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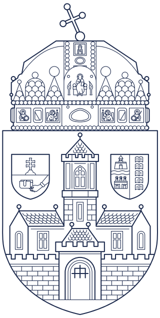
PhD Theses summary



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

by

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Contents

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
RTLS	Real-time Location System
VSM	Value Stream Mapping
WEBA	Work-content Effect on a BArista
WHO	World Health Organization

1 Background of the research

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 Industry 4.0 (I4.0) [R1], 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 [R2], production time [R3], energy [R4], and operational cost [R5]. Lean 4.0 is a new generation of LM with the implementation of I4.0 technologies [R6], creating a unique effect for LM deployment in the operational strategy, and in designing, operating, monitoring, and optimizing manufacturing systems [R7]. An integrative model for LM and I4.0 resulted in a flexible and reconfigurable manufacturing system [R8]. I4.0 technologies enabled the integration of human operators with manufacturing processes and equipment into Human-Cyber-Physical Systems (H-CPSs) [R9, R10] as a new generation of workers (i.e., Operator 4.0 (O4.0) [R11]), with O4.0 types corresponding to different core I4.0 technology gadgets [R12, R13]. 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 [R14]: Humans should never be subservient to machines and automation, but machines and automation should be subservient to humans. The Industry 5.0 (I5.0) paradigm was formulated by the European Commission (EC), calling for a sustainable, human-centric, and resilient European industry [R15]. Fostering the transition toward the I5.0 will be the key objective of every modern economy. 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) [R16, R12], which aims at a socially sustainable manufacturing workforce, proposing resilience requirements for human operators and human-machine systems.

However, there are gaps and hurdles within the manufacturing companies when they want to apply Lean 4.0 and O4.0 solutions in front of the I5.0 era. Not all companies invest in newly released and modern machinery. Many older generation devices lack connectivity but still perform good operations, even though the operational collaboration, power consumption, and carbon emission are not as good as new ones. Many industries adopt the retrofitting approach [R17], each facing different problems integrating legacy equipment into the I4.0 environment. The need for retrofitting solutions emerges in Small and Medium-sized Enterprises (SMEs) [R18], which is the most vulnerable object of being left behind in the I4.0 development [R19]. 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. Besides the scattered development, 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 [J1], despite a growing research interest in human factors within manufacturing systems. The O4.0 is expected to naturally evolve into O5.0, but both paradigms are underdeveloped since their common key element (i.e., human-centricity) is still underappreciated [R20], suggested by a low number of studies and disruptively connected keywords. Though the transition toward I5.0 is inevitable with many appearing signs, a lack of foundation and technical readiness toward O5.0 still exist.

2 Research objectives

This thesis especially looks for solutions that utilize sensor technologies and data sciences, to support the implementation of Lean 4.0 and O4.0 solutions, thus addressing the industrial problems within the previously stated context. Without high investment in new equipment and technologies, companies can retrofit existing equipment with the Internet of Things (IoT) capability to adopt the I4.0 [R21]. I studied how sensor technology can be deployed in retrofitting and Lean 4.0 projects. The ultimate goal of retrofitting is the readiness of KPIs, which give insight into a real-time system operation [R22]. The potential of Lean 4.0 is unlocked by the integration of operational technology (OT) and information technology (IT) as IT tools can improve the real-time value stream. One of the most promising Lean-enabled IT tools is the Indoor Positioning System (IPS) [R23]. I studied the use of IPS for the implementation of Lean 4.0, and proved that 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.

Observation with Gemba walk is the most popular method for assessing human performance in LM [R24]. With I4.0 technologies, innovative ways are expected to replace this traditional expert-dependent and time-consuming method. I developed a Lean 4.0 solution for assessing worker performance with the Microsoft Kinect sensor, with its advanced 3D depth-sensing technology [R25], marker- and calibration-free characteristics are appropriate for industrial application [R26]. 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, with a continuous improvement approach based on LM philosophy.

The current development of O4.0 is scattered and intermittent with lack of human-centered configuration and customization [J1], despite a growing research interest in human factors within industries. Psychological stress should be incorporated into the Human Digital Twin (HDT) as a vital role in human behavior and performance [R27, R28]. To further integrate humans into the Human-Cyber-Physical System (H-CPS) [R29], more knowledge should be developed to understand the effect of work content and environmental setup [R30, R31] on human workers, as well as their stress-performance relationship. I elaborated a foundation for the O4.0 stress-performance monitoring and simulation solutions, enabling the timely adjustment of any unfavorable work content to optimize worker performance, with several research topics as follows.

Stress recognition by assessing Heart Rate Variability (HRV) is scientifically proven by neurobiological evidence [R32, R33]. I explored the available evidence on HRV as an indicator of Acute Work-Content Related Stress (AWCRS) in a manufacturing environment, thus providing a basis for JITAI to avoid any long-term accumulation of occupational stress. An in-depth Human Digital Twin (HDT) with human details and functional status [R34] is expected to simulate, predict, and monitor the well-being of human workers/operators in I5.0. I developed a system dynamics conceptual model for the simulation of AWCRS and the performance of human workers. Psychological stress is incorporated as a vital role in human behavior and performance [R27]. The lack of controlled experiments and validated evidence prevents the applicability of physiological parameters (i.e., HRV) as indicators for AWCRS [J2]. 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. I explained how the Work-content Effect on a BArista (WEBA) dataset can be generated, which facilitates further study of the Acute Work-Content Related Stress effect on human performance.

