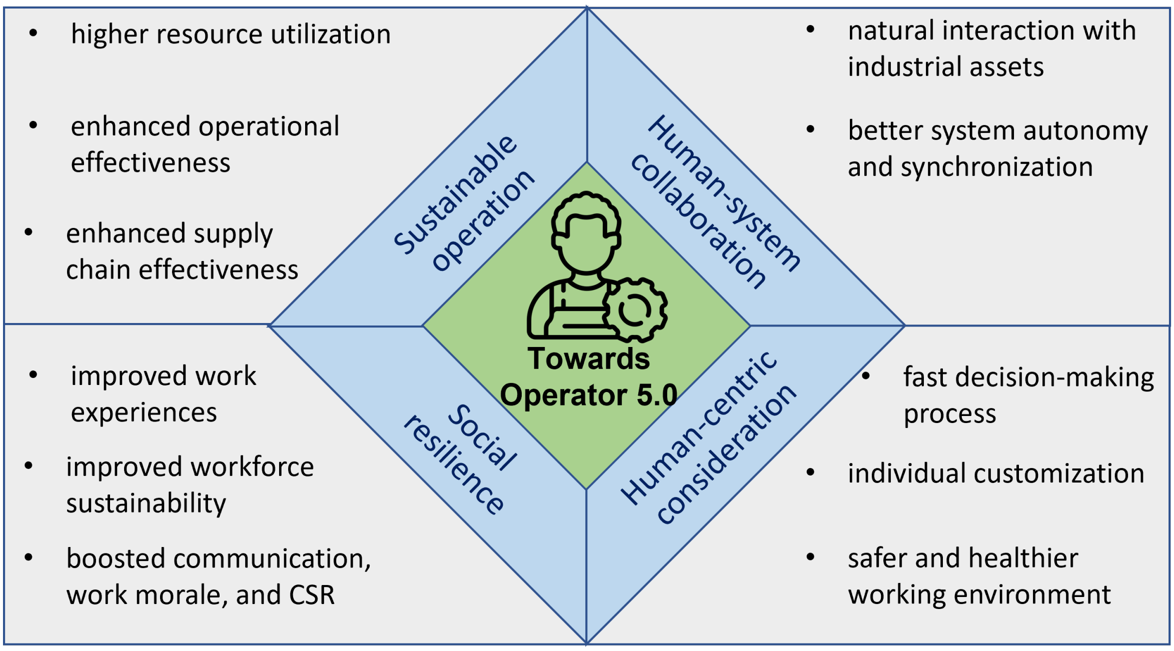


Figure 1.1: The expectable benefits towards the Operator 5.0. Source: Own work [J2].

1.3 Gaps and hurdles in front of Industry 5.0

Many companies still utilize legacy machinery that performs acceptable operations, even though the lack of connectivity, power consumption, and carbon emissions are not as good as modern ones. The IoT upgrade for better utilization of existing infrastructure of legacy equipment and software with IoT connectivity is named brownfield development, or retrofitting [R48, R49, R50, R51]. Retrofitting targets include the hardware of machinery and the production method, operator, and management [R52]. However, there are technical concerns due to the non-scalability of retrofitting solutions between different manufacturing industries [R50]. The most challenging obstacle of a retrofitting project is that there are machine tools from different manufactured times, having different communication protocols [R53]. Such a legacy system with minimal connectivity is not eligible for data-driven management approaches, which require data collection and analysis [R54]. Due to the lack of sensors and actuators, process control needs to be conducted manually by observing, sensing, estimating, and adjusting the machine parameters [R55].

The need for retrofitting solutions emerges in Small and Medium-sized Enterprises (SMEs) [R56], which are the most vulnerable to being left behind with I4.0 development [R57]. Lessons from the previous I4.0 implementation show that the fragmented approach with domain-specific technical developments will lead to more challenges from the management perspective [R58]. Several I4.0 maturity models aim to assist comprehensive guidance over this problem, however, most of them show a gap for a holistic, structured, organizational alignment approach [R59]. In the I5.0 threshold, the ambiguity of digitally transforming legacy manufacturing systems remains untouched, with a lack of updated guidance that fulfills the previous gap of I4.0.

Though the transition toward I5.0 is inevitable with many appearing signs, there is a lack of foundation and technical readiness for the evolution from O4.0 toward O5.0. Both paradigms are underdeveloped with a low number of studies and disruptively connection [R60, J2]. As can be seen in Fig. 1.2, human-centric technology development was mentioned in almost every O5.0 experimental study (28 over 32), dominant over the other aspects, i.e., sustainability and resilience. Within these studies, the asymmetric development between O4.0 pillars is shown. Instead of a holistic view, researchers rather focused on how to leverage worker productivity and minimize ergonomic pain [R61, R62, R63, R64].

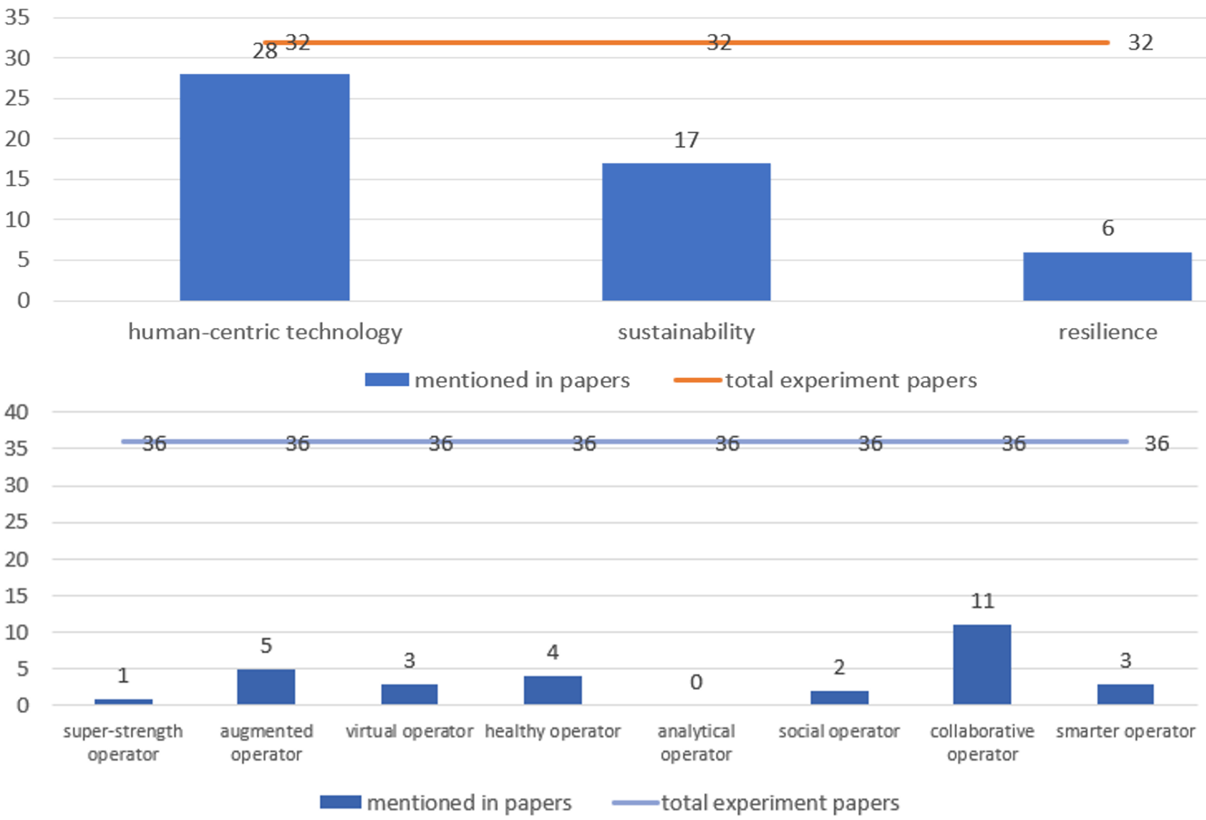


Figure 1.2: Experimental studies with the I5.0 focus: Resilience was not favored, while the O4.0 types were not equally developed. Source: Own work [J2].

On top of that, the technical readiness of the O4.0 solutions in particular, and the I4.0 human-centric technologies in general, was not ready for the I5.0 application. There are missing links between the I5.0 with other technical aspects of the I4.0, and with social aspects of the O4.0. Lack of multi-disciplinary knowledge urges for high-level scientific evidence and applicability of human integration into H-CPS [J3]. Inter- and multi-disciplinary efforts should be conducted to link knowledge from different fields, creating a trustful and solid foundation for future improvements.

The five most frequently mentioned drivers and restrainers of adopting human-centric technology and O4.0 solution were illustrated in Fig. 1.3, with the arrow size reflecting the appearance frequency of the factor [J2]. The most significant driver was the in-depth analysis and management of a manufacturing process. Equally important was the well-designed interaction between humans and machines. Since human factor study in the manufacturing context required the incorporation of many disciplines, the lack of multidisciplinary knowledge was the strongest restrainer. Lack of standards and guidelines, and technological accuracy concerns posed the same negative impact. Data-related concern, with associated handling, management activities, and security, was the least mentioned factor.

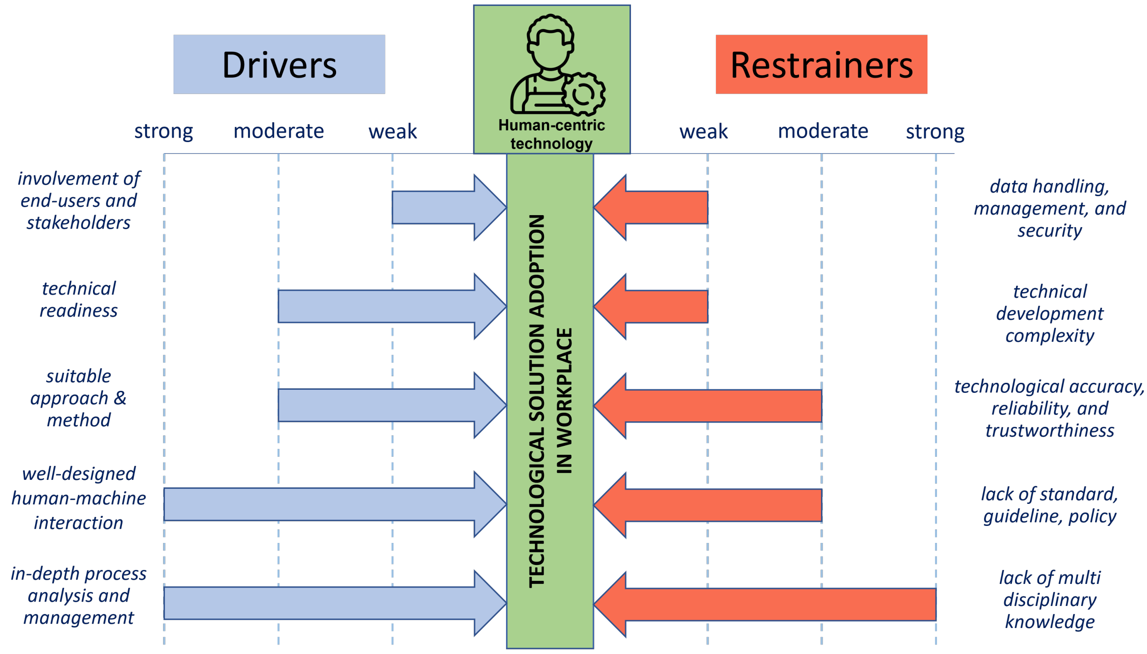


Figure 1.3: Drivers and Restrainers of adopting human-centric technology. Source: Own work [J2].

1.4 The addressed problems within the thesis

This thesis looks for solutions that utilize sensor technologies and the available toolbox of data science [R65], to address problems within the stated industrial context.

Without high investment in new equipment and technologies, companies can retrofit existing equipment with the IIoT capability of low-cost sensors and actuators [R66], generating great opportunities to re-design business and expand service activities while facilitating data-driven business strategy making [R67]. In Chapter 2, I studied how sensor technology and data science can be deployed in retrofitting and Lean 4.0 projects. After conducting a systematic overview of the existing I4.0 solutions to upgrade the old-fashioned system into a connected one, it can be seen that sensor technology can be applied for hardware improvement, then data science can support advanced management such as Lean 4.0 and O4.0. The ultimate success of retrofitting is the readiness of real-time KPIs, which give insight into system operation [R68]. Therefore, the potential of Lean 4.0 can be unlocked even on legacy systems, through the integration of operational technology (OT) and information technology (IT), in which the Indoor Positioning System (IPS) is a promising candidate [R69]. In the second section of this chapter, I studied the use of IPS as a low-cost retrofitting solution, that can offer a set of Lean KPIs with a real-time value stream for the implementation of Lean 4.0.

Observation with Gemba walk is the most popular method for assessing human performance in LM [R70]. With I4.0 technologies, innovative ways are expected to replace the traditional expert-dependent and time-consuming ones. The advancement of Artificial Intelligence (AI) camera sensors enables capturing a tremendous amount of data from intended objects. One ideal candidate for this approach is the Microsoft Kinect sensor due to its advanced 3D depth-sensing technology [R71], with its marker- and calibration-free characteristics are appropriate for industrial application [R72]. In Chapter 3, I developed a Lean 4.0 solution for assessing worker performance with a Kinect sensor. The proposed pattern mining-based continuous improvement approach is aligned with I5.0 objectives since it is human-centric and aims at sustainably building a resilient workforce.

In a manufacturing environment, when workers face the work content with demanding physical or psychological tasks that exceed their abilities or resources [R73, R74], stress appears as mental or physical tension [R75], with either positive or negative effects [R76]. A low level of acute stress is associated with vigilant or sustained attention, therefore produces the optimal performance [R77] with enhanced mental and physical efficiency [R78]. To utilize the positive arousal state of acute stress while avoiding negative overload or any long-term accumulation of occupational stress, more knowledge should be developed to understand the effect of work content on human workers [R79, R80], as well as the stress-performance relationship. This insight provides a foundation for work content design, and helps to monitor and adjust any unfavorable work content timely with the early stress sign. In Chapter 4, I elaborated a foundation for the Operator 4.0 stress-performance monitoring and simulation solutions, with several research topics. In the first section of this chapter, I explored the evidence of using Heart Rate Variability (HRV) as an indicator of Acute Work-Content Related Stress (AWCRS), to provide a basis for Just-in-the-Moment Adaptive Interventions (JITAI) to optimize worker performance.

Psychological stress should be incorporated into the HDT as a vital role in human behavior and performance [R81, R82]. To further integrate humans into the Human-Cyber-Physical System (H-CPS) [R83], an in-depth stress-performance model with subtle human details and functional status [R84, R85] is expected to simulate, predict, and monitor the well-being of human workers/operators in I5.0. In the second section of this chapter, I developed a system dynamics conceptual model for the simulation of Acute Work-Content Related Stress and the performance of human workers.

The lack of controlled experiments and validated evidence prevents the applicability of physiological parameters (i.e., heart rate) as indicators for AWCRS [J4]. Most of the datasets on human research are generated in a laboratory environment and lack focus on element factors of work content, which limits the realistic generalization. In the last section of this chapter, I explained how the Work-content Effect on a BArista (WEBA) dataset can be generated, which facilitates further study of the AWCRS effect on human performance.

Finally, the conclusion and possible industrial application are mentioned in Chapter 5.

2

Retrofitting and IPS technology as solutions for Lean 4.0 and Industry 5.0

> ***Thesis 1:***
> **I developed a near-online retrofitted monitoring function to generate Lean KPIs based on analysis of the position data extracted from the Indoor Positioning System (IPS) to support the Lean 4.0 implementation.**

Publications relevant to the thesis: [J5, J1, J6].

2.1 Retrofitting-based development with sensor technology as Industry 5.0 solution

Though the IoT capability is a built-in function for modern machines, many legacy machines are still in operation with limited or without digital communication. The need to connect them became popular to improve overall production efficiency. In the I5.0 era [R36], manufacturers should enhance workforce empowerment as a way to support their workers during production tasks [R86]. This integration of human employees should be built upon the achievement of I4.0 technology-driven orientation as a way toward a digitized production of the future [R87]. Retrofitting should adopt concepts such as O4.0 [R29, R33, R32], O5.0 [R47], thus the retrofitted system with the data analysis and monitoring capability can gradually benefit its operator. Besides, continuous improvement in process monitoring, quality management, and energy utilization are criteria that need to be considered sustainable metrics.

A systematic literature review was conducted in databases of Scopus, Web of Science (WoS), and Google Scholar, with relevant keywords within the desired scope as "retrofit*", "brownfield", "legacy", "Industry 4.0", "Industry 5.0", "maturity", "strateg*", "implement*". Full-text scanning was carried out on 98 studies, to provide insights from successful case studies in brownfield developments. Extracted details from these retrofitting projects are discussed in the next sections.

2.1.1 Enabling technologies - Existing Solutions for Retrofitting

In this subsection, enabling technologies and solutions for retrofitting projects are reviewed in four groups of activities: sensor and actuator deployment, connectivity enhancement, data management, and operational application.

Sensors and Actuators deployment

Several retrofitting projects perform the sensors and actuators deployment at the initial phase as the first step to integrating the physical and virtual worlds. Sensors and actuators go in pair with an interested process parameter [R88], thus their simultaneous consideration and selection can develop a functional Digital Twin (DT) from low-level. In this layer, sensors and actuators play a vital role in process automation in general and the IoT approach in particular.

Sensors deployment

Existing legacy equipment lacks sensors to indicate their operating status [R89], thus additional sensors should be integrated. Several researchers stated the difference between a general-purpose sensor and an IoT-specific purpose sensor [R90]. Though there is a significant difference between on- and off-the-shelf sensors in the market, an overview was conducted of which were deployed in previous retrofitting projects without digging into that difference. The types of deployed sensors are categorized in Table A.1, Appendix A.

The sensors can be divided into measuring the parameters of the production environment (e.g., temperature and humidity) or measuring the machine parameters (e.g., vibration, energy consumption, tension) [R56]. The use of sensor types is closely related to the process parameters and quality, mentioned later at the end of this section. Energy retrofitting is still an underdeveloped concept [R91]; thus, the use of energy sensors in past projects is scarce. A system of high-frequency sensors is deployed to track the energy utilization of various equipment in the food processing system to enhance energy efficiency [R92]. Meanwhile, accelerometers and temperature sensors are among the most frequently used, and on-the-shelf products are preferred in many studies. The type of chosen sensors is different from industries such as textile [R68], food processing [R93], and car assembly [R94]. On the other hand, within the same industry (e.g., metal cutting [R95, R91, R96]), different sensors are chosen due to the different machine status and various operational needs. This fact reflected the realistic heterogeneity of the legacy system and the un-scalability of the retrofitting solution.

Along with the usage of the commercial sensor, there are types of sensors that are especially suitable for retrofitting purposes, such as the ultra-thin silicon chips [R97]. There is an evaluation of alternative manufacturing methods for 3D Mechatronics Integrated Devices (MID) sensors for retrofitting purposes [R96]. With this ongoing interest, retrofitting-purpose sensors will be available on the shelf shortly.

Actuators deployment

Legacy systems usually require human manipulation with adjusting and controlling tasks. For brownfield development, these manual tasks can be performed by actuators to ease the attentive presence of human workers. Several actuators and their usage in retrofitting development are given in Table A.2 of the Appendix A. The existing legacy actuators can be incorporated with automation capability to facilitate process control [R98]. An additional actuator or end-effector can be deployed to extend the system capability for performing the related process [R99, R23]. An IT-based integration of additional sensors and actuators with the existing legacy system can be established with a self-built invasive unit [R100], thus providing a digital retrofit solution for operational purposes such as process automation, production control, or quality assurance. An industrial wireless sensor and actuator network can perform distributed sensing, data fusion, and collaboratively decision-making with human workers [R101].

In most scenarios, the existing legacy actuators can be integrated into the system control, thanks to the newly established system connectivity [R102]. The application of integrated control, control algorithm, and process simulation helps to manipulate the actuators effectively, with predefined control sequences [R98]. Process and quality control functions can be incorporated into the local automation, in pair with respective sensors [R103].

In other cases, new sensors and actuators are deployed [R100]. Additional actuators can perform controlling on process variables automatically in a real-time manner [R104], with the signal being monitored by respective sensor readings, or governed by an embedded board that can receive user command, or automated by a retrofitting platform [R49]. The search for the suitable sensor and matching actuator can adopt the static or dynamic model creation in [R88]. Noticeably, besides existing variables, the retrofitting attempt may introduce new variables that share an impact on the process [R105]. New actuator deployment can extend the capability of the existing hardware, thus incorporating new aspects into the system [R99], such as safety [R104, R53]. The actuator types can be self-built or commercial, depending on the specific need of the retrofitting purpose. Self-built actuators opened a wider range of applications as they can adapt to the design of existing mechanisms and structure [R106] or provide a unique function [R107]. The safety aspect can be integrated into the intrinsic design of the actuator [R106].

Connectivity enhancement

The weak point of a legacy system is that there are homogeneous IT systems and machines with different interfaces and protocols [R88]. This connectivity enhancement came into the retrofitting projects after the sensors were deployed, as communication is a crucial characteristic of I4.0 [R49]. Once the connectivity is established, new options for operation monitoring, forecasting, and controlling can be available on the shop floor [R99]. PLCs already have taken place in legacy systems. They will continue to exist for a long life-cycle time, thus urging a reasonable need to integrate them into IIoT infrastructure [R108]. The first subsection of this section is devoted to the development of retrofitting the manufacturing systems with PLCs. In the second subsection, the IoT components deployed to retrofit the connectivity of legacy systems are described.

I4.0 PLCs retrofitting

Many retrofitting projects involved the use of a PLC. In legacy manufacturing systems, PLCs are still in charge of controlling the production processes with relatively long life cycles, with their natural characteristics of being hardware-based and mission-critical. However, due to their limited processing and communication capabilities, plant monitoring and data analysis cannot be incorporated into I4.0 architecture [R109]. In this scenario, I4.0 retrofitting attempts were made to access these data of PLCs and forward them into new interconnected environments. In other cases, the deployment of new PLCs is also considered a way to automate processes and enhance field-level control of the legacy manufacturing system. Noticeably, there are cases in which reliability concerns, vendor restrictions, and outdated programming environments make the PLC irreplaceable, obstructing the retrofitting attempts [R109].

Retrofitting efforts aim at broadening the capability of existing PLCs or accessing and integrating their data [R102]. Several retrofitting concepts for interfacing legacy PLCs in I4.0 scenarios are proposed in [R109], which consider the case of factories containing PLCs from different manufacturers. The LoRaWAN connectivity is integrated into a PLC in [R110], which enhances the field device connection. To retrofit an old system, new PLCs can be deployed to perform logic control on system modules such as conveyors [R111]. Generally speaking, to integrate legacy PLCs with limited connectivity into an IoT system, several components such as communication protocols, programming language, and execution environment should be taken. A middle layer can be formed based on the features of the existing PLCs to enhance the connectivity that makes the system fully I4.0-compliant [R112]. This connectivity enhancement will be discussed in the following subsection.

I4.0 connectivity retrofitting

Regarding establishing the shared communication and connectivity between devices and networks, hardware such as micro-controllers, micro-computers, and gateways are added, and protocols such as communication, messaging, and platforms should be defined [R95]. Embedded controllers and micro-controllers (e.g., NodeMCU and Arduino) can be implemented for embedded control, and process automation, especially with continuous production type [R113, R114]. Micro-computers such as Raspberry Pi are considered promising low-cost and effective candidates to integrate into the existing machine and enhance data acquisition, and simultaneous processing [R115]. Raspberry Pi is the dominant candidate for its reasonable price, simple configuration, and ease of operation with an open-source ecosystem. The connectivity of legacy systems can be enhanced by utilizing on-the-shelf gateways, and industrial providers such as Laird, SECO, and Siemens are trustable partners for the choice. A self-developed kit such as SmartBoxes is deployed in the retrofitting of the industrial loom and metal forming jigs and fixtures [R88]. Meanwhile, traditional field-bus such as PROFINET have been under development to enable the use of legacy devices. A virtual PROFINET architecture is proposed and validated through experiment as a promising low-cost and reduced-resources solution [R116]. For wireless communication technology, enhancement adoption based on LoraWAN technology is proposed as a gateway toward legacy networks [R117], which shows the flexibility and scalability of the application. Another similar approach emphasized the usage for IoT development in brownfields [R110, R109].

There are many promising candidates for retrofitting, such as Profibus, CAN-Open, and DeviceNet, which are proposed as the core communication protocol in Reference Architecture Model Industry 4.0 (RAMI 4.0) [R118]. OPC UA is an appropriate option with simple data acquisition, monitoring, control, and analysis [R66]. A case study is conducted to integrate OPC UA with legacy devices with proprietary protocols [R119]. Alternatives such as OPC DA and AMQP are utilized, dependent on the specific case of legacy system [R120]. Deployed protocols must comply with the recent industrial standard, as legacy machines are usually accompanied by old communication protocols [R121]. An integrated solution such as Modbus-OPC UA wrapper is proposed to adapt to a large part of legacy machines [R122]. Noticeably, the variants of Modbus, such as Modbus RTU and Modbus TCP, can also be coupled with protocol converters, consequently enhancing the retrofitting possibilities. Programming platform such as Node-RED is mentioned as a low-cost execution environment, and favorable for legacy PLCs [R109, R110]. In general, the connectivity enhancement for a legacy system is implemented according to an architecture that the authors usually suggested in their projects [R123, R57, R109]. These architectures are the prerequisite output that needs to be designed in the very beginning stage of retrofitting projects.

Data management

Up to this level, the process data are available and need to be connected to integrated storage for further processing [R124]. With the data shortage in quantity and quality as the nature of the legacy system, smart data modeling, simulation, and visualization is a promising approach to full automation ideas [R125]. Separate software is mentioned for different purposes. Industrial big data management tools are used for comprehensive platforms due to their abundant add-on packages, such as Apache Kafka [R121]. Free services such as Blynk [R126] are also an option for a low-cost solution. Commercial cloud platforms are deployed from Microsoft, Amazon, Siemens, Google, and SAP. Real-time processing capability is the desired requirement in choosing the product [R68, R127]. On the availability of data, machine learning techniques can be applied for further optimization [R94]. By integrating legacy devices into the cloud-based IoT platform, even the geographically dispersed manufacturing system can be monitored remotely [R128]. In general, the availability of data is the foundation for the higher application toward smart manufacturing [R129], which is discussed in the next section separately. It is worth mentioning that once the legacy system is retrofitted with the data visualization [R130] and equipped with web service [R49], or mobile HMI [R104, R126]. The operators will be the ones who benefit the most from their work. This aspect is the main focus of the next industrial revolution, thus reflected in the concept of O4.0 discussed in the following.

Operational application

After the aforementioned retrofitting work is done, the automation and connectivity level of the factory is enhanced. Therefore, monitoring and management activity [R131] supported with data is available in hand. This application level is on the top of the IoT level, which deals with management philosophies and techniques.

Process management

With the retrofitted system, there are process management philosophies can be applied. A legacy system without any advanced PLC or Supervisory Control and Data Acquisition (SCADA) system infrastructure usually faces unexpected downtime, which undermines the business [R92]. Noticeably, the most prevailing advantage that comes from retrofitting is the process parameters tracking ability of the system [R122]. Taking into consideration that process critical parameters consideration is one of the beginning steps in the conducted projects [R100, R132], this advantage is the inherent characteristic. This advantage is preferred in processing industries with continuous manufacturing systems such as oil extraction, food processing, water processing, and mining [R105, R93, R133, R123, R102]. It can lead to process automation which cuts down the manual work [R49]. With process automation, the loss of raw materials can be decreased by the automatic activation of valves, switches, and actuators [R102]. Equipment conditions can also be kept a close eye on in the same way [R134], based on the acquired data. Machinery parameters, which are vital for production, usually being under monitoring [R135, R113]. Tool condition monitoring is applicable for machine tools that have machining tools that need to be replaced for quality and safety purposes, such as CNC machining [R136].

Thanks to the data-driven management for each elementary process, an IoT-based manufacturing monitoring system can be constructed as the guiding rule for future ways of improving overall performance and management [R129]. Based on the elementary processes in the system, the material flow in the work cell, in particular, [R137], or in the facility in general [R138], can be monitored. Scheduling tasks will be more manageable and can be conducted automatically [R139]. This advantage can link to the concept of just-in-time production discussed in the later subsection. The process optimization can be taken further based on the available data, and process-oriented knowledge [R124] regarding the produced quality, machine condition, or material flow. The highest application in this aspect is production monitoring, in which the production KPIs or objectives can be adjusted and manipulated remotely [R102].

Quality management

Quality management is essential in every manufacturing plant. For the legacy system, the lack of connection between machines makes it more challenging to discover the source of quality defect and variation, as well as track the passage of the defect order [R125]. However, along with the retrofitting process, there are philosophies of quality management that are ready to be deployed. By applying along with the fused technologies, the operator decision factor can be eliminated [R127], and human inconsistency can be reduced, thus reducing the quality variation and defect products as well as scrap materials [R139].

The detection of a defective product can be recognized directly by product specification-related sensors such as tension with fabric product [R140], or indirectly with other derivative parameters such as noise with gears [R127]. In the next step, when the process parameters that affect product quality are defined and kept track of, and quality data is collected throughout the production phase, the variation that causes the quality problem can be tracked easily [R139]. Thus, it leads to a higher level of quality management: defect prevention, in which the possible defect can be prevented proactively, regardless of the human decision on which product is good or bad [R127]. At the organization level, the historical data can be used for further improvement on quality aspect [R124], including the parameters self-adjustment of the machine [R140], or the group work of operators in diagnosing the manufacturing processes [R127].

Digital twin

DT is one of the critical players in I4.0 development in terms of plant-wide optimization [R141]. The development of DT is desired in many retrofitting projects, as the goal of full-scope digitization is to be the foundation for other managerial activities, and resource planning [R111]. DT can be used as the tracking simulator and integrated with the existing legacy control system of brownfield manufacturing facilities [R142].

The generation of DT is a significant step toward complete digitization. The most frequently used method of DT elaboration is sensors-based, with the use of the sensors mentioned in the previous section. The operational status of the machine is not enough [R143], thus additional sensor must be installed for DT elaboration. A vision system is a convenient tool to gather data from the physical world, for instance, a camera system [R111], or LiDAR scanning [R142]. Other commercial tools also proved their applicability in the industrial context, such as Microsoft HoloLens [R144] and Smart Glasses [R107].

In some retrofitting projects, the authors were unable to elaborate the DT of the whole system; thus, a critical part of the system is chosen to build the DT upon [R105]. Another way to develop the DT is with the aid of simulation software. Siemens Tecnomatix Process Simulate is the most preferred tool due to the capability of obtaining soft real-time data directly from the OPC UA server [R103]. In this way, a large-scale DT can be developed, with the whole facility restored in the digital world [R111].

Security

Data security initiatives that protect the system from intentional and accidental destruction are one of the main obstacles in SMEs [R145]. As brownfield development is about modifying and fusing new technologies into the existing factories, where most of their dated machines only have been through a few security updates, the risk aroused [R146]. This aspect of the old system is a raging problem, as they have been designed with little sense of security in mind, thus making them vulnerable to many types of attack [R147]. Taken into consideration that legacy machines only have limited built-in IT security functions (i.e., default password, no access control, undocumented back-doors) [R148], and their security perimeter mechanism is opposed to the desired zero-trust network [R146], a retrofitted system can be more vulnerable for cyber-attacks. The use of sensors in the retrofitted system can create multiple attack surfaces, such as data proofing and sensor data transmission breaches [R147]. The retrofitting solution with Raspberry Gateway is cheap, thus posing a threat to security problems [R48]. Noticeably this solution has been applied widely in many previous projects. Thus another industrial-grade hardware platform should be taken instead of this low-cost option.

Due to the few retrofitting studies that mentioned the security aspect, it can be seen that this problem is underrated compared to the newly developed system. However, it may become more severe soon [R146], as the use of retrofitted machinery may continue to be in place for a long time from now. Several solutions are given to secure the weakness in legacy machine connections, such as integrating legacy machines into a blockchain framework to prevent cyber-attacks on weak connections between them [R147], or adding an industrial gateway [R149]. In a textile retrofitting project, a centralized server is utilized instead of a cloud solution for the sake of data security [R55]. This problem raises the fact that a full-scope IoT architecture may not apply to every legacy system without considering its intrinsic characteristics, and can be handled by providing appropriate data access with

General Data Protection Regulation (GDPR) consideration [R133]. Attempts to retrofit the security of legacy systems could introduce new bugs and vulnerabilities [R148], and it is also hard to ensure that new systems are thoroughly tested. New technologies such as Secure Multi-Party Computation and Distributed Ledger Technology should be deployed [R150], which followed comprehensive design principles to bring the retrofitted system an immutable and transparent registry.

2.1.2 Retrofitting developments as stepping stones for Industry 5.0

From the previous section, it can be seen that the technologies now are abundant and very well-suited for brownfield development. However, while retrofitting works are implemented in the I4.0 context, the next I5.0 is introduced. This new industrial revolution is the extension of I4.0 with a sustainable mindset and focuses on human workers. In preparing for this strategic transformation, several important I4.0 retrofitting-specific developments are described, considering the foundations for I5.0. Based on Energy 4.0 in energy management, the new possibilities of Lean 4.0, the concept of O4.0, and new methods of Maintenance 4.0, these developments to I5.0 focus are established, providing guidance for managers to consider the corresponding targets.

Industry 5.0

I5.0 is still a new innovative concept but has shown some of its future aspects from early research, such as the future of work between human-robot [R151], a symbiotic factory where human-machine can contribute their value [R152]. The EU stated that the I4.0 had positively impacted digitization and Artificial Intelligence (AI) -driven technologies to increase production efficiency. Now is a proper time to move on to I5.0, where societal and environmental problems should be emphasized [R36], with a focus on human-centricity, sustainability, and resilience. With this sustainability in mind, human workers will be accepted as an irreplaceable factor of any manufacturing system, thus requiring a human-centric approach from both economic and productivity points of view [R60]. Sustainability is also strongly emphasized, as different opportunities for sustainable manufacturing in I4.0 are discussed [R137]. Retrofitting is an enabler for the existing manufacturing equipment approaching economic and environmental dimensions of sustainability. It can also be considered as machine preparation to enable smart communication and capabilities for technological aspects and business requirements as well [R153].

Taking into consideration the different emphasis between I4.0 and I5.0 [R154], novel innovation trends for I5.0 are enabled by several technological aspects [R155]. Several primary pillars can be listed as individualized human-machine interaction technologies, DT, and simulation for human-machine systems modeling, data transmission, and storage, analysis technologies, technologies for energy efficiency, renewable, storage, and autonomy [R156]. A retrofitting project can bring benefits to its operators in learning, manipulating, and performing their production tasks [R144]. Along with a detailed understanding of the process, and favorable conditions for quality management, retrofitting can be considered as a way to aim at a sustainable business model [R100].

This promising result urges a comprehensive approach for retrofitting to improve energy management and reliability, sustainability aspects of a manufacturing system, and enhance the working efficiency of its human operator in the forthcoming I5.0. The following parts are the specific developments considered stepping stones for I5.0.

Energy 4.0

Energy efficiency is an emerging topic in the modern manufacturing system, with the term Energy 4.0 indicating the digital transformation of the energy sector as a sustainable goal in the I4.0 context [R157]. The energy utilization can be an objective for retrofitting [R91]. However, the energy footprint is unconnected and hidden from the database with a legacy system, making it hard to apply any optimization.

Energy improvement is one key sustainability focus in I5.0. After retrofitting, the enhanced energy utilization is mentioned as one of the most promising results [R91], making it closer to the scope of I5.0. The energy footprint can be tracked with the sensor deployment [R158, R92], creating an IoT-based architecture for energy efficiency tracking [R159]. Based on the trained data from the normal energy consumption, the abnormal ones such as high consumption and unbalanced energy load can be pointed out, with corresponding notification and alert [R92]. A recommendation can be given, aiming at a higher efficient operating condition [R49]. In ideal cases, the improvement in the energy aspect can be performed through actuators and switches based on predefined energy indicators [R106, R51]. This step reflects the self-optimization ability of the system.

Maintenance 4.0

A legacy system puts a heavy burden on maintenance activities, as outdated machinery lacks technical documents and historical degradation records [R143]. The retrofitting approach can provide old machines with predictive maintenance and does not require cost-intensive re-engineering activities [R160]. The availability of process monitoring sensors in the I4.0 framework offers a favorable condition for predictive maintenance [R161, R162], which is a core concept of smart maintenance and Maintenance 4.0 [R163]. Besides, there are more advantages of the system that can be expected, and they can be defined as enabling factors for Maintenance 4.0, with their benefits demonstrated in several industries.

The first significant advantage of retrofitting the legacy system is the operating time recognition of machinery, which the operators usually need to perform by hand [R164]. After this step, the maintenance-related parameters such as Overall Equipment Efficiency (OEE), Mean Time Between Failures (MTBF), and Mean Time To Repair (MTTR) can be calculated for further production efficiency assessment [R165]. Then with the use of machine learning, the failure state of the machinery can be recognized by learning from the normal-state data [R166]. When the system runs into a problem, then the machine part and the mechanism in which the situation happened can be pointed out, making it easier to locate and replace the broken part [R167].

For higher applications, predictive maintenance initiative is supported, as the maintenance task can be suggested and planned based on the historical data [R92]. The specialized maintenance DT can offer suggestions of condition-based or corrective maintenance activity [R143]. Instead of the traditional maintenance approach of time-based replacement, the retrofitted system can save unnecessary maintenance work and spare parts due to the integrated condition monitoring capability [R88]. These advancements enhance maintenance efficiency, while the maintenance cost can be cut down.

Operator 4.0

The O4.0 is mentioned as the future of human workers [R29, R33]. At the first stage of I4.0 brownfield development, employees should be involved and motivated to support the change, as one of the three main elements in the smart retrofitting concept [R107]With the elaborated DT, cognitive O4.0 can enable a smarter decision-making environment [R168].

The ideal advantages for the O4.0 initiative after retrofitting are given in Table A.3, Appendix A, along with benefits for the operators that can be expected.

Along with these benefits, an enterprise can overcome the lack of educated operators to increase its competitiveness [R140]. Providing the person in charge of each process with its relevant parameters can be considered as analytical support for his task [R88]. This aspect fosters the decentralized decision-making capability of workers, allowing them to take part in more knowledge tasks in sustainable manufacturing from the human factor [R137]. In some particular conditions, the human worker is the primary motivation to retrofit the legacy system [R169] so that its workers can feel more comfortable with their work [R170]. With the machine failures detected by the system, special tuition and knowledge are not required from the operator, thus leaving him a more relaxed work environment [R134].

O4.0 and even I4.0-related managers play crucial roles in the manufacturing processes; thus, their convenience must be of higher priority when retrofitting a system [R52]. With the assistance of the developed system, human intervention can be decreased, and the operators can have more time to concentrate on the process optimization [R139]. In the meantime, by isolating the error of operators, consequently reducing the number of non-conformance products, the operation efficiency can be improved [R102].

A critical aspect of sustainable manufacturing is the development of human resources [R36]. For this purpose, two retrofitting advantages that need to be considered are job training effectiveness and the prevention of accidents. With the advances in technology, data visualization augmented reality can aid the job instruction for workers, helping them to learn the tasks quickly with actual situations example [R144, R140]. On the other hand, the system has more built-in safety functions that can halt or stop production once a hazard is detected to prevent a further accident or danger that can happen on the shop floor [R132, R129]. It can be observed that, by applying new technologies in a human-centric approach in a retrofitting project, not only the managers but also the operators will be the ones who get the crucial benefit during their daily performance [R170].

As workforce resilience is severely tested during the COVID-19 pandemic, its importance is realized, along with other possible adverse realities such as resource scarcity, climate change, and skill gaps that can be added into the manufacturing context. The concept of O5.0 is built upon the vision and paradigm of O4.0 to guarantee manufacturing operations continuity, especially in difficult and unexpected conditions [R29].

Lean 4.0

The implementation of I4.0 technologies creates a unique effect for LM deployment in the operational strategy [R27]. LM shares the same continuous improvement approach with the technical improvement of I4.0, thus considered as assistance for smart retrofitting [R107]. Consequently, legacy manufacturing systems can adapt themselves to bring advantages under the proposed Lean 4.0, as some examples are listed in Table A.4, Appendix A.

A critical aspect of LM supported by retrofitting is work standardization. The recorded data from the retrofitted system are suitable for this purpose [R102]. The Just-In-Time (JIT) production can be facilitated to create a smoother material flow and avoid excessive stock [R137]. A more balanced, stable material flow can be supported by removing the bottlenecks, which are easily discovered by the retrofitted system [R171, R127]. The flexibility and agility of the manufacturing equipment can be enhanced due to the Quick Change-Over (QCO) that is supported by the re-configurable system [R138]. Other LM concepts, such as reducing the waiting time of machines and equipment, can be achieved [R132, R140], especially useful in industries well-known for long change over time (i.e., steel mill and mining) [R52, R102]. Continuous improvement is an essential factor in LM in general and in maintaining the effective usage of the system in the organization [R23].

The core of this concept is the kaizen activity, which is done by a group of people to solve an organizational problem [R24]. For the retrofitted system, this kind of activity is highly supported due to the availability of data, the visualization of the critical parameters, and the human-centric approach when designing the retrofitting solution [R89].

These aforementioned I4.0 developments can be considered stepping stones for the I5.0 initiative. As their characteristics indicated, the gained benefits bring manufacturers advantages and readiness for further development. Fig. 2.1 represents the connection between these I4.0 developments and the focus of I5.0. At first, in terms of Sustainability, the efficient usage of energy and manufacturing resources, from the concepts of Energy 4.0 and Lean 4.0, respectively. These concepts support a strong foundation for a sustainable operation of the firm at the micro-level and the whole value chain of the economy at the macro level. Lean-digitized manufacturing not only offers companies survivability in the I4.0 context but also a prior sustained competitiveness [R172]. Energy utilization is an essential factor that may create an immediate impact on sustainability [R157].

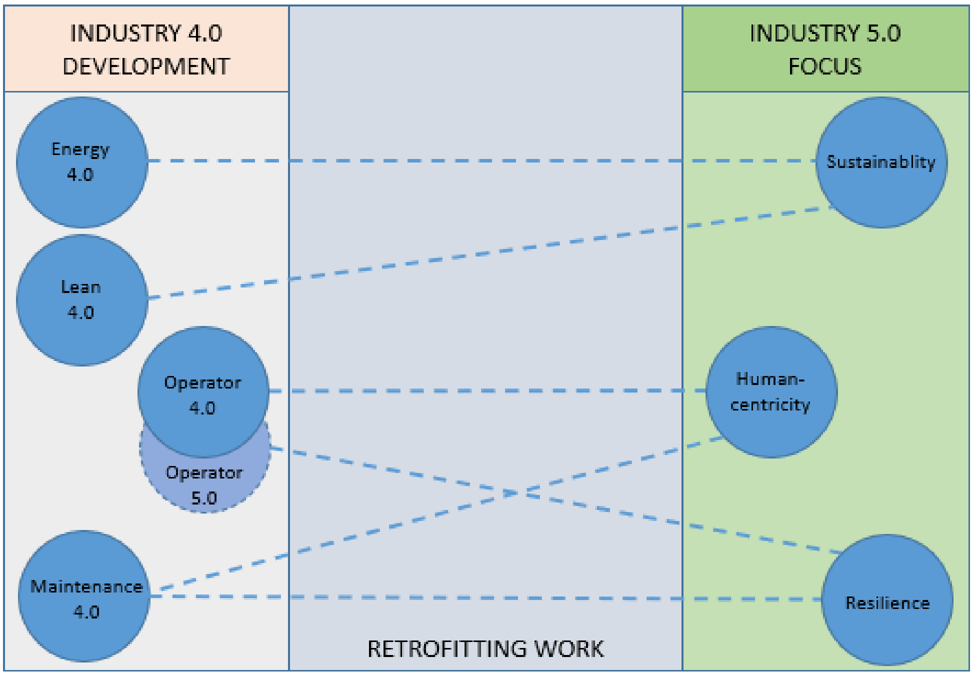


Figure 2.1: The retrofitting developments as stepping stones for Industry 5.0. Source: Own work [J5].

The O4.0 concept focuses on the human-centricity aspect, as workers and operators benefit from technology and digital transformation, which helps them fulfill their job requirements with less effort and higher value-added contribution [R29]. Then the self-resilience of O5.0 concept can be applied, aiming toward a system effect from both human-machine system resilience and human operator resilience [R47]. Meanwhile, the advantages of Maintenance 4.0 enhance the Resilience of the system, as its readiness and reliability are strengthened and can provide input for a learning Human-Machine system for resilience prediction and control [R173]. Due to the reported advantages, these developments are recommended as targets for every retrofitting project.

2.2 The use of IPS for the implementation of Lean 4.0

One of the most promising IT elements that can support Lean 4.0, is the Indoor Positioning System (IPS) [R69], which enables full traceability of manufacturing processes. A typical

IPS is an indoor wireless positioning technology [R174] that works with radio-frequency, optical, or acoustic tags and chips. The IPS tags are always active and continuously broadcast signals to beacons [R174]. Tags and fixed reference points can be transmitters, receivers, or both, resulting in numerous possible technology combinations [R175]. IPS can identify object location in a closed structure, thus widely applied in an office building, hospitals, facilities, and warehouses [R176].

Compared with other technologies including RFID and bar-code scanners, IPS is robust to any layout change and can exclude human error and systematic flexibility. Due to intrinsic appropriateness for monitoring logistics units within a facility - from items up to packages, transport units, and pallets - IPS has been widely applied in many aspects such as cycle time optimization [R177], monitoring production line activities [R34], logistics management [R178], pallet management [R179], safety management [R180].

2.2.1 Proposed framework

RFID-based systems are especially suitable for monitoring LM parameters [R181]. Utilizing RFID tags within an IPS is a favorable approach in different industries, such as construction [R182], fast-moving consumer goods production [R183], automotive part manufacturing [R184], automobile assembly manufacturing [R185], agriculture equipment machine part manufacturing [R186] and the job shop floor environment [R187]. In a manufacturing shop floor environment, IPS can be beneficial as it can enrich data acquisition for LM [R188] and it can be used to obtain dynamic spaghetti diagrams used for the visualization of the value streams [R189]. The proposed framework that utilizes IPS data for a Lean 4.0 manufacturing system is presented in Fig. 2.2. The prior knowledge such as information about the process, and the technology are used as "supportive data", to establish the base of the standardized process, such as planned routing, process cycle time. The information on the overall layout is added, as well as some designated areas for buffer inventory, waiting for queues, and maintenance preparation.

In addition to IPS data, acquired data from manual input (e.g., bar-code scanner) or existing technologies such as machines, and event logs from MES system, other sensors/wearables can be incorporated to provide a comprehensive view of the current system state. During "data processing", process- and data mining are performed on the collected and contextualized data, to explore frequent patterns of material flow and states of the production process. After the filtering of redundant data based on machine logs, the raw data will contain only timestamps and position data. Software with built-in visualization and animation tools such as Disco [R190] is applied in this step. Based on the standard routing of each product, the automated process discovery with a fuzzy miner in Disco software is set up to show the main processing steps while preserving the highest level of abstraction. The aftermath is the reconstructed process with the extra re-work loop or reverse flow are maintained. By comparing the mined process with the standard routing and cycle time, operational wastes can be discovered and become input to further calculation of LM KPIs. The method for calculating these KPIs is described in Table 2.1.

Additional states of manufacturing processes and resources (e.g. temporal inventories) can be defined and assigned to the product and material flows. The explored states and additional timestamps provided by the IPS process mining algorithms can be utilized to update the Value Stream Mapping (VSM). As the final results, the movement heatmap is sketched based on the mined data and the facility layout, to visualize the materials movement with congestion and bottleneck. To analyze deeper one operation period, a Gantt diagram can be extracted for each selected period. Compared with the data only collected from the MES, the waiting time as temporary inventory, and reverse flow of re-work will appear as many missing periods in the Gantt diagram, as these material flows are not officially registered in the MES database. When incorporating the IPS data to monitor the real-time position of the process flow, these motion-based anomalies can be detected, and enrich the information in the Gantt diagram.

After data processing and computation of LM KPIs, different system improvement techniques can be applied, such as "production planning" for optimal layout, material route, optimal labor assignment, and "production control" with adaptive sequence, dynamic balancing, dynamic takt-time, JIT preparation. Another initiative that can be considered is the Plan-Do-Check-Act (PDCA) cycle of continuous improvement, which is a typical feature of LM. It can be seen that the usage of IPS data supports the Lean 4.0 data-driven development in several steps, as marked in yellow color in Fig. 2.2.

Fig. 2.3 shows how IPS supports the continuous improvement with PDCA [R191]. The core element is the process model (represented as the VSM block) which contains all the essential information about manufacturing processes. The improvement cycle updates the model with the help of IPS data, by continuously and automatically monitoring the production. The developed framework can discover the real process model based on the IPS data with the toolset of process mining. The resulting models are used to update the VSMs and evaluate the performance of the process by calculating the Lean KPIs. The most apparent benefit of Lean 4.0 KPIs is the readiness for decision-making and optimization based on real-time information about the manufacturing system.

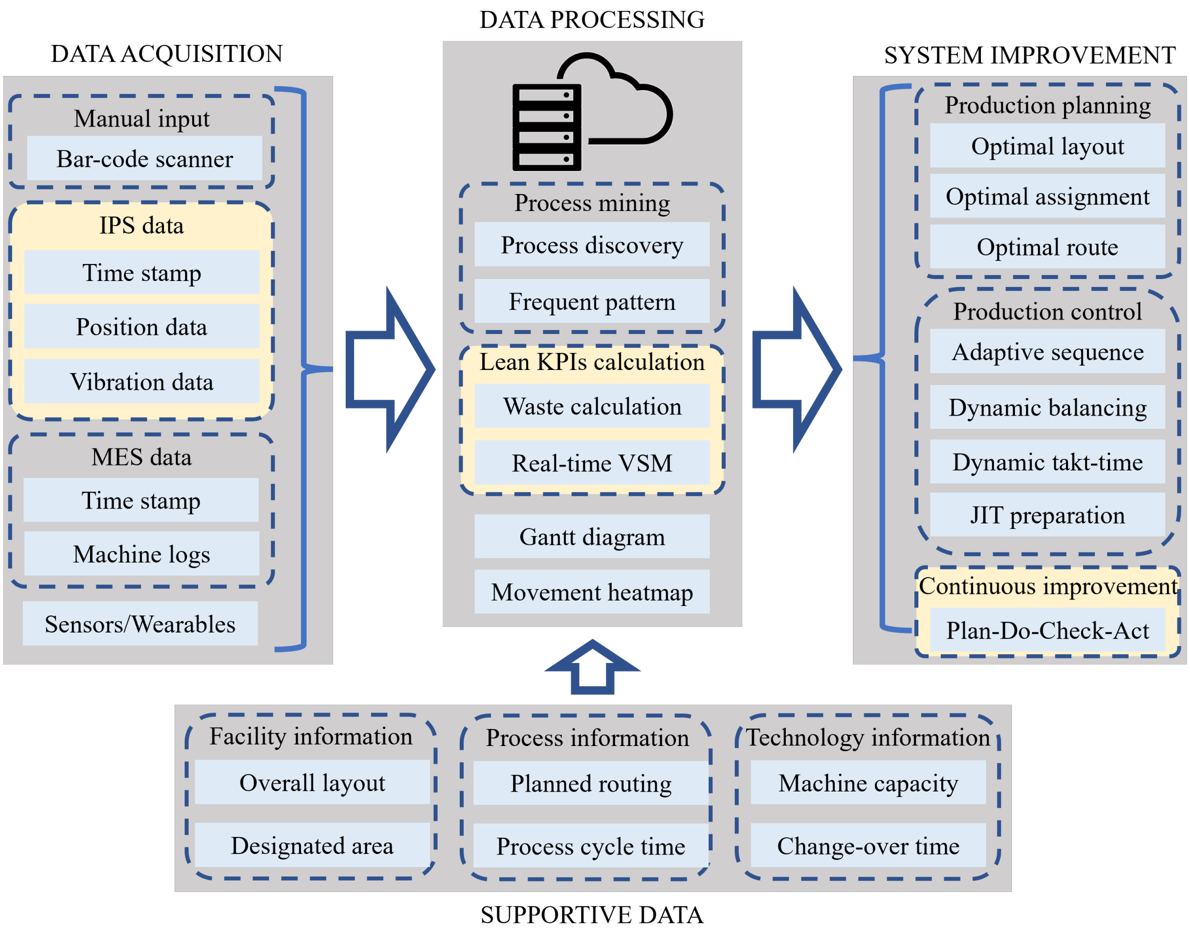


Figure 2.2: The proposed framework of Lean 4.0 data-driven development. Source: Own work.

Table 2.1: Proposed method for Lean 4.0 data acquisition and mining with IPS usage.

Lean concept	**KPIs**	**Method of recognition**	**Deployed sensors**
Shortest lead time	Average lead time	= (position at finish area + timestamp) (position at beginning area + timestamp)	Position sensor + bar-code scanner
	Average cycle time	= position data at the same workstation + time stamp	
	Added value ratio	= vibration data + position data at the same workstation + time stamp	Vibration sensor + position sensor + bar-code scanner
7 wastes	Waste of motion	=vibration data + standard allowance time	Vibration sensor + position sensor + bar-code scanner
	Waste of transportation	= time stamp + position data between workstation	Position sensor + bar-code scanner
	Dead stock and slow-moving inventory	Not applicable	
	Waiting time	= time stamp + vibration data between two stationary period	Vibration sensor + bar-code scanner
	Defect	Not applicable	
Less inventory	Number of WIP	Not applicable	
	Inventory value	Not applicable	
Standardized work	Standardized work deviation	= real measured cycle time the standard time	
	Time to fetch necessary part	=standard time for the next step - timestamp of the previous step	Position sensor + bar-code scanner
Continuous flow	Takt-time	Not applicable	
	Queueing time	= time stamp between two workstation transportation (with position data at each workstation)	Vibration sensor + bar-code scanner
	Lot size	Not applicable	
Line balance	Line balance factor	= deviation of (measured time pre-defined takt time) in each workstation	
Quick change-over	Set-up time	Not applicable	
	Change-over time	= time stamp + position data from the last product in the old batch to the first product in the new batch	Positioning sensor + bar-code scanner

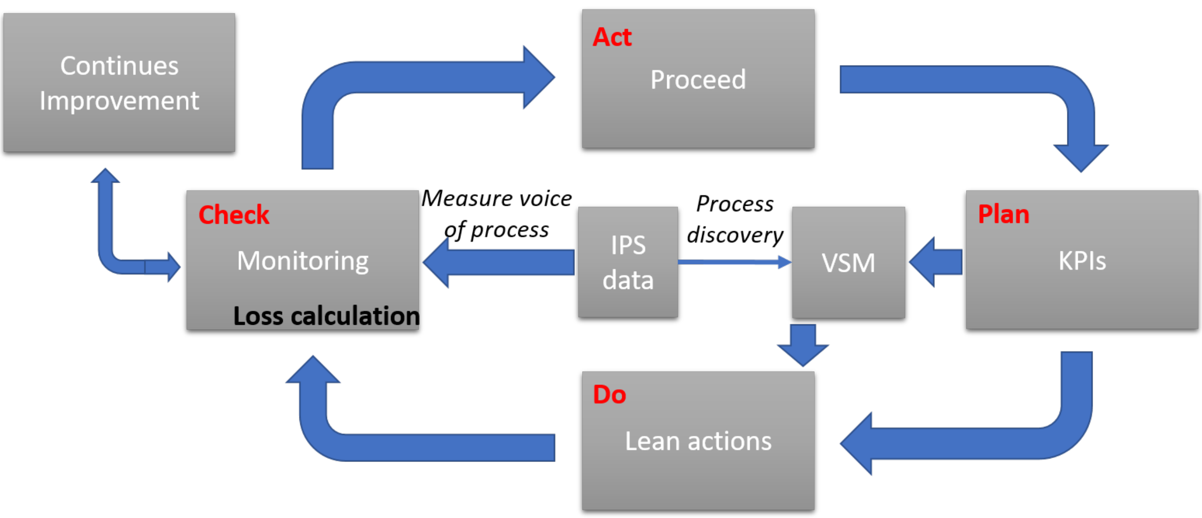


Figure 2.3: IPS data as the key element of PDCA methodology. Source: Own work.

2.2.2 Use case in automotive production

A Lean 4.0 project is conducted in an automotive company producing metal parts, to monitor a production area of five CNC machines, one assembly station, one assembly line, and a packaging station. The orders (tasks) follow different paths during production, depending on the production routing. This project aims to monitor the cycle times, identify the waiting and queueing times, and reduce transportation waste. Due to the changing number and variations of product families, this activity is not a one-time improvement. One small change in the product architecture can cause changes in the assembly sequence, which leads to significant performance losses. Traditionally, LM masters will detect these 3M (Muda - Mura - Muri) via eye observation, then make re-calculation and re-arrangement to find a new optimal point. By following the proposed framework, manufacturing activities can be easily tracked and automatized. The position data from the moving carts is analyzed to identify whether they are not in a pre-defined value-added area (like assembly stations). The extracted cycle times are used to find the potential wastes (changing times, manual work) and focus on these areas, such as defining a standardized digital work instruction that depends on the current position information of the semi-finished product. Fig. 2.4 illustrates the IPS hardware architecture.

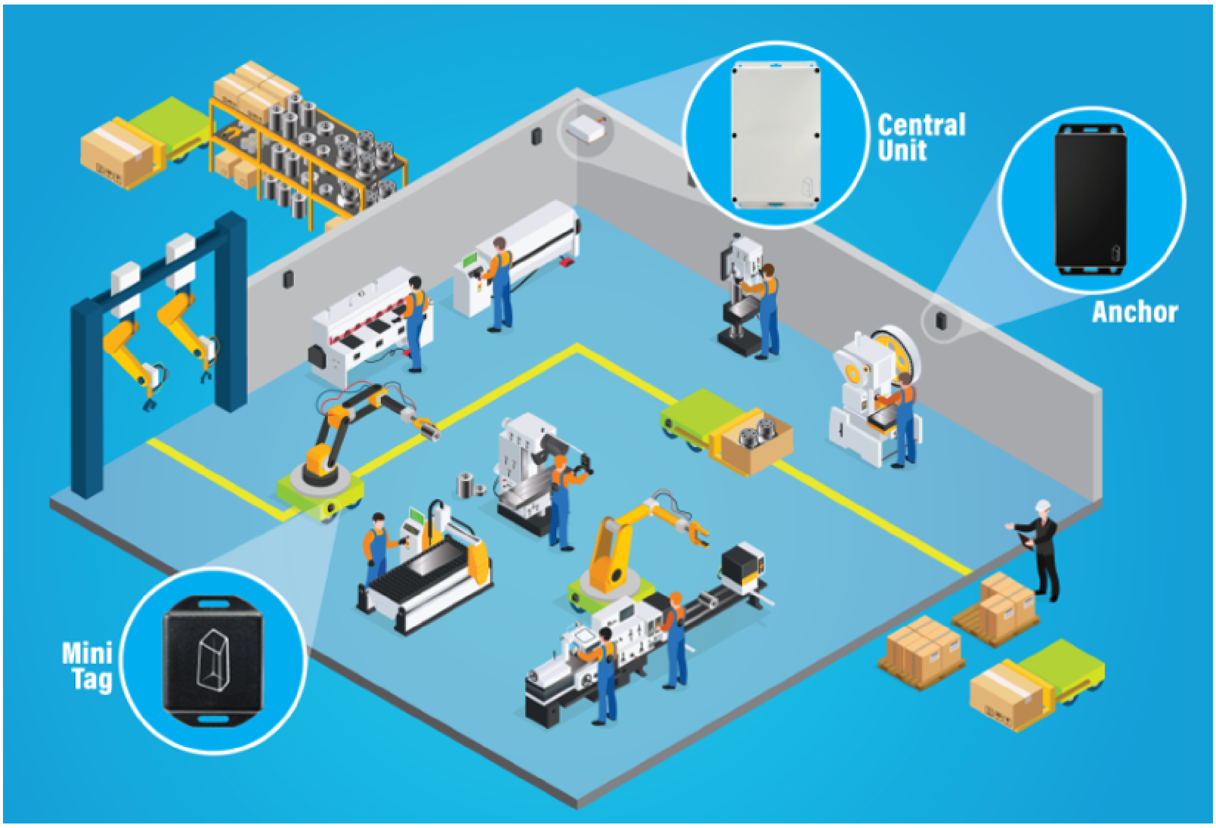


Figure 2.4: The hardware architecture of the applied IPS (based on Sunstone-RTLS Ltd.).

The applied Ultra-Wide Band (UWB)-based real-time locating system (RTLS) uses active tags and 15 anchors for localization, installed on the $2000m^2$ shop floor. The anchors are connected to two central units. The raw sensory data are transferred into the position calculation server. The position calculation is based on the TDoA (Time Difference Of Arrival) method and applies the Kalman filter to obtain more accurate information. The IPS is installed to track 40 carts with semi-finished products moving (manually) between the workstations. Each cart has a dedicated IPS tag, and the IPS sends information to the MES if the actual cart with the defined (paired) product has arrived at the actual station.

Whenever a semi-finished product is put on a cart, the operator pairs the order number with the tag ID with a timestamp. The position data accuracy is around a half meter, enough to get an accurate spaghetti diagram from each produced order.

The collected position data contains the tag IDs with the x-y position $[m]$ according to the predefined coordinate system (fitted for the shop floor layout). Table 2.2 describes an example of the raw data. The raw data are collected for every manufacturing activity ("Job ID" column), which includes the moment when the tag entered the zone ("Timestamp" column) and the corresponding zone in the shop floor area ("Workplace" column). Since every tag is reused whenever the previous product is finished, a key table is provided that decodes the tag ID to the beginning time of the production ("Beginning time" column) to distinguish the products that are produced at a different time that used the same tag. In this example, the raw data are a list of different customized product variants observed by the tags and chosen for analysis, with the related activities recorded.

Table 2.2: The raw data from the proposed IPS system.

(a) Event timestamp

JobID	Timestamp	Workplace
Job 1	20/5/2019 10:50:05 AM	Heller 3
Job 1	20/5/2019 10:57:23 AM	KTK
Job 1	20/5/2019 11:01:30 AM	Daewoo
Job 1	20/5/2019 11:07:39 AM	D-Hole
Job 1	20/5/2019 11:12:21 AM	AO-1
Job 1	20/5/2019 11:14:44 AM	Packing 2
Job 1	20/5/2019 11:20:20 AM	Heller 3
Job 1	20/5/2019 11:25:04 AM	Daewoo

(b) Product information

Beginning time	TagID
1/9/2019 12:00:01 AM	2103
1/9/2019 12:00:31 AM	2103
1/9/2019 12:01:01 AM	2103
1/9/2019 12:01:31 AM	2103
1/9/2019 12:02:00 AM	2103
1/9/2019 12:02:30 AM	2103
1/9/2019 12:03:00 AM	2103
1/9/2019 12:03:59 AM	2103

These data are updated every three seconds (the sample time can be set - maximum $1kHz$) to capture most of the motion of the carts. The factory layout with the zone (workstation) definitions are provided by the rectangles (Fig. 2.6a) to match the activity order. This layout is elaborated based on the facility layout, with designated areas represented where the production activities are carried on, considering the capability of the IPS hardware. The entering and exiting times define the time that a product spends on one process step. The MES stores the information (resources, produced pieces, quality issues) for every *Task* ID, which includes the *Start* time when the tag entered the zone (*Workplace*). By tracking the location of all components together, the IPS provides the overall heat map of the most frequent transporting patterns of all the tags (Fig. 2.5). The busiest workstations and machines are visible, serving as a traffic indicator. The shop floor with a tracked motion of one product is shown in Fig. 2.6a, which illustrates that the analysis of the positional data allows the identification of temporary stations and the motion paths.

After filtering outliers and glitching errors, these raw data were input into Disco software. The level of abstraction of the process was adjusted to be at least 80% matched with the process steps in standard routings. The applied process mining algorithm discovers the process model as presented in Fig. 2.7. Due to the process flexibility of the manufacturing press, the extracted model is not trivial and varies over time, therefore the model is continuously updated based on the real-time position data. The discovered process flows serve as input for work standardization projects. According to the most frequently conducted steps, a pattern of main material flow is recognized in Fig. 2.7a, where the main workstations and machines are highlighted in blue. There is no leading process flow. Along with the material flow map, the average cycle times are recorded, as illustrated in Fig. 2.7b. The thickness of the arrows represents the time delay between the two stations.

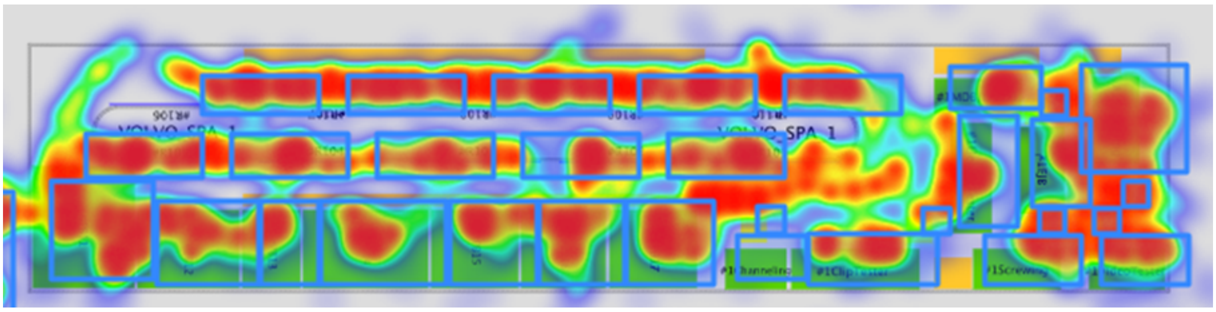
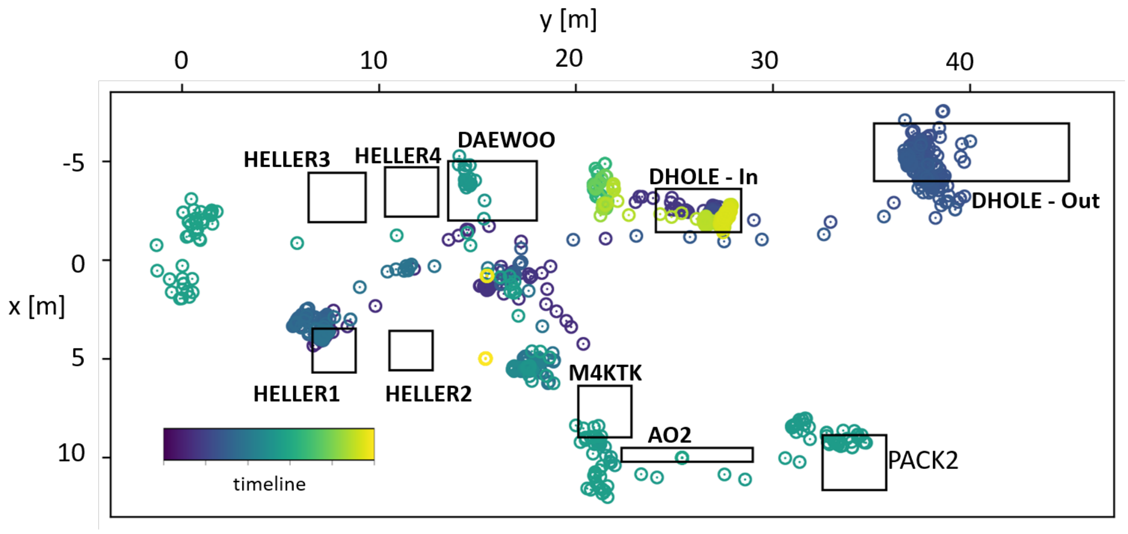
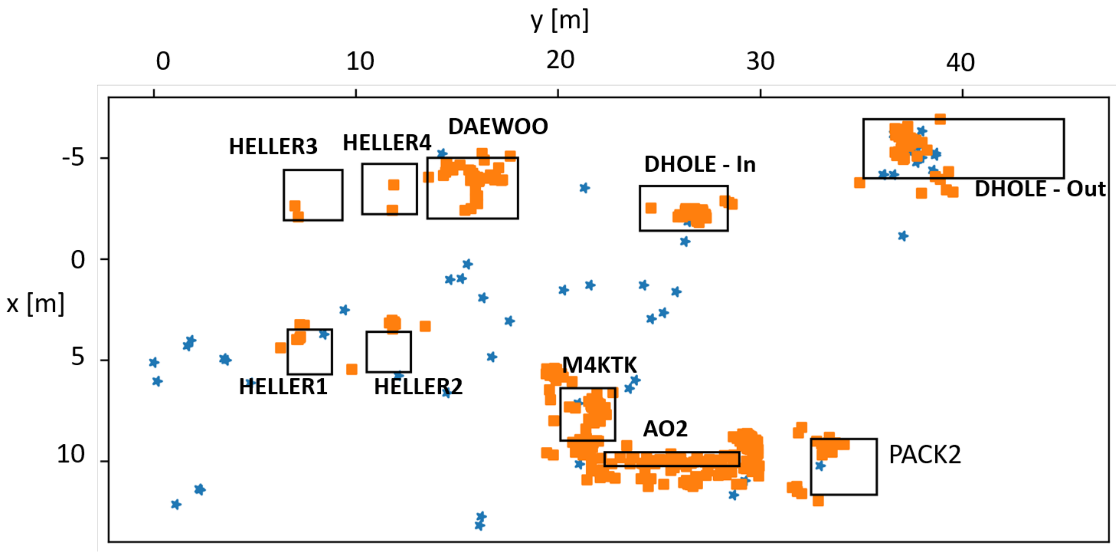


Figure 2.5: Heat map of all tags.

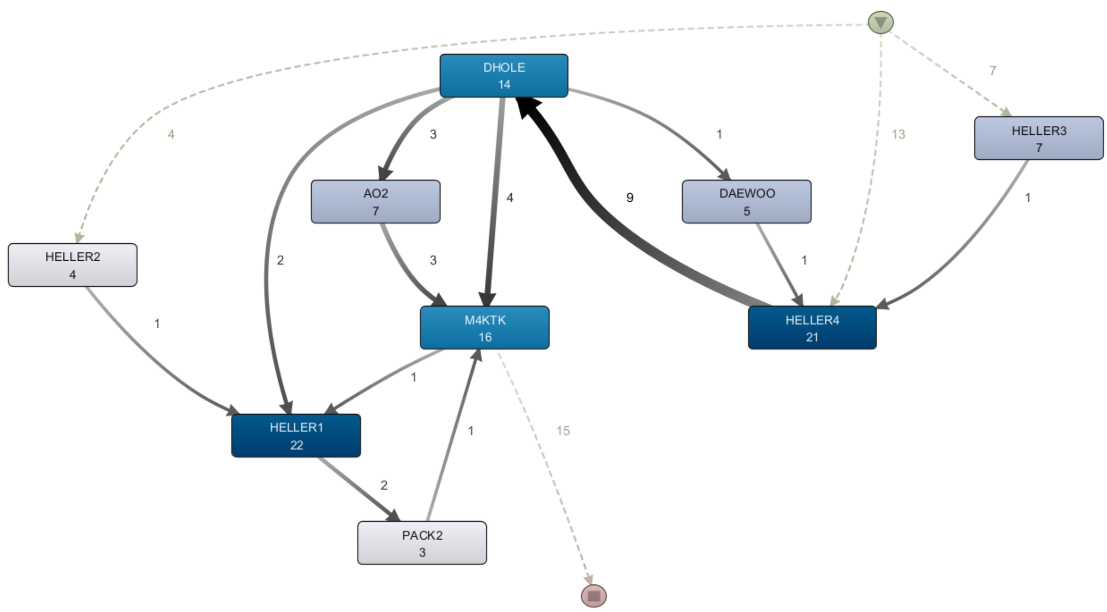


(a) Tracked path of one product on the shop floor. The rectangles define the workstations and the dots represent the position data. The timeline is presented by the colors of the dots.

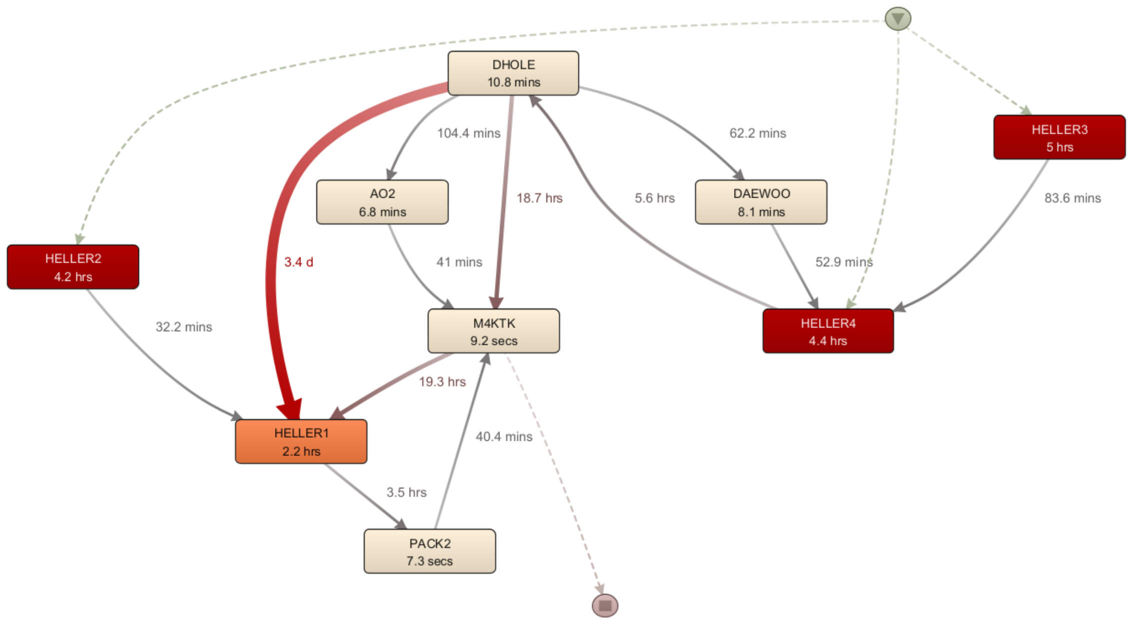


(b) The discovered status based on position data. The blue stars are the transportation while the orange markers are the queueing positions.

Figure 2.6: The analysis of the positional data supports the identification of the internal inventories, the waiting and cycle times.



(a) The frequency of the material flows, with colors representing utilization of the workstations.



(b) The stations as nodes with colors reflecting the discovered average cycle times. The *HELLER* stations are the bottlenecks of the process. The transition times on the arrows highlight the hidden wastes.

Figure 2.7: A production flow discovered by process mining based on IPS and MES data.

2.2.3 Calculation of the IPS based indicators

IPS sends signals to the MES when the actual cart arrives at the pre-defined station. The lean analyses are performed on the production data from MES and the position data from IPS. The IPS data is used to calculate the process waste and analyze the transportation path. Thus, the hidden temporary storage and queuing times were identified. The mined data, along with the average lead time of product variants, are provided in Table 2.3. The transportation waste is determined by comparing the followed path of a tag with the standard route. Along with the total lead time of a product tag (calculated from the interval between the arrival of the first and departure from the last workstation), the motion waste is recognized as idle time within each workstation. The waste identification result is shown in Table 2.4 for six product IDs after one production day.

Table 2.3: Real-time Lean KPI from the proposed IPS system

Lean KPIs	Value	Unit	Lean KPIs	Value	Unit
Product variants	169	variants	Average cycle time of step 1	89.8	minutes
Main steps	5	steps	Average cycle time of step 2	3	minutes
Maximum re-work loop	12	steps	Average cycle time of step 3	86.8	minutes
Average lead time	660	minutes	Average cycle time of step 4	132	minutes
Maximum/minimum lead time	2880/30	minutes	Average cycle time of step 5	112	minutes
Number of jobs in progress	14	cases	Average value-added ratio	51.59	percent

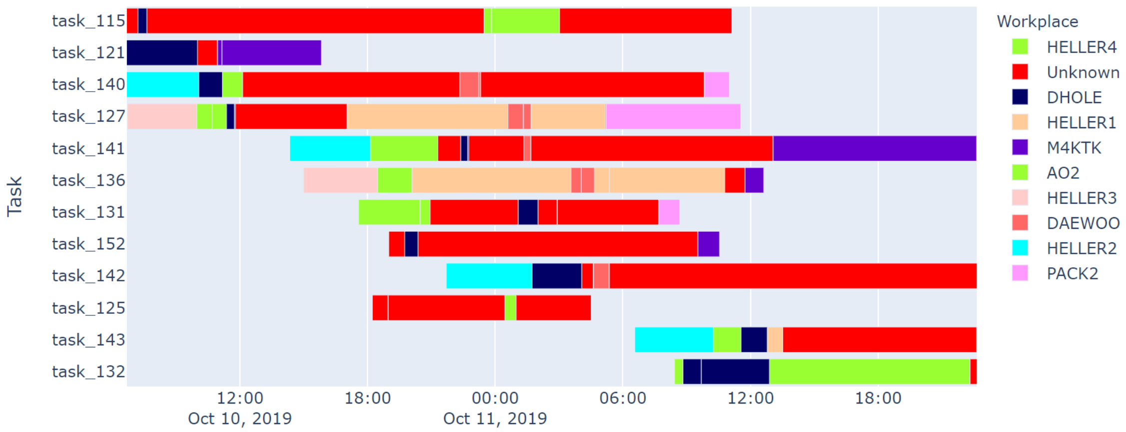
Table 2.4: Waste captured by the novel IPS system.

Part no.	Product ID	Transportation waste (m)	Lead time (s)	Waste time (s)	Waste ratio (%)
1	H179618	0.347960646	2054	1995	9%
2	H179620	24.23493139	22207	5511	25%
3	H179622	3.22646171	29634	88	0%
4	H179816	0.29573319	61	6	10%
5	H179835	61.78363592	16595	1406	8%
6	H179872	124.8997761	38528	14806	38%

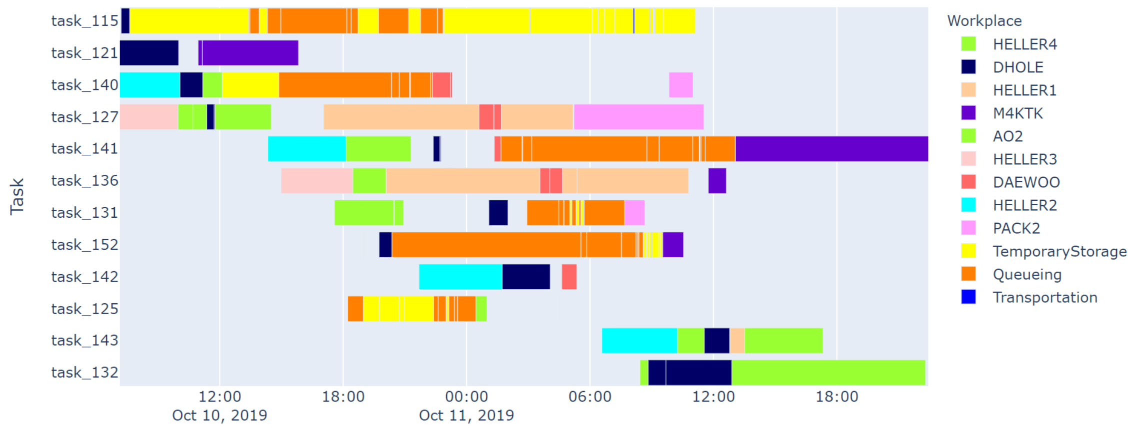
After one full working day (two shifts), the total productivity aftermath is calculated as a waste of time and distance. The waste time represents how much time the actual batch excessively spent in the production area, by comparing the designed processing time for each zone with the actual time. In this example, the waste time ratio is 36.8%, which tells us that the resource utilization is not well handled. The moving activities of all tags allow the distance to be accumulated. By comparing this value to the predefined transportation path in the facility, the excessive path was 197m.

A Gantt diagram has been developed to further study what is the reason for the long transition times of the semi-finished products (see Fig. 2.8a). The rows of the Gantt chart show the orders (*Tasks*) and colors represent the workstations. The *Unknown* station shows the period where no data is available (from MES). These periods are denoted in Fig. 2.8a with red lanes and these periods could be the source of the long period between two stations on the results of process mining and could be the hidden wastes of the manufacturing process. The *Unknown* period is the 19.74% of the studied period.

The IPS data from 22 days were utilized for further root cause analysis. The velocity is calculated to determine the *Waste of transportation* periods. Fig. 2.6b shows an example of that period with the blue stars. Temporary storage is the positions that are closely located out of the pre-defined zones (workstations). When the carts with the products are located in a pre-defined zone (but it is not logged to the MES, thus not under production), these products are assumed to be queued before the actual workstation (see the orange points on Fig. 2.6b). Fig. 2.8b shows the new Gannt-chart with three more defined stations related to queueing, temporary storage, and transportation. The results are shown in Fig. 2.9, where the *Queueing time* and *Wasting time* are almost 20% of the analyzed manufacturing time. Table 2.5 summarises these times for each station. The *AO2* station has the most significant queuing time and needs to be improved primarily.



(a) Gantt diagram based on MES data



(b) Gantt diagram based on IPS and MES data

Figure 2.8: The Gantt diagrams show the production status of a given product, with more insights from IPS information.

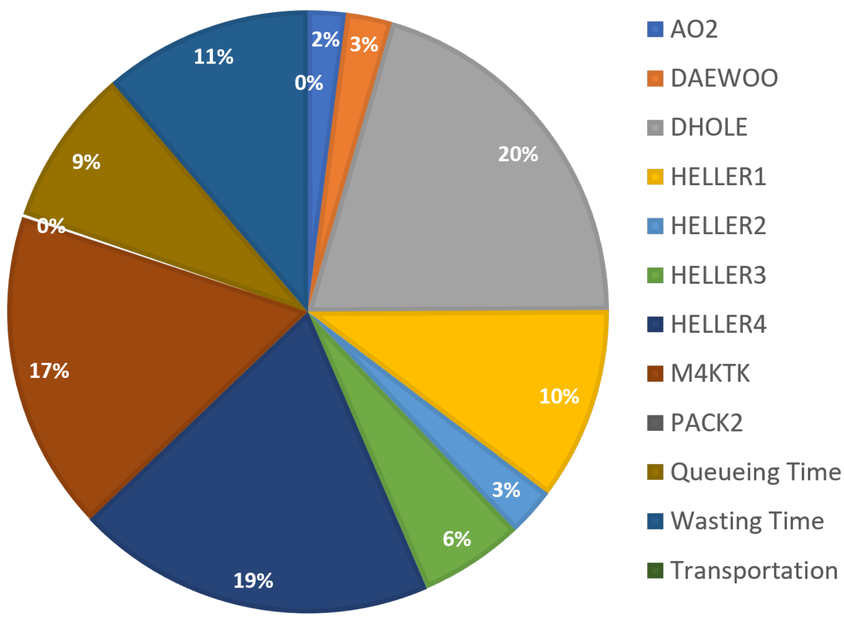


Figure 2.9: The average time distribution based on the IPS and MES data.

Table 2.5: The cycle and queueing times are calculated with the IPS data.

Workplace	Average Cycle Time (minute)	Queueing Time (minute)	Produced Tasks
Waiting time	119.47	-	54
Waste of transportation	2.73	-	27
AO2	77.73	102.86	56
DAEWOO	84.71	84.05	49
DHOLE	88.69	5.09	163
HELLER1	99.36	91.80	72
HELLER2	228.53	46.74	34
HELLER3	197.16	59.56	32
HELLER4	124.82	42.18	146
M4KTK	61.91	84.61	145
PACK2	30.30	47.72	31

The IPS serves as a monitoring system that contributes to the daily work of LM specialists. An alarm system can be set up at each workstation to notify if the working or the waiting times exceed predefined limits; so the line advisor can take supportive actions on time. The integrated application IPS and process mining supports the redesign of the layout thanks to its ability to detect bottlenecks and hidden states within processes.

2.3 Chapter summary

An approach of retrofitting-based development as an I5.0 solution is suggested. After aligning the business situation and market potential with the long-term vision of the firm, an organizational approach should be taken to ensure radical and systematic developments. Firstly, retrofitting-based development should follow a comprehensive approach that covers every operational dimension to ensure a fully digital transformation. These dimensions can be realized by adopting a maturity model and the strategy planning mindset in the initial assessment phase. Secondly, managerial purposes can only be deployed with a balanced and integrated technical enhancement in every IoT layer. Thirdly, the process and quality management can only be achieved by employing an integrated solution with carefully selecting, target-specific sensors and actuators, effective connection, with additional tools for analysis and decision support. This consideration should be kept in mind during cost-benefit evaluation. Fourthly, the I5.0 focus on a worker-friendly and stress-free work environment will be built upon the stepping stones from the existing I4.0 development.

The final result of the retrofitting project is the readiness of KPIs, which enable the implementation of Lean 4.0 with the real-time value stream. The process mining-based analysis of the collected data from the IPS can provide insight into the key factors that determine the productivity and efficiency of production systems. The concept of continuous development is embedded into the PDCA cycle, which has been proven effective in reducing non-value-added activities [R192]. The usage of IPS in Lean 4.0 is expected to soon be dominant due to its hardware maturity, the readiness of data, and the need from the manufacturer. A case study is conducted in a manufacturing firm to show the possible output of Lean 4.0 KPIs and improvement based on activity data. The accuracy of the result from the system is much dependent on the hardware characteristics. The most frequent error happens when the location sensor cannot distinguish between two adjacent areas. Due to the current technology limitation, the defined areas need to be separated by a distinctive distance. Fortunately, with process mining tools, meaningless noise and error can be excluded. However, with a large amount of operation data and production monitoring parameters, the management dashboard needs to be discussed and adjusted by managers. The consultant of an LM expert in setting the KPIs is recommended.

3

Lean 4.0 solution for assessing worker performance with Kinect sensor

> ***Thesis 2:***
> **I developed an algorithm using supervised learning combined with pattern mining to determine ergonomic metrics and movement patterns based on skeletal data recording, supporting ergonomic assessment and human resources development within Lean 4.0 continuous improvement.**

Publications relevant to the thesis: [J7].

This thesis seeks an innovative use of camera sensors with integrated data processing algorithms to automatically assess labor performance and Overall Labor Effectiveness (OLE) [R193]. The traditional way of assessing the ergonomics and well-being aspects of human workers are self-reports [R194], observational-based assessments like Rapid Upper Limb Assessment (RULA) [R195], Manual Handling Assessment Charts (MAC) [R196]), or direct measurements with sensors [R197], video-based assessment [R198]. However, as these assessments are dependent on the experience of the observers [R199], Motion Capture (MoCap) technologies are more preferred, along with the rapid development of advanced algorithmic methods such as filtering and Machine Learning (ML).

A low-cost Motion Analysis System (MAS) built from commercial MoCap sensors can be deployed to study the work movements, ergonomics, performance, and productivity improvement [R200]. One ideal candidate for this approach is the Microsoft Kinect sensor due to its advanced 3D depth-sensing technology, with its marker- and calibration-free characteristics appropriate for industrial application [R72]. Many solutions to improve industrial working conditions have been developed based on the Kinect tracking ability, such as RULA assessment with corrected skeleton data in a manufacturing environment with occlusions [R201], or RULA assessment by calculating the joints angles or estimating the angles by volumetric pixel for assembly operation [R202], ergonomic movement assessment in water pump assembly workstation [R200], or optimization of the walking path of workers in paced automotive assembly [R203].

With the advancement of data science and ML algorithms [R65, R204], different data processing methods including unsupervised and supervised learnings are applied to automatically extract human-related metrics, saving time and effort from human experts. After extracting the ergonomics feature from depth images with ellipsoid wrappers, a random forest classifier is deployed for posture classification and ergonomics assessment [R205]. A deep neural network is deployed to predict the RULA score from the projected 2D pose

[R206]. In addition, pattern mining is a data mining task deployed to discover the pattern from a set of data. Its application is widely used in many research areas in manufacturing operation management of machines [R207]. With the aid of a matrix profile, motif searching can be done more efficiently [R208]. By applying these data mining techniques to the skeleton data from the Kinect sensor, the performance of workers can be diagnosed automatically. However, most experiments mentioned above are applied for offline analysis, and the results are used for re-designing the process after the production has taken place. There is no direct application for improving human performance on a larger scale (i.e., a manufacturing line) or in a long-term scheme (i.e., developing a work enlargement, or work rotation plan based on the characteristics of the work movement). These initiatives require exhaustive observation and analysis of work movement and prior knowledge of the human workers. Consequently, setting up a new manufacturing line with multiple workstations can pose a complicated and time-consuming problem.