3 Materials and methods

During my research, mixed methods from both theoretical and practical viewpoints are used such as literature research, simulation, and case studies. Systematic literature reviews were deployed to collect and analyze data from relevant research in the following areas, thus establishing the context for the later research and proposed theses:

- Retrofitting: to analyze the possibility of using sensor technology for digitalizing legacy manufacturing systems, thus deploying data-enabled management strategies. The data collected includes information about the development context, used sensors, and deployed strategies from reported industrial retrofitting projects.

- Current development of Operator 4.0/5.0 concept: to predict the expected contribution from future O4.0/5.0 technological solutions. The data collected includes information about used technology, usage context, and supported human-centric performance from reported O4.0 use cases.

- The use of HRV as an indicator of AWCRS: to look for evidence of using HRV as AWCRS indicator of different work content factors. The data collected includes the Population, Interventions, Control, and Outcomes (PICO) from experiments that test the response of human subjects against different work content factors.

System dynamic simulation was used to replicate the effect of each work content factor on the perceived workload, stress, and performance of workers. Case studies were conducted in real-life sites with the deployment of sensors, including manufacturing facilities, to collect practical data, thus enabling further data analysis and solution development. The collected data are:

- Use case 1: IPS data of material carts in a manufacturing facility, with supported production data such as process steps and timestamps from the MES system, and technical data such as facility layout, used machine, and product information.
- Use case 2: Skeleton data from Kinect sensor from an electronic assembly line.

One dataset collection effort was conducted in a chosen environment, to generate a dataset for further study on the effect of work content on human performance. The data collected are heart rate and acceleration data from a real-life work environment, with activity logs. The data science and data mining tools used on these collected data are:

- Review on current development of Operator 4.0/5.0 concept: Text mining and BERTopic were applied to the abstract texts which are collected from included articles from query search, to find the emerging trends and prominent topics in the field.
- Use case 1: Process mining was applied to the IPS and MES data collected in the first use case, to reconstruct the model of manufacturing processes.
- Use case 2: kNN clustering and linear classification were applied on the hand coordinates from skeleton data. Then motif searching with matrix profiles was used to pattern-mine the work characteristics, thus automatically generating the ergonomic assessment.

4 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.

Publications relevant to the thesis: [J3, J4, J5].

The architecture and usage of IPSs are elaborated, and their possible application in the Lean 4.0 system is discussed. The proposed system helps gather informative data from manufacturing systems and aids in monitoring the production process, according to LM principles and the Lean 4.0 parameters that are derived automatically from the acquired data by using process mining techniques. An alarm can be set up at each workstation to notify if the work in that station will exceed the standard allowable time in the next few minutes; then, the line advisor can take required supportive action on time. A case study is conducted in a mechanical manufacturing firm to show the possible output of Lean 4.0 KPIs. The suggested framework for process analysis provides the basis for further system optimization, which directly removes waste and enhances human-machine activity cooperation in a firm.

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: [J6].

An approach of pattern mining the Kinect sensor skeleton data to assess human worker performance is proposed, with a Python package for post-processing the skeleton data from the Kinect sensor developed, specialized for Industry 5.0- related human-centric improvement projects for manufacturing processes. The process takes advantage of supervised learning and motif-searching algorithms to discover the characteristics of work movement. The elementary movements and times with associated patterns can be collected and analyzed for line balancing purposes, and variance monitoring for real-time production. The mined patterns reflect the working behavior of the workers. The assessment result can be utilized for performance enhancement and individual and systematic human-centric improvement in the short and long term. 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.

A use case on an electrical assembly line validated the approach, with the work movements segmented, the work behavior can be diagnosed, and these data can be used to develop a HAR model for recognition and prediction. 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 benefit the organization in both the short and long term and facilitate the Lean 4.0 transformation.

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: [J7, J2].

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, like 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 and task requirements.

Our dataset is introduced as a reflection of the effect of work content on personal workload perception and performance 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. 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 dataset contributes a missing piece of evidence enabling in-depth studies about the applicability and reliability of HR as an AWCRS indicator [J2], and facilitating further development of understanding the work content effect on labor performance and well-being. 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.

5 Industrial applications of the results

5.1 Application of IPS for the implementation of Lean 4.0

The proposed IPS with the redefined set of Lean KPIs that can be derived automatically from IPS-based data can facilitate the digitalization and Lean 4.0 implementation by using IPS as a retrofitting solution. Fig. 1 shows that the proposed methodology supports the Plan-Do-Check-Act (PDCA) cycle of Lean 4.0 continuous improvement. The core element of the method is the process model (represented as the VSM block) generated from IPS data, which contains all the essential information about the manufacturing process.

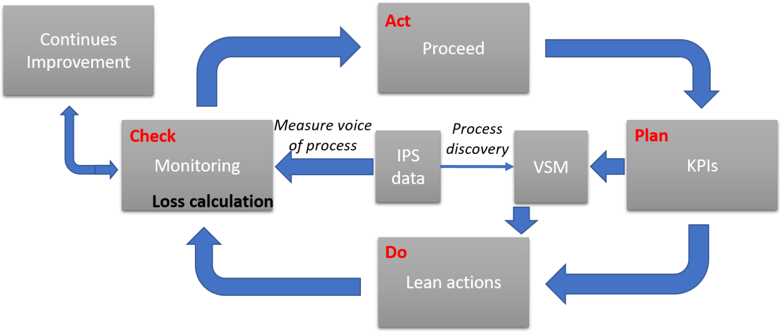

Figure 1: IPS data is the key element of the proposed PDCA cycle-based methodology

The proposed method enables