Though the I4.0 concept has resulted in technological and social changes that reshape manufacturing processes [R209], it is not able to address deep social tensions such as the well-being of workers [R154]. Innovative I5.0 enabling technologies should be developed, thus supporting and empowering workers, optimizing human-machine interaction, enhancing human physical capabilities, and skill-matching between humans and tasks on the factory floor [R155]. In addition, the introduction of indicators that aim at workforce well-being, resilience, and overall sustainability is emphasized as one of the essential differences between I4.0 and I5.0 [R154]. These human-centric indicators should be designed for each industrial ecosystem and integrated into the system management to ensure progress in improving human performance. The above-mentioned bottlenecks (i.e., lack of automation and incorporated human-centric assessment indicators) make the available surveillance technology not yet ready to replace Gemba observation for field application in manufacturing facilities. Regarding these challenges, this thesis focuses on utilizing the tremendous data from current camera sensors (e.g., Kinect) to automatically generate the human performance assessment, and how to align the assessment result with the human-centric improvement, considering I5.0 objectives. The novelty of the proposed approach lies in the application of supervised learning and pattern mining algorithms on the captured data, which can be the core of organizational performance improvement initiatives.

3.1 Human performance assessment with Kinect sensor skeleton data

Camera sensors are widely used for surveillance, however, their application for production monitoring is limited. Some industrial customers require their manufacturers not to store any product-related images due to proprietary reasons. Thus, skeleton data is a suitable option for analysis. In this section, a method of using supervised learning and pattern mining algorithms to diagnose the skeleton data for assessing human performance is presented and shows sufficient knowledge for further human-centric improvements. A real-time usage model for industrial applications is given with the available open-source packages, with possible improvements discussed.

The raw skeleton data from the Kinect sensor can be processed as described in Fig. 3.1. After extracting the skeleton data from Kinect for Windows SDK, coordinate transformation, re-sampling, and filtering are applied. These steps are mathematical operations based on the camera setup information, which will be introduced in the next section. Supervised learning algorithms are applied in the work movement identification step to segmentize and recognize working status and movements. This classification can be done by considering 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. The working zones in which the hands are actively moving can be determined, considering that these zones do not contain any other stationary joints such as the head. Kinematics values (i.e., velocity) can also be utilized as thresholds to identify the movement.

Motif-searching algorithms are applied to find the similarities between the extracted movements in the pattern-mining step. The interest objects are the time series of the joint coordinates, along with their kinematic values. The mined patterns reflect the working behavior of the workers, from ergonomic and productivity aspects. Other work characteristics (e.g., cycle time) can also be recognized. 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 I5.0. With the recognized work patterns, statistical features can be extracted to build a Human Activity Recognition (HAR) model [R210]. The recognized result can be used to predict the worker movement for a real-time application. The details of these steps will be discussed in the following sections.

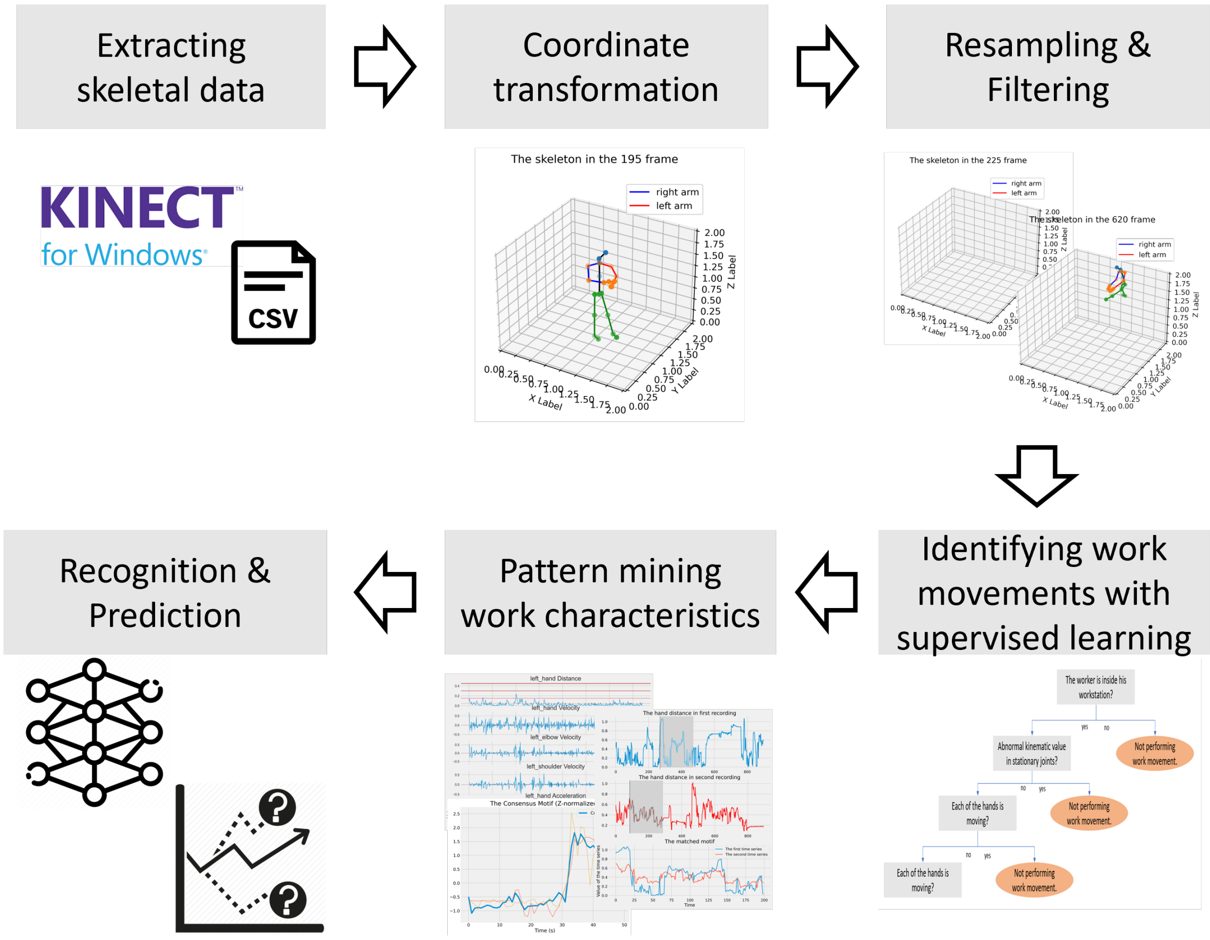


Figure 3.1: The proposed flowchart to process Kinect skeleton data. Source: Own work.

3.1.1 Processing the raw data

To capture the work movements, the Kinect should be located within the working space. Considering O_C is the origin of the camera coordinate system, the origin of the world coordinate system O_W is defined by the perpendicular projection of the origin O_C into the floor. Each joint $\mathrm{P}_W = [x_W, y_W, z_W]$ in the world system is captured as one corresponding point $\mathrm{P}_C = [x_C, y_C, z_C]$ in camera system. Since the Kinect tracking ability is limited in a predefined space, the main working position should be placed within the full-length visibility of from 0.8 to 3 meter in the camera system. The furthest corner of the working zone should not exceed three meters; thus, the Kinect can capture all work movements. Any frame with excessive joint coordinate from this value will be considered as the worker is out of the work zone and filtered out. The setup parameters should be recorded for the later data analysis. For clarification, H_Z is defined as the distance between O_C to O_W in the Z direction, H_Y is the horizontal distance from the O_W to the approximate center of the captured object in the Y direction, and H_X is the distance between O_W to object in X direction. The α is the rotation angle of the Kinect around its X axis. The camera setup is described in Fig. 3.2.

The Kinect v2 provides the skeleton data of 25 different body joints (Fig. 3.3a). Each joint has 3D coordinates recognized in the Kinect coordinates system (Fig. 3.3b), and in the form of time-series in X, Y, and Z directions (Fig. 3.3c). After acquiring the raw skeleton data in the Kinect coordinate system, the coordinate transformation can be done with the pytransform3d package [R211].

The Kinect v2 supports tracking the skeleton for up to 30 frame per second, and this frame rate is excessive for assessment purposes. In industrial engineering practice, the MODular Arrangement of Predetermined Time Standards (MODAPTS) is widely adopted [R212], thus the raw Kinect data was re-sampled to 1 MOD (1 MOD = 0.129 seconds). This resampling enables the comparison of extracted movement patterns with standard movements from MODAPTS as a benchmark [R213].

In the filtering step, frames without any skeleton or containing joints further than three meters in X or Y direction were filtered out. The left frames captured the movements of the worker in the observation space, including both working and non-working status. Supervised learning and the kinematic value of the work were used to segment the movements. Supervised learning (i.e., clustering and classification) was applied to the position data of the limbs to define the work zones. The target objects for clustering are the hands and the head, representing the moving and stationary parts of the body. While supervised learning identifies the work zone, the kinematic value of the limbs confirms it. As working movements may not exceed the allowable velocity, faster movement can be identified as non-working. The details of identifying work movement will be discussed in detail in the next section.

After defining the frames that contain the work movement, the time series of joint coordinates can be used as input data for pattern mining. Besides the raw coordinates, the informative derivatives are:

- The distance between joints: The Euclidean distance between two arbitrary joints (e.g., the distance between two hands).
- The angle between three joints: The 3D angle formed by three arbitrary joints (e.g., the arm extension angle that is formed by the shoulder, elbow, and wrist).
- The kinematic characteristics of an arbitrary joint (e.g., moving distance, velocity, acceleration, jerk) can be calculated from the displacement in time of the raw coordinates of the joint.

Once these time series are extracted, different work performances by one worker or multiple workers can be compared. Pattern mining techniques (such as AB-Join, multivariate, and consensus motif searching) by open-source packages (i.e., STUMPY [R208]) are applied to find the motif pattern that happened within them, analyze their characteristics, to have an insight into how the worker performs his work. Based on the movement patterns in the form of time-series of the joints, statistical features can be extracted to build a Human Activity Recognition (HAR) model [R210]. The recognized result can be used to predict the worker movement for a real-time application.

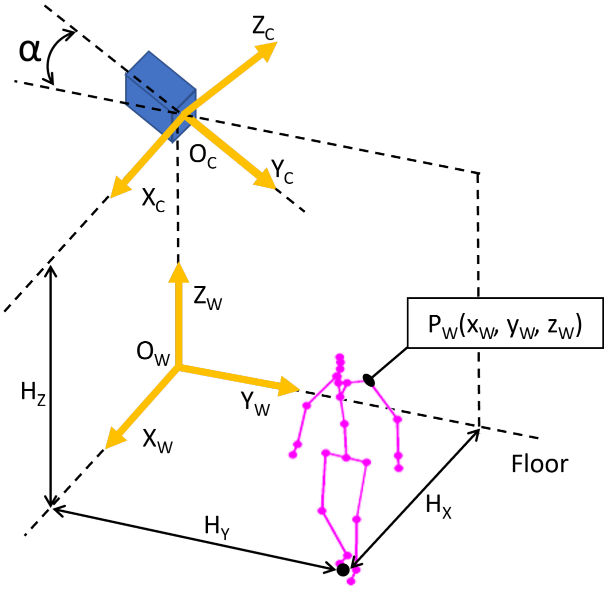
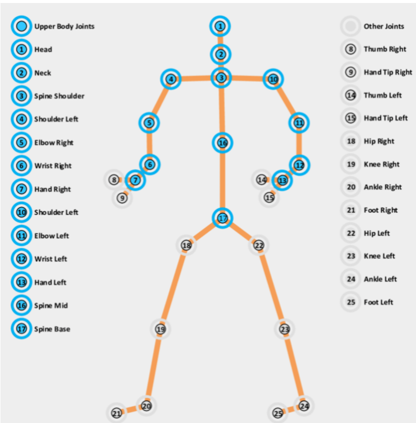
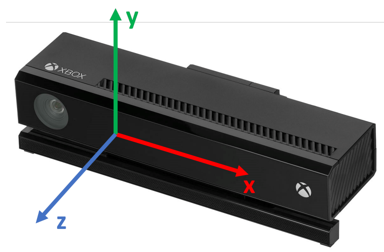


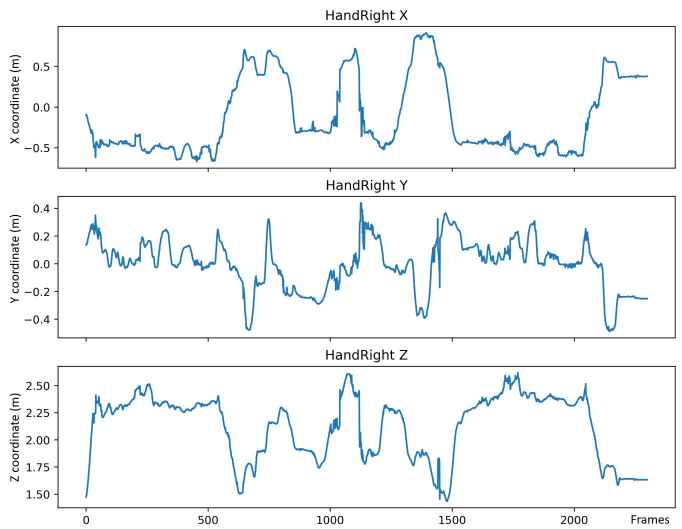
Figure 3.2: The Kinect camera setup suggestion on the shopfloor. Source: Own work.



(a) Kinect body joint system.



(b) Kinect coordinate system.



(c) Example of the 3D coordinates of one joint - the right hand.

Figure 3.3: The Kinect sensor description and the raw skeleton data. Source: (a),(b): Adapted from Kinect documentation; (c) Own work.

3.1.2 Identifying work movement and work characteristics

Firstly, the relevant data that contains the working movement of the worker can be extracted based on the decision tree illustrated in Fig. 3.4. The steps can be described as:

- Step 1: Whether the worker is in his workstation: The standing zone is assumed to be where the worker spends most time working; thus, it can be defined by applying supervised learning such as clustering (e.g., kNN, perceptron) on the position data of the head and the hand joints, considering the head will be the stationary joint and the hands the most active joints during the work session. These zones can be confirmed by the position of the head and its low velocity.

- Step 2: Check for abnormal kinematic value in stationary joins: 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.

- Step 3: Each of the hands is moving or not: To recognize that the worker is working and not standing idle, the kinematic characteristics of the two hands are calculated. Based on the moving distance, velocity, and acceleration of each hand, the frames in which he is performing work can be recognized. After this step, the Gantt chart of the working state can be created, as described in the following section.

- Step 4: Extract the work movement: After the aforementioned steps, the relevant frames in which the worker is performing work movement can be defined, with the ergonomics assessment can be applied. The given work instruction can be utilized to identify the movement, and the motif-searching techniques can be applied to find the movement pattern. These techniques will be described in the next section.

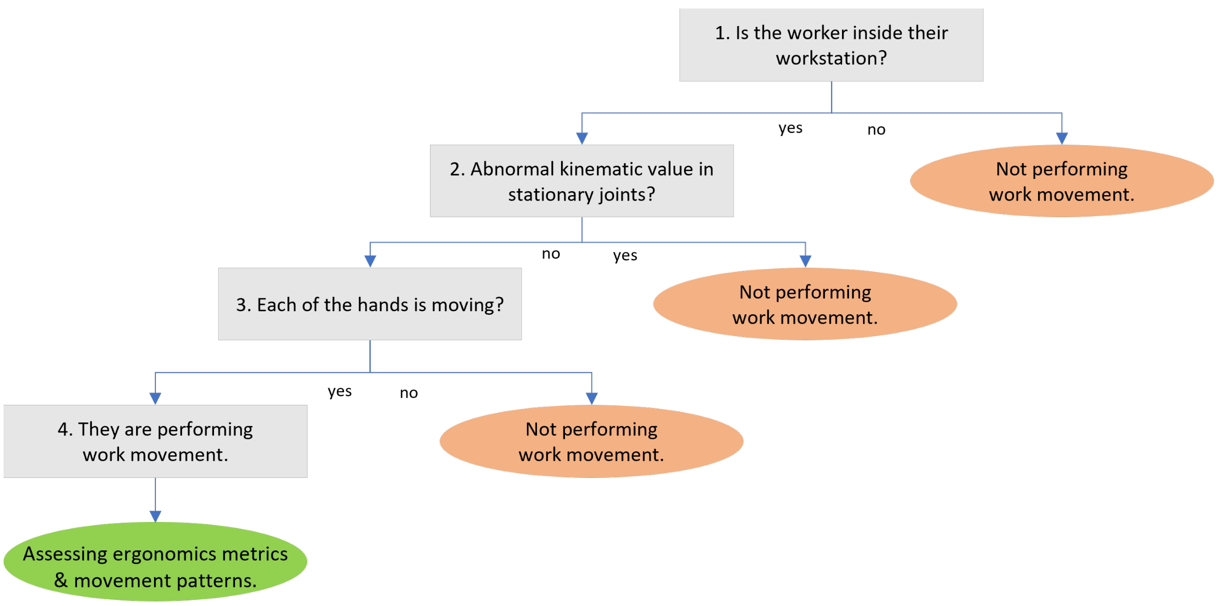


Figure 3.4: The decision tree to filter the relevant movements. Source: Own work.

The rationale of clustering is described in Fig. 3.5, which shows the top-view working posture of a worker. Since the working surface is parallel to the XY surface, X and Y coordinates are sufficient to filter the working movements, in relative position to the head. The primary work zone is the comfortable region for repetitive access in front of the worker, while the close vicinity is the secondary work zone for occasional access, and further away is the tertiary work zone for seldom access [R214]. For ergonomic reasons, the parts will be placed in the primary work zone, and the hands will repetitively move around it to perform the working movements. The hands will be actively moving within the secondary work zone for other movements such as waiting, resting, and taking additional parts. Based on these characteristics, the position of the head and two hands will define different clusters in the X-Y plane. For each frame, the vector $[x_{left}, y_{left}, x_{right}, y_{right}]$ is defined, in which:

- $[x_{left}, y_{left}]$ is the X and Y coordinates of the left hand.
- $[x_{right}, y_{right}]$ is the X and Y coordinates of the right hand.

Then by applying a clustering algorithm (i.e., kNN) on the set of the hand point vectors, the cluster centers which have the same size of four with the hand vectors, in the form of $\left[x^c_{left}, y^c_{left}, x^c_{right}, y^c_{right}\right]$ can be achieved. Each is represented as one line connecting the centroids for the left and right hands. The number of clusters is dependent on the working area. If the working area is small, a smaller number of clusters is needed. In Fig. 3.5 two clusters can be seen: the cluster 1 ($c = 1$) is right in the primary work zone, and the cluster 2 ($c = 2$) is in the secondary work zone. These cluster centers have different positions, which represent different working postures. By recognizing the clusters of the hand positions, the working status of the worker can be defined when the hands access the respective working zones. The same process can be applied to position data of the hands in the X and Z plane, which will show the different heights at which the hands were working.

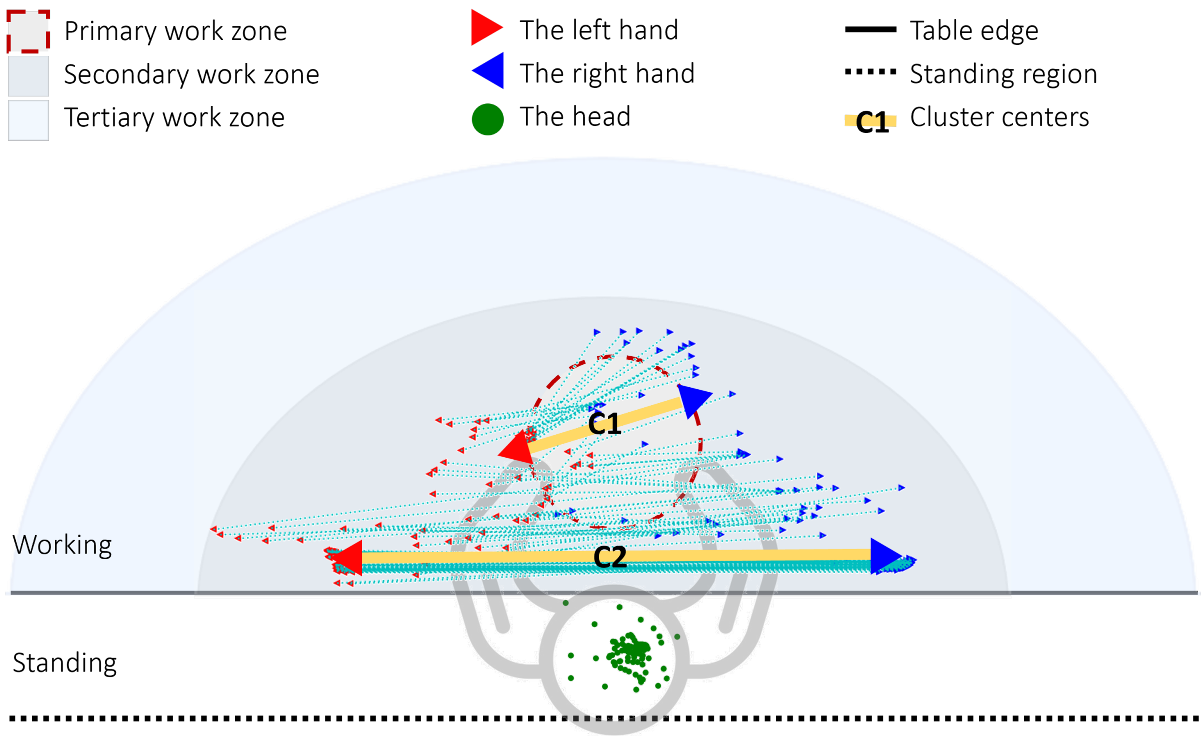


Figure 3.5: The positions of the head and hands in working posture. Source: Own work.

The second thing to notice is the head position during work. While working, the head of the worker mostly stayed within a small region, while his hands moved around the processing parts. The zone in which the head stays will be of an elbow distance to the primary work zone for a comfortable working posture. A straight line can always be drawn to separate the hand points and the head points, representing the physical edge of the table or the conveyor and forming an area where the head barely appears. The line can be defined by any linear classification algorithm (i.e., perceptron). The region where the head stays during work can be named the standing region, while the region where only the hand points can be found is named the working region. Based on ergonomics working distance, the boundary between the standing and working regions can be defined by offsetting the conveyor edge. It is recommended to use an elbow-wrist length from the conveyor edge ($450mm$) to determine the standing region, assuming the worker stands straight during work. The working region is defined on the conveyor, so that the maximum distance from the standing region to the working region equals an upper limb length ($750mm$). These data can be taken from anthropometric measurements of Europeans [R215], and adjusted according to the male-female ratio of the workforce population.

The other factor to consider is the velocity of the moving limbs. If the worker is working, the head should be moving slowly within the pre-defined standing zone. If the worker is walking, the velocity is much higher than the working state. The same principle can be applied to the hand. The criteria described in Table 3.1 are considered based on the position and velocity of the head and the hands. Therefore, several elementary movements, along with the working and non-working statuses, can be identified.

Table 3.1: The criteria to distinguish working movements.

No.	Head position	Head velocity	Hand position	Hand velocity	State
1	Out of the standing region.				Out of the workstation.
2	In the standing region.	High ($> v_{max}^{head}$)			Moving in the workstation.
3	In the standing region.	Low ($\leq v_{max}^{head}$)	At least one hand in the working region.	High ($> v_{max}^{hand}$)	Reaching.
4	In the standing region.	Low ($\leq v_{max}^{head}$)	At least one hand in the working region.	Low ($\leq v_{max}^{hand}$)	Working with one hand.
5	In the standing region.	Low ($\leq v_{max}^{head}$)	Both hand in the working region.	Low ($\leq v_{max}^{hand}$)	Working with both hands.
6	In the standing region.	Low ($\leq v_{max}^{head}$)	Both hand in the working region.	Too low (≈ 0), for $\geq t_{max}$	Staying idle.

The recommended working posture is the worker has his head in the standing region and moving with a velocity lower than v_{max}^{head}, and has at least one of his hands in the working region with a velocity lower than v_{max}^{hand}. These limits are taken from the raw data and consulted by the production supervisors. As illustrated in Fig. 3.6, by filtering out the head position with a higher velocity than $v_{max}^{head} = 0.2\frac{m}{s}$, the clusters show the head position in the standing area. The distant points indicate the worker is resting out of the workspace. The same velocity threshold can be set for the hand movements with v_{max}^{hand}. However, to filter out the resting status of the hands, its timestamps should be examined. If the hand moves in a very low velocity (i.e., $\leq 0.05\frac{m}{s}$) and remains for a period longer than t_{max} (with $t_{max} = 3MODs = 0.516sec$), it can be considered staying idle. This t_{max} is chosen as three MODs as the sufficient time for a worker to move his arm and get something.

As the work is done in cycles, cyclic behaviors and associated characteristics can be found in the time-series data:

- Work cycle time: There are several ways to perform this recognition, such as accessing the auto-correlation of the time series of the distance between two hands or clustering the coordinates of the two hands and looking for the sign of moving to the original position. The cycle time can be recognized when the hands come back to their original position, with the same working distance between the two hands. This concept can be applied to the location of the head, but on a larger scale than inside a workstation.

- Personal efficiency: The utilization efficiency of a worker can be calculated by comparing his movement to the standard proposed by industrial reference (i.e., MODAPTS). The value-added ratio can be calculated based on the segmentation between working and non-working periods. This information can be used to calculate the OLE, one important KPI for the HR department and production planning [R193].
- Body part utilization: The usage frequency and characteristics of the different parts of the body can be considered once the movements are recognized and their timestamps are collected. For simplicity, states such as working and non-working, working with comfort gestures, and non-comfort gestures can be defined. The assessed result can be visualized as a Gantt chart for better improvement in the later phase.
- Body asymmetry: Body symmetry is an essential factor, as it prevents fatigue in the short term and occupational disease in the long term. The period in which only one side of the body is working can be calculated and can be a target for improvement.
- Work complexity: The work complexity within a workstation can be assessed by several criteria, e.g., cycle time, performance variation (i.e., the same work performed by the same or different workers), and body asymmetry. This information can be used to design and balance the workload, thus alleviating the time variation in each workstation and optimizing the line [R216].

An example of cyclic behaviors can be seen in Fig. 3.7. In this scenario, the worker works on a conveyor and takes the product to a nearby cart. After completing the clustering on the head positions, three cluster centers were identified as $C1$, $C2$, and $C3$, which represent the conveyor, the open area as the worker walks from the conveyor to the cart, and the cart itself. The right part of the figure shows the cluster labels over the frame. The worker worked in the conveyor for 300 frames before moving to the cart, and came back to the conveyor at the $550th$ frame as indicated by an abrupt change of the cluster label. This sign indicates that he started a new cycle, and the recognized cycle time is $\hat{t}_C = 550(MODs)$, or 70.95 seconds.

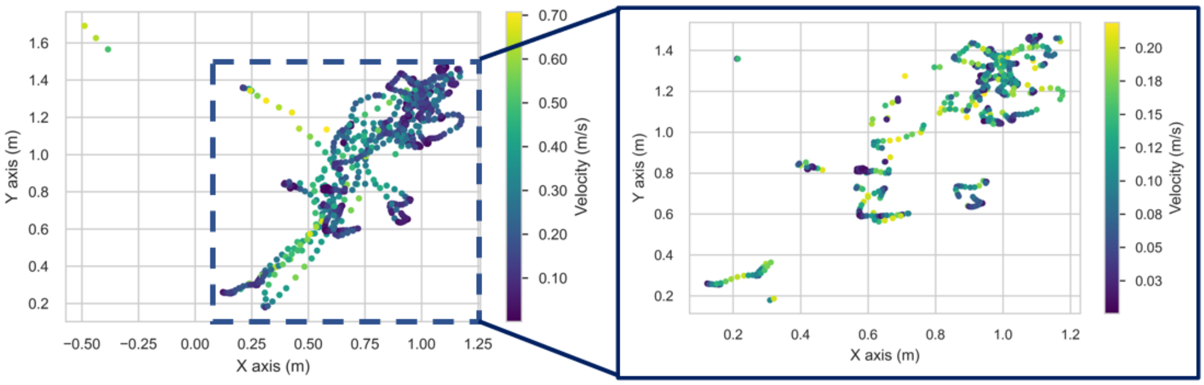


Figure 3.6: Head positions filtered by velocity in the first workstation. Source: Own work.

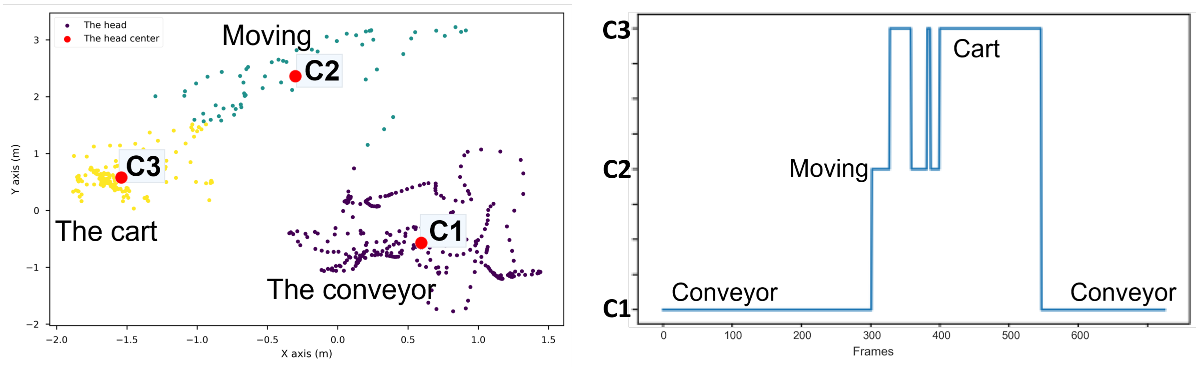


Figure 3.7: The cyclic pattern in the head position clustering labels. Source: Own work.

This recognition can be more precise in a smaller area of a workstation, with the clusters of the hand positions. If several recordings are taken, the recognized cycle time will be the average value of all cycles. Other important parameters can be defined such as:

- The cycle time difference is the ratio of the absolute difference between the recognized cycle time $\hat{t}_C$ versus the theoretical value t_C, over the theoretical value.

$$C_{diff} = \frac{|\hat{t}_C - t_C|}{t_C} \tag{3.1}$$

- The cycle time variation is the ratio of the absolute difference between the maximum value of recognized cycle time $\hat{t}_C^{max}$ versus the minimum value $\hat{t}_C^{min}$, over the theoretical value t_C.

$$C_{var} = \frac{|\hat{t}_C^{max} - \hat{t}_C^{min}|}{t_C} \tag{3.2}$$

For one recording of one worker in one workstation, based on the classified work movements, the total ratio of each movement can be calculated as a relative percentage of the entire recording duration. More information can be extracted on the manufacturing line scale for several workstations with different workers as discussed in next section.

3.1.3 Movement patterns and possible application

Pattern mining techniques incorporated in STUMPY were applied, with different features were searched to highlight work characteristics of the monitored objects as follows:

- Mining a repetitive task conducted by one worker multiple times with AB-join, to recognize the normalities and the abnormalities. The starting time of each compared segment is chosen based on the cyclic patterns after clustering. The search window can be adjusted to equal a long duration, e.g., 78 MOD, equals to 10 seconds.

- Applying consensus motif search on the same work movements between different workers, to recognize the personal work behaviors. The compared segments are not limited to certain cycles. Since more deviation exists in this case, the search window is limited to micro-movement with shorter intervals, i.e., 50 MODs.

When assessing the repetitive task of one worker, the normalities exhibit skill competence (e.g., the time variation between each cycle), and the abnormalities show the achievement in learning a new movement, or a recent physical problem. When comparing the same moving pattern of one worker to the others, the technical skill competence of the workers can be assessed. This information is helpful for the workstation allocation [R217]. The best movement can be found and used as a reference for best practice sharing between workers as a byproduct. This practice helps to improve the performance of the workforce systematically. These patterns can guide the process engineers to work on their accumulated database from their workforce. The optimized work movement and the acceptable patterns can be recorded for later reference when setting up a new production line and training purposes.

Another critical application of movement pattern results is the real-time ergonomics assessment, based on the time series of several elements, such as the distance of the hand from the hips and the angles between the joints. Instead of the traditional assessment done by a human expert, the standards can be integrated into the physical limit for the distance and angle between joints and limbs, thus making it easier to implement real-time monitoring and warning. These assessments can be used as a clue for further improvements.

When multiple workstations are set together to form a manufacturing line, the ergonomics assessment can be performed on each station with the same principle. By comparing the work pattern performed by different workers in the same workstation, the ergonomics setup of that workstation can be assessed. For example, the workstation that causes the same bending posture for most workers should be elevated, and the specific worker with the bad working posture can have customized support.

3.1.4 Machine learning model for automated application

As several ML algorithms are proposed in this approach with available open-source packages that have data streaming possibilities, a real-time assessment model by Kinect sensor can be built for more convenient usage. This model can automatically process the acquired data and perform the HAR function with more in-depth analysis such as movement recognition and prediction. To facilitate end-to-end ML software development, the iterative-incremental process in the Machine Learning Model Operationalization Management (MLOps) [R218] is adopted. A framework with three main steps: *Model Design*, *Development*, and *Operation*, is illustrated in Fig. 3.8, with step-by-step details in building such an ML application for a particular manufacturing industry.

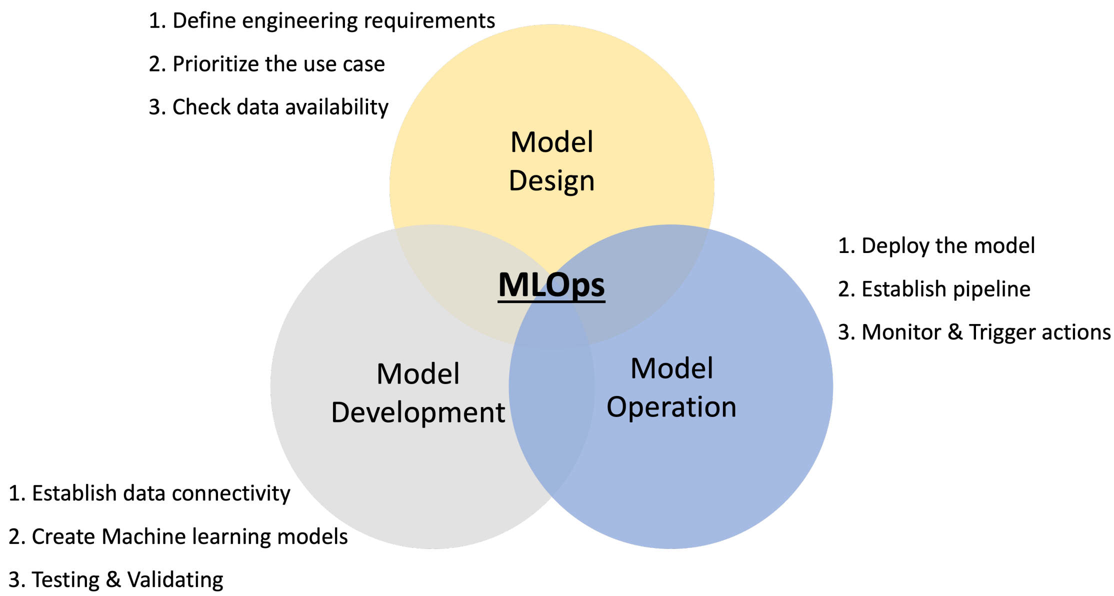


Figure 3.8: The proposed Machine Learning Model development. Source: Own work.

In the *Model Design*, the engineering requirements for industrial practice should be defined. These requirements should consider the nature of the work movement (i.e., how many joints are required to perform the work) and the workplace (i.e., how many workstations need to be under observation), the suitable sensors (i.e, video-based or wearables), the types of connectivity and database that are compatible. After that, a use case should be well-defined for a smaller facility area where there is no obtrusion from other objects. For the use case, the engineers may prefer the line with a similar type of work movement (such as assembly or material handling), and each workstation has a pre-defined work cycle and designated area of work. An open workstation with no designated area and no cyclic work pattern can be troublesome to assess, even with human observation. The data availability will be checked and tested with the sensor. The essential criteria here can be: how long the recording duration should be, how much data distortion is caused during work (due to the natural obtrusion of the worker), and how long the distortion last (due to the appearance of facility equipment, such as the conveyor). The engineers need to consider if these skeleton data are sufficient for the assessment.

In the *Model development*, the architecture, such as data acquisition and storage, should be ready, and the connectivity should be established. Time series databases (such as InfluxDB or OpenTSDB) can be suitable candidates for storing the processed raw data from Kinect. The number of required Kinect sensors and the setup positions are also considered. Based on the available data, the model can be developed with real-time ML and pattern-mining algorithms and packages. The teaching criteria for supervised learning should be described in this step. The model then should be tested and validated by the confusion matrix between principal movements that can be recognized.

In *Model operation*, the model can be deployed with the established data pipeline and become ready for real-time monitoring application. There should be pre-defined signs to trigger the model (i.e., abrupt changes of the cluster label during the production period). These signs may come from the natural characteristics of the work movement.

By applying these MLOps principles, the early adoption and fast delivery of the resultant real-time industrial application can be expected. The practicability of this approach is promising for ML-based software, which aligns with the key assessment metrics from high-performing software development organizations [R219].

3.1.5 Human performance improvement in Industry 5.0

Since human performance makes a significant contribution to the efficiency of the line, enhancing the former will affect the latter. In the previous paragraphs, the different movements can be mined from Kinect skeleton data, and their application for human performance assessment is discussed. Thanks to these results, the normal and abnormal patterns in the movement of workers can be considered, and industrial managers can seek improvement on two scales: individual level or systematic level:

- Individual improvement: the changes that can be applied to each specific individual, affecting the work of a single worker, or changing a workstation layout (e.g., customized skill training, ergonomics posture training, work-cell arrangement).
- Systematic improvement: the changes that can be applied to more than one worker, affecting the work of multiple workers, or changing the entire manufacturing line (e.g., workload design principles, line balancing, job rotation)

As inspired by the Human Resource Development (HRD) approach of Lean manufacturing [R220], these improvements can also be categorized into short-term and long-term initiatives. As I5.0 aims to build a resilient workforce, the long-term HRD is one of the main pillars for the sustainable and competitive growth of a firm.

- An example of an HRD short-term initiative is developing customized job training, providing workers with specialized training based on their skills. A cross-training program between workstations is proved to have a positive impact on worker performance [R221], taking into consideration the specific skills of each worker. The combination of individualized skill-based training and assignment plans will eventually lead to an increase in overall efficiency [R222]. By endorsing workers to improve their skills, greater flexibility can be achieved within the workforce [R223].

- An example of an HRD long-term initiative is the job rotation, switching the worker between a routine of different workstations with different skills to avoid occupational hazards [R224] and physical ergonomic risks [R225]. This initiative will alleviate the boredom of the workers [R226], reduce the physical workload [R227], and enhance the ability of the firm to cope with unexpected changes and uncertainties [R228], while increasing the work satisfaction [R229] in the long term.

Considering that the I5.0 objectives are human-centricity, sustainability, and resilience, the improvements mentioned above facilitate the firm to achieve its I5.0 goals. Their corresponding contribution to the I5.0 objectives is as illustrated in Fig. 3.9.

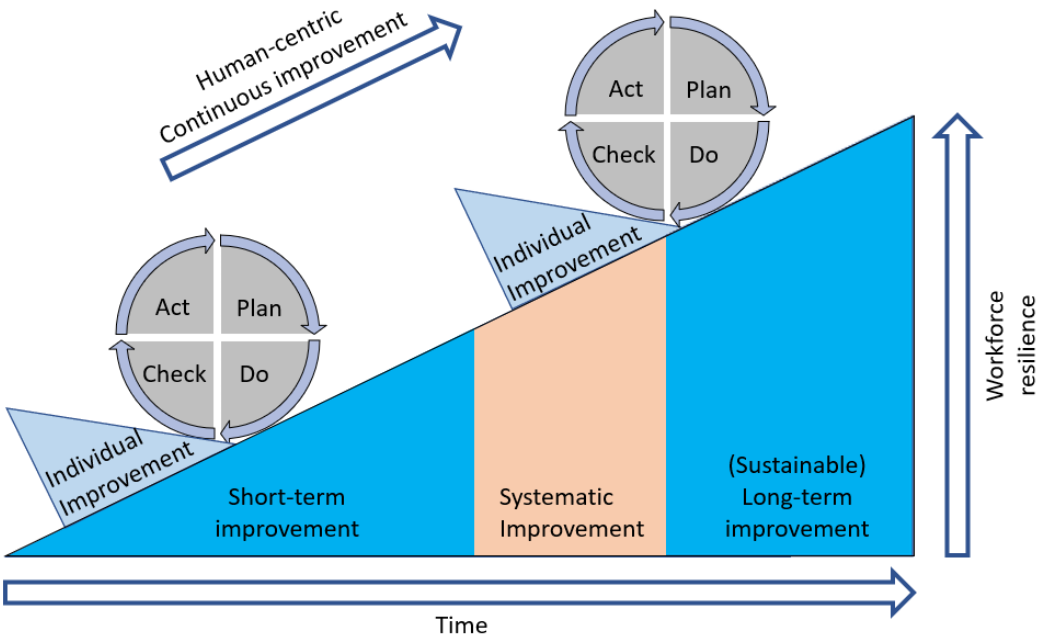


Figure 3.9: The proposed human-centric improvements with Industry 5.0 focuses. Source: Own work.

- By examining the work behavior and preference of a worker in a workstation, individual improvement can be made to help him achieve higher performance, according to his special physical condition. As this individual improvement can establish a new standard in designing and performing work, human-centric improvements in the firm can be continuously facilitated.

- After the short-term improvements in one workstation, systematic improvement can be deployed on a manufacturing line. The results will improve the performance of more workers, ensuring robustness and resilience productivity.

- The long-term HRD plan plays a vital role in permeating the effect within the workforce and ensuring the long-term sustainability of the firm. As the PDCA circle is carried on, short- and long-term improvements are achieved, and the resilience level of the whole workforce is increased.

In I5.0, these improvements can be data-driven and carried out continuously, as the skeleton data from the Kinect sensor is sufficient, and with the aid of a real-time ML model. The overall initiative is depicted in Fig. 3.10 with a PDCA framework established around the organizational database of movement records from workers.

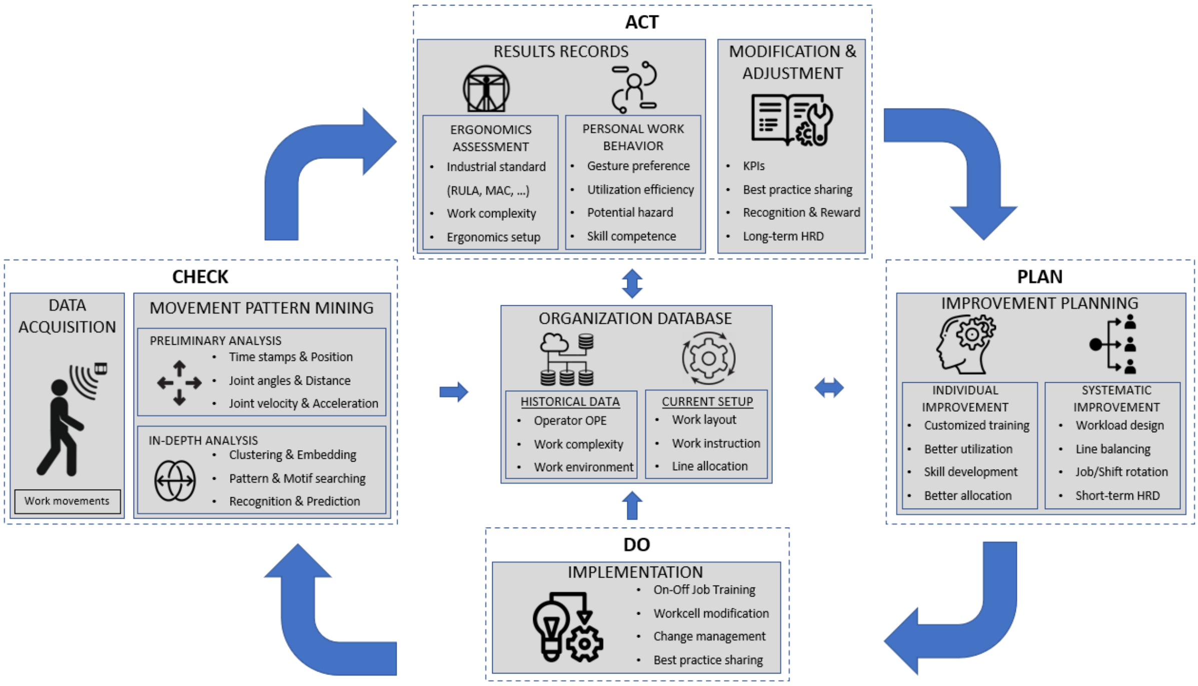


Figure 3.10: The proposed PDCA circle with pattern mining framework. Source: Own work.

As the traditional kaizen starts with observation, the pattern mining is deployed in the *CHECK* phase. A Kinect data acquisition system is established to collect human-centric data. The target objects are movements of workers in a specific workstation, for a particular shift. Any arbitrary type of additional sensor can further enhance the data accuracy, such as wearables, smartphones, etc. Then ML and pattern mining tools can be applied to the acquired data with preliminary and in-depth analysis. The mined patterns are stored in a database structured by each operator, work instruction, and specific conditions of the environment. This storage serves as the organizational database for human-centric improvement. Additional data properties such as the cell setup, the work instruction, and the line allocation can be stored for later reference.

In the *ACT* phase, movement pattern mining results are categorized into ergonomics assessment or personal work behavior, or in ergonomics and economics performance [R230]. These results can be compared with the database records to modify and adjust the KPIs and long-term HRD strategy or reasoning for recognition and reward activities.

In the *PLAN* phase, the individual and systematic improvements can be planned based on the result records and the benchmark from the database. While individual improvements aim to utilize human skills and customized development for the individual, systematic improvements focus on a larger scale and on short-term effects, such as balancing a line, creating a skill training schedule, or a job rotation plan for the next month. These HRD plans can take the historical records from the database as a benchmark.

The *DO* phase integrates the planned improvements through the on- or off-the-job training and best practice sharing with other implementations, such as modifying and rearranging the work cell. The changes in this phase should be recorded in the database as a change management practice. After any change, the effect of kaizen implementation is recorded in the *CHECK* phase, with the new movement patterns recognized and diagnosed. It is noticeable that the proposed PDCA approach is built in a human-centric way, utilizing the movement pattern mining techniques fully.

3.2 Use case in an electrical product assembly line

The previous section discussed the usage of Kinect skeleton data to assess human worker performance and generate improvement ideas. In this section, a use case is described to show the practical application of the proposed approach. The real problem is discussed in the following paragraphs, with the purpose of the improvement projects and the utilized equipment setup. Then the data processing details and assessment results are given. Based on this foundation, improvement ideas to improve the human performance of this manufacturing line at both individual and systematic levels are generated.

3.2.1 Use case description of an assembly line

A case study is conducted in an electronic assembly line consisting of $N_{ws} = 12$ workstations, denoted by w_i, where $i = 1, 2 \ldots N_{ws}$. The main assembly tasks of every workstation are performed on a moving conveyor, requiring both hands to work on the current product. As the assembly tasks require manpower, the human workers are irreplaceable. The workflow description in each workstation is roughly defined from the previous similar product in the product family. However, as the manufacturing time is dated and measured by the performance of the old batch of workers, the task time becomes unreliable and cannot be used to ramp up a new production line.

The improvement purpose is stated by the management board, along with the description of the technical apparatus and software being used. As product assembly depends on manual tasks, when the need to increase productivity is demanding, the practical way is to enhance the performance of workers. The traditional way of improvement is to perform frequent Gemba walks and make careful observations, which takes time and expert knowledge to deliver a possible improvement idea. Besides, the sustainable optimization approach should regard the physical and fatigue limit of the human body, not only the economic aspects. The traditional observation method can be replaced by using the Kinect sensor and applying pattern mining techniques to automatically solve the problem of assessing human worker performance.

The experiment is designed as in Fig. 3.11, in which each workstation in the assembly line is equipped with one Microsoft Kinect sensor from the most convenient angle to observe the working gestures of the workers. Each workstation is limited within a defined space and assigned a predefined workflow, and the conveyor moves at a predefined pace. The total number of workers is $N_w = 15$ workers, which is larger than the number of workstation N_{ws}, and denoted by o_j, where $j = 1, 2, \ldots N_w$. The recorded shift is denoted by (s_k), where $k = 1, 2, \ldots N_k$, with N_k as the number of shifts per day.

The recorded skeleton data from Kinects are stored under the label of each workstation, each operator, and each shift, with the syntax of $yyyymmdd.wX.oY.sZ$. For example, $20220506.w1.o2.s1$ is the recording in the first workstation, with the work done by the second operator in the first shift of the sixth of May, 2022. Data is extracted with Kinect for Windows SDK and programmed in Python language.

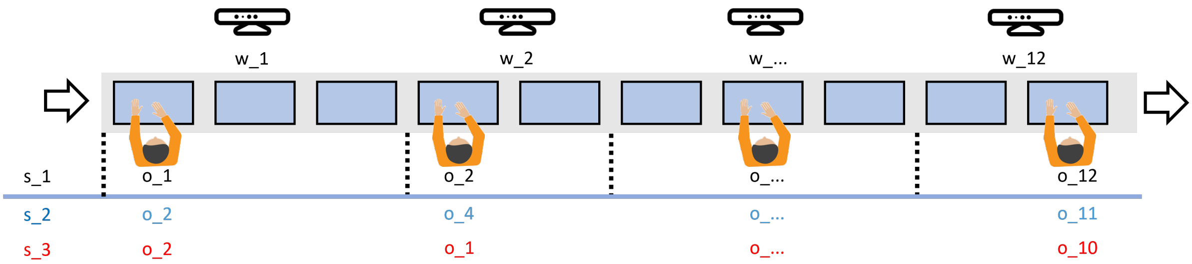


Figure 3.11: The designed experiment in an assembly line with Kinect sensors.

3.2.2 Performance assessment results by pattern mining

In this section, supervised learning is applied to segmentize the movements and pattern mining tools are used to find the work characteristics in the form of time series.

Identify work movements for each workstation

The first step is to recognize whether the worker is in his workstation and performing work movements. Considering that the assembly movements are performed on a conveyor, the conveyor edge is a rigid physical separation between the position of the working hands and the head during the production period and can be identified as described in Fig. 3.12, with the data from the first workstation.

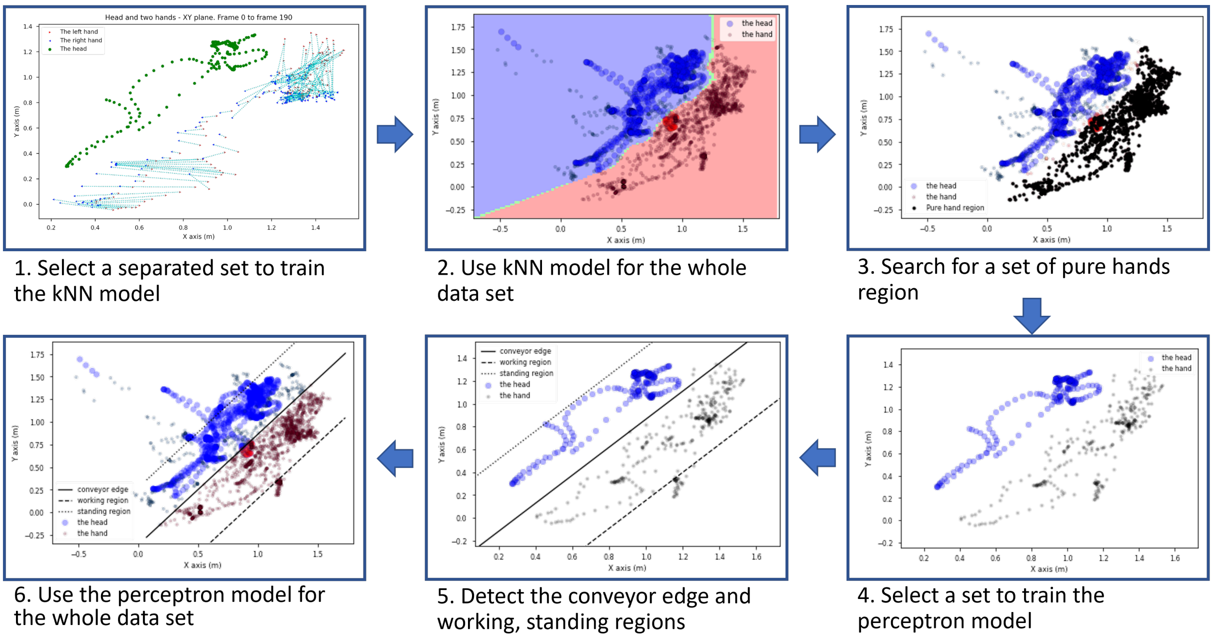


Figure 3.12: The steps to perform the conveyor detection in the first workstation.

The conveyor detection utilizes a supervised ML algorithm, such as k-nearest neighbors (kNN) clustering, followed by a linear classifier (i.e., perceptron) as follows:

- At first, a set of data with the head and two hands positioned in the X-Y plane are collected as training data for the kNN model. This set is taken from the working period, so the head and two hands are separated in the different regions by the conveyor.

- Secondly, the kNN model is used to predict the label of the whole data set. The decision boundary is not perfectly a straight line, as the hands and head points can be mixed in some regions (i.e., while the worker walks toward the conveyor).
- Thirdly, based on the suggested label, a set of hand positions can be identified, whose neighbors are hands only, without any head position. It can be named the "pure hand region", and mostly this region is on the conveyor. There are a few unusual cases where the pure hand region is out of the conveyor, but they are neglectable.
- Fourthly, a set of hand positions from the pure hand region is taken to train the linear classifier, as scattered as possible, along with the head position.
- Fifthly, the conveyor edge is detected. Based on ergonomics working distance, the boundary of the standing and working regions can be defined by offsetting the conveyor edge. The offset value is mentioned in the previous section, taking into consideration the male-female ratio of the facility workforce.
- Based on the perceptron classifier result, the whole data set will be examined.

Noticeably, the conveyor edge detected here does not reflect the actual edge of the physical conveyor. However, it can serve a similar function as a rigid boundary between the working and standing regions and is critical for movement identification purposes. Based on these criteria, the different movements in one workstation can be recognized as depicted in Fig. 3.13, with the conveyor represented.

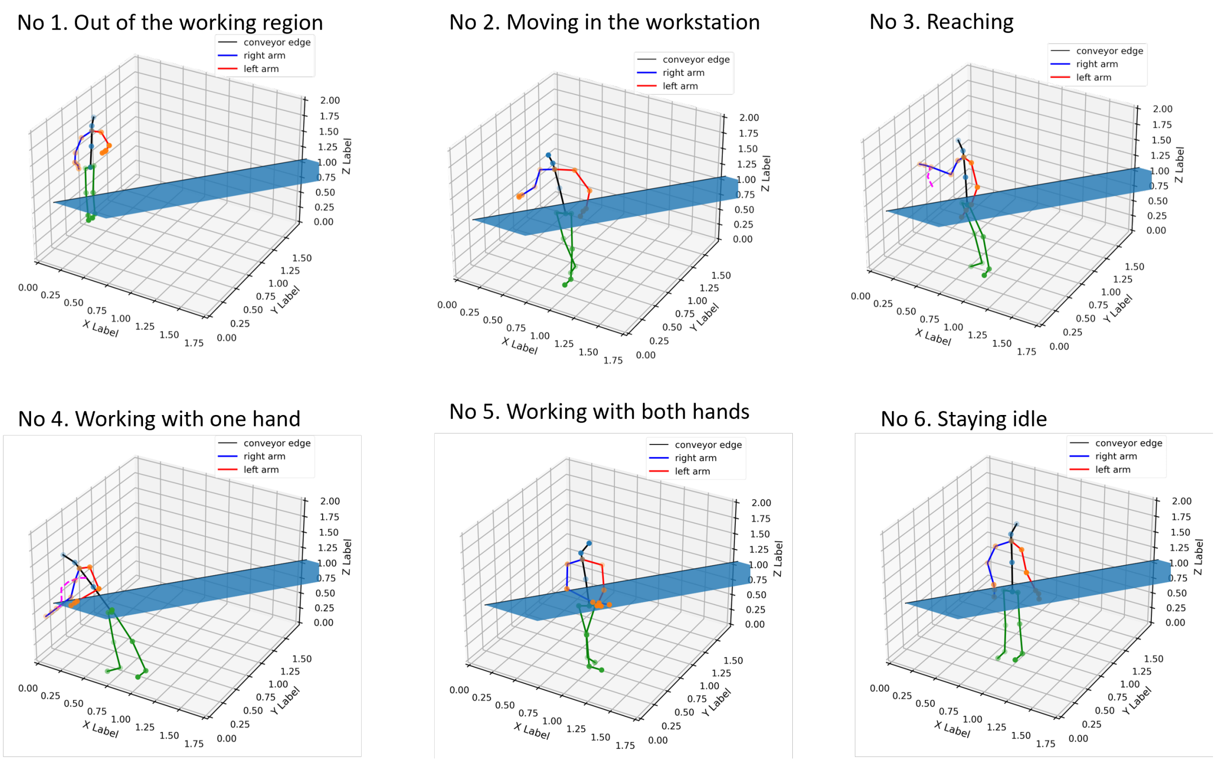


Figure 3.13: The different movements in the first workstation with the conveyor.

The velocity limits (v_{max}^{head} and v_{max}^{hand}) are taken from the raw data, as the $90th$ percentile of respective velocity in all recordings, from all workers. After consulting the production supervisors and taking into consideration the nature of the assembly work, $v_{max}^{head} = 0.2\frac{m}{s}$ and $v_{max}^{hand} = 0.8\frac{m}{s}$ were chosen. A hand moves at a very low velocity (i.e., $\leq 0.05\frac{m}{s}$) for a period longer than $t_{max} = 3MODs = 0.516s$ will be considered staying idle. Applying the same procedure, the whole conveyor with its workstations and the head and hand position of workers can be constructed as in Fig. 3.14. The first workstation (w_1) has a broader distribution of the head and hands location; since it is the beginning of the line, the worker needs to take the raw product from a separate cart. The other workstations have smaller scatter since the workers mostly perform their work in a smaller defined space.

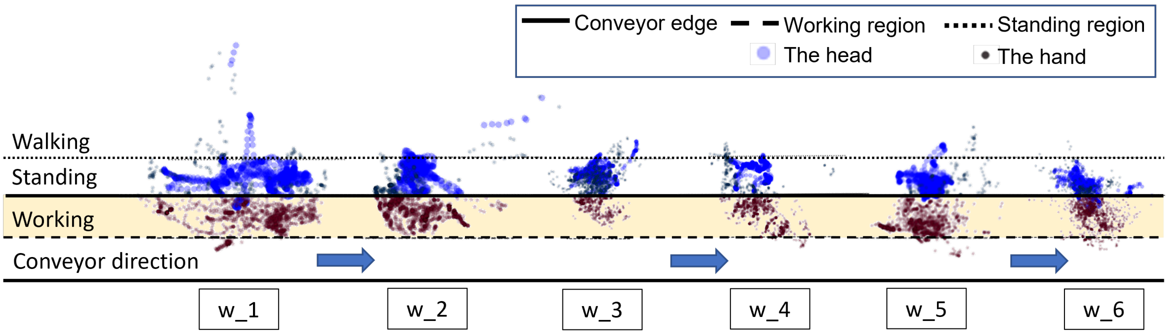


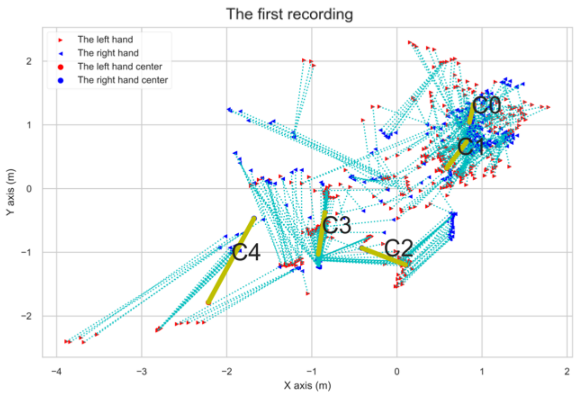
Figure 3.14: An elaborated section of the assembly line.

Cycle time recognition

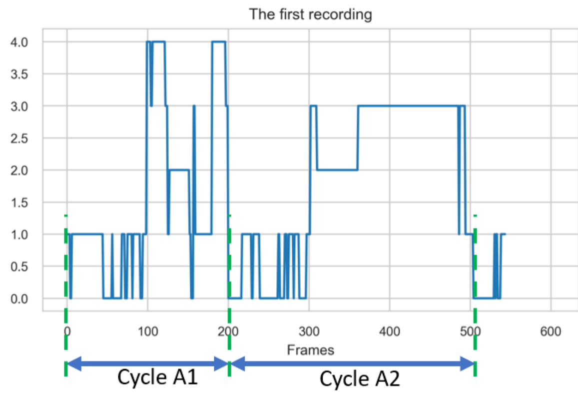
Due to the characteristics of assembly work, the hands of the workers follow a periodic trajectory in the working space (i.e., they come back to the original area when they start a new cycle). Since most of the work movements are done on the flat surface of the conveyor, the Z component is not considered. One work cycle can be traced with the cyclic pattern of the hand position. In this section, the cycle time is recognized by applying K-means clustering on the vector $[x_{left}, y_{left}, x_{right}, y_{right}]$.

The result of clustering applied in one workstation with its different recordings is illustrated in Fig. 3.15. In Fig. 3.15a, the cluster centroids from the first recording of a workstation are illustrated. Based on the cluster label plotted in Fig. 3.15b, it can be observed that there are two work cycles $A1$ and $A2$, last 200 and 305 frames, respectively. For one work cycle, the hands move near the clusters $C0$ and $C1$ for a while, then into the clusters $C2$, $C3$ and $C4$ which are further away. For every new work cycle, the hands come back to cluster $C0$ and $C1$ and repeat the pattern, which results in an abrupt change from cluster $C4$ to $C0$ (the quick movement in a short period - defined by $t_{max} = 3MODs = 0.516sec$ will not be considered, as the worker sometimes forget the tools and reaching out to take it).

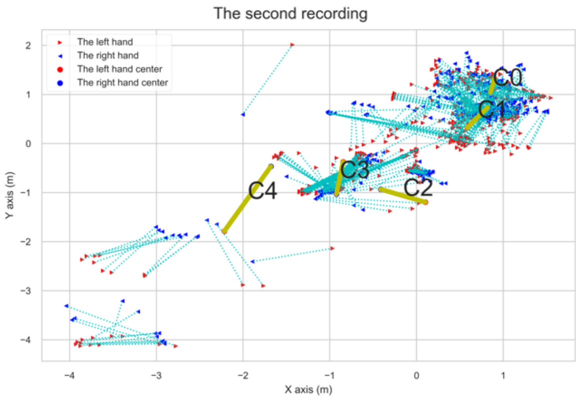
The existing cluster centroids are applied to predict the cluster labels of the other recordings from the same workstation in Fig. 3.15c. The second recording shows the worker working on the conveyor in the same position. However, as the rack for the work-in-process (WIP) is further from the first recording, he needs to reach out further than cluster $C4$ to take it to start a new work cycle. Consequently, the cycle B1 lasts longer for 340 frames, as shown in Fig. 3.15d. The cycle times from these two recordings are calculated in Table. 3.2.



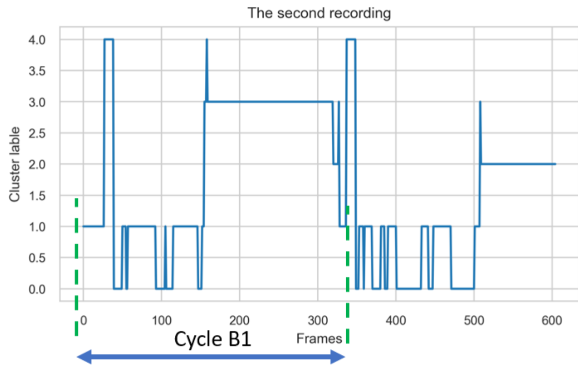
(a) Clusters result from the first recording



(b) Work cycle from the first recording



(c) Clusters result from the second recording



(d) Work cycle from the second recording

Figure 3.15: Cycle time recognition in different recordings from one workstation.

Table 3.2: The calculated cycle time from two recordings in one workstation.

No.	Work cycle	Number of frames	Number of MODs	Time (sec)
1	A1	200	200	25.8
2	A2	305	305	39.345
3	B1	345	345	44.505
Average cycle time			**283.3**	**36.55**

Body part utilization

The hands are the most frequently used limbs in assembly work, thus the utilization ratio of two hands is essential information for industrial managers. Based on the movement identification, the timestamps of the head and the hands between each working duration can be recorded. A Gantt chart is built, as illustrated in Fig. 3.16 to show the status of the worker during the work period. It can be seen in the first recording, that the worker spent most of the time in the standing region, but only partly in his working state, and even less time spent on working the assembly task with two hands. From this information, the utilization ratio can be calculated for this workstation, as metrics exhibited in Table 3.3. By comparing recordings from two different workers, it can be observed that both workers only worked with both hands for half of the total recording time, and slightly worked more with only the right hand than with only the left hand. Besides, the worker in the second recording utilized his right hand more dominantly than the other worker. Further investigation is needed to see if it is due to the workstation arrangement or the natural right-handedness.

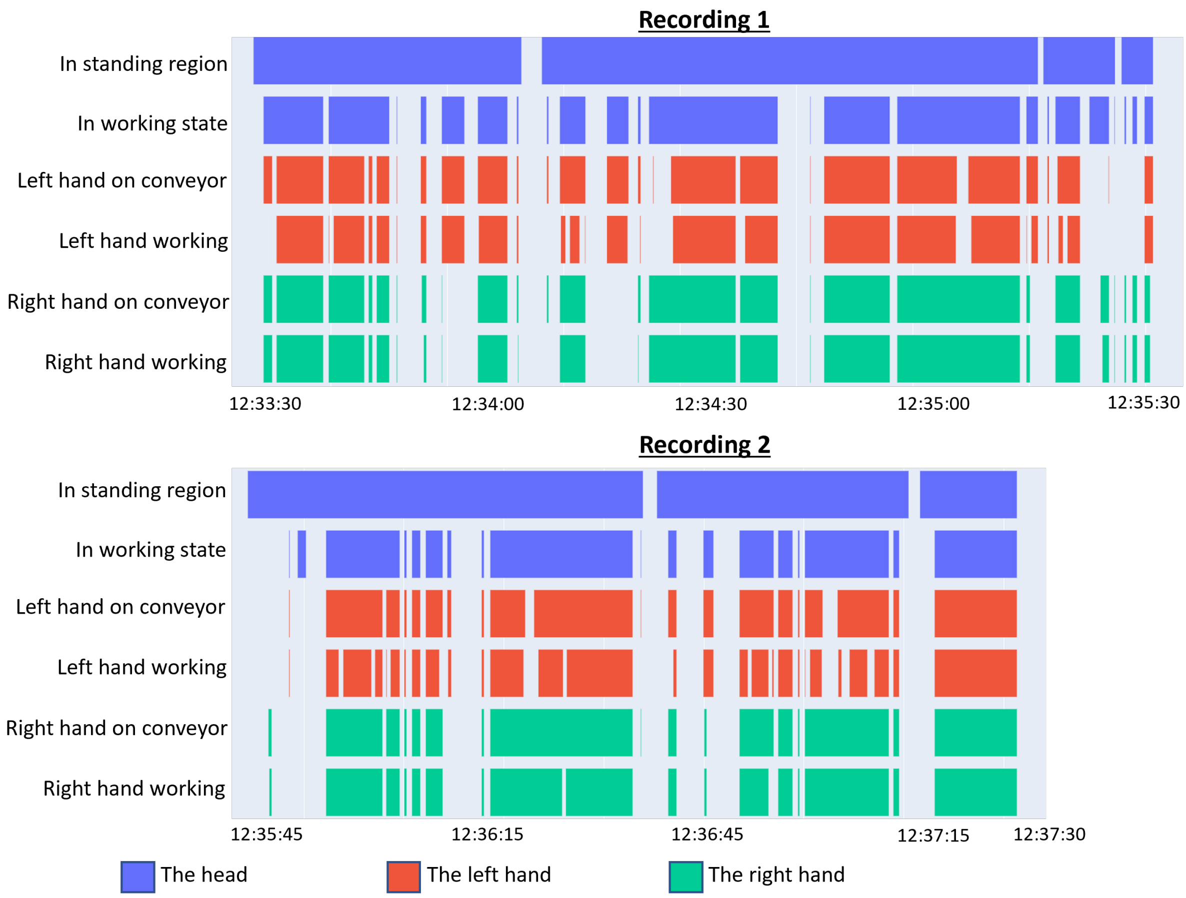


Figure 3.16: The Gantt chart of the worker statuses in one workstation.

Table 3.3: The assessment result of body part utilization of the worker in one workstation.

		Recording 1			Recording 2		
No.	**Metrics**	**MODs**	**Seconds**	**Ratio (%)**	**MODs**	**Seconds**	**Ratio (%)**
1	Total recorded duration	900	116.10	100	896	115.58	100
2	In standing region	879	113.39	98	867	111.84	97
3	In working state	626	80.75	70	623	80.37	70
4	Working with both hands	418	53.92	46	458	59.08	51
5	Only left hand working	69	8.90	8	36	4.64	4
6	Only right hand working	117	15.09	13	97	12.51	11

Movement pattern searching with kinematic characteristics

The interesting kinematic characteristics are the moving velocity and acceleration of each hand of a worker in the form of time series, and they will be the object for the pattern-searching step. Besides this information, the calculation of RULA angles (such as arm abduction, arm extension, etc. [R231]) can be considered for a similar approach. However, only kinematic time series are chosen to be diagnosed further. Based on the previous result of cycle time recognition and body part utilization in Fig. 3.17, these characteristics for a specific part of the work cycle can be analyzed. Knowing that both of the hands are working in the cluster $C0$ and $C1$ during the first period of the first work cycle, a closer look at the kinematic characteristics in Fig. 3.18 can show us that though the two hands were working together, the right hand was more preferred, characterized by a higher velocity value, and a more extended period with acceleration.

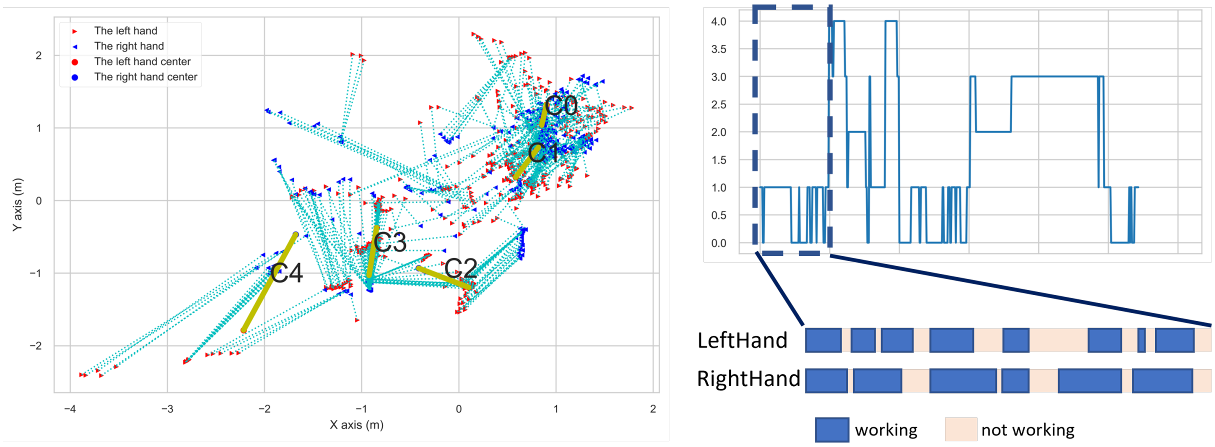


Figure 3.17: The kinematics of two hands in the first area of one workstation.

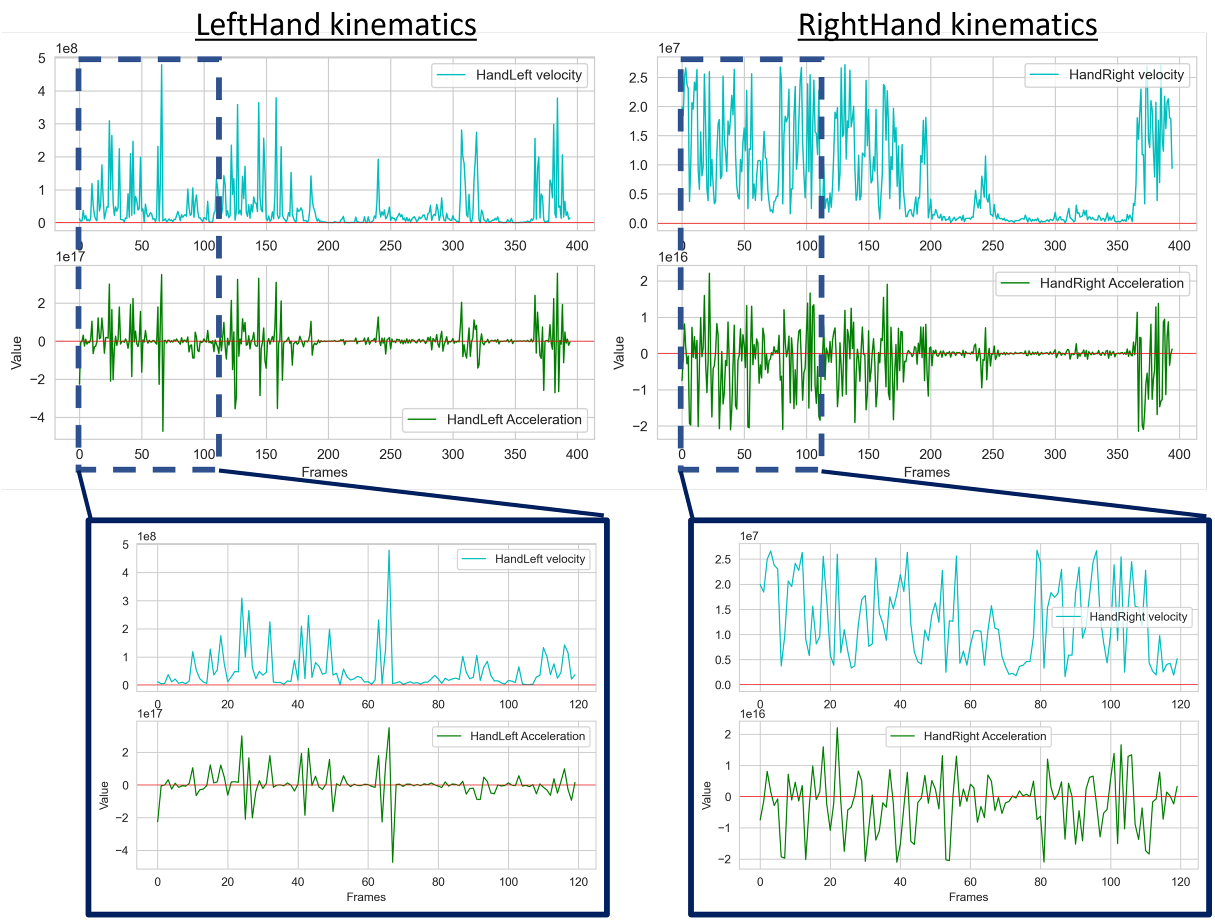
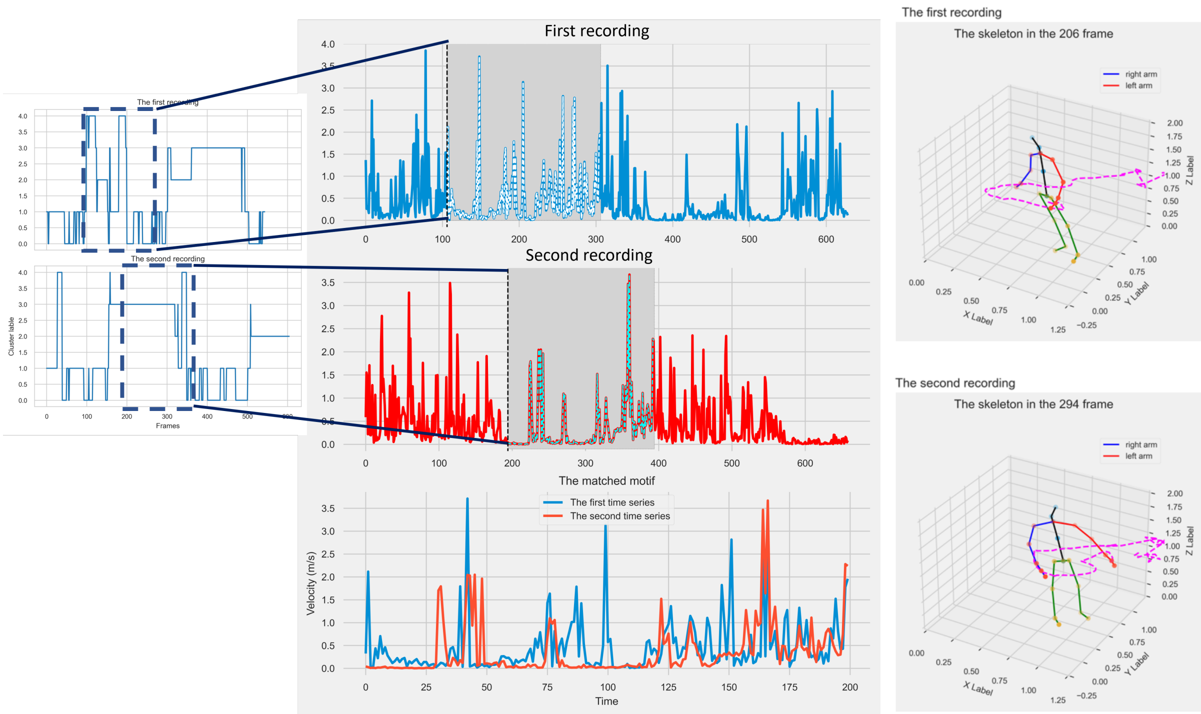


Figure 3.18: Kinematics characteristics of left and right hands.

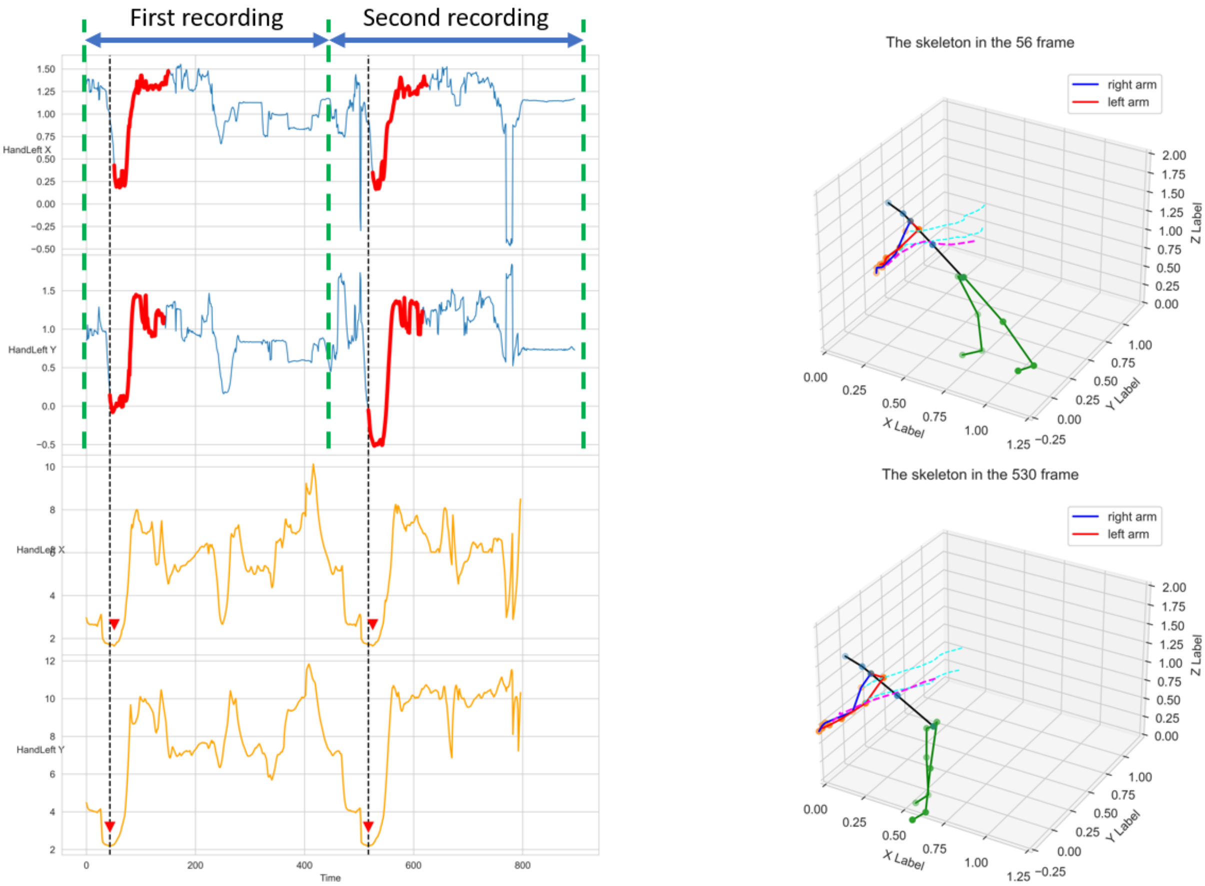
The motif searching technique is applied to looking for the same movement patterns that appear during the work period, performed by the same or different workers. Finding the same pattern of one worker will show an insight into individual work, while the same pattern by many workers helps us find the best movement practice. By applying the AB-Joins on the velocity time-series of the left hand from two different recordings, a motif can be found as illustrated in Fig. 3.19. The respective movements of the workers with their left hands are shown in Fig. 3.19a. The movement happens when the worker finishes one work cycle and needs to bring a new product from the rack into the conveyor to start a new one. The trajectory of the left hand as the dotted lines in Fig. 3.19b indicate that the worker in the second recording has a better way of performing the work; thus he did not need to turn his body around.



(a) The motif in the velocity of the left hand. (b) Actual movements.

Figure 3.19: The matched motif in left-hand movements of workers in the first workstation.

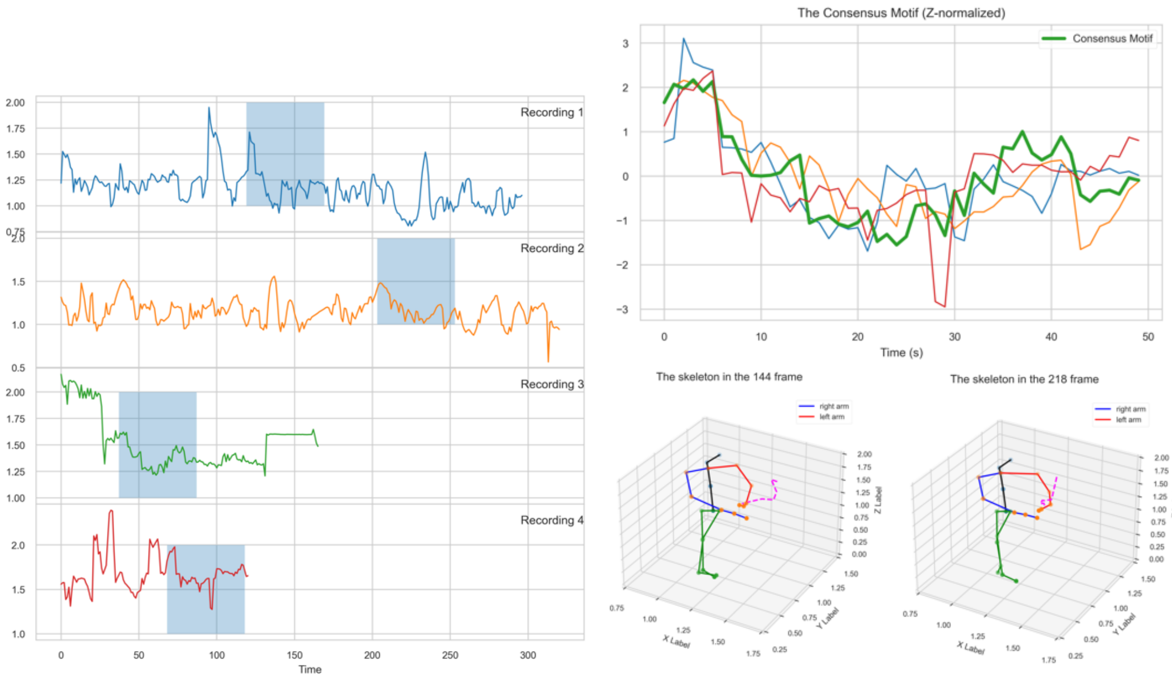
To recognize the movement pattern performed by both hands, multi-dimensional motif searching can be applied on the time series of the velocity of both hands. As in Fig. 3.20, the time series from different recordings are joined together in Fig. 3.20a, and similar movements with both hands are spotted in Fig. 3.20b. The dotted lines marked the trajectories of the wrist-elbow-shoulder system indicate that the upper body movements are similar; however, different workers have different working postures. To expand the motif searching for many workers, a time-series consensus search can be performed on simple data, such as the Z-coordinates of the left hand: a consensus of a "swing" movement is found in different recordings as in Fig. 3.21a, while different workers executed it differently with his left hand as indicated by dotted lines in Fig. 3.21b.



(a) The positions while the motif happens.

(b) The actual movements.

Figure 3.20: The matched motif of two hand movements performed by different workers.



(a) The positions while the motif happens.

(b) The motif and the actual movements.

Figure 3.21: Consensus motif in the height of the left hand performed by different workers.

By aggregating the metrics from the constituent workstations, an overall picture of the assembly line can be constructed as in Table 3.4. Seven criteria are proposed to assess each workstation, and their ideal values can be set from the historical standards. The information from the first six workstations is given here for demonstration purposes.

Table 3.4: The assessment result from the first six workstations in the assembly line.

Metric	Calculation	Unit	Ideal value	w_1	w_2	w_3	w_4	w_5	w_6
Utilization ratio	The average of working duration over the recorded duration.	%	The higher the better	70	69	69	65	58	67
Hard-to-perform ratio	The average of working duration where the gestures exceed RULA recommended limit angle.	%	The lower the better	21	14	19	6	23	12
Cycle time difference	The difference between the recognized cycle time over the line takt-time	%	The lower the better	15	32	22	18	35	19
Cycle time variation	The cycle time variation from different cycles over the recognized cycle time	%	The lower the better	34	17	26	41	39	13
Left-hand utilization	The duration when the left hand is working.	%	The higher the better	55	61	57	26	35	59
Right-hand utilization	The duration when the right hand is working.	%	The higher the better	61	52	29	15	25	63
Body asymmetry	The total accumulated duration in which only one hand is working.	%	The lower the better	18	22	36	24	21	14

3.2.3 Possible human-centric improvements

Based on the aforementioned assessment, several improvement ideas can be brainstormed as described in Table 3.5 follow in the order of execution priority. The sole intention is to create a favorable physical work condition that suits the current human workers, from the workstation scale to the line scale. The suggested relationships between the possible improvements with the assessed value are proposed in Fig. 3.22.

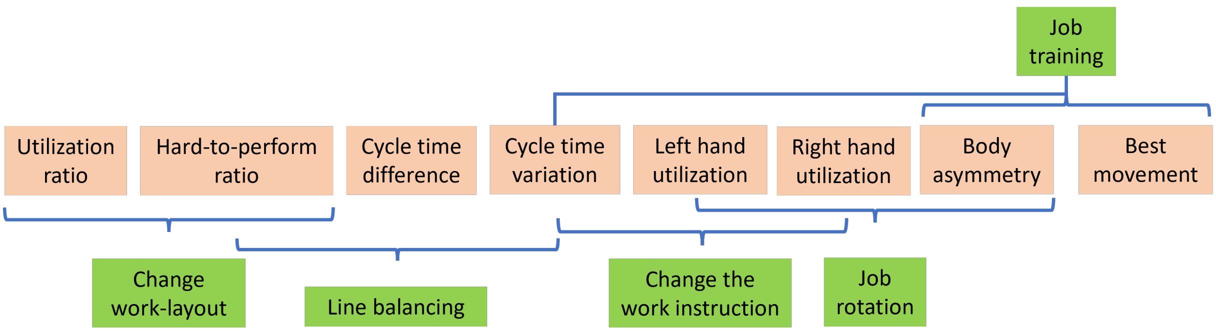


Figure 3.22: The criteria hierarchy of possible improvements. Source: Own work.

Table 3.5: The possible improvement ideas based on the assessment result.

Indicators	Physical meaning	Possible improvement	Possible initiative
High cycle time variation & High difference between left and right-hand utilization	The work procedure is complicated The workload is not distributed equally for the hands.	Modifying work instruction	Enhance hand utilization Enhance body symmetry Reduce work complexity
Low utilization ratio & High or varied hard-to-perform ratio	More irrelevant movements than working. The workstation layout does not fit for the workers.	Re-arranging work-layout	Reduce non-value-added moving Avoid reaching and awkward gestures
High variation of hard-to-perform ratio, cycle time difference, and cycle time variation	The workstation is not optimized. The work procedure is complicated.	Line balancing	Reduce the complexity of work procedure. Risk-based line balancing
Unbalanced value of left and right-hand utilization & Varied value of body asymmetry ratio	The workstations require different parts of the body and dynamic asymmetry.	Job rotation	Rotate workers to balance their body usage
High cycle time variation & Varied body asymmetry ratio or best movement is found	The un-skilled workers cause the cycle time variation. There is better movement in ergonomics or fatigue aspects.	Job training	Serve the rotation plan Increase individual skills Multiple the best movement

A high value in the cycle time variation of the same workstation by different workers indicates that the work procedure is hard to follow; thus different workers require different times to finish a work cycle. Low utilization of the hands can be due to rest or hesitation during work. A high difference between left and right-hand utilization can be an indicator of a poor work design. These problems (as in workstation w_4) should be addressed in the workstation scale using the Left and Right-Hand process chart. The process engineer should reduce the work complexity and aim at equal use of two hands.

The low utilization ratio within a workstation indicates that the worker paid more time for other movements (i.e., walking, searching, quality checking) than working, and the high hard-to-perform ratio means he suffers from the unreasonable arrangement of the work cell. Varied values of the hard-to-perform ratio by different workers indicate that the cell arrangement is not suited for most of the workforce. As these problems occurred in workstation w_5, a new arrangement should be made to remove unnecessary body movement based on the ergonomics of most of the workers. If the work procedure is not optimized, time variation is too high, and uncertain; then the line becomes harder to balance. The solution for this line is to stabilize the worker performance in its workstation (such as in workstation w_1, w_4, and w_5), then re-balance the line based on the new value or add risk-based factors into the calculation of the line performance.

The unbalanced usage of the body parts can cause localized muscle fatigue and occupational disease for a long time. The varied value of the body asymmetry ratio proved the heterogeneity of the work in the workstation. To avoid these negative consequences, workers should be rotated between workstations based on these values (i.e., w_1 and w_2), both short- and long-term. The cycle time is another essential factor to consider when assessing the fatigue impact of the body asymmetry. The high variation of cycle time performed by one worker can indicate that the worker lacks work proficiency. Along with preparing for the proposed work rotation plan, job training initiatives should aim at increasing the skills of individuals and sharing the best movement within the workforce. One best example is the movement described in Fig. 3.19.

3.3 Chapter summary

An approach of pattern mining the skeleton data from the Kinect sensor to assess human worker performance is proposed, which takes advantage of supervised learning and motif searching algorithms to discover the characteristics of work movement. Online matrix profile is integrated to handle streaming data and facilitate real-time usage. As the work movements are segmented, the work behavior can be diagnosed, and these data can be used to develop a HAR model for recognition and prediction. A case study is conducted on an electrical assembly line to validate the approach. With the data processing rooted in MODAPTs standards, the productivity aspect can be diagnosed by comparing the movements with the ideal sample. The work performance of each workstation and the whole manufacturing line can be assessed in several aspects, saving human expert efforts and generating data for further mining activities. The individual and systematic improvement plans are beneficial for the organization in both the short and long term.

Some recommendations are associated with the use of the Kinect sensor. Firstly, data distortion due to the limited capability of the Kinect sensor and the occlusion of the human body can be solved by installing multiple Kinect sensors [R200]. If any obstruction causes distortion, these distorted frames can be classified due to the intrinsic value of human movement limitations, such as distance and angle between joints. The proposed procedure can apply to MoCap sensors in general besides the Kinect sensor. As there are plenty of commercial sensors on the shelf that are suitable and capable of delivering the same result, industrial managers can choose the hardware that fits their needs.

4

Operator 4.0 stress-performance foundation for monitoring and simulation

Thesis 3: **Based on the proposed system dynamic conceptual model from the evidence of validated relationships between Acute Work Content-Related Stress (AWCRS) and the work performance of human operators from the literature, I developed an extended formula for Overall Labor Effectiveness (OLE) calculation to predict complex human behavior under the effect of AWCRS.**
Thesis 4: **I generated an experiment to collect a data set to reflect the effect of work content factors on the workload, AWCRS perception, heart rate, and human performance in real-life working conditions.**

Publications relevant to the theses: [J3, J4].

4.1 Stress effect in industrial manufacturing environment

Work-related stress appears when workers face work demands that outweigh their abilities, from main sources are work content and work context [R75, R232], which consequently affected work performance [R233]. Repeated exposure to stressful work content generates both acute and chronic stress, posing a detrimental effect on physical and mental health [R234]. Acute stress with a short duration (i.e., seconds to minutes), which can pose either positive or negative effects [R76]. To avoid any long-term accumulation of occupational stress, any unfavorable work content should be adjusted timely with the early signs of Acute Work-Content-Related Stress (AWCRS) [J4].

A low level of AWCRS is associated with sustained attention [R82], improved decision-making with stimulated cognitive functioning, augmented cognitive capacity [R235], produce the optimal performance [R77]. A higher value or prolonged duration under acute stress causes more anxiety [R236] and risk preference [R237], and a long exposure leads to chronic stress with long-term psychological disorders [R238], accumulated allostatic load with declined cognitive and physical functioning [R239].

To provide timely intervention or work content adjustment, many studies claim to successfully capture the personal perceived workload with real-time monitoring procedures and platform [R240], however, none of them achieve the true instantaneous value. The effects of acute and chronic effects were not separated [J4]. This requires a multi-disciplinary approach with activity recognition from sensors and subjective and objective assessments. I collected evidence to examine if Heart Rate Variability (HRV) can be a valid and reliable indicator of AWCRS in real-time during industrial work.

A systematic literature review was conducted in four databases: Scopus, IEEEXplore, PubMed, and Web of Science. The publication type was limited to English-written publications in journals, with the period between January 2000 and June 2022. Four groups of keywords have been identified:

- The first group of keywords involves terms: "industr*", "product*" and "manufactur*".
- The second group contains only the term "stress*", representing a general approach including both acute and chronic stress.
- The third group contains the terms "Heart rate variability" and "HRV".
- The fourth group indicates the objects of HRV measurement: "worker", "operator", and "employee".

The PRISMA-based flowchart of the selection process is illustrated in Fig. 4.1.

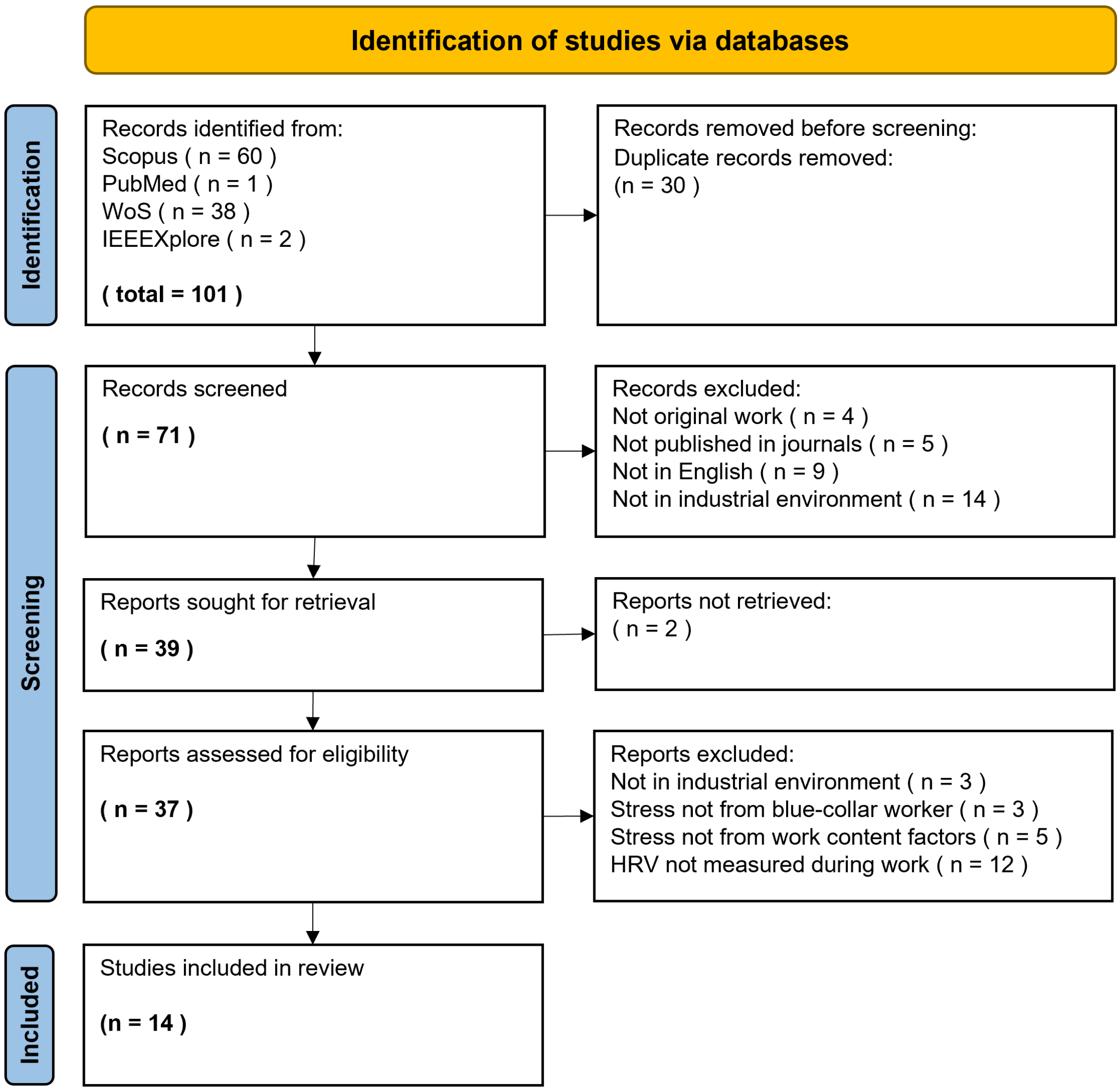


Figure 4.1: The PRISMA-based flowchart diagram of the selection process.

4.2 Real-time Acute Work-Content- Related-Stress monitoring with HRV

HRV is a well-known stress indicator with intrinsic mathematical chaotic characteristics [R241]. Stress recognition by assessing HRV is proven by neurobiological evidence [R242]. With the attributes of non-invasive, safe, easy-to-use, and simple diagnostic tests, HRV measure can replace traditional cardiovascular diagnostic tools [R243] to assess job-related cardiovascular stressors [R244], and exhibit different induced effects by acute and chronic stress [R245]. Real-time stress monitoring is the core concept for Just-in-the-Moment Adaptive Interventions (JITAI) [R246], with the deployment of individual tracking devices to create a monitoring system [R247], detect the stress and tiredness level of workers and deliver safety cyber-intervention [R240]. However, as the technology is ready, the concern becomes whether HRV can be an indicator of AWCRS in an industrial environment.

4.2.1 The study of stress caused by work content

Work environment and additional stressors

Observational studies were conducted in real manufacturing environments; thus involved additional stressors besides the work content, such as noise [R248], hazardous exposure [R249], temperature and humidity [R250]. Experimental studies were performed in a laboratory environment (except for the study of Hsu et al. [R251]); thus, tight control could be deployed upon other work environment factors, such as different ambient oxygen contents, different weights, and safety shoes [R252], or fixed posture during the experiment [R253].

Work-content type and induced stress

Observational studies considered a few work-content factors derived from the existing work environment and cannot be adjusted. Shift work was the most frequent factor, with a day or night shift [R249] or different shift patterns [R248]. The second frequent object was the general job demand and job control [R254, R250]. Physical workloads were the least frequent object [R254].

Experimental studies show a variety of work-content factors. The physical aspect was the most studied factor, such as physical efforts [R255], lifting movements [R252], and repetitive tasks [R253]. The cognitive requirement aspect was the second most frequently mentioned factor with the intrinsic demand of the work [R256] or different difficulties, [R253]. Tele-operation task with robots and machines was the next frequent topic [R257, R258], comparing the effectiveness of the proposed consoles.

The work-content types were physical workload [R250, R252], or mental workload [R255, R253] or both [R255]. It was ambiguous to compare the levels of work content in these studies, as they took the information from the perception of workers without a specific description of the jobs, and there was no common scale of the experimental designs.

Stress evaluation

Separated evaluations were conducted to validate the stress status, with the most popular tool being questionnaires. Karasek Job Content Questionnaire (JCQ) [R259] was used most frequently [R248, R254], and Effort-Reward Imbalance (ERI) [R260] was the second popular option [R254, R249]. Some studies employed more than one tool [R254, R249]. NASA Task Load Index (NASA-TLX) was used for working with equipment [R261], or with machines [R256], or assessing cognitive task performance [R262]. Other tools were Cohen

Perceived Stress scale [R249], visual scale [R255], Situation Awareness Rating Technique (SART) [R256], Borg CR-10 scale [R253].

Stress was also evaluated based on physiological parameters, such as by comparing electrocardiography (ECG) recordings from resting and working periods [R250, R255, R251, R258]. The same approach was used with heart rate, and respiration rate [R252], electromyography (EMG) [R256, R261]. Other physiological signals were employed scattered, such as O2 consumption and energy expenditure [R250], end-tidal CO2 [R256], respiration rate [R252], blood pressure and blood sample [R249, R263].

Another additional stressor, such as workplace noise and ambient oxygen content, was assessed with the Ising questionnaire [R248] and the ventilation response [R252], respectively. Self-designed parameters, e.g., the number of correct responses or answers [R255, R253], task efficiency and danger indices [R257], were used. Biological specimens (e.g., urine or saliva samples) were deployed to strengthen the assessment [R249, R263, R253].

HRV measurement instruments

Several studies employed professional electrocardiogram (ECG) machines [R248, R254, R249, R263, R250, R256, R261, R252, R253], while others employed sensors such as wristband ECG [R264], or wearable such as Polar S810 [R255], Polar RS800CX [R251], Samsung Gear S smart-watch [R258] for the mobility demand of the experiments. There were no data accuracy complaints.

HRV baseline measurement condition

Usually the baseline is measured in the non-working state, such as during sitting still [R250, R255, R264, R251, R253], or during sleeping [R248, R254, R249, R263]. Other baseline conditions were training sessions [R252] and short breaks during experiment [R258, R256]. The baseline duration varied from ten minutes [R256] to two hours [R252]. Noticeably, there was no baseline condition representing the normal working status.

HRV measurement condition

With the studies adopted throughout-the-day measurement approach [R248, R254, R249, R263], the HRV measurement lasted for the whole working day, or working shift. The rest studies measured HRV in a shorter duration, varying from five minutes [R252, R258] up to the whole working period [R250, R255, R256, R261, R253].

4.2.2 Association of HRV with AWCRS

The HRV in the included studies were categorized into time- and frequency-domain:

- Time-domain: HR (mean heart rate, beats/minute), RR (RR interval, seconds), CVRR (coefficient of variance of RR intervals), SDNN (standard deviation of RR intervals, milliseconds), SDNNi (square root of the mean squared difference of successive RR intervals, milliseconds), SDRR (standard deviation of the IBIs for all sinus beats), RMSSD (root mean square of successive differences), NN50 (the number of pairs of successive RR intervals that differ by more than 50 ms), pNN50 (the proportion of NN50 divided by the total number of RR intervals)

- Frequency-domain: LF (low-frequency, milliseconds), nLF (normalized low frequency), %LF (percentage of LF power represents the relative power in proportion to the total power), HF (high-frequency, milliseconds), nHF (normalized high frequency), %HF (percentage of HF power represent the relative power in proportion to the total power), LF/HF (LF/HF ratio), VLF (very-low-frequency band).

With workers facing high-demand tasks and high strain [R250], higher carrying load [R250], or a higher task frequency [R252], a higher elevation of holding handheld scanner [R261], the HR was elevated, and shift workers had a higher mean HR than day workers [R248]. However, with a light scanner [R261], the effect of different elevations became insignificant. HR decreased during consecutive sessions of physical tasks [R253]. The difficulty level of the cognitive task did not significantly affect HR value [R253].

The RR interval decreased when workers in stress condition [R258], with a heavier workload of working with light scanners in high elevation [R261], or higher lifting frequency [R252]. However, this result differed between the two study replications. CVRR increased with the new control method in *Ref.* [R257]. SDNN was higher with high carrying weight [R250], laser scanner device [R261], higher task frequency or requirement of more muscles to perform [R255]. SDNN also decreased with increased force exertion level [R255] and was associated with age increase [R250]. SDRR showed different behavior with the type of safety shoes and within replications [R252]. SDNNi was elevated with rotating night shifts [R248]. RMSSD reduced in workers experienced faster changing night shift [R263], and higher ERI ratio [R263]. This association depended on other factors such as age [R254]. RMSSD did not show a similar trend within two replication in the study of *Ref.* [R252]. During the consecutive sessions of physical tasks, RMSSD was increased [R253]. NN50 showed a discrepancy between two replications in the study of Ghableb et al. [R252], and the proportion of NN50 divided by the total number of RR intervals, pNN50, were differentiated by the types of safety shoes with a specific lifting frequency.

LF decreased when the operators experienced stress during work without biofeedback training [R264] or working with a 3D scanner at a high elevation level [R261]. However, in the same study, LF was also decreased in operators working with a light 3D scanner. Increased working surface height decreased the nLF [R251]. On the contrary, %LF increased under high JCQ demand and rotating night shift [R254]. HF decreased with a high level of attention demand [R256] and a higher elevation level of handheld devices [R261]. HF was more responsive to physical movements, as suggested in the same study. However, the reverse effect was observed with different laser scanners. HF increased during physical tasks but showed no association with cognitive difficulty levels [R253]. nHF elevated with increased working surface height [R251]. The LF/HF ratio was significantly lower within workers working on higher surfaces [R251] or with a higher elevation of handheld device [R261], or higher lifting frequency [R252]. VLF was decreased value corresponding to higher lifting frequency [R252]. Lower oxygen content resulted in decreased VLF value, but only with the frequency of one lift per minute.

4.2.3 The usage of HRV to assess AWCRS

No Randomized Controlled Trial (RCT) was conducted to assess the association between HRV and AWCRS, and none reported a high level of valid evidence of HRV as an indicator of AWCRS. The study design in the included studies was not robust against bias, as some studies only adopted a partly randomization procedure [R261, R253].

In some circumstances, there were associations between HRV and AWCRS. With workplace noise and job strain, AWCRS from physical activity can be reflected by HRV [R248]. HRV contributed to the proposed ALI to measure the stress-related wear and tear of the body [R263]. AWCRS from the physical workload and walking speed in the sugar industry [R250], or in lifting work [R252], tele-operation between humans and machines [R257], during equipment control [R258], working at height [R251], sustained monitoring work [R256], work with a 3D scanner [R261] were also be reflected by HRV. These studies recommended HRV as a task performance measure and a feedback source to design the work.

On the other hand, the rest studies stated different suggestions. There was no association of HRV with AWCRS, or the effect on HRV was caused by multiple stressors and could be separated to make any clear statement. The association was unclear and only appeared in $35-44$ years old workers [R254]. The mental workload corresponded closely to task differences as indicated by HRV, only when the physical workload was negligible or consistent [R255]. On the other hand, the cognitive task difficulties did not yield a significant effect [R253]. The effect of biofeedback training on the cognitive performance of the operator could be a long-term effect than an immediate one [R264]. No suggestion on HRV usage was given in *Ref.* [R249, R253]. More studies are needed to have a deeper understanding before using HRV as a stress indicator.

Though in most studies, stressful situations were associated with reduced HRV, none of them were adequately designed to provide a sound scientific conclusion, nor did they successfully confirm the relationship between AWCRS and HRV. As HRV strongly depends on too many factors (e.g., work context, individual physical and mental status), its real-time usage for stress monitoring can be problematic. Based on the available evidence, a firm conclusion cannot be drawn as to whether HRV is a candidate indicator of AWCRS in an industrial manufacturing environment that deserves further investigation and validation work. Researchers can either develop a well-isolated simulation with pre-defined settings to discover the association and interpolate the result with relevant constraints during real-time monitoring, or utilize HRV along with other additional metrics within a strictly controlled environment. Future research should study the effect of work-content factors separately before combining them.

4.3 Conceptual model for simulation of Acute Work-Content Related Stress and performance of human worker

Within industrial manufacturing systems, workers can perceive psychological stress (hereinafter referred to as "stress") from three main sources [R265]: the physical environment [R266], the work setting (i.e., work context), and the work content which is the demand of assigned tasks [R75, R232]. As the first two sources have stable effects, the work content is the dominant source directly related to physical symptoms [R267]. When workers face physically or psychologically demanding tasks that exceed their abilities or resources, the perceived workload becomes a stressor [R74], causing physiological stress as mental or physical tension [R75, R268]. Too much work content causes high perceived workload, stress, and fatigue that negatively impacts productivity performance and health outcome [R269, R270]. Thanks to the development of wearable, stress status can be monitored and detected in real-time with physiological parameters [R271, R272]. An ideal application is a platform for real-time monitoring of workload and stress [R273], thus interfering with the work content adjustment, or Just-in-the-moment Adaptive Interventions (JITAI) when the perceived workload reaches an unfavorable level [R274, R246]. Besides the current approach of stress recognition using big data analysis from simulated experiment [R275, R273], a computational model reflecting the workload perception and the natural work-content-induced stress process can serve as a base simulation and prediction tools for enhanced stress recognition accuracy, paving the wave for work-content design and adjustment as interventions, thus optimizing the performance.

Simulation models for a similar purpose have not incorporated altogether these aspects in the model structure and simulation mechanism. Dear et. al. [R276] modeled productivity loss, but only heat stress was considered, without discrete value calculation. The agent-based simulation model in Ref. [R277] employed a stress level calculation and predicted productivity with task objects coming in time steps, but the tasks were only relevant to an IT office, with a lack of physical demand. Similar incompatibility can be found with the discrete-event stress-performance simulation of financial document processing tasks [R278]. The human performance in the automotive line in Ref. [R279] is calculated with time step, but the work content definition is simplified, without a personal profile. There are dynamic models and platforms [R280, R240] aimed at simultaneous stress and attention monitoring for individual [R281, R282, R247], to predict potential stress, tiredness, comfort level [R283, R240, R284]; however, due to a lack of elaborated stress mechanisms and interdisciplinary approach [R285], they are not able to simulate the stress effect from combination of work-content factors, which is critical for the design and assessment of industrial work content and stress-relieving interventions.

Consequently, a model constructed with these considerations significantly contributes to the development of work content planning as a simulation tool, and provides a base of expected behavior for real-time stress-performance monitoring. A qualitative system dynamics conceptual model is proposed, regarding the stress and performance of an individual worker under the effect of the work content in a certain work environment and setting. The system dynamics approach is chosen as the modeling technique since it can reflect and assess multiple non-linear behaviors and multi-loop structures over time [R286] within a complex system of a human being (e.g., with physical, mental, and psychological behaviors modeled as internal sub-systems) while considering its interactions with the work environment and work requirement as external sub-systems. During model development, stress behaviors and the effect of relevant work-content factors, and personal profiles with basic workload preferences were considered, which enable task design and stress profile customization. In return, the model distinguishes static and dynamic effects that reflect subtle stress-performance associations under different work scenarios. Based on the work content configuration and stress mechanism, stress-relieving interventions were suggested along with demonstrated usage in the use case.

4.3.1 Problem formulation and Preliminaries

This section describes the building pillars of the model with relevant preliminary theories, stress behaviors, and effects collected from the literature. The "workload" from industrial tasks is the "primary stressor", along with the "personal perception profile" of the worker, and the "circumstantial factors" from the environment as the "secondary stressor". The stress mechanism is elaborated, with relevant integrated stress states, interventions, and associations with personal performance.

Primary stressor: Task load - Workload

As work content is considered the main source, the primary stressor in this model includes the task requirement that the worker needs to perform in a predefined work position. This subsection defines the elementary "task load" components (physical and mental) with the scope for each type, distinguishes between the "task load" and perceived "workload", and defines the "workload component interaction".

Physical and mental task load

Although stress is a mental state, physical "task load" (regarding energy, muscle, physical strain) has an interactive effect on mental "task load" (regarding cognitive activities) [R287] and also contributes significantly to stress formation. The proposed model considers both these types as primary dynamic stressors:

- The physical "task load" with three components: posture, force, and time as inspired by Berlin et al. [R288], and can be measured by separate measures such as REEDCO Posture Score Sheet [R289] for posture, force in Newton and time in second, or collective measure such as Cardiovascular Load (CVL) [R290].

- The mental "task load" with four components according to the VACP model [R291]: visual, auditory, cognitive, and psychomotor. This load can be measured by subjective methods such as self-reported questionnaires, i.e. Borg Workload Scale and National Aeronautics and Space Administration Task Load Index (NASA-TLX) [R292].

Scopes of physical and mental "task load" are given in Table 4.1, and their relationship with "personal perception" is illustrated in Fig. 4.2. Each "task load" has three physical and four mental components. "Workload" components can pose additional "interacted load", thus the "workload" is the combination of "perceived workload" and "interacted load".

Table 4.1: The two types of workload included in the proposed model.

	Measured in relevant studies	**Component**	**Scope**	**Direction of effect**
Physical workload	HR [R293, R294, R295], energy expenditure [R295], RPE [R296, R295], calorie consumption [R297], oxygen uptake [R294], blood pressure, gas exchange [R296]	Posture	Task-required posture	Non-ergonomic, demanding postures, leg imbalance, with out-range movements cause pain [R298] and tiredness [R288].
		Force	The required force	High force level leads to muscle fatigue [R299] and degrades physical force capacity quickly [R300].
		Time	The cycle time for a task, and work pace between tasks	Short cycle time induces stress [R301], long cycle time requires sustained force. Fast work pace [R302] with repetitive motions [R303] causes musculoskeletal disorders and harmful effects [R300, R304]. Cycle time with a flexible work/rest ratio allows control and stress relaxation [R305].
Mental workload	NASA-TLX [R293, R297], MRQ, JCQ [R259], VACP varieties [R306], ECG, EMG, EEG, eye movement, HR, HRV, respiration, etc. [R307]	Visual	Required visual efforts	Demanding visual task or bad visual ergonomics [R308] degrades the task performance.
		Auditory	Required auditory efforts	Listening effort can lead to fatigue [R309], thus decreases hearing abilities and performance [R310]
		Cognitive	Required cognitive efforts	High cognitive demand results in greater muscle activity [R311], decreased motivation [R312], finish time and performance [R313].
		Psychomotor	Required psychomotor efforts	Intensive psychomotor requirements place an additional burden and mental engagement [R314].

HR: Heart rate. HRV: Heart rate variability. RPE: Rating of Perceived Exertion. JCQ: Job Content Questionnaire, MRQ: Multiple Resource Questionnaire. VACP: Visual, Auditory, Cognitive, Psychomotor. ECG: Electroencephalography, EMG: Electromyogram, EEG: Electroencephalogram

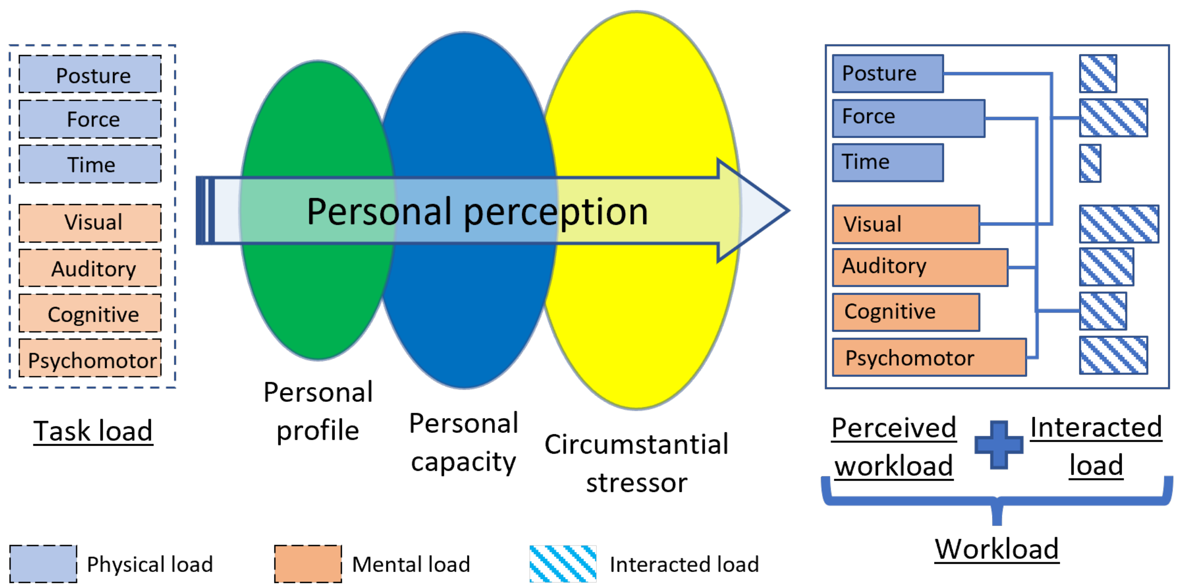


Figure 4.2: The relationship between "task load", "workload", and "personal perception". Source: Own work.

Task load and workload

While "task load" is the task requirement designed by production engineers, the "workload" is the perceived load that is subjective and dependent on individuals [R315]. To comply with this approach, each task should be designed with a known level of the above-mentioned load components. One approach to model and diagnose the effect of "task load" on human workers is quantifying the "workload" using multiple resources (visual, auditory, cognitive, and psychomotor), with an additive value at the beginning and being subtracted at the end of the task duration [R316]. However, this technique is insufficient to reflect the fact that one person can feel an elevated workload when tired, or under unfavorable working conditions (i.e., noise, heat [R317], being close to a robot [R318]), or workers with more experience perceive a lower "workload" [R319] for the same task. Therefore, the "workload" in this model is introduced as a value that is dependent on each personal profile.

Interacted load

"Workload" components can interact with each other, based on their amplitude, occurring time, and duration [R287], thus creating an additional "interacted load". This can happen within a type of "workload" as suggested by the cube model for physical "workload" [R320], e.g., a combination of poor posture and fast repetitive task [R321], or due to the effect of one type on another, such as demanding physical "workload" leads to decreasing situational awareness [R262] and higher mental "workload" [R255], while physical capacity (regarding fatigability and recovery) is negatively affected by mental "workload" [R322]. This model defines "interacted load" as an additional amount of "workload", that occurs if "workload" components exceed a predefined value.

Personal perception: Personal profile - Personal capacity - Basic task load

This subsection describes how each worker perceives a "workload" from a "task load" differently, based on the "personal profile" and "personal capacity", with the "basic task load" defined as the work preference.

Personal profile

Every worker has a unique "personal profile" of professional and occupational backgrounds, setting up the initial conditions before a working day, and how he receives a stressful work demand. An adjustable set of factors is proposed, which are characterized by long effect periods (months, years) and are categorized into different groups:

- Static profile: Factors that require time to undergo a natural increment or degradation without external intervention, and can be considered static, e.g., work experience, age, physical impairment, and chronic stress effect.
- Dynamic profile: Factors that have long effect periods but are subjected to change under possible training and intervention during the working session, such as training experience, skill decay, and problem-solving ability.
- Stress-related profile: Factors that are explicitly related to the stress accumulation mechanism of a person, such as stress endurance, thresholds for task demand and capability, sustained attention value and duration, acute stress value and duration.

Table 4.2 describes the factors that were considered during the development of the personal profile in the proposed model.

Table 4.2: Different factors considered in a personal profile.

	Factor	Scope	Direction of effect
Static profile	Work experience	The duration of working in a position with similar requirements.	Performance gradually increases with work experience but decreases slightly after 20 years due to work boredom [R323].
	Age effect	The effect of aging on personal working capacities.	Posture, muscular power, and psychomotor functions decline with age, especially after 50 [R324, R325]; with lower sustained attention limit, reduced training and learning efficiency [R325], reduced stress resilience and adaptation [R326].
	Physical impairment	The impaired health condition reduces work functioning [R327].	Workers with physical impairment have reduced work capability and productivity [R328], requiring improved resources and support to avoid stress and frustration [R329].
	Shift work	The accumulating hours working in night shift or rotating shift.	Working at night with abnormal working hours [R330, R331] plus the risk of sleepiness decreases the psychomotor [R332], cognitive [R333] and posture capacity [R334].
	Sleep quality	The sleep-wake cycle of undisturbed sleep pattern.	Frequently disrupted and restricted sleep causes disorders that reduce stress endurance [R335], thus leading to mental fatigue and burnout [R336].
	Chronic stress effect	The accumulated long-term stress from daily life events.	Chronic stress reduces cognitive ability [R337], increases vulnerability to mental illness, and decreases the stress recovery ability [R338].
	Job motivation	The incentive level to carry out the assigned task in the work position.	Well-motivated workers have better stress endurance to avoid emotional exhaustion [R339], and are willing to spend more effort and persistence on their task [R340].
Dynamic profile	Training experience	The duration of being trained in the current assigned position.	A sufficient amount of training helps to increase psychomotor fatigue threshold [R341] and prevent significant psychomotor performance degradation [R342].
	Learning ability	The reduced task time variation and defect rate in repetitive tasks.	The actual cycle time will be reduced after a certain number of finished products [R343] due to familiarity with the operation and tools [R344].
	Skill decay	The task time variation, reflecting the skill proficiency in the current position.	The position-related skills naturally undergo a gradual exponential decay. Regular reviews and refresher training help to maintain the values [R345].
	Problem-solving ability	The skills and confidence to solve production problems.	High problem-solving ability increases job control [R301], thus reducing the perceived workload from occurred problems and positively impacting the performance [R346].
Stress-related profile	Stress endurance	The personal resilience against sustained attention and stressful situations.	Mental toughness as a personality helps the worker in stress coping [R347], and becomes stress resilient with a low level of anxiety and enhanced physical endurance [R348].
	Task demand threshold	The personal limit of workload that is acceptable for the worker.	When the task demand requires higher effort than the worker can dedicate, the perception of workload becomes a negative process with decrements in performance or willingness to perform [R349].
	Capability threshold	The personal limit of capability degradation that the worker does not feel a burden.	Significant physical and mental capacities deterioration that exceeds the "natural degradation" can cause reduced professional efficacy, which refers to feelings of insufficiency, incompetence, under-productiveness [R350] and burnout [R351].
	Sustained attention threshold	The minimum and maximum value and duration of sustained attention.	Tasks that lack alertness with a low level of sustained attention cause drowsiness [R352], while a prolonged duration of vigilance stimulates acute stress [R77].
	Acute stress threshold	The maximum value and duration of acute stress before it transforms into chronic effect.	Exposure to a certain level of acute stress results in sustained remodeling of neuroarchitecture, which leaves a long-term disorder outcome last for 24 hours or more [R353].

Personal capacity

Work capacity was widely analyzed in clinical research [R354] as the work physical and mental capacity. Each individual with a certain level of physical fitness has a predefined Physical Work Capacity (PWC) [R355], representing the available energy [R356]. Mental capacity can be determined similarly [R357]. While physical work capacity is affected by personal experience, training, motivation, and environmental factors [R358], mental capacity is influenced by innate characteristics [R359], historical medical record [R360], and both capacity types be affected by common factors such as age [R361].

Each worker has a "personal capacity" with six components corresponding to "task load", namely posture, force, visual, auditory, cognitive, and psychomotor, except for the "time" load. Inspired by the concept of workload margin [R362] and maximal mental capacity [R357], these capacities behave as resources with a "natural degradation" over time, while further reduction happens when the worker experiences the negative effect of stress (e.g., encountering a heavy task load or complex problem), which named "stress degradation". An ideal worker with normal physical and mental condition (i.e., no physical impairment) has 100 percent of each "work capacity" at the beginning. Each "personal profile" sets up a different "initial personal capacity" less than this optimal value, e.g., a worker with a minor injury in an arm starts the working session with 90% of posture capacity and 80% of force capacity, while having 100% of all mental capacities. The "Personal capacity" of a worker when he receives a task indicates the actual capacity at that time and makes him perceive the same "task load" differently [R363]. Except for time, six other "personal capacity" components follow the same behavior as illustrated in Fig. 4.3.

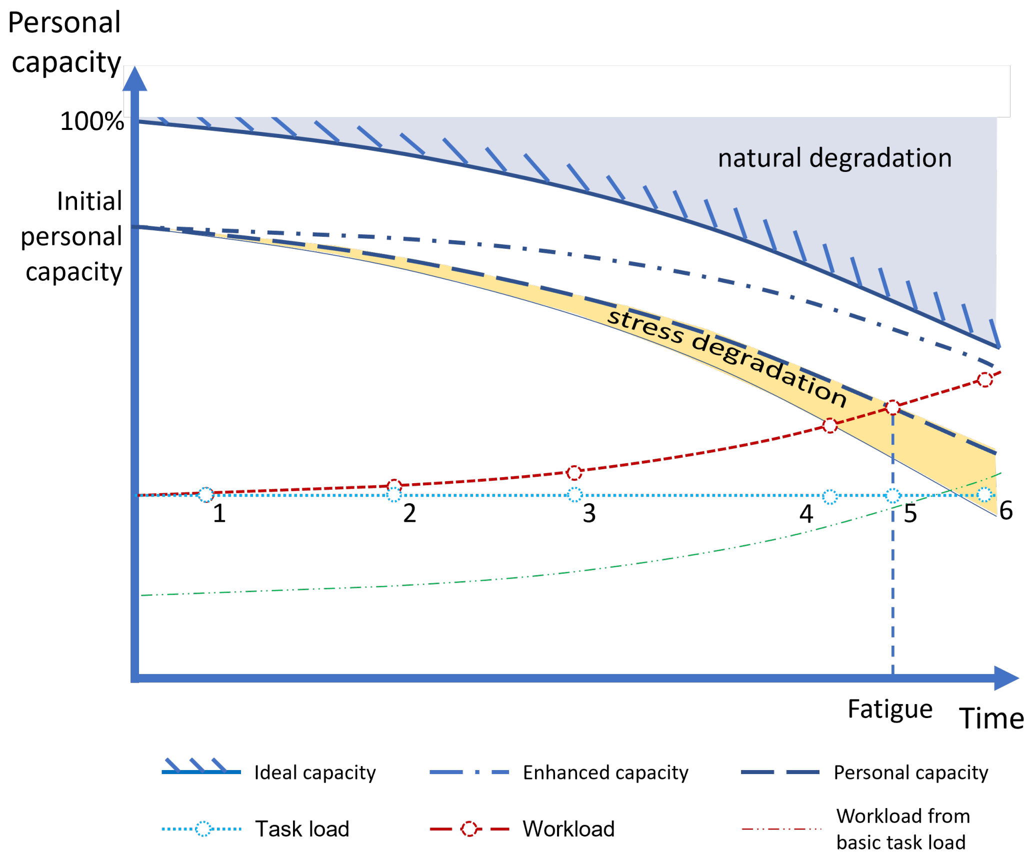


Figure 4.3: The relationship between "task load", "workload", "basic task load", and "personal capacity". Source: Own work.

When the work began on the first milestone, the worker hardly felt any deviation between "task load" and "workload". Under the "natural degradation" through time toward the sixth milestone, the difference becomes significant. Fatigue happens at the fifth milestone when he perceives a task as demanding and over the current "personal capacity", though the "task load" remains the same. The "basic task load" can generate a "workload" that does not exceed "personal capacity" at the end of the work shift. With the "capacity degradation" equals the total of "natural degradation" and "stress degradation", fatigue can come earlier (i.e., at the fourth milestone), and even the "basic task load" can pose an overload status at the end of the working session. In contrast, a "motivated capacity" can be achieved as an arousal state, under which the worker has a vigilant state and slower capacity decreases.

Instead of a "personal capacity" for the time factor, a worker will have a "time variation" which reflects the work proficiency, and this variation will be reduced by the learning effect [R364]. New workers during the skill decay period may have higher "time variation" than old and experienced ones [R345]. As the available "time" in a work shift is equal for every worker, therefore the "time" factor does not follow the "natural degradation". However, time already affects the accumulation and relaxation of all stress types, while the occurrence of "time pressure" increases the "perceived workload" [R365], defect/problem probability [R366], and "capacity degradation" of the worker. Though the worker perceived the time "task load" as an indirect factor, he still has a preference for a working pace, which can be considered as the "basic time load", as mentioned in the next subsection.

Basic task load

Considering each worker has a limited PWC, the physical "basic task load" is the safety margin to work on a specific task with no sign of fatigue throughout a work session [R367]. The "basic task load" can be identified with physiological indicators such as the Rating of Perceived Exertion (RPE) and relative Heart Rate (HR) [R296], for a predefined duration (i.e., 4-hours, 8-hours, etc.) based on the Maximum Acceptable Work Time (MAWT) [R294]. The mental "basic task load" can be defined similarly [R357].

Seven "basic task load" components corresponding to the seven "task load" components should be measured and set up individually from the beginning of the work, and validated after certain intervals. Any loads that exceed these values will pose a demanding situation. The "basic time load" has two components: "basic task time" (i.e., the duration required to finish a task) and "basic pace time" (the interval between two adjacent tasks). Any deviation from the basic values can create "time pressure" [R319], which imposes an additional demand and perceived strain on the worker [R368]. The relationship between the "basic time load" component and the time effect in the model is illustrated in Fig. 4.4. If the "time variation" of the worker varied within the "no perceived pressure" region around the "basic task time", there is no effect of time load on the perceived workload (e.g., task 1, 3, 5, and 6). Once the required time of incoming tasks exceeds the basic time load, a "time pressure" appears (task 4). If the task is too easy or the allowed time is longer than needed (e.g., task 7), no pressure is perceived and no stress is accumulated, but the stress "relaxation rate" is increased. The effect of the "basic pace time" is similar: for tasks 1, 2, and 3 that come at a normal pace, there will be no "time pressure". Between tasks 3 and 4, the worker has time to recover from stress status. However, if one task is missed due to a problem or rework (e.g., task 5), then the worker will face "time pressure" when the next task comes, similar to the situation of two tasks coming in a short period (tasks 7 and 8).

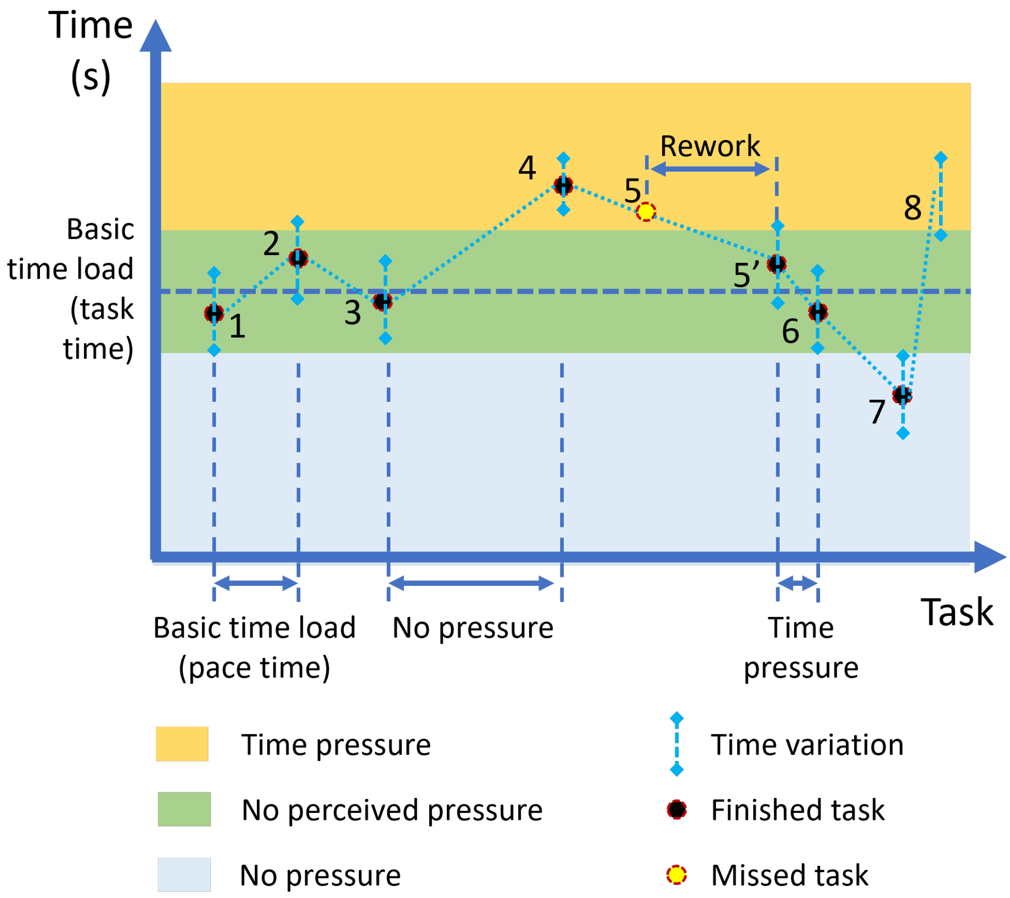


Figure 4.4: The relationship between basic time load and time pressure. Source: Own work.

Secondary stressor: Circumstantial stressor - Stress exposure

This subsection discussed the environmental and work setting factors as "circumstantial stressors", along with their effect under exposure.

Circumstantial stressors

Other factors that are related to the work environment and setup (e.g., buffer level [R301], the physical environment [R369]) also determine how the worker perceives the primary stressors from the "task load", thus posing an additional "workload". Therefore, these "circumstantial stressors" are considered secondary stressors, and can be categorized based on their temporal behavior:

- Static stressors: Factors depending on the surroundings, work setting, and initial setup, such as environmental disturbance and buffer level. These factors are set up at the shift beginning and remain unchanged throughout the working session, therefore can be considered static.

- Dynamic stressors: Factors heavily depend on the natural characteristics of the work and have varying values throughout the working session, such as working hours, failure rate, and work pace are also dynamic stressors.

Table 4.3 describes several "circumstantial stressors" and their effects.

Table 4.3: Different circumstantial stressors integrated into the proposed model.

	Factor	Scope	Direction of effect
Work setting: Static	Environment disturbance	The comfort from physical, functional and psychological aspects [R80].	Physical environment can either support the tasks, activities, learning efficiency [R370] and the cognitive function [R371] with comfort condition, or slows them down with uncomfortable condition and stress [R266].
	Work pace	The interval of incoming tasks.	Intensive pace than normal will be demanding and cause stressful perception [R301].
	Buffer capacity	The number of WIP in buffer inventory.	No buffer caused reduced output due to personal task time variation [R372], low inventory instills fear of causing idle time, thus the slow worker tends to work faster [R373], too high inventory cause waste and idle time. A suitable buffer allows pace control and compensates for task time variation, thus reducing stress [R305].
	Pattern change	The changes in the assigned incoming tasks or product sequences, or job rotation.	The change in work pattern reduces the monotony and ergonomic risk [R374, R375] and supports the recovery from demanding tasks and position [R376], reduces assembly errors and enhances product quality [R377].
	Ergonomic layout	The ergonomic design of the work cell and work layout.	Worker- and work-oriented ergonomics improves performance [R378], while ergonomic difficulty hinders work movements, thus induces stress [R301].
	Support readiness	Social support from co-workers or advisors.	Support from team and supervisors reducing stress [R301, R259], while absentee co-workers increase work pace and intensity, thus increasing physical demand and stress [R301].
Work characteristic: Dynamic	Weekly working hours	The accumulated working hours from the beginning of the week.	Longer weekly working hours than desired increases physical demand [R305], decreases all the capabilities, and increases stress during the extra hours [R301, R379].
	Failure rate	The occurring rate of failures or problems during work.	Failures/defects create blame feelings that persist for a long time after occurrence [R301], high occurring frequency poses additional pressure [R305].
	Body asymmetry	The asymmetric difference of body part utilization.	Asymmetric task design or work behavior reduces work capacity [R380], causing muscle fatigue [R381] and musculoskeletal pain [R382], thus negatively impacting the perceived workload and reducing the recovery rate [R381].
	Finished product	The accumulating number of finished products.	The cycle time is shortened due to the learning effect after a certain number of finished products [R343]. The visualization of finished individual output facilitates personal commitment, therefore reducing perceived stress [R305].
	Problem complexity	The difficulty of the occurring failure/defect/problem.	Complex problem with no previous training poses extra workload, causing idle time. Problems that lead to line stoppages induce stressful impressions [R305, R301].

Circumstantial stress exposure

When an individual with a "personal profile" is exposed to a "circumstantial stressor" (i.e., being assigned to a certain workstation (WS), with a certain physical setup), two types of effects can be distinguished:

- Static effect: The "initial personal capacity" of a worker is affected by the natural characteristics of the assigned WS and associated tasks, in both positive and negative directions. Unfavorable setups (i.e., poor lighting, unergonomic design, heat, noise) cause a capacity reduction or additional load [R383], or vice versa, additional buffer quantity gives more time for responding that increases the "basic work pace". These effects are pre-determined at the beginning, and consistent during the work session.

- Dynamic effect: Stressors such as occurring problems and machine failures randomly occur, pose an additional "workload" and contribute to a faster "capacity degradation" than the "natural degradation" (e.g., poor lighting reduces visual capacity).

Fig. 4.5 provides an example describing the effect on an individual worker (i.e., worker "A") from the static "circumstantial stressors" such as unergonomic design, Work-In-Process (WIP) buffer, and poor lighting, or with dynamic ones such as material defect and machine breakdown in different workstations (WSs) of a production line. In the first WS with an unergonomic cell design, his posture, force, and psychomotor capacities are reduced further than his "initial personal capacity", with 10%, 15%, and 5% respectively. Due to performing uncomfortable movements, his posture capacity degrades 15% faster than the "natural degradation". In the second WS, the input materials usually have low quality, worker "A" therefore feels additional visual and cognitive load to check carefully the incoming materials. Thanks to the high number of WIP buffers in this WS, he has an additional 10% of capacity to cope with the time requirement of the task. In the last WS, due to the poor lighting condition, worker "A" loses 10% from his basic task time as he needs more time to react and recognize problems, and loses 15% of his visual capacity, while his visual capacity degrades at the rate of 110% than the "natural degradation". Frequent machine breakdowns in this WS create time and cognitive loads to adjust the machines, which makes worker "A" feel more "workload".

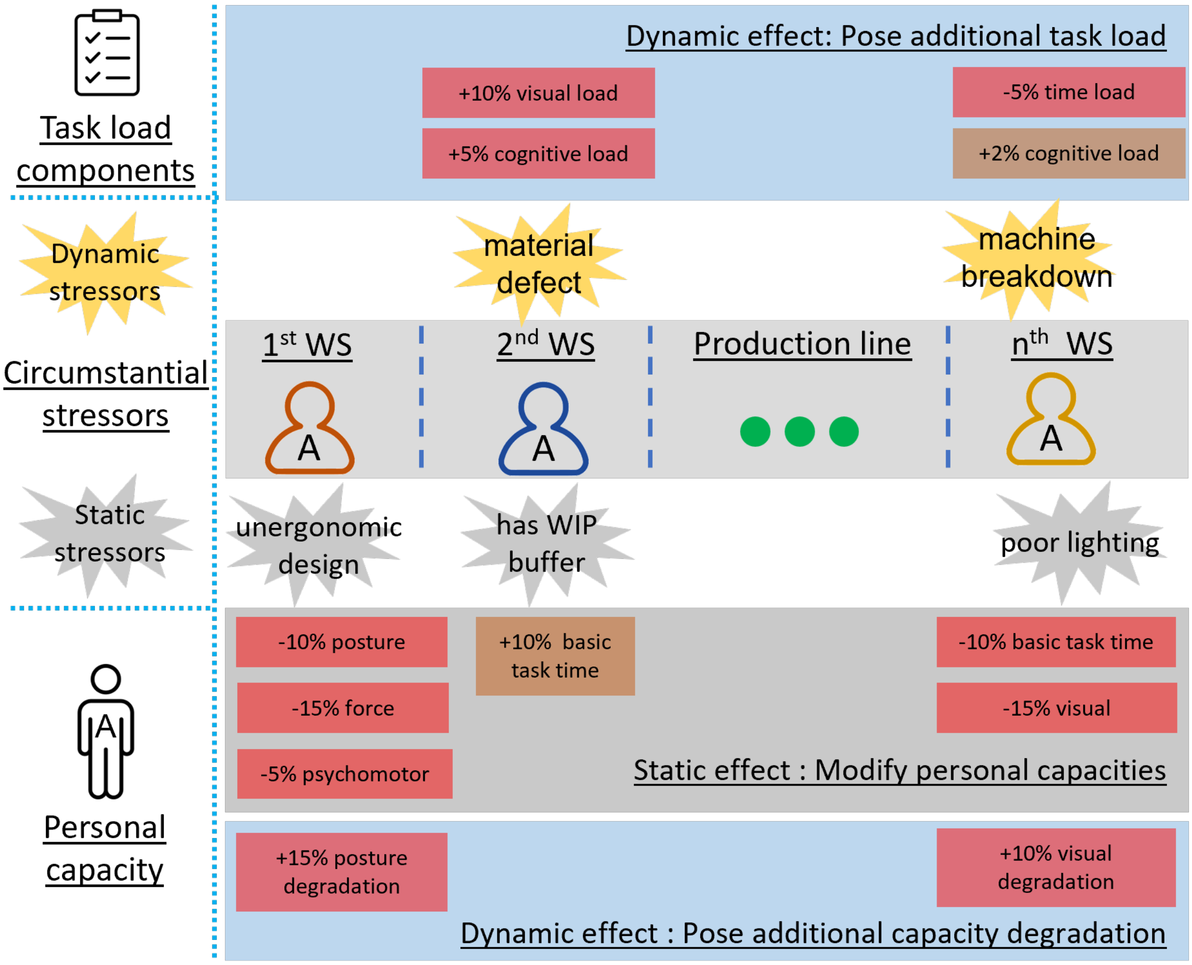


Figure 4.5: The static and dynamic effect when worker "A" is exposed to circumstantial stressors. Source: Own work.

Stress mechanism

This subsection describes the "workload reception" process when the worker encounters a task and the stress mechanism that happens afterward.

Workload reception

In the working process, under an ongoing task, there are two aspects a worker experiences a demanding situation:

- Perceived situational demand: The difference between the incoming "task load" and the "basic task load" is the "perceived situational demand". The more surplus value of task components, or more task components which exceed the "basic task load", the more challenging the incoming task is. The average value of "perceived situational demand" is calculated from these component differences, considering the current "personal capacity" at the time of receiving the task. If the average overload exceeds a certain personal threshold for "Demand", the worker can feel this difference and perceive the task as too demanding from a physical or mental aspect.
- Perceived capability: is achieved similarly by comparing the current "capacity degradation" with the "natural degradation". If the stressors cause the "capacity degradation" to be drastically reduced compared to the natural rate, it can create the feeling of lacking the required capability to perform the work. The average value of "perceived capability" is calculated from the component differences regarding the current "personal capacity", and if it exceeds a personal threshold for "Capability", the worker perceives himself as incapable of handling the incoming "task load".

The current "personal capacity" of the worker plays an intermediate role in calculating both above-mentioned average values. Lower capacity levels show a tiredness and exhaustion status, thus the worker feels the load more demanding and sees himself more vulnerable, even when facing the same level of "task load". Generally, when the "Demand" is greater, while the "Capability" is lower than the personal threshold, then the worker will consider his current task as a kind of threat and trigger his stress response mechanism. Fig. 4.6 illustrates an example "task load" reception process of an individual worker "A". Knowing his "basic task load", an incoming "task load" that has a posture score of 7 on the REEDCO scale and a visual score of 3.7 on the VACP scale is challenging, makes him hardly perceives the other easy task components (e.g., the required force is only $20N$, less than his preference of $50N$). Only the challenging task components are considered for calculating the "Demand" score, regarding the elasticity of his current "personal capacity". The same relative comparison is between his actual "capacity degradation" and his "natural degradation". The posture, time, visual, and psychomotor capacities that degrade faster than the normal rate affect his incompetent feelings, and be used to calculate the "Capability" score. As the "Demand" score is higher and the "Capability" is lower than his threshold, worker "A" perceived this "task load" demanding.

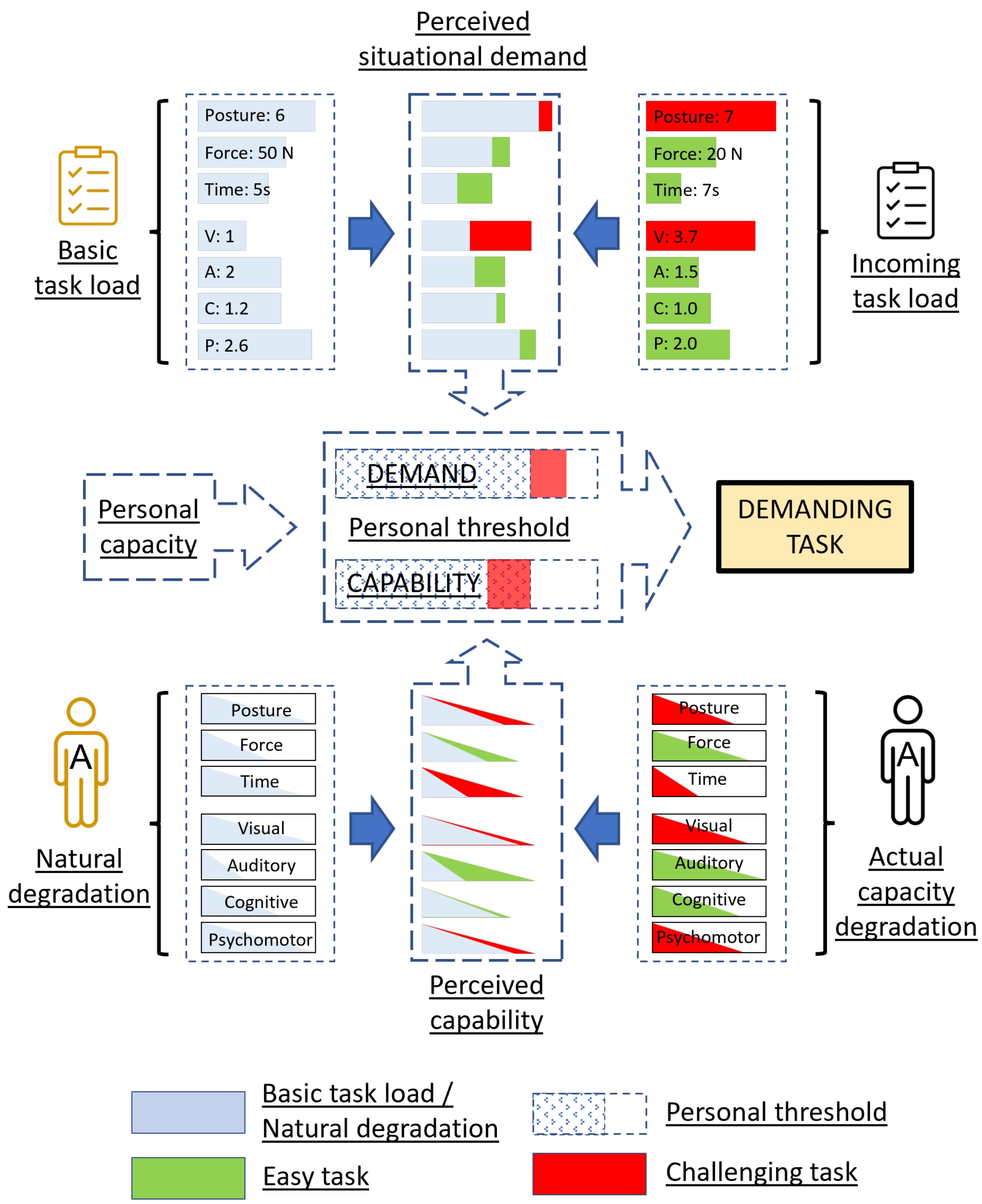


Figure 4.6: The task reception of perceived situational demand and perceived capability of worker "A". Source: Own work.

Stress accumulation, recovery, and transformation

The stress process undergoes the transition from the demanding task that the worker received, to his perceived attention, vigilance/"sustained attention" [R384], "acute stress", and "chronic stress". Each type of stress has an accumulation and a recovery period before transforming into another type.

Monotonous and easy tasks result in disengagement and drowsiness, yielding negative individual and cooperative outcomes [R385]. When perceiving a "demanding task", "sustained attention" is accumulated with an "accumulation rate", creating the positive vigilance attention [R352] that breaks out the risk of "boredom" and ignites the "arousal" of the worker with an elevated corticosteroid stress hormone (cortisol in humans) [R386] which enhances the working memory [R387]. Under this condition, the worker experiences high awareness with "enhanced capacity" (i.e., the "capacity degradation" rate is reduced than the "natural degradation"), thus improving his efficiency [R388]. "Sustained attention" has a "natural relaxation" rate that differs individually, which takes effect in the idle periods between going tasks and form lapses when mind wandering can happen and the worker disengages from the current task pressure [R389].

However, this positive effect will be reversed if the stressor exists for a long period [R390]. If accumulated "sustained attention" accumulates over an "attention endurance" or intensity level [R391], namely "value threshold" or "duration threshold", it becomes another source of stress [R77, R280], and "acute stress" is activated. In a normal healthy adult, these short-lived acute reactions decrease and disappear when the stressors cease [R392], thus this short-term stress also has a "relaxation rate" activated if the perceived attention returns to a normal level. Similar to "sustained attention", "acute stress" is relaxed only when it is not accumulated, but at a slower rate. This recovery process takes place during work time (internal recovery). Once "acute stress" is in effect, the positive effect of "sustained attention" fades, and the worker feels his capacities degrading faster than the "natural degradation".

"Chronic stress" accumulates with a similar mechanism: if the "acute stress" exceeds the personal threshold value and duration, "chronic stress" appears with long-term influences on the "personal profile" (i.e., reduced stress endurance), leaving the worker with less "initial personal capacity" before a new working day. The appearance of "chronic stress" comes along with "fatigue", while "burnout" is the extreme state with an over-arousal level.

When facing demanding tasks for a long time based on the task duration or repetition, the physiological stress of worker "A" will undergo the accumulation and transformation mechanism of different stress types as in Fig. 4.7.

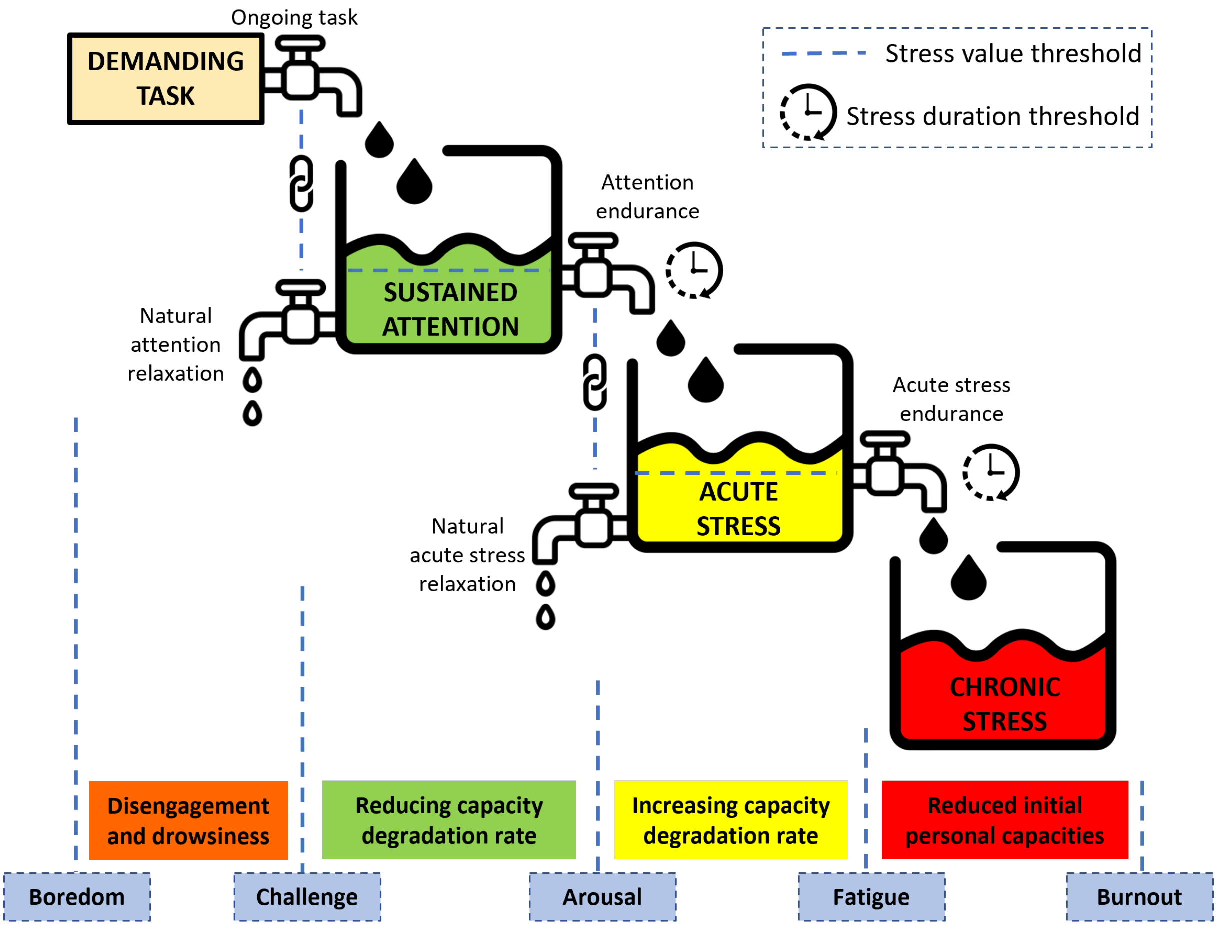


Figure 4.7: The accumulation and transformation mechanism of different types of stress. Source: Own work.

Each stress type has an accumulation and a recovery period before transforming into another type. When perceiving a "demanding task", "sustained attention" is accumulated with an "accumulation rate", breaks out the risk of "boredom" and ignites the "arousal" of the worker with "enhanced capacity" and improved efficiency. If accumulated "sustained attention" accumulates over "attention endurance", "acute stress" is activated with negative effects. These stresses have a "natural relaxation" rate that takes effect in the idle periods between going tasks. If the "acute stress" exceeds the personal threshold value and duration, then "chronic stress" appears, which brings long-term influences on the "personal profile", and takes a longer time to relax, therefore not included in this model.

Stress-induced states - Intervention - Performance

This subsection describes different stress-induced states that are incorporated into the proposed model, how personal performance can be predicted from predefined parameters, and different interventions can be considered. This model does not consider the detrimental effects and relaxation of "chronic stress".

Stress-induced states

Under the effect of work-content, the worker may experience different states with characterized symptoms and behaviors as follows:

- Under-load: an easy, not challenging, and repetitive "task load" causes boredom and asleep transition [R352, R385, R393], leads to human labor waste, occupational discomfort, and mental illness [R394]. "Under-load" is considered as detrimental and stressful as "overload" [R395], and prolonged exposure also leads to "fatigue" and injuries [R396]. Interestingly, this condition is neglected in many relevant research [R397]. In this model, this state is characterized by a repetitive pattern of "sustained attention" for a long duration without the appearance of demanding tasks.

- Optimal performance: A moderate "workload", under an acceptable "circumstantial stressor" helps the worker escape the "under-load" condition with an aroused vigilance and engaged with the current task [R77] thus yield the best performance [R269]. This state can be recognized with the regular accumulation and relaxation of "sustained attention", with a low and intermittent quantity of "acute stress".

- Overload: When the worker perceives an excessive "task load" exceeding his "personal capacity", stress is stimulated by both increased need for work capacity and current capacity decrease [R393], negatively affects job satisfaction, and performance [R398]. In this model, a continuous "acute stress" existence causes a faster "personal capacity" degradation.

- Fatigue: Working with any physical or mental "overload", or using a maximum capacity for a long duration leads to "fatigue" [R399], which results in decreasing muscle performance in different body parts [R400], cause the worker to fail to maintain a required force, or feel tired and lack of energy [R401], leads to reduced functional capacity and performance decrements [R402]. This state can be identified when one component of the "personal capacity" is depleted.

- Burn-out: Under adverse working conditions with the existence of "chronic stress", the worker is burdened with overwhelming exhaustion and impaired job functioning [R403], thus his productivity and coping skills are significantly reduced [R404]. This state is associated with the depletion of all "personal capacity" components, thus the worker can quit his position even in the middle of the working session.

Both "under-load" and "overload" states lead to lower performance [R387], and a medium workload condition can induce an optimal level of response and learning, which results in "optimal performance" [R77]. The next paragraph discusses how the "performance profile" can be analyzed based on the previously elaborated factors.

Performance profile

Inspired by the Lean philosophy, personal performance is assessed with three aspects of the Overall Labour Effectiveness (OLE) [R405]: "availability-", "productivity-", and "quality performance". In other studies, "productivity performance" is measured as the number of completed orders per time unit [R373], supervisor reports [R403] or effective working time [R297], while "quality performance" is measured by the number of correctly assembled parts [R406]. However, considering the stochastic nature of human behavior, this model only predicts these performances as the probability that one single worker can perform an appropriate output quantity and quality. At the beginning of the working session, the worker has a 100% probability for these three performances, according to his "initial personal capacity". These performances will vary according to the external influence factors during the work session. The "optimal performance" of a worker with maximum OLE can be reached when he can keep the predefined work pace, maintaining a good physical maneuver and focused attention. In the long term, his OLE still decays due to the natural depletion of his "personal capacity". The cooperation between workers is not considered as additional factors are required.

Personal performance is assessed with three aspects of the Overall Labour Effectiveness (OLE) as suggested in Fig. 4.8 in the framework of force field analysis. Availability performance is assessed by the capability of keeping a predefined work pace, which is supported by time and psychomotor capacities. If these capacities degrade faster than the "natural degradation" (due to stress), then the worker becomes less able to keep the standard pace. Availability performance is hindered by distraction possibilities such as work pace increment and problem occurrence rate. Productivity performance is affected by physical degradation (which is dependent on the force and posture capacities), and the physical degradation under stress (dependent on the degradation of force and posture capacities caused by stress). Quality performance is associated with quality-related attention (which is related to the degradation of cognitive and visual capacities, i.e., for tasks that require a visual check of input materials). As "sustained attention" can help the worker stay focused, the quality attention compensation also contributes to "quality performance".

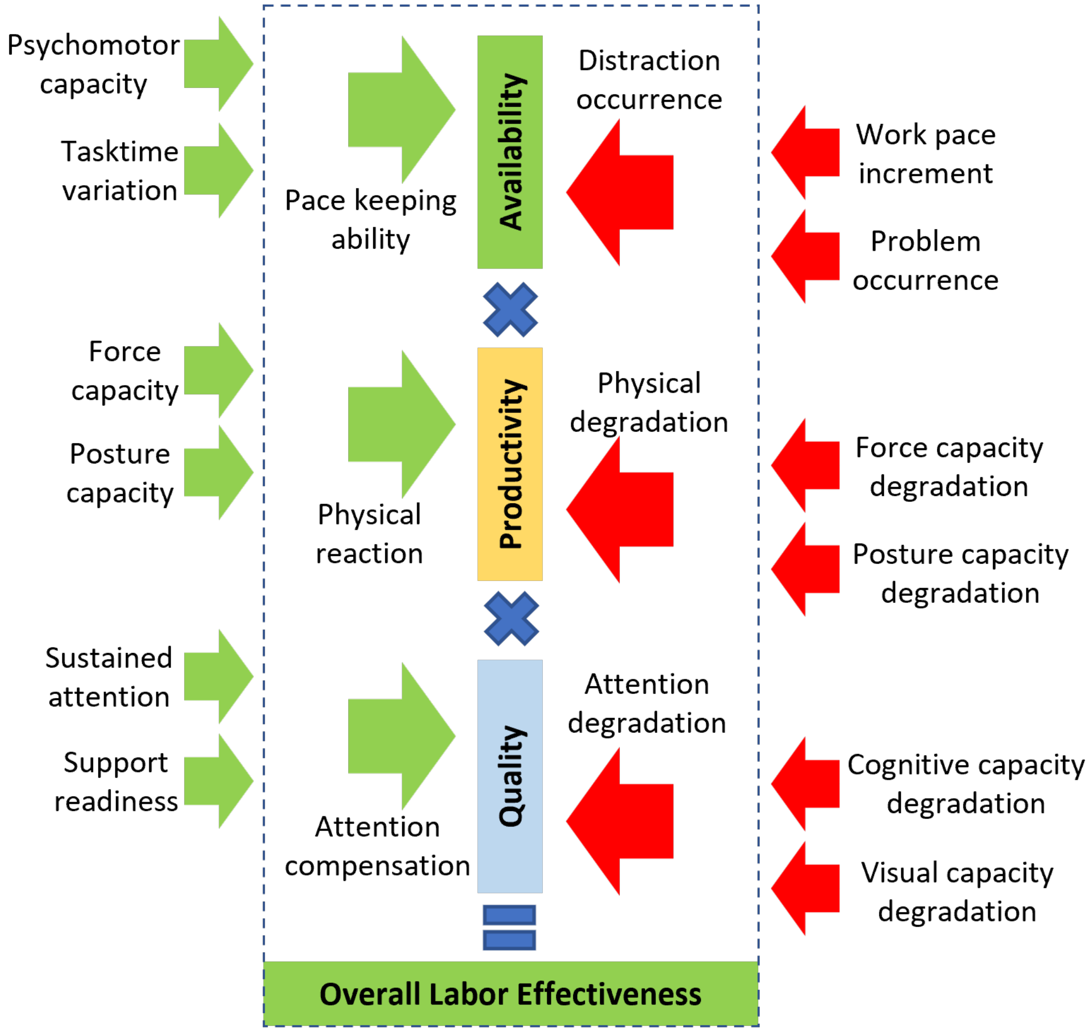


Figure 4.8: The Overall Labor Effectiveness with relevant factors. Source: Own work.

Stress-relieving intervention

The elaborated conceptual model is not only capable of reflecting personal performance under specific working conditions but can be used as a platform to deploy stress-relieving interventions, which are modifications or interfered activities that can be applied to change the stress process. Some interventions have a lagged effect or take time to shape such as giving rewards [R407] or job motivation [R408], increasing stress endurance [R409], whose effect is hard to measure and control, therefore, only interventions with shorter effect duration and aiming at "sustained attention" and "acute stress" are considered.

4.3.2 Human-centric stress-performance simulation

To validate the proposed concept, a qualitative system dynamics model was constructed in the Vensim simulation environment [R410]. This section describes the industrial background with a predefined "personal profile" representing a worker of interest, to test the modeling capability of reflecting the above-mentioned working process, stress mechanism, and stress-induced statuses under different scenarios.

Description of industrial assembly line environment

To narrow down the scope of the use case, some assumptions are made as follows:

- At the shift beginning, the worker has a "personal capacity", which is affected by his "Personal profile".
- At the end of the simulated duration, the remaining capacities in case of stress-free work can be estimated, therefore the "natural degradation" can be determined.
- The "circumstantial stressors" of the assigned workstation have a static effect on the worker, at a constant rate that is proportional to their uncomfortable level.
- When encountering incoming "task load" as stressors during working, the worker experiences a situational demand that is proportional to the perceived "workload".
- For simplicity, it is assumed that the components of the perceived "workload" are under their thresholds, thus there will be no "interacted load".
- The "accumulation rate" and "natural relaxation" of each stress type can be measured by the unit of "stress per second".
- Three types of stress have their effect in different confidence intervals of 15, 30, and 60 minutes for "Sustained attention", "Acute stress", and "Chronic stress", respectively.
- When the worker is under the effect of a stress type, his "stress degradation" is proportional to the current amount of that stress.
- At the shift beginning, the worker has a 100% probability of yielding the expected "availability-", "productivity-", and "quality performance", which can be estimated from his "basic task load". These performance constituents are naturally degrading but can be optimized, or prolonged until the end of the predefined shift length.

Fig. 4.9 described the components of the use case and their relationship. After defining the personal profile and work capacity of the worker of interest, the circumstantial stressors in his workstation with associated tasks are assessed. Based on these data, his stress-induced state and performance profile can be simulated.

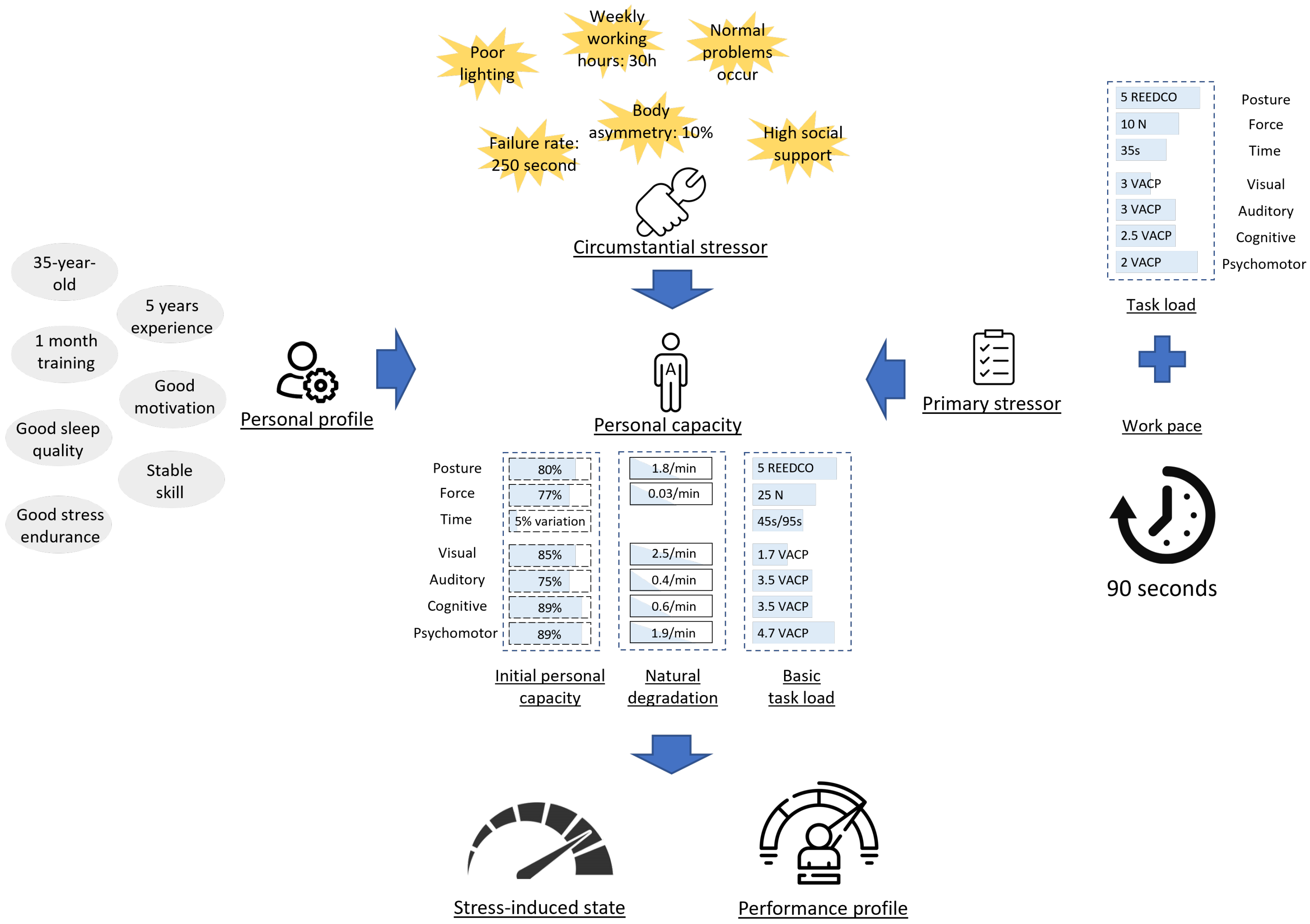


Figure 4.9: The components of the simulated use case.

Model structure and important variables

For better comprehension, the model structure in the Vensim environment was developed in separate views, with each view represented in separate figures in the Appendix B, where the details of the use case setup with the important variables are also described.

Work positions in an assembly line are characterized by different work-content requirements with a common feature of repetitiveness, which requires the design of the "task load" and a "work pace". For simplicity, this model demonstrates one assembly position, which requires a fair posture score (5 on the REEDCO scale), a force of 10N, an average task time of 30 seconds, 90-second work pace, a visual quality check with a sample product, low requirement of auditory on checking the working tools, a fairly simple autonomous task and discrete actuation during assembly (scored 3, 3, 2.5 and 2 on the VACP scale, respectively). According to the designed standardized work, this workstation has a lower lighting quality than the industrial standard, with 10% body asymmetry.

The "personal profile" is created with different work preferences and stress-related profiles and assumes that the worker is medium-aged with good experience, normal physical condition, good learning ability, in the stable phase of skill decaying period, with intermediate problem-solving skills, and an average ability to cope with stress. He has a "basic task load" slightly higher than the required "task load" (e.g., 25N to 10N, respectively), which means he can work through a working day with no negative consequences. Extreme conditions such as sleepiness and serious physical disabilities are more complicated and require in-depth modification, therefore excluded in this use case.

Simulated scenarios

A random function is used to generate the "task load" components, and the arrival time of new tasks is created randomly around a "basic work pace" of three minutes. The fixed duration of the simulation is 8 hours (480 minutes), with a 15-minute lunch break. Four scenarios were simulated:

- Working with a normal schedule: The "task load" components are generated randomly but close to the "basic task load". It is expected that the worker can maintain his performance during the work day with a fairly remaining "personal capacity".
- Working with high workload: This scenario introduces a "task load" that is higher than the "basic task load", or the worker has a physical impairment that leads to a shortage of working capacities.
- Working with additional breaks: The first intervention is to provide a ten-minute short break after every hour to prevent stress accumulation and facilitate relaxation.
- Working with a reduced work-pace: The second intervention is to reduce the "task load" at the end of the working day, by reducing the work pace, to prevent the above-mentioned mild stress.

Simulated results

Working with a normal schedule

Fig. 4.10 exhibits the simulated response from worker "A". His "Sustained attention" level was accumulated slightly, and "Acute stress" appeared several times due to demanding tasks and occurring problems. However, he has enough time between ongoing tasks and demanding situations to get relieved. His OLE was stable at the beginning, though slightly decreased due to his work capacity degradation. Due to the positive effect of "Sustained attention", his OLE reached an optimal level between the 60^{th} to 180^{th} minutes before lunch break. Noticeably, the "Acute stress" and "Sustained attention" were still relaxing throughout during the lunch break. After the lunch break, though the task loads were still the same, his performance kept decreasing which led to a negative effect of "Acute stress". After a working day, "A" perceived an increasing workload with a high number of demanding tasks, and a very infinitesimal level of "Chronic stress". He has utilized all of his work capacities without leaving a long-term stressful feeling about his job. However, if he continues to work overtime, even with the same amount of workload (not to mention the occurred failure/problem), then he will encounter the "Fatigue" status, when his performance decreases more significantly, with a remarkable sign of "Acute stress", or even "Chronic stress".

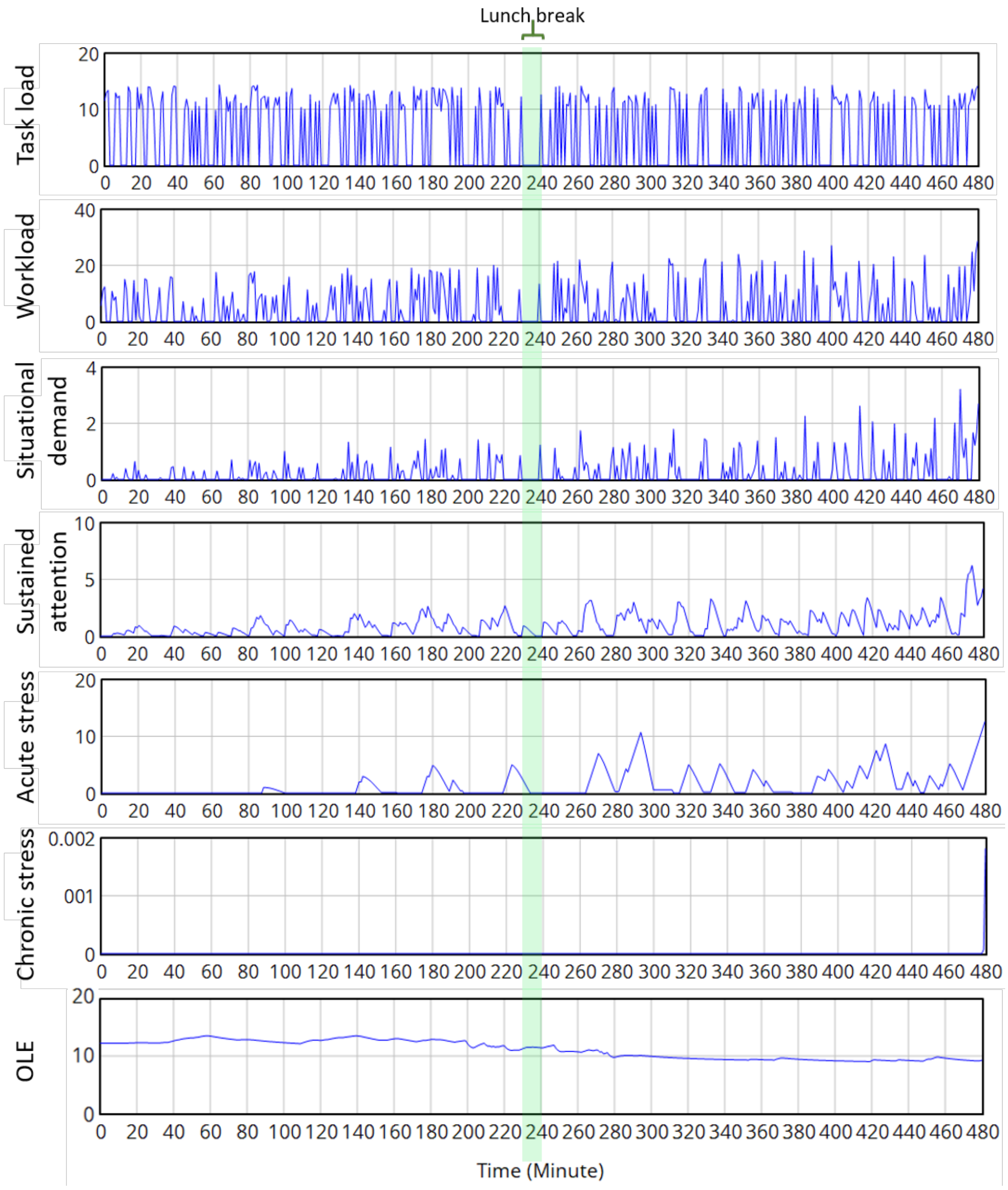


Figure 4.10: The simulated results of worker "A" in the 8 hour working day.

In the first scenario, the model successfully reflected the relationship between "task load", "workload", and "personal capacity", with different stress accumulation and relaxation behaviors. The worker started working at his full initial "personal capacity", with increasing attention and interest in the task. An "optimal performance" peak can be recognized in the bell-shaped OLE curve when the work capacity is still sufficient, and the "sustain attention" level is within the personal threshold without any extra stress. Due to the "natural degradation", the performance degrades slightly at the end, thus the worker experiences mild stress which does not accumulate into serious "chronic stress" and can be relieved with reasonable after-work activity and a good sleep to regenerate working capacity and vigor [R411]. However, if the working day lasts longer (i.e., overtime hours), the stress symptoms will exaggerate with significantly decreased performance [R412].

Working with high workload

The simulated results from the second scenario can be seen in Fig. 4.11.

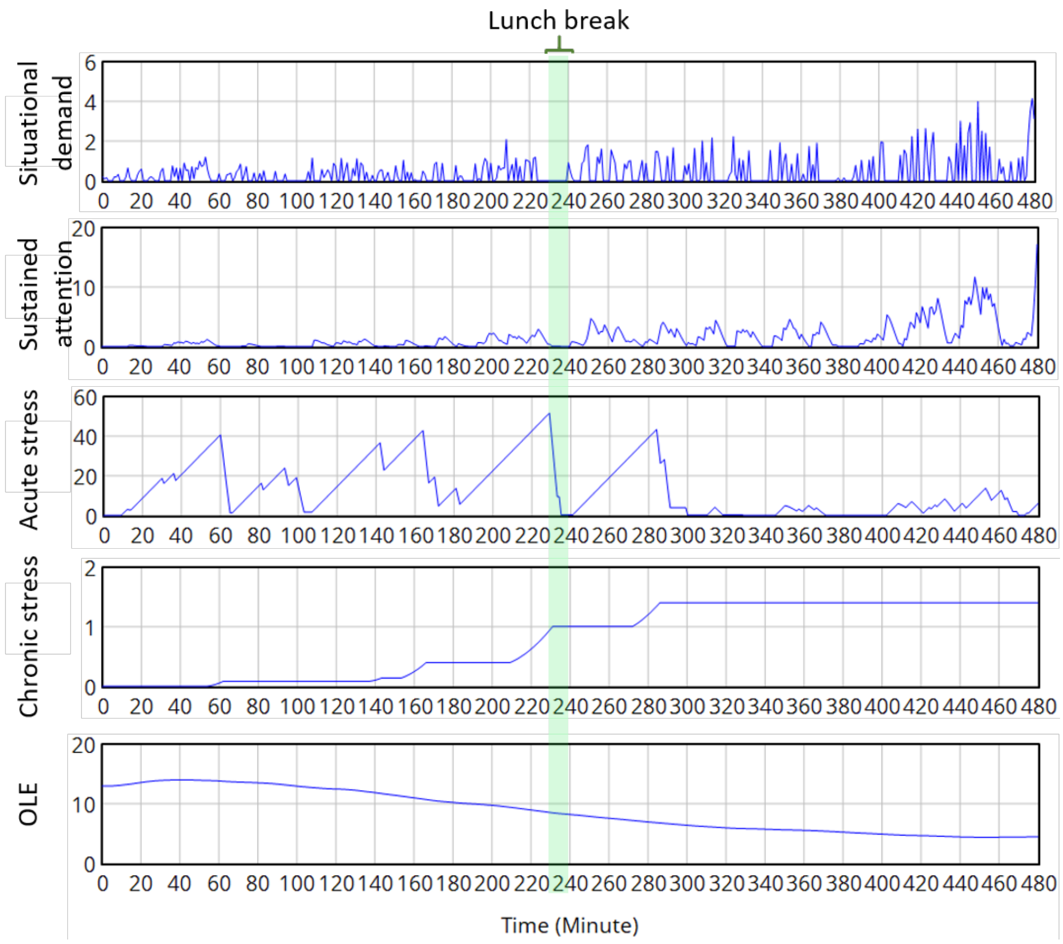


Figure 4.11: The simulated results of worker "A" under overload condition.

Our worker experienced demanding situations from the early time of the morning shift, while the "Sustained attention" can not be accumulated in the beginning, then built up quickly and reached a higher level than the personal threshold from the middle of the morning shift. "Acute stress" existed almost all of the morning shift and did not cease, thus suggesting the "Overload" and "Fatigue" status, with the sign of "Chronic stress". The situation stops escalating during the lunch break but gets worse during the afternoon shift. His OLE performance curve slightly increased in the morning when he encountered the first hour of hardship, but degraded much faster until the end of the day, which can be due to the extremely stressful perception when the worker feels the tasks are out of his capability and control. Our worker left work with a low value of remaining "personal capacity", an obvious sign of "Fatigue" at the end of the day. A significant value of "chronic stress", whose effects last for a longer period, will reduce his vigor for the next day and affect his working capacities, as he becomes more vulnerable to "burn-out". The more serious the negative impact of "fatigue", the harder the recovery from the on-job effort [R413]. It can be concluded that the work is too stressful for his capability and experience. In reality, this scenario happens when a high-level task load is assigned to an inexperienced worker, or a temporary physical impairment happens that reduces his personal initial working capacity, or an uncomfortable physical environment condition, a negative impact of "Overload" can happen immediately. Working for a long time in this condition ensures a "Burn-out" in occupational life, with a long-term reduction of "Personal capacity". This scenario emphasized the importance of a well-designed job with tailored work content for individuals.

Working with additional breaks and with a reduced work-pace

The third and fourth simulated scenarios reflecting the working schedule with work-content interventions are exhibited in Fig. 4.12. When additional breaks were added hourly (left), the number of tasks naturally reduced, which led to less demanding situations. This is because his "Sustained attention" did not have enough time to accumulate, and the worker did not have enough attention and preparation for the coming tasks. Thus, he perceived a higher value of demand requirement and is more vulnerable to demanding tasks, which results in a higher peak value of "Acute stress", which harms his cognitive performance and further degrades his work capacity. When a reduced work pace is applied after the lunch break (right), though the working capacities were already decreased in the afternoon shift, the "Sustained attention" was still building up while having enough time between coming tasks to relax, resulting in less "Acute stress", also no imposed "Chronic stress".

In the third scenario, though there is no chronic stress, the OLE of the worker of interest constantly decreases, due to the natural degradation of working capacities and lack of quality attention. This is a sign that he might work in the "Underload" status. In the fourth scenario, the OLE of this worker was increased even in the afternoon shift, which can be explained by a high vigilant attention level, with enough time for his muscles to rest and reflect upon coming tasks.

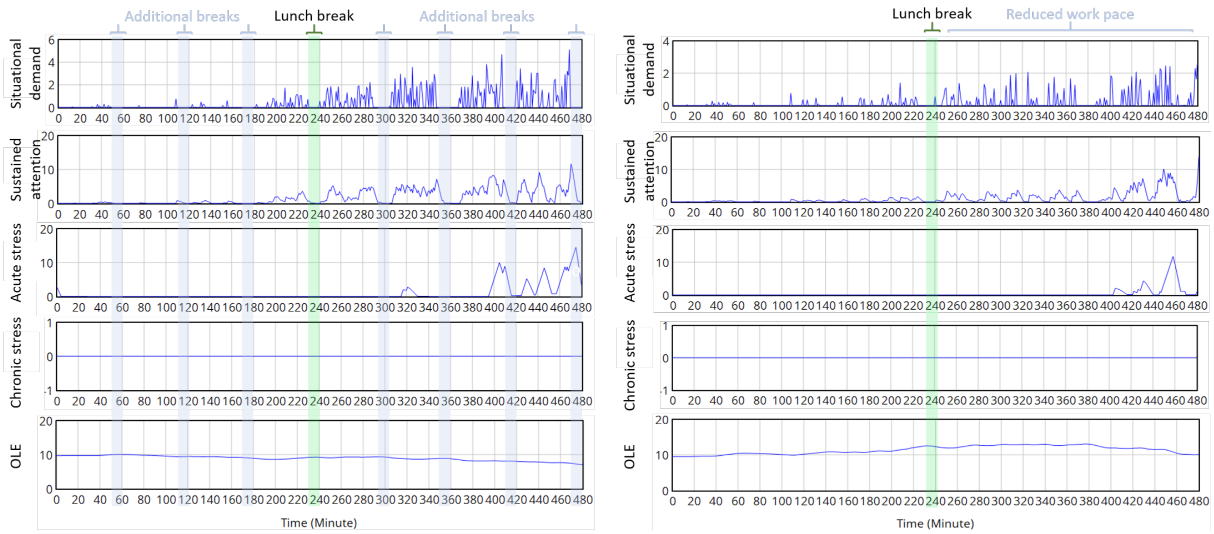


Figure 4.12: The simulated results with deployed interventions.

The third and fourth scenarios showed the capability of the proposed model with stress-relieving interventions, that were designed as a work-content modification. The first intervention with additional breaks did not improve the performance of the worker but rather set him in the "under-load" status with a reduced "sustained attention" level, thus he faced more demanding situations due to a lack of preparation and focus. Though this intervention created no "chronic stress", his performance was continuously degrading, which can harm his safety and long-term well-being [R414]. In the fourth scenario, the worker had time to rest between incoming tasks in the afternoon shift. Though the tasks were still demanding, the "sustained attention" had enough time to accumulate and exert its positive effect. Only a trivial sign of "acute stress" appeared, and no "chronic stress" was left at the end of the working day. The OLE of the worker even slightly increased in the afternoon shift, as he is well aware of his performance. Practically, this intervention can have a form of rotating into less demanding work positions.

4.4 Facilitate further study of Acute Work-Content Related Stress with WEBA dataset

The ideal HDT craves the digital representation of human beings with their unique characteristics directly coupled to system design and its performance [R415, R416]. However, to comprehensively elaborate a decent human digital representation in a certain work occupation, many gaps should be considered. Human factors are sensitive to work intrinsic and extrinsic factors, physically and mentally. To diagnose the individual perception of workload and further adjust the work characteristics according to personal preference, separating the work content and work context factors is necessary. Unfortunately, the work-content effect was poorly formulated in the past [J4]. Several studies focused on only environmental stress [R266] or physical [R227] or mental workload [R417], without an interdisciplinary approach to separate their individual and interactive effect.

Regarding the research on the effect of work content on AWCRS, the lack of properly controlled experiments and validated evidence prevents the applicability of physiological parameters such as the HRV [J4] as real-time indicators. Most of the datasets on human research are generated in a laboratory, which limits realistic generalization, especially where the population of the research usually are students within one university. However, it is problematic to design a real-life experiment with a well-controlled condition. The lack of available data, especially from real-life scenarios, hinders HDT development [R416].

This experiment conceptualizes the effect of work content on humans from different aspects such as emotion, perceived workload and stress, and performance. A specific occupation of the barista is used to generate the Work-content Effect on a BArista (WEBA) dataset, though the principles are intended for all other occupations and industrial positions alike. The reason for choosing this occupation is due to the intrinsic nature of its task: The work sequence is not continuous, and the employee has time in the middle of the task to rest. Fortunately, this characteristic provides a chance to scrutinize the momentary effect of the work content factor on human behavior. With the proposed conceptualization and work content consideration, the working conditions in a coffee shop are utilized to generate a real-life dataset in the best way of reflecting the interested aspects. Further utilization of the WEBA dataset to generate in-depth knowledge of human working behavior is highly encouraged, as well as other exploratory research on different aspects of the work content, and from different occupations.

4.4.1 Research scenario and conceptualization approach

Inspired by the work of Lazarus et al. [R265], possible stress sources of this work position are categorized into the "work environment" [R266], the work setting which is known as "work context" [R75], and the "work content" which is the demand of the assigned tasks [R75, R232]. As the main object of interest is the work content, work context, and work environment factors are isolated as discussed in the next subsections, with the intrinsic characteristics that made the chosen coffee shop ideal for the data collection purpose also explained. The generated outcome includes the output as the finished orders from customers which accumulated in the monetary value of revenue, and the work content effect is captured with the perceived workload, kinetic, and physiological signal. The categorization of study aspects is illustrated in Fig. 4.13.

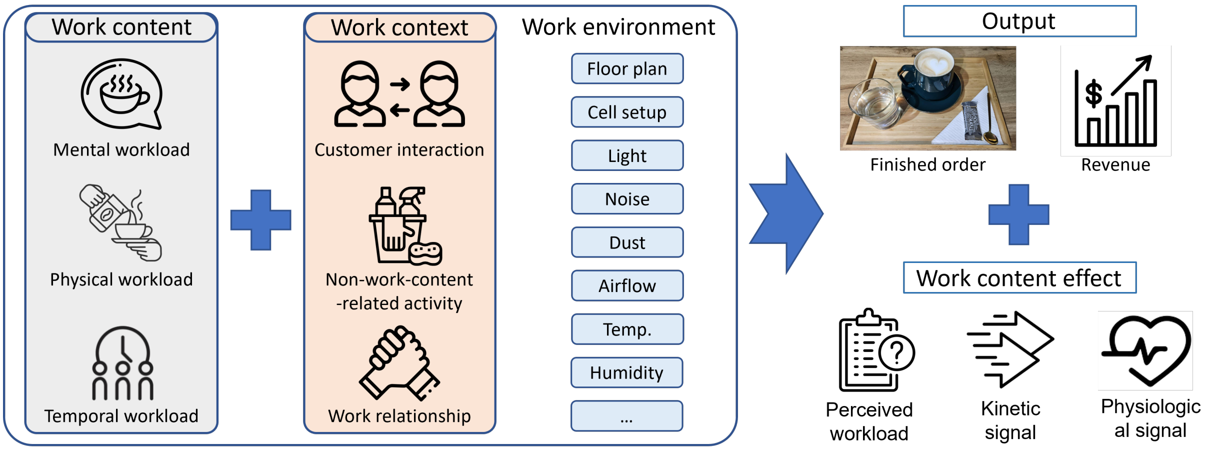


Figure 4.13: Categorization of study aspects: the work process consists of "work content" and "work context" within "work environment", results is "output" and "work content effect".

4.4.2 Work environment

The floor plan of the coffee shop in the study is illustrated in Fig. 4.14. Due to the small scale, whichever bartender works their shift can only stand in two "zones" to work, with pre-defined tasks associated with that zone as follows:

- Zone 1 is the primary working zone, where the barista makes coffee or drinks, and does the dishwashing. There are two areas to prepare the drinks, the "prep. area 1" and "prep. area 2", which are opposite. There is one under-counter three-door fridge that is under the preparation area 1 and the coffee machine, and one freezer to store the ingredients such as milk and fresh lemon. The washing basin is on the corner, with the drying rack hanging above.

- Zone 2 is the secondary zone, where the barista takes the order, issues bills, and then performs the plating before bringing the order to customers.

The main work cell in Zone 1 has a determined layout illustrated in Fig. 4.15, with fixed positions for materials, machines, and tools within the reach distance for convenience. The main working surfaces are in 90 centimeter, a convenient height for light work [R418]. All the baristas are trained with the same work sequence, and thus remain the same layout throughout their working sessions. Before the data collection, a Lean expert assessed the ergonomic risk factors of the work layout in Zone 1 according to RULA tools, considering the work activities in this zone mostly are upper limb tasks. After re-arranging some hard-to-reach items, and preparing a sufficient quantity for each tool to avoid searching during work, the final score was 2 for most of the main activities.

Since the coffee shop is a closed space as exhibited in Fig. 4.16, the working environment is stable with parameters illustrated in Table 4.4. To avoid effects from the outside environment, data collection is canceled during extreme weather such as too-high or too-low temperatures, rain, and snow.

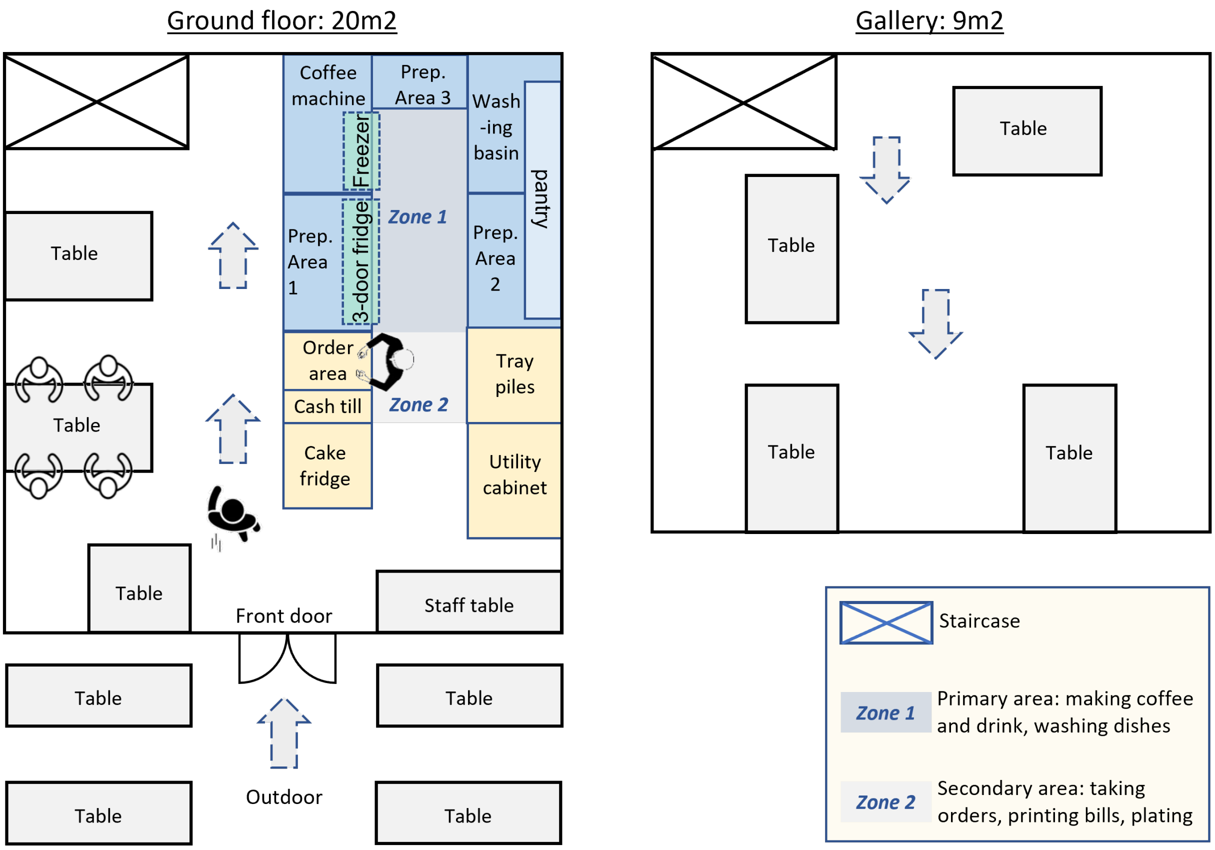


Figure 4.14: Floor plan of the studied coffee shop: The ground floor with indoor tables (left) and the gallery with indoor tables (right).

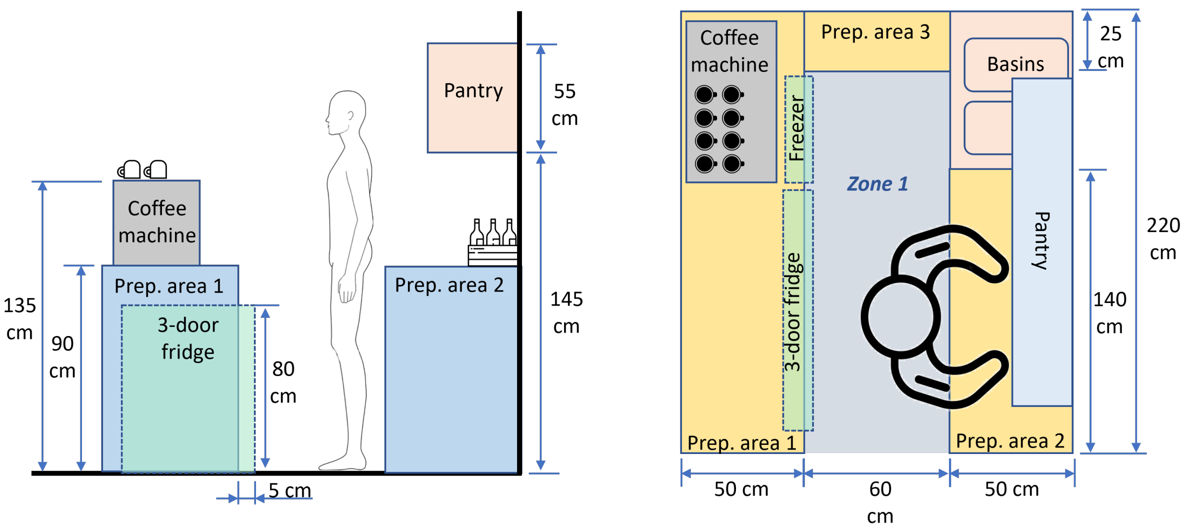


Figure 4.15: Details of layout in Zone 1. The side view (left) with the three-door-fridge located under the preparation area 1 and the top view (right).

Figure 4.16: The work environment in the studied coffee shop: (a) The ground floor of the coffee shop from outside. (b) The gallery with four tables and an air conditioner on the wall. (c) The bar counter with two working zones marked by dotted yellow lines. One barista is working with the coffee machine in Zone 1. (d) The staircase is in the corner of the ground floor.

To comply with the General Data Protection Regulation (GDPR), no video or image was captured. Instead, sensors were installed with fixed locations within the working environment to facilitate activity recognition of surrounding events, while wearable sensors were equipped on the barista to recognize her performed activities. The technical specification and intended usage of all these sensors are explained in Table 4.5, while the installed positions are illustrated in Fig. 4.17.

Table 4.4: Parameters of environmental condition in the coffee shop.

Name	Value (unit)	Measured method	Controlled condition
Light	58 (lx)	SensorTek STK33911 light sensor on Samsung Galaxy S23	The lighting condition is static during the work with only one main switch.
Noise	66 (dB)	Noise sensor on Samsung Galaxy S23	The coffee shop is located in a deep and quiet alley, with no sound from the street. The only sound in the shop is the repetitive instrumental music.
Dust content	-	-	The coffee shop is located far from the street, in an environment with no dust sources such as construction and insects or animals. There is no dust appearing during the working process.
Airflow	255 (cfm)	Handheld Anemometer	The airflow is regulated by the air conditioner, which is placed on the gallery to avoid direct flow into the working area.
Temperature	23 (C)	Indoor thermometer	Due to the close space and controlled airflow, the inside temperature is stable throughout the whole day within the season.
Humidity	-	-	The indoor environment is in normal condition with no significant source of water with an open surface. The humidity is stable thanks to the air-conditioner.
Odour	-	-	There were required cleaning activities at the beginning and the end of the working day.

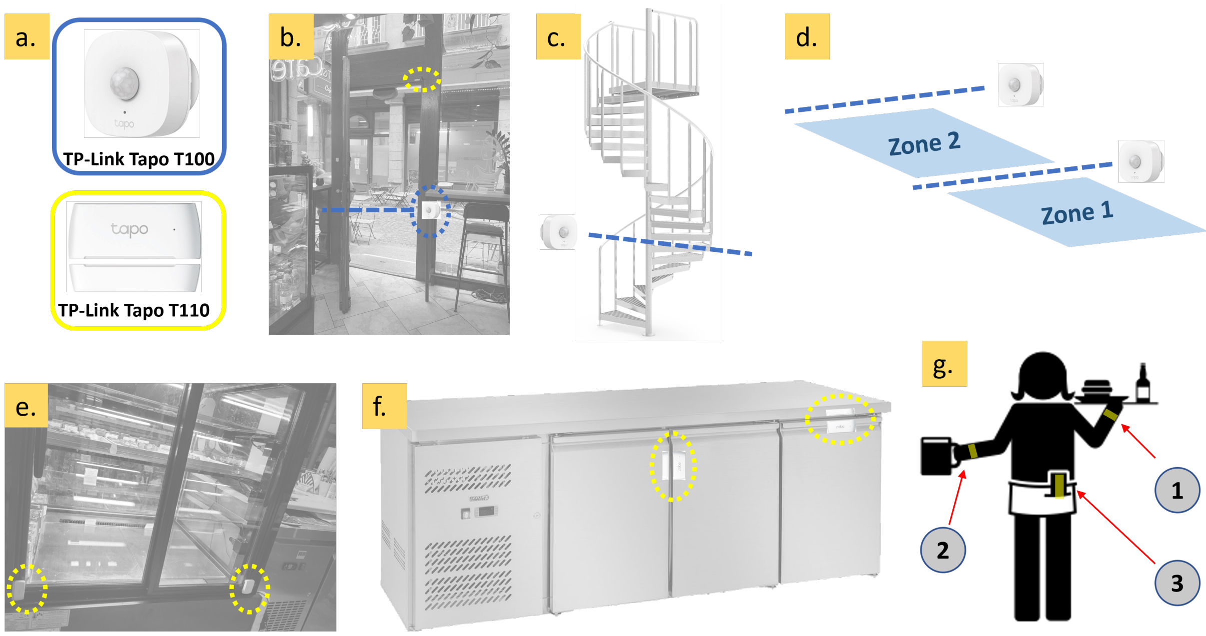


Figure 4.17: The deployed fixed and wearable sensors: (a) The motion sensor Tapo T100 and door activity sensor Tapo T110. (b) One Tapo T100 (blue circle) with its active zone (blue line) and Tapo T110 (yellow circle) is attached to the front door. (c) One Tapo T100 is attached to the staircase. (d) Two Tapo T100 are attached in the boundary of the defined Zone 1 and Zone 2. (e-f) Two Tapo T110 are attached to two hinges of the cake fridge and the three-door fridge. (g) During the working session, the barista wears one armband HR sensor (1) on her non-dominant hand, one armband acceleration sensor (2) in her dominant hand, and another acceleration sensor (3) placed in her apron.

Table 4.5: Deployed sensors for activity recognition.

	Sensor	Intended usage	Set up	Data acquisition
Fixed sensor	TP-Link Tapo T100	Notify when someone enters the front door, goes through the staircase, or enters the defined zones.	Next to the front door, on the staircase, and the margin of two working zones	Record the movement events as timestamps, transmitted to Tapo H100 Hub via the local wireless network.
	TP-Link Tapo T110	Recognize the opening/closing activity of the front door, the fridge, the freezer, and the cake fridge.	Attached to the hinge of the front door, the freezer, the three-door fridge, and the cake fridge.	Record the opening/closing events as timestamps, transmitted through Tapo H100 Hub via the local wireless network.
	Raspberry Pi with Adxl345 3-Axis Digital accelerometer	Recognize the operations being carried out on the coffee machines.	The accelerometer is attached to the coffee machine with a 25 Hz sampling frequency.	Record a time series, stored in local memory, and transmitted to a personal computer through an SCP connection.
	TP-Link Tapo H100 Hub	Receive the signals from other TP-Link Tapo sensors, stored in a log file.	Placed within the local wireless network.	Data copied to a personal computer through Rust API Client via the local wireless network.
Wearables	Polar Verity Sense	Record the Heart Rate (HR) of the barista during work.	Wear on the non-dominant hand.	Record a time series, stored in the local memory of the device, extracted through the Polar flow mobile application.
	Metamotion-S sensor	Record the acceleration of the hand movement of the barista during work.	Wears on the dominant hand, sample at 12.5 Hz.	Record a time series, stored in the local memory of the device, extracted through the MetaBase mobile application.
	Mobile phone acceleration sensor	Record the body acceleration of the barista during work.	Set at 25 Hz sampling frequency, and put in the apron.	Record a time series, stored in the local memory of the phone, extracted through the Sensor logger mobile application.

4.4.3 Work content and work context

Work content

Besides the setup work environment, the work content and work context factors are categorized in this section. According to the World Health Organization (WHO) [R75], the work content includes the demanded activities and consideration of the assigned tasks, while work context is the background other than the work-content activities [R75]. These factors are categorized as follows:

- Work content: The factors belonging to this group come from three constituent requirements that represent the work of a barista: physical and temporal workload (as inspired by the work of Berlin et al. [R288]), along with mental workload (as the workload measured by subjective methods [R292]). These requirements are closely associated with the number and frequency of incoming customers, the required type and quantity of coffee cups made, and generated revenue.

- Work context: Besides the work content, any other activity and interaction that are not directly associated with the work, but related to the scope of working in the predefined work environment are grouped into the work context category.

As the main focus, the work content is defined beforehand as a part of the experiment design. A typical order consists of a drink, a glass of tap water, and possibly a cake. While a water glass or a standardized cake does not require any special consideration to prepare other than standard steps, the drink does. Based on discussions with the shop owner and the current baristas, the current drink menu is divided into two levels of preparation difficulty: easy and difficult. The coffee-based drinks (mixtures of espresso base with possible flavored syrup, steamed milk, and milk foam) are considered easy by the barista, with fewer steps and less required attention, while chocolate-based drinks (mixtures of chocolate base) are considered more difficult, with high attention demand to fulfill the output quality. As the espresso base is processed by the coffee machine and the chocolate base is prepared beforehand and stored in a dispenser, the activities for all order preparation only require physical movements of pushing buttons on the coffee machine or the dispenser, mixing, whisking, and plating, without any cooking. Details of requirements while preparing orders with these drinks are illustrated in Fig. 4.18. Based on the defined work content, it is necessary to recognize the constituent work-content-related activities, factors, and interactions, thus estimating their occurrence and effect during a working period, which accumulates into the work content. These process- and barista-centered activities are defined and categorized in Table 4.6, which allows them to be recognized, or captured from the WEBA dataset.

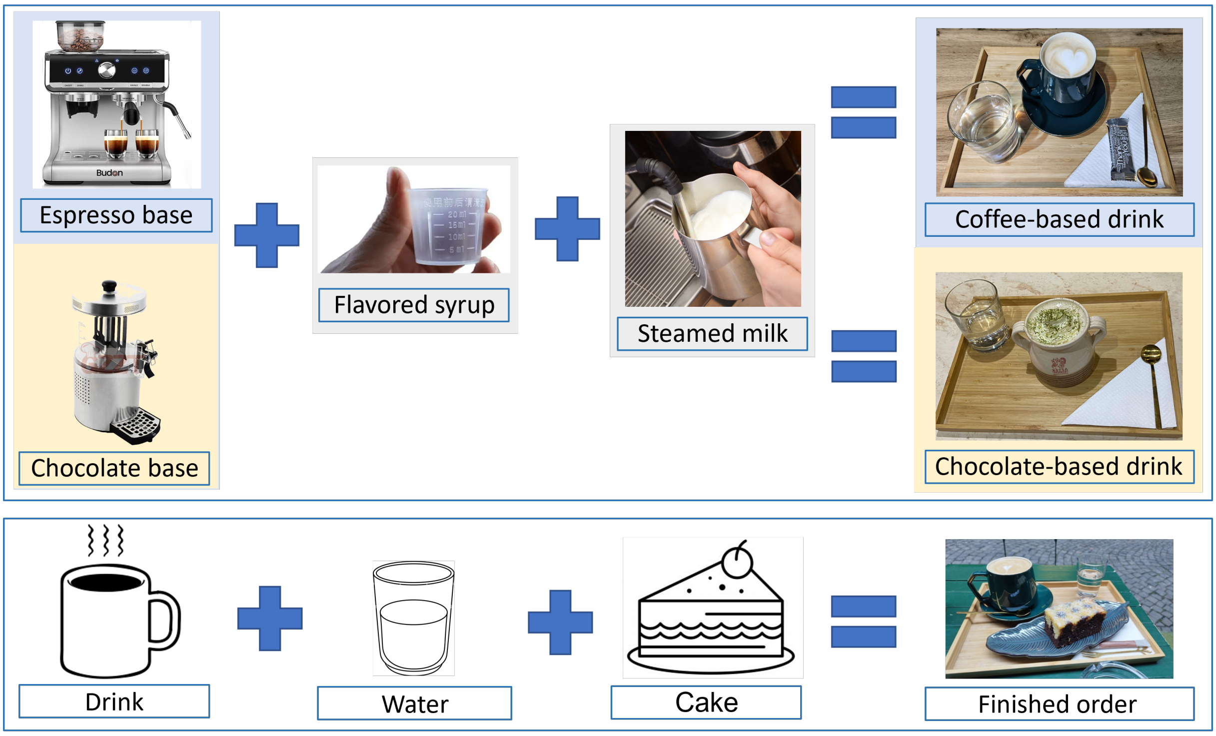


Figure 4.18: The components of typical orders: coffee-based and chocolate-based (upper), and a finished order with a drink, a water glass, and a piece of cake (lower).

It can be seen that the work content of the barista requires more effort from the physical aspect, including the most frequent product-oriented activity, including taking orders, making drinks, plating, serving, etc. Other working activities are not significant, such as dispensing the chocolate base from the chocolate dispenser, since the barista only needs to pull the trigger until fulfilling the measuring cups with prepared marks, therefore no sensor is deployed to recognize it. From the mental aspect, the work content relates to the difficulty of making the orders, considering that all employees were trained in the same way, with a similar standard of product quality. It is assumed that the difficulty of each order creates a different impact on the perceived workload of individual, mainly depending on their work experience in the shop. Regarding the temporal aspect, the intensity of incoming customers with the quantity of each order will create time pressure on the barista. To highlight the effect of this factor, sample data were collected from the preparation of different drinks by each barista during the beginning of the working shift, when the barista can work at a normal speed in comfortable conditions with no time pressure. During rush hours, customers were coming but could not wait to be served. Though they left, their presence still posed a temporal load on the barista. Although the work duration also affects the perception of workload, such as working for long hours can cause additional exhaustion, this factor is not incorporated into the work content, as its effect is limited by assigning fixed work shift duration for every participant during the dataset generation.

Table 4.6: Work content factors with elemental tasks of the barista.

	Tasks	**Scope**	**Captured by the acquired data**
Physical	Taking orders	Interact with customers, write order notes, issuing bills	Happens when a new customer enters the shop, then the barista enters Zone 2, standing with no body acceleration and small hand acceleration.
	Take out the materials	Take the milk, foaming product from the fridge or freezer.	When the fridge or freezer doors are opened.
	Operate the coffee machine	Prepare the espresso base for coffee-based drinks.	The vibration signals from the coffee machine (several vibration samples labeled with drink type are included)
	Prepare drinks	Perform repetitive handwork of making drinks	When the barista enters Zone 1, standing with no body acceleration and small hand acceleration.
	Prepare the cake	Take the cake from the cake fridge or the freezer.	When the cake fridge doors are opened.
	Plating the orders	Take one tray and place the products on it.	The barista standing in Zone 2 with no body acceleration and has small hand acceleration.
	Serving outside ∗	Serve or clean ordered tray outside	Bring the tray of ordered products to or from outside tables, with body movement has pulses of walking, leave the working zones, and open the front door.
	Serving outside ∗	Serve or clean ordered tray outside	Bring the tray of ordered products to or from outside tables, with body movement has pulses of walking, leave the working zones, and open the front door.
	Serving upstairs ∗	Serve or clean ordered tray upstairs	Bring the tray of ordered products to or from upstairs tables, with body movement has pulses of walking upstairs, going through the staircase.
	Washing dishes	Washing the accumulated dirty dishes.	The barista stands in Zone 1, with no body acceleration and has a small hand acceleration.
Mental	Difficulty level of the orders.	The difficulty levels of the ordered drinks	Based on the order notes collected after the shift.
	Interaction with customers	Mutual communication while taking orders and issuing bills	As this interaction is the intrinsic characteristic of the work, its effect is assessed by questionnaires after the shift
Temporal	Waiting customers	A new customer comes in ♯	Opening activity at the front door, with customers step inside.

∗: These activities require a pair of two-way commutating walkings. If the barista did not leave the working zones, one activity or both two of the pair were conducted by the customers themselves, e.g., self-serve or take-away orders.
♯: During rush hours, customers come and leave after lined up waiting.

Work context

Besides the above-listed activities that are directly related to the work content, the work context contains the other intrinsic tasks that add up to the work content, or the interactions that can generate extra emotional and psychological stimulation during work. These activities and interactions are categorized into different groups as in Table 4.7. To keep the most steady conditions for focusing on the work-content influence and avoid threats to the internal validity (i.e., history factor), extraneous factors such as some activities and interactions are limited, reduced, or avoided during the data collection. For activities that can not be controlled, such as the personal rest duration when there is no customer, its data can be recognized based on associated characteristics.

Table 4.7: Work context activities and interactions during a working session.

	Activity - Interaction	**Normal frequency**	**Controlled condition during WEBA dataset collection / Associated characteristics**
Activity	Cleaning the shop	Twice per day	These durations before and after opening hours are excluded from the data collection period.
	Working in collaboration with colleagues	None	Only one barista works at a time with no other colleagues. They only appear in special conditions when the barista feels the workload is unbearable.
	Rest or do personal work	Frequently	The barista is out of any working zone, has no body acceleration and very small hand acceleration, HR slows down.
	Personal activities	Randomly	When there is no activity in working zones, no sign of new customers.
Interaction	Interaction with managers	Several times per day	The manager is advised not to appear during the data collection, and maintain no contact via phone as well.
	Interaction with colleagues	Once per day	The transition period of 30 minutes is avoided during data collection.
	Interaction with suppliers	Twice per week	Supplier encounters are avoided during the data collection.
	Interaction outside of work context	Randomly	Participants are advised not to use their phones during the data collection.
	Encounter with unexpected abnormal events or accidents *	Randomly	If any event is recognized as abnormal or unusual from everyday routine, the data in 15 minutes after that event will be discarded.

*: If the event has a severe effect on the barista, the data from the whole shift will be discarded.

4.4.4 Work content assessment

Different measures were taken at the end of a shif to assess the amount of work content. The served quantity of drinks and cakes was taken from the point-of-sale system, with the revenue is used as an objective measure. The International PANAS Short Form (I-PANAS-SF) [R419] measures the emotional perception, while a paper/pencil version of the NASA Task Load Index (NASA-TLX) measures the perceived workload [R420]. Details of these measures are mentioned in Table 4.8.

Table 4.8: Measures to assess the work content.

	Name	**Scope**	**How to measure**
Objective	Total drinks made	The number of drinks served	Recorded from order notes from the barista after the measured shift.
	Ratio of easy/all drink	The ratio of easy drinks over the total number of drinks made	Recorded from order notes from the barista after the measured shift.
	Number of cakes served	The number of cakes served	Recorded from order notes from the barista after the measured shift
	Total made revenue	Total revenue from the measured shift in Hungarian forint (HUF)	Extracted from issued bills from cash register machine.
Subjective	Emotion	Positive and negative feelings from the work in the shift.	I-PANAS-SF questionnaire, filled out after the shift.
	Perceived workload	The mental, physical, and temporal aspects of work demand, with impressions about performance, effort, and frustration.	NASA-TLX questionnaire, filled out after the shift.

4.4.5 WEBA dataset generation

This section describes the other data that are collected from human participants, and deployed methods to make the work schedule and data generation plan.

Human participant

In the current phase, possible participants are the five baristas who are already working in the coffee shop, with different experience levels. The participation was voluntary, with consent forms provided while the investigators explained the research objectives and answered aroused questions. Besides the above-mentioned data, no photo or video was taken. According to the company policy, each barista has attended a work capability assessment before they enter the job, and repeated yearly. Before experimenting, the participants were scanned with a medical history questionnaire, to avoid negative effects from recent disappointments sleep problems, or hidden diseases that can influent the collected HR. Once the participant is involved, a baseline collection is performed with two days of 24-hour continuous HR measurement, except for the personal hygiene period. One of the two days is the week-end, while the other day is a weekday. Participants were instructed to carry out their daily routines without any abnormal activities.

Characteristics during data collection

Different factors that affect the relationship of perceived workload with the work content can be considered:

- The time of work shift during the day: Currently, the coffee shop runs with a schedule of two shifts: morning and afternoon, each lasting for five or six hours from 9 and 2 pm, respectively. To avoid the effect of working long hours, each participant can only work one shift per day. The measurement always started from the beginning of the shift, after the initial routine cleaning.
- The experience of the barista: The working experience of the barista also determines how he/she reacts to workload and stress. Currently, the experience of working with drink types in the chosen coffee shop can be divided into two levels: less than one year and more than one year.
- The revenue level: Increasing revenue means increasing workload. The revenue can be divided into two levels: lower and higher than a value of 35000 HUF, which equals 101 United States Dollar (USD).
- The order difficulty, which is represented by the ratio of easy/all drinks within a shift also affects the perceived workload. With the same number of drinks made, the higher value of this ratio means more easy drinks were made, which posed less mental workload on the barista.

Noticeably, though some of these factors can be scheduled (e.g., the experiment of the barista, the time of shift), in real-life conditions, other factors appeared randomly (i.e., the revenue of a shift). Therefore, there is no need to perform masking the condition assignment from the participants. Different from a laboratory experiment with a well-controlled environment, this experiment is carried out continuously until the resulting space is filled with the desired factor levels and also continued through different seasons to avoid the seasonal effect (such as more chocolate-based drinks being consumed in cold weather). In this way, the sampling and selection bias faded away, and the Hawthorne effect [R421] is also neglectable as the participants do not know data from which measured days will be used for further analysis. The structure of the WEBA dataset is shown in Fig. 4.19.

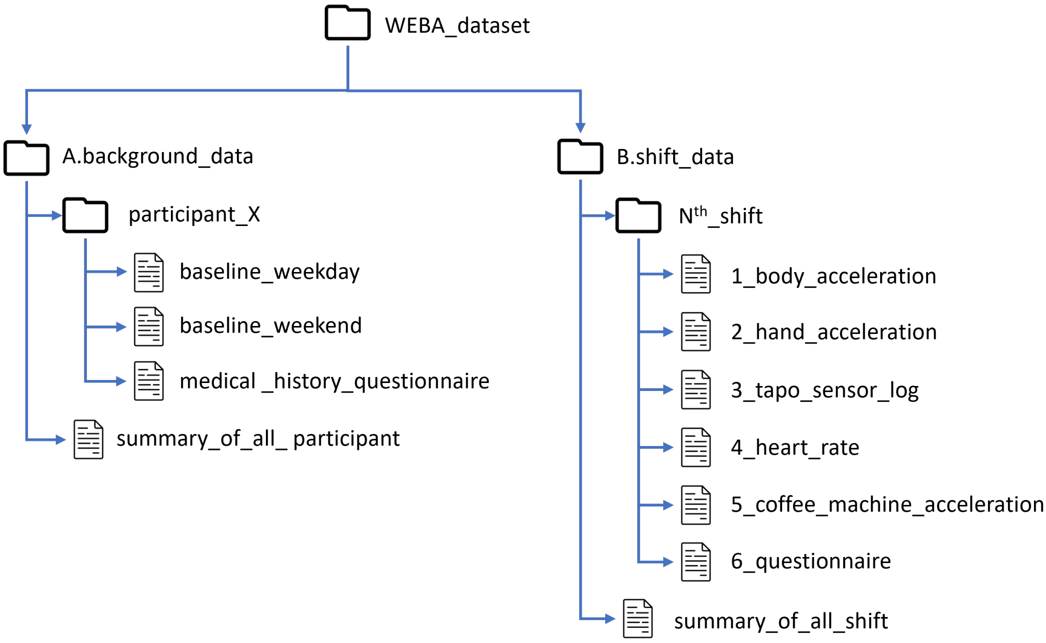


Figure 4.19: The WEBA dataset structure: the background data of each participant (left), and the measured data after each shift (right).

4.5 Chapter summary

The current research on AWCRS in the industrial environment is still developing, mainly from an engineering perspective. More elaboration and distinction of AWCRS from other stress types are necessary. Though stressful situations were associated with reduced HRV in many studies, none of them were adequately designed to provide a sound scientific conclusion. As HRV strongly depends on too many factors (e.g., work context, individual physical and mental status), its real-time usage for stress monitoring can be problematic. Further research can either develop a well-isolated simulation with pre-defined settings to discover the association and interpolate the result with relevant constraints during real-time monitoring, or utilize HRV along with other additional metrics within a strictly controlled environment. A good example is the study proving that the impulsive sound could elevate the workload [R422]. In addition, the association of HRV with the acute stress condition should be measured beforehand, such as the HRV can be sampled from the normal working condition as a reference, not only from the resting period.

Once the association between AWCRS and HRV was thoroughly studied, JITAI could be applied to improve human worker performance, which aligns with the vision of Operator 4.0 and long-term benefits in the forthcoming Industry 5.0 and Society 5.0 [R423]. More experiments, RCTs, and clinical trials are needed to adopt a proper design and validate this approach before any commercialized platform can be built for real-time monitoring of HRV to manage AWCRS.

4.5.1 Modelling the effect of Acute Work-Content Related Stress on performance

A conceptual model is developed to reflect the AWCRS of industrial workers under the effect of work-content factors and predict their OLE performance. Though the model is constructed based on the diagnosed literature, its factors and scope are not fixed within these boundaries. Besides proposed parameters and their directions of effect, additional modifications should be considered based on different applying contexts, such as the characteristics of the workforce population, or the nature of the work. Other aspects (e.g., the effect of a learning curve, or skill decay) can be examined similarly. Throughout four simulated scenarios, the results from the proposed model sufficiently meet the expectations from the literature. The usage of this model results in a better understanding of human worker capacities, regarding the interaction of their workers with the working conditions, line setup, and task requirements.

Model capability

Industrial engineers can take advantage of diagnosing individual reactions, to find the most suitable work-content levels and settings thus better utilizing a "personal profile". Well-designed "task load" with sufficient task variety or pattern change can utilize the working capacities of workers, and available social support can motivate the worker to voluntarily engage with their tasks without compromising physical and mental health [R424, R425]. Through the loop of planning and simulation, a deep knowledge of worker capacities and thresholds can be achieved along with their behaviors, thus industrial engineers can design and arrange the allocated tasks accordingly. Further studies and experiments can be designed to check the causality and effect of each factor within the model, by controlling the relevant factors and adjusting the interested element. Subtle associations between work-content factors and the perceived stress of the worker in a complex manufacturing system can be studied, such as the number of WIP in the product-mix production system [R426].

The proposed model enables real-time work monitoring with possible work-content modification and timely intervention. For a long-term vision, a human-centric development strategy can be elaborated based on individual data collected during model usage. Not only tailored work content but built-in interventions can also be diagnosed and applied based on the status and recorded performance of each individual, for the sake of personal as well as workforce development. Possible suggestions for individual level can be gradual training to improve skill acquisition and avoid skill decaying [R427], and customized assistance for impaired or disabled workers [R428]. On the scale of workforce development, companies can have a record of the optimal allocation for their workforce, while each worker will have the opportunity to learn about their work capacities, strengths, and weaknesses, which helps them choose a suitable work schedule and life-long career for their work-life balance.

Model limitation

The first limitation is the lack of quantitative measures and numerical thresholds, which limits this conceptual model to a qualitative tool. Though there are different scales and measurements for workload assessment, physically and mentally [R429], however, the quantified association between these scales is not available, nor is there a relative comparison between them. Many factors have well-known directions of effect (i.e., years of experience, age), but their representative curves lack quantitative milestones. The inhomogeneous measurement of factors (i.e., some are measured by physiological parameters or bio-markers, some by questionnaire) is challenging in both model development and usage phases. Several variables do not have specific measurement scales, such as stress endurance and personal stress threshold. The accumulation/relaxation rate of different types of stress has also not been elaborated in the previous literature. Consequently, the model is not able to predict the exact stress level according to current popular stress measurement scales. However, users can qualitatively predict the increasing, or decreasing behavior of stress and performance status of each individual, as a time-based function.

The second limitation is the significant customization for each individual regarding their unique physiological features. It is widely accepted that years of experience have a positive effect on performance, however, the scale of this effect on individuals is unclear. Not to mention the basic workload should be measured based on the natural ability of each worker, the sensitivity and relaxation rate for each type of stress is also dependent on the cortisol level regulation of each individual [R430], which is in the close influence of the HPA axis [R431]. The efficiency of stress recovery is also affected by working hours [R432] and environmental noise [R433], which are varied individually, and reflect different symptoms of stress burden on a single person [R434]. Low self-esteem, stressful life changes, and recent minor life events can also affect individual stress recovery under acute stressors [R435]. These associations require in-depth detailed personal customization regarding historical medical and stress disorder records.

Another limitation is the limited amount of high-level evidence, i.e., RCT. A combination of both objective and subjective measurements can be used to validate the human status [R362], as the use of a sole physiological parameter such as HRV to validate the AWCRS is still in the immature phase [J4]. The effectiveness and impact duration of proposed interventions should also be validated before implementation during the simulation, as they yield different effects under various usage contexts, such as caffeine and caffeinated energy drinks can have both positive (e.g., increased alertness, reaction time, and cognitive performance [R436]) and negative (e.g., decreased sleep quality [R437, R438]) effects with unknown risk/benefit ratio [R437]. The job rotation intervention can pose different effects within different work settings [R439]. Last but not least, in a practical manufacturing environment, not only the personal performance be considered, but the collective performance of workers in a manufacturing line should be investigated. Different workers with different stress effects may affect collaborative work [R373].

4.5.2 The contribution of WEBA dataset

The WEBA dataset is introduced as a reflection of the effect of work content on the personal workload perception, stress, performance, and heart rate (HR) of a barista in real-life working conditions. By in-depth analysis of the work characteristics from a multi-disciplinary approach, and utilizing a specific condition with event-driven sensors and wearable technology, a controlled environment is created in the closest way to a laboratory experiment. With a well-structured conceptualization and setup, the work content factors are emphasized and become the main stressors that impose their effect on the participants. The WEBA dataset contributes to the further development of understanding the work content effect on labor performance and well-being.

The WEBA dataset contributes a missing piece of evidence enabling in-depth studies about the applicability and reliability of HR as an instantaneous AWCRS indicator [J4], thus preparing Just-in-the-moment adaptive interventions [R246]. By the detailed description of the experiment, the possibility of using HR and acceleration signals as indicators for personal perceived workload can be diagnosed. Last but not least, a similar approach can be used to generate another dataset in other real-life conditions. Researchers are encouraged for further research with a similar approach to different occupations and work conditions, thus paving the way for a realistic HDT in the I5.0 context, with real-time monitoring of human factors.

5

Conclusion

My thesis solved four main problems within the context of implementing Lean 4.0 and Operator 4.0 solutions as illustrated by red boxes in Fig. 5.1. The proposed solutions for the identified problems are given in blue boxes. As the literature pointed out, brownfield development is fundamental in terms of the continuous development of I4.0 and I5.0, with abundantly available I4.0 technology.

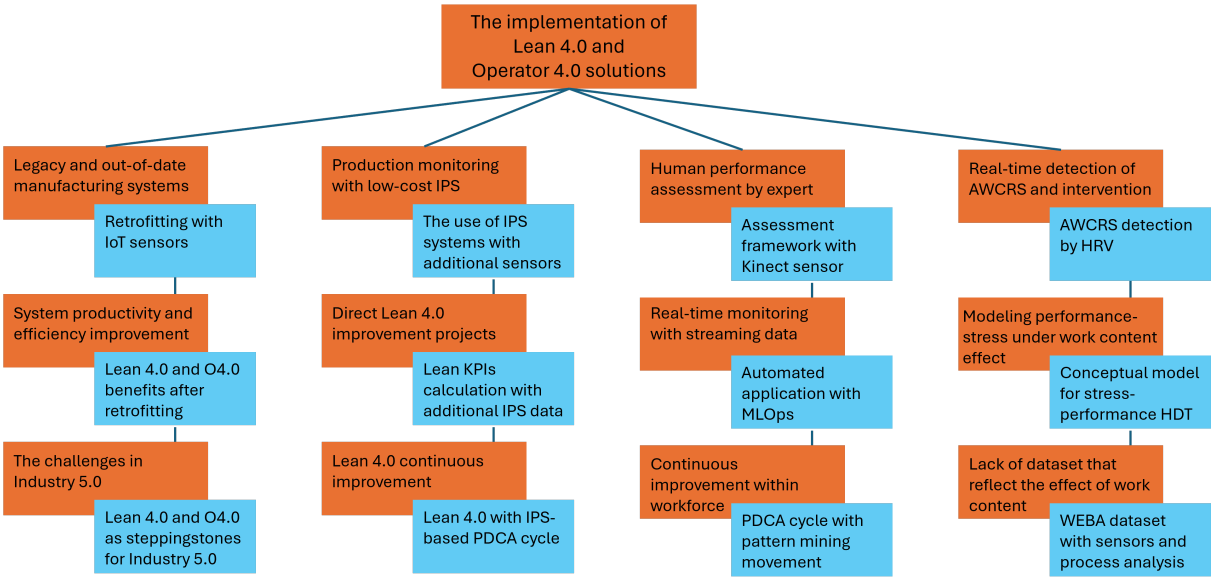


Figure 5.1: The contribution of the thesis: The retrofitting solution with IoT sensors; The production monitoring and Lean 4.0 implementation with IPS system; The assessment of human performance by Kinect sensor that facilitates Lean 4.0 workforce improvement; and The foundation for enhancing human performance with stress-performance knowledge.

In Chapter 2, to guide the retrofitting-based development with sustainability goals of I5.0, I categorized existing I4.0 sensors to upgrade the old-fashioned system into targeted layers for digitization, providing managers and decision-makers a holistic picture of how to conduct brownfield developments, organize the development activities, permeate the digitization spirit, and prepare for possible obstacles. I also collected evidence to prove that brownfield retrofitting with sensor technology can support Operator 4.0, and Lean 4.0 as Industry 5.0 solutions. In the same chapter, I proposed the use of a low-cost IPS with additional sensors for production monitoring. Based on a re-designed set of Lean KPIs, the production insight with fused data from IPS and MES systems can be utilized for directing Lean 4.0 improvement projects. A continuous improvement with the PDCA approach based on IPS data can facilitate continuous improvement initiatives. In Chapter 3, my proposed framework of using skeletal data from Kinect sensor can replace the traditional human performance assessment by a human expert, while an automated application will be enabled by MLOps principles. As continuous improvement within a workforce scale is a special interest in both Lean 4.0 and O4.0, I suggested a PDCA cycle with data from the Kinect sensor, based on the work movements from the pattern mining results. In Chapter 4, I established several foundations for utilizing human performance based on the stress-performance association of human workers in the industrial environment. The applicability of HRV as an indicator for AWCRS serves as a scientific foundation for later stress monitoring solutions. A suggested conceptual model for simulating the stress-performance can be the core of a modern HDT, support monitoring human performance, and adjust the work content in a real-time manner. Finally, I utilized activity sensors and wearables, along with process analysis, to contribute a dataset for later research on AWCRS.

New scientific results

***Thesis 1:* I developed a near-online retrofitted monitoring function to generate Lean KPIs based on analysis of the position data extracted from the Indoor Positioning System (IPS) to support the Lean 4.0 implementation.**

The proposed IPS architecture incorporates different kinds of sensors to acquire not only position data but also other data such as vibration, which enables them to recognize motion and transportation activities. Based on the acquired data, I redefined and redesigned the traditional set of Lean KPIs to be derived automatically. I also presented how positional data from IPS can enrich the Lean 4.0-based continuous development toolkit, with a detailed guideline of an IPS-enabled LM project. Process mining is applied for developing Value Stream Mapping (VSM), for recording processes and identifying waste. I proved that IPS is effective in supporting the implementation of Lean 4.0 projects, and the proposed method enables further system optimization, which assists managers in monitoring their manufacturing systems effortlessly with an IPS system [J6, J1].

***Thesis 2:* I developed an algorithm using supervised learning combined with pattern mining to determine ergonomic metrics and movement patterns based on skeletal data recording, supporting ergonomic assessment and human resources development within Lean 4.0 continuous improvement.**

I proposed an approach to assess the human worker performance based on the skeleton data from the Kinect sensor by applying pattern mining and supervised learning algorithms, with integrated data processing algorithms to provide an automatic way of assessing labor performance. I verified that the analyzed results are suitable for ergonomics assessment and human resources development within Lean 4.0 continuous improvement. I suggested the integration of MLOps with relevant open-source packages for a real-time application. The assessment result can be utilized for performance enhancement and individual and systematic human-centric improvement in short- and long-term organizational HRD plans. This monitoring system is effective for the development and dynamic operation of O4.0 solution, facilitates the future of human workers in manufacturing industries, and especially contributes to the Healthy Operator pillar of the O4.0 and O5.0 concepts [J7].

***Thesis 3:* Based on the proposed system dynamic conceptual model from the evidence of validated relationships between Acute Work Content-Related Stress (AWCRS) and the work performance of human operators from the literature, I**

developed an extended formula for Overall Labor Effectiveness (OLE) calculation to predict complex human behavior under the effect of AWCRS.

I proposed a qualitative conceptual model to reflect the acute stress of industrial workers under the effect of work-content factors and predict their OLE performance. The model not only helps to structure the unclear relationship between work-content factors and induced stress but also conceptualizes personal performance in the industrial work environment. With an interdisciplinary perspective, the incorporated effects reflect many subtle aspects of worker behavior when receiving work-content elements as stressors. The proposed approach with a conceptual model enables different work-content-related planning, and the simulation, monitoring stress conditions on industrial operators, which could increase their work efficiency. The model helps to foresee the effect of possible changes and compare the expected performance of workers under different work conditions, thus supporting production supervisors in their daily monitoring tasks to harvest optimal human resource utilization and plan human-centric improvements.

Thesis 4: **I generated an experiment to collect a data set to reflect the effect of work content factors on the workload, AWCRS perception, heart rate, and human performance in real-life working conditions.**

I conceptualized the effect of AWCRS on human beings from different aspects such as emotion, perceived workload, and performance, utilizing an enclosed work environment of a coffee shop to collect the "Work-content Effect on a BArista" (WEBA) dataset. Process analysis and sensor technologies are applied to capture the effect of work content. The WEBA dataset can be considered a reflection of work content factors on the personal workload perception of baristas in real-life working conditions. This dataset contributes a missing piece of evidence for the use of real-time HRV monitoring and facilitates further research about AWCRS.

Lean 4.0 offers companies survivability in the I4.0 context and prior sustained competitiveness. The O4.0 concept focuses on the human-centricity aspect, as workers and operators benefit from technology and digital transformation, which helps them fulfill their job requirements with less effort and higher value-added contribution, and the self-resilience of the O5.0 concept facilitates a system effect from both human-machine system resilience and human operator resilience. The application of sensor technology and data science for these organizational improvements can be considered stepping stones for the I5.0 initiative. As their characteristics indicated, the gained benefits bring manufacturers advantages and readiness for further development. Fostering the O5.0 transition is necessary for industrial stakeholders and requires knowledge of the favorable context and corresponding enablers. Thus it is worth considering how the I4.0 smart technologies and the O4.0 paradigm could adapt to the I5.0 requirements, and how the smooth transition toward the O5.0 can impact workplace sustainability, social issues, and resilience. Industrial managers and practitioners can refer to this work for better preparation and implementation of O4.0 technologies to support the daily production tasks of their operators.

Appendix A

Deployed sensors and actuators and benefits of retrofitted systems

The types of deployed sensors in retrofitting projects are categorized in Table A.1.

Several actuators and their usage in retrofitting development are given in Table A.2

Table A.3 shows the advantages for O4.0 from retrofitted systems.

Advantages of Lean 4.0 from retrofitted systems are listed in Table A.4.

Sensor (Description)	Specific type	Industries & Use cases
Temperature sensor (Measure the temperature of the subject)	General type	Textile [R164, R56, R55], Metal cutting [R95], Food processing [R120]
	Thermal couple	Metal forming [R102]
	LM35	Didactic plant [R49]
	DHT11	Flexible Manufacturing System (FMS) [R129]
	Sensorkits	Car assembly [R94]
	Thermocouples perfluoroalkoxy K-type	Electronic manufacturing [R132]
Pressure sensor (Measure the pressure within a pipe or a furnace, or any close space)	General type	Food processing [R120], Didactic plant [R49]
	Honeywell Silicon Ceramic gauge-type	Electronic manufacturing [R132]
	Setra 280E; Foxboro 841GM-CI1; Foxboro IDP-10	Oil extraction [R105]
Flow sensor (Measure the flow of the substances)	Foxboro Magnetic Flowtransmitter	Oil extraction [R105]
	Foxboro Vortez DN 50	Oil extraction [R105]
	General type	Didactic plant [R49]
Position sensor (Define the position of the interest object in a defined space)	Festo cylinder position sensor	Assembly line [R103]
	Radio-frequency Identification (RFID) chip	Fabric knitting [R140]
	Baumer Ident RFID tag	FMS system [R440]
	Laser displacement sensor (LDS)	Aluminium casting [R99]
Acoustic sensor (Measure distance with acoustic waves)	Self-built sensor	Oilfield [R133]
Current sensor (Measure the amplitude of current inside a wire)	Inductive current clamp sensor Sensorkits	Car assembly [R94]
	Non-invasive SCT-013	Didactic plant [R49], Industrial robot [R106]
	Non-invasive current transformer	Didactic plant [R49]
CO2 sensor (Measure the part per million of CO2)	General type	Metal cutting [R95]
Energy sensor (Measure the amount of consumed energy)	Schneider Electric Power Tag	Metal cutting [R91]
Motion sensor (Detect the movement of objects)	Camera motion sensor	Iron & Steel production [R135]
Magnetic sensor (Sense the magnetic field generated during the machinery movement)	Hall-effect sensors	Industrial motor-driven system [R167], Textile [R56]
Metal sensor (Detect metal material appearance)	MSPA13 NPN transistor	Industrial robot [R106]
Color sensor (Detect the color of a material)	TSC230 RGB	FMS system [R129]
Accelerometer (Measure the vibration, or acceleration of the machine structure)	General use accelerometers without specific type	Industrial equipment [R207], Textile [R164], Metal cutting [R137]
	Bosch BMX160	Metal cutting [R96]
	Bosch BMA280	Computer Numerical Control (CNC) machining [R160], Industrial robot [R441]
	ADXL345	Limestone processing [R113, R114]
	Bruel & Kjaer 4535-B-001	Metal cutting [R136]
	Sensorkits	Car assembly [R94]
	Raspberry-Pi accelerometer	Metal cutting [R143]
	MMA7361	Aluminium casting [R99]
Visual sensor (Capture the movement, position, or characteristics of objects)	Raspberry Pi 1.3 camera	High-bay warehouse [R442]
	USB camera	Industrial robot [R106]
	Yarn breakage sensor	Textile [R56]
	Knot sensor	Textile [R56]

Table A.1: Most frequently used sensors to retrofit legacy system.

Method of deploying actuators	**Retrofitting usage**	**Specific type**	**Industries & Use cases**
Integrate existing actuators to control the process variables	Adjust and control the state of liquid inlet/outlet flows.	General control and binary valves	Oil & Gas processing [R98]
		Level switch	Water processing [R122]
	Control the weld tool path.	ABB6640 robot controller	Metal de-burring and grinding [R139]
	Control the direction and speed of a conveyor.	Siemens three phase asynchronous motor	Material handling [R126]
	Detect the status of a mechanism.	Limit switch	Assembly line [R103]
	Control the steam pressure of the metal pressing machines.	Hydraulic pressure recuperators, Steam valves	Metal forming [R102]
	Control the velocity of the conveyor.	Motor control switch	Material handling [R138]
	Control the process of gassing and ventilation. Control conveyors and fixtures.	Pneumatic and hydraulic valves	Sand core [R443]
Employ new actuators to control the process variables	Adjust and control the state of the gas/liquid inlet/outlet flows.	Pneumatic solenoid valve ECKARDT MB6713	Oil extraction [R105]
		Solenoid valve	Didactic plant [R49]
	Control the on/off and emergency states	Self-built switch and controller	Metal machining [R104]
	Control machine tools spindle speed.	Speed drive & Spindle descent meter	Metal machining [R104]
Employ new actuators to extend the capability of existing hardware	Serve as end actuator to an robotic arm.	Self-built gripper.	Industrial robot [R106]
	Transport a sensor to the interested location for measurement.	Linear motor and encoders, general type	Aluminium casting [R99]
	Transport the machined part to the interested location.	Pneumatic linear actuator	Aluminium casting [R99]
	Prevent injuries from spindle rotation during machining process.	Self-built movable protection screen	Metal machining [R104]
	Providing clamping force for the welding fixture	Pneumatic clamps	Metal forming [R68]
	Clean the cutting tool after machining	Self-built mechanism.	CNC machining [R107]
	Close the protective door and vice of the CNC machine.	FESTO pneumatic cylinders with solenoid valves	Experimental plant [R53]

Table A.2: Most frequent used actuators to retrofit legacy system.

Main advantages	Description	Industries & Use cases
Analytical support	The worker can be supported by the relevant data and visualization to analyze the situation and make quick decisions based on given tutorials.	Steel Mill [R52], Oilfield [R133], Fabric knitting [R140], Metal casting [R125], CNC machining [R107], Electrical cabinet maintenance [R88], Metal cutting [R143], Material handling [R126], FMS system [R129], Metal forming [R102]
Stress-free work environment	Faults and machine failures are easy to detect without human consideration and require less work experience.	Plastic injection [R134], Oil extraction [R105], Steel Mill [R52], Metal cutting [R137], Fabric knitting [R140], FMS system [R129]
Higher-value contribution from human worker	Due to the data-based automation, the worker can have more time for value-added tasks, than monitoring the machine, waiting, doing manual data collection	Textile [R164], Metal cutting [R137], Fabric knitting [R140], Industrial robot [R106], Metal de-burring and grinding [R139]
Human error reduction	The unintended error from the manipulation of the workers is stopped by the system, to avoid consequences of absent-mindedness.	Steel Mill [R52], Car assembly [R94], Metal de-burring and grinding [R139], Metal forming [R102]
Supported job training and learning	Provided the visualized data of normal and abnormal events, and real situation examples for the personnel training.	Textile [R68], Metal casting [R170], Oil extraction [R105], Steel Mill [R52], Metal forming [R144, R68], Oilfield [R133], Fabric knitting [R140], Textile [R56]
Healthy operator	Occupational Safety & Health (OSH) hazard will be prompted to the operator timely through the user interface, and smartwatch. The system can be stopped in a preventive manner.	Electronic manufacturing [R132], Oil extraction [R105], Oilfield [R133], FMS system [R129]

Table A.3: Operator 4.0 benefits on retrofitted system

Main advantages	Description	Industries & Use cases
Work process standardization	The work process can be standardized to avoid waiting time.	Metal forming [R102]
Just-in-time production	Materials and tasks can be scheduled at the exact time of need, avoiding excessive stock of waiting lines.	Metal cutting [R137]
Quick Changeover	Shorten the time to changeover between different states of the equipment configuration or product variant.	Material handling [R138]
Reduce machine/equipment waiting/waste time	Reduce idle time, or time to set-up, time to repair of machine/equipment, and stoppage time by recognizing and controlling its state.	Electronic manufacturing [R132], Steel Mill [R52], Oilfield [R133], Fabric knitting [R140], Metal forming [R102]
Remove bottlenecks in material flow	Rearrange the processes to avoid bottlenecks that cause production deficiency.	Aluminium production [R171], Gear production [R127]
Continuous improvement	Process optimization and root cause analysis activity can be developed gradually with the available data.	Aluminium production [R171], Fabric knitting [R140], Textile [R56], Metal casting [R125], Gear production [R127], Metal forming [R89]

Table A.4: The possible advantages of Lean 4.0 in retrofitted system

Appendix B

Structure and details of the simulation with proposed conceptual model

For better comprehension, the model structure in the Vensim environment was developed in separate views, with each view represented in the following figures. Fig. B.1 exhibits the static effect of the "Personal profile" on the initial "Personal capacity" of a worker at the beginning of the working day. The dynamic effects of circumstantial stressors on the perceived workload and working capability degradation are depicted in Fig. B.2. Fig. B.3 visualized the model structure to generate task load components, and how the work capacities are modeled by stock variables.

Fig. B.4 described the structure to create the accumulation and relaxation mechanism of different stress types and their effects on workload and capacity degradation. The OLE is defined by its constituent as exhibited in Fig. B.5.

The details of the use case setup with the important variables are described in Table B.1. For the sake of simplicity, a non-denationalization technique is used in this model, with partial removal of physical dimensions from its equations. It is also worth mentioning that in this qualitative model, the stress-related variables ("sustained attention", "acute stress", and "chronic stress") are not real values with physical meaning, but variables that represent the accumulation and relaxation behavior of these stress types.

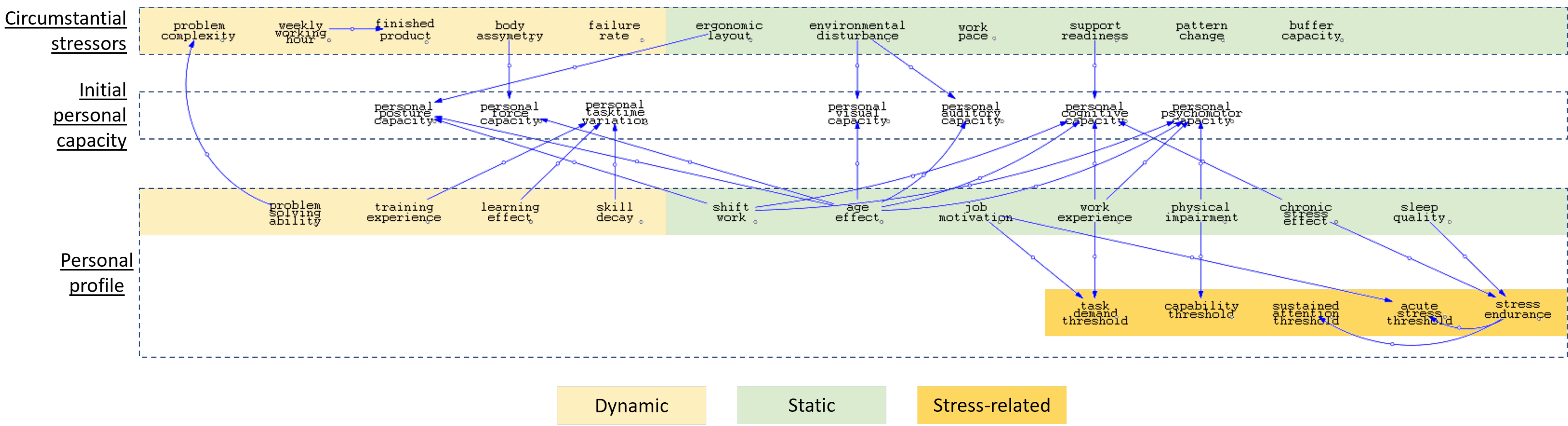


Figure B.1: The initial personal capacities are defined based on the personal profiles

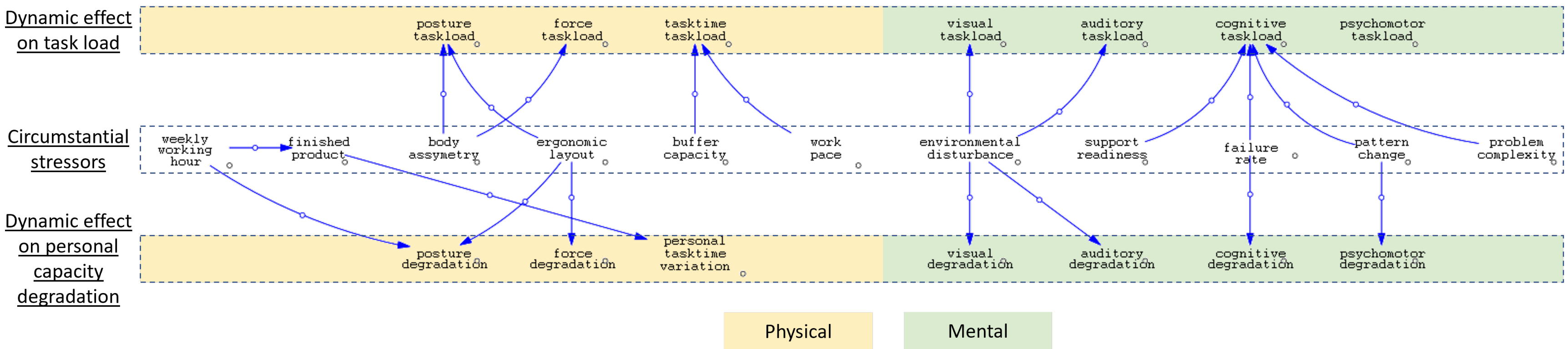


Figure B.2: The personal initial work capacities are defined based on the personal profiles.

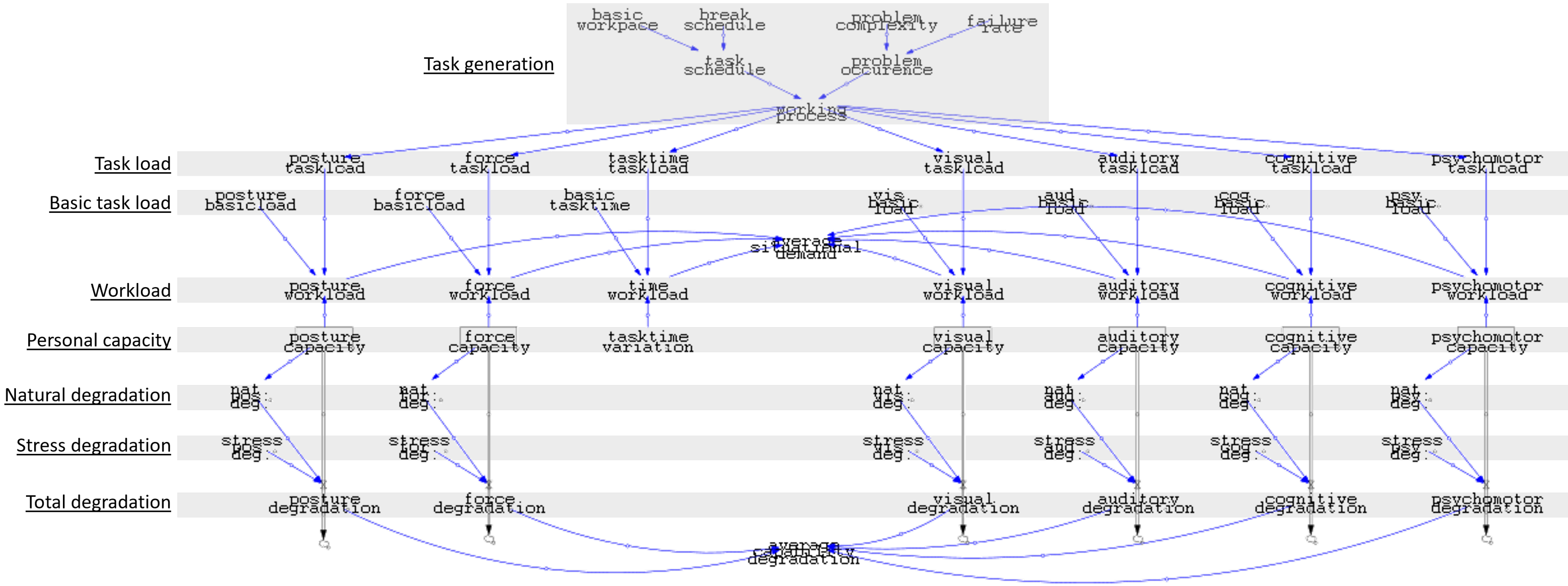


Figure B.3: The task perception with different task load components.

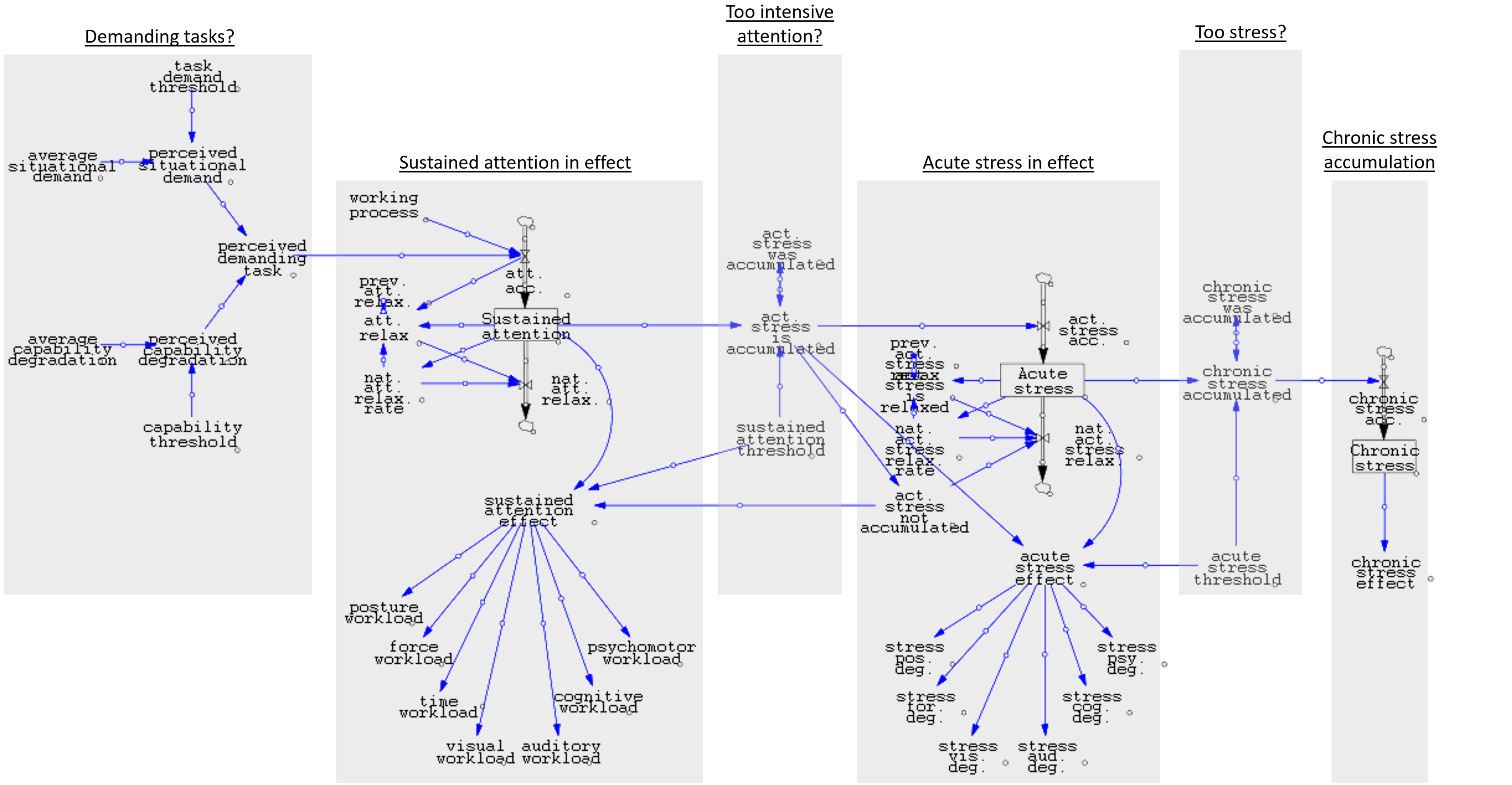


Figure B.4: The stress accumulating mechanism during a working session.

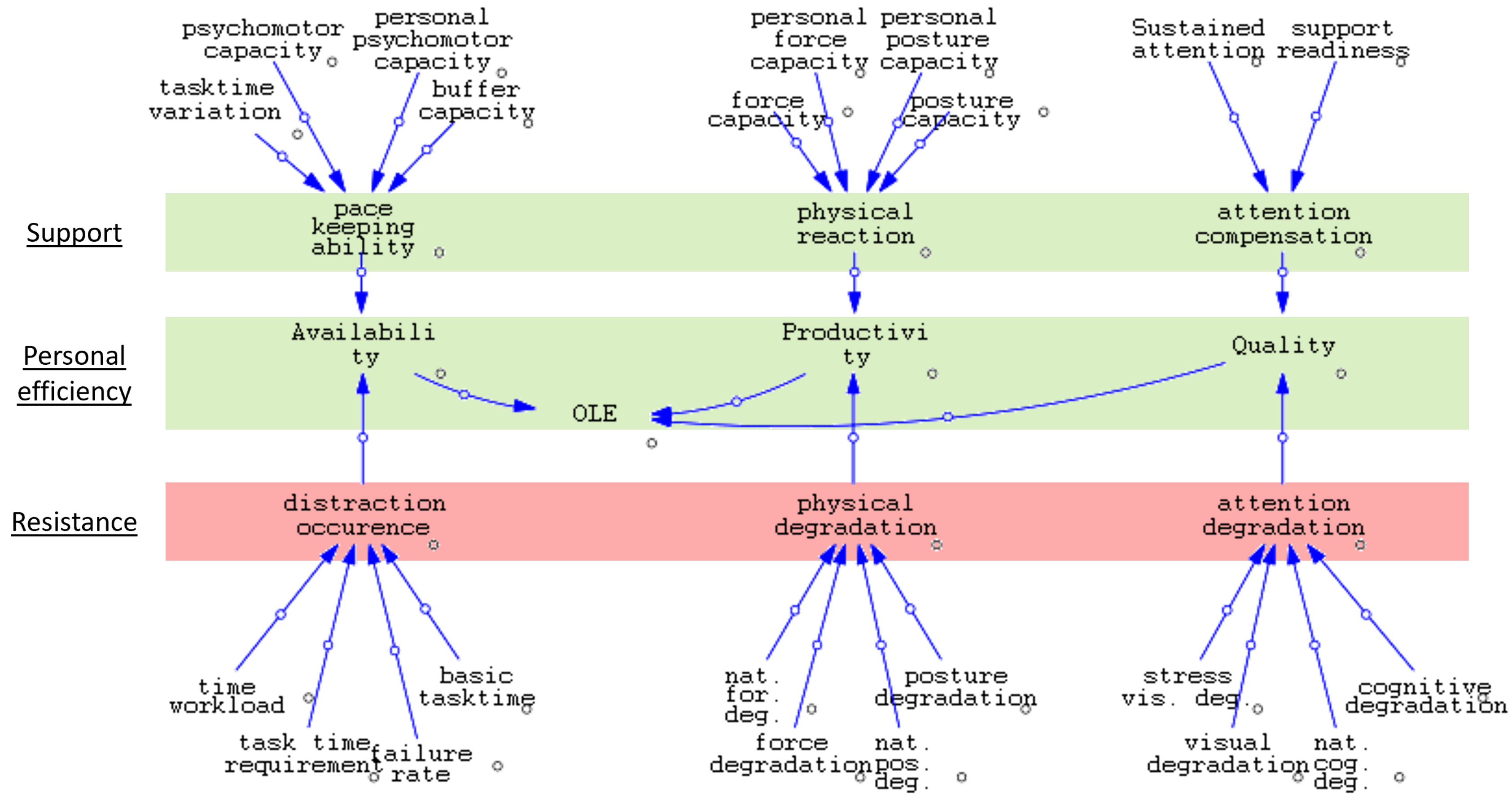


Figure B.5: The personal initial work capacities are defined based on the personal profiles

Table B.1: Model important variables with value and equation.

	Variable (#)	Explanation	Value/Equation
Personal profile	Work experience (C)	The positive effect on personal initial cognitive and psychomotor capacities, task demand threshold.	A lookup function by year value from an exponential curve.
	Age effect (C)	The negative effect on all personal initial capacity (except time).	A lookup function by year value from an exponential curve.
	Physical impairment (C)	The negative effect on all personal initial capacities and capability threshold.	A lookup function by impairment score (assessed by the physical performance test [R444]).
	Shift work (C)	Zero effect for the day shift and a negative effect for the night shift.	A lookup function by working hours from shift beginning.
	Sleep quality (C)	The negative effect on all personal initial capacities and capability threshold.	A lookup function by sleep quality score [R445].
	Chronic stress effect (C)	The negative effect on stress endurance.	A lookup function by allostatic load level (assessed by biochemical marker [R446]).
	Job motivation (C)	The positive effect on stress endurance.	A lookup function by work motivation score [R447].
	Training experience (C)	The positive effect on all personal initial capacities.	A lookup function by training hours.
	Learning ability (C)	The positive effect on personal task time and task time variation.	A lookup function by the number of finished products from the learning curve [R448].
	Skill decay (A)	The percent of task time variation.	A lookup function by hours of working from the skill decaying curve [R345].
	Problem-solving ability (C)	The positive effect of individual problem-solving skills on reducing the perceived workload from occurring failures/problems.	A lookup function by the personal problem-solving score [R449].
	Stress endurance (A)	The personal threshold for different types of stress.	Stress endurance = - Chronic stress effect - Sleep quality - Weekly working hours
	Task demand threshold (A)	Personal threshold for perceived situational demand.	Task demand threshold = Basic task load* + Job motivation + Work experience
	Capability threshold (A)	Personal threshold for working capacity degradation.	Capability threshold = Average of Natural degradation rates - Physical impairment
	Stress threshold (C)	Personal threshold for different types of stress.	Stress threshold = Lookup functions by perceived stress score [R450] for each type of stress + Stress endurance.
Circumstantial stressor	Environmental disturbance (C)	Zero effect if the environment is in normal condition, negative effect with unfavorable conditions.	A lookup function by environmental comfort parameters [R451]
	Work pace (C)	The predefined value for work pace between incoming tasks.	An input constant in minutes.
	Buffer capacity (C)	The task time variation that is allowed by the number of work-in-process buffers.	A lookup function by buffer quantity.
	Pattern change (C)	The positive effect on reduced cognitive workload and psychomotor degradation.	A lookup function by the boredom cost of employee [R452].
	Ergonomic layout (C)	The positive effect on reduced posture and psychomotor workloads.	A lookup function by RULA [R453] score.
	Support readiness (C)	The positive effect from external support on cognitive capacity.	A lookup function by social support score (assessed by JCQ [R259])
	Weekly working hours (C)	The negative effect on stress endurance.	A lookup function by weekly working hours from an exponential curve.
	Failure rate (C)	The occurring rate of failure/problem.	An input constant in minutes.

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	Variable ([#])	Explanation	Value/Equation
	Body asymmetry (C)	The percentage of asymmetry when using body parts.	An input constant in percent.
	Finished products (A)	The accumulating number of finished products after incoming task.	Finished products = Task schedule / (Work pace + Actual task time)
	Problem complexity (C)	The difference of additional workload caused by problem compared to the basic task load.	An input constant in percent, with different values for different complexity levels.
Initial condition	Initial personal capacity* (A)	The work capacities of each individual (except time) at the beginning of work session, depending of personal profile and the circumstantial stressors in the assigned position.	Initial personal capacity = 100 - Effect from personal profile + Effect from Circumstantial stressor
Initial condition	Task time variation (A)	The percent of time variation from preferred basic task time, depending on the individual skill level with the tasks in the assigned position.	Task time variation = Training experience + Learning ability + Skill decay
Work load	Basic task load** (C)	The personal preference of task load, measured for each individual.	An input constant in REEDCO Score, Newton, seconds, and VACP score respectively.
Work load	Task load** (A)	The task requirement, designed by industrial engineers.	An input constant in REEDCO Score, Newton, seconds, and VACP score respectively.
Work load	Workload** (A)	The perceived difference between basic task load and incoming task load, of each task load component.	Workload = (Task load - Basic task load)/Basic task load + Dynamic effect from circumstantial stressors
Work load	Task schedule (C)	The timing of incoming task.	An input sequence of 0 and 1, indicating the status of idle and incoming tasks during the working duration.
Work load	Problem occurence (C)	The timing of happening problems, as a sequence of 0 and 1, with 1 indicating the occurrence of problem/failure.	An input sequence * Problem complexity
Work load	Working process (A)	A sequence of 0 and 1, representing the schedule of generated incoming tasks and occurring problem/failure.	Task generation = IF THEN ELSE (Task schedule + Problem occurrence = 0 , 0, 1)
Personal capacity	Working capacity * (S)	The current level of working capacities of each individual, started from the "Initial personal capacity" in the beginning and degraded throughout the shift.	Personal capacity = Personal initial capacity - Total degradation
Personal capacity	Actual task time (A)	The duration that the worker finishes a task.	Actual task time = Basic task time * (100 + Random value of (Task time variation))
Personal capacity	Natural degradation * (C)	The capacity degradation rate in a normal working session.	An input constant in percent per minute.
Personal capacity	Stressed degradation * (A)	The degradation rate that happens during stressful working duration.	Stressed degradation = Stress effect on capacity degradation
Personal capacity	Total degradation * (F)	The total degradation of a working capacity at a certain time	Total degradation = Natural degradation + Stressed degradation
Stress mechanism	Average situational demand (A)	The average demand from the perceived workload.	Average situational demand = Average of all Workload
Stress mechanism	Average capability degradation (A)	The average degradation of working capacity.	Average capability degradation = Average of all Working capacity
Stress mechanism	Perceived situational demand (A)	A sequence of 1 and 0 indicating the status of considering the current task demand exceeds the personal threshold or not, respectively.	Perceived situational demand = IF THEN ELSE (Average situational demand $\geq$ Task demand threshold, 1, 0)

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	Variable (#)	Explanation	Value/Equation
	Perceived capability degradation (A)	A sequence of 1 and 0 indicating the current capacity degradation exceeds the personal threshold or not, respectively.	Perceived capability degradation = IF THEN ELSE (Average capability degradation $\geq$ Capability threshold, 1, 0)
	Perceived demanding task (A)	A sequence of 0 and 1 indicating the status of considering the incoming tasks as not demanding and demanding, respectively.	Perceived demanding task = IF THEN ELSE (Perceived situational demand = 1 :AND: Perceived capability degradation = 1 , 1, 0)
	Stress accumulation rate (F)	The accumulation of each type of stress when perceiving the current task is demanding.	Task schedule * Perceived demanding task * stress unit
	Stress value (S)	Accumulated values of each type of stress.	Stress value = Stress accumulation rate - Stress relaxation rate
	Stress effect on perceived load (A)	The additional load from stress types on perceived workload, negative value (reduced perceived workload) in case of sustained attention, positive value in other cases (increased perceived workload).	Stress effect on perceived load = (Stress value / Stress threshold) * Workload
	Stress effect on capacity degradation (A)	The effect from stress, negative value in case of sustained attention, positive value in others.	Stress effect on capacity degradation = (Stress value / Stress threshold) * Natural degradation
	Stress relaxation rate (F)	The natural relaxation rate from stress value, that is in effect while there is no incoming task, or that stress is not accumulating.	Stress relaxation rate = IF THEN ELSE (Task schedule = 0, (Stress value - Stress threshold) / Stress threshold, 0)
Performance profile	Pace keeping ability (A)	The ability of each individual to keep the "basic work pace" during the working session.	Pace keeping ability = Task time variation + (Psychomotor capacity / Personal initial psychomotor capacity) + Buffer capacity
	Distraction occurrence (A)	The probability of distraction or finishing the task late.	Distraction occurrence = Failure rate + (Time task load / Basic task time) + (Work pace / Basic work pace)
	Physical reaction (A)	The readiness of physical reaction to perform expected work movement.	Physical reaction = Posture capacity / Personal initial posture capacity + Force capacity / Personal initial force capacity
	Physical degradation (F)	The degradation of physical capability to meet the planned productivity demand.	Physical degradation = Posture stress degradation / Total posture degradation + Force stress degradation / Total force degradation
	Attention compensation (A)	The positive effect of Sustained attention on quality performance.	Attention compensation = Stress effect on perceived load (with the value of Sustained attention) + Support readiness
	Attention degradation (F)	The degradation of quality-oriented attention.	Attention degradation = Visual stress degradation / Total visual degradation + Cognitive stress degradation / Total cognitive degradation
	Availability (A)	The probability that the worker is ready for incoming tasks.	Availability = Pace keeping ability - Distraction occurrence
	Productivity (A)	The probability that the worker is able to perform correct task movement in time.	Productivity = Physical reaction - Physical degradation
	Quality (A)	The probability that the worker can produce a task output that meets quality expectation level.	Quality = Attention compensation - Attention degradation
	OLE (A)	The personal probability of effective work.	OLE = Availability * Productivity * Quality

#: C: Constant / A: Auxiliary / F: Flow / S: Stock
*: posture/force/visual/auditory/cognitive/psychomotor (except "time")
**: posture/force/time/visual/auditory/cognitive/psychomotor
stress: sustained attention / acute stress / chronic stress

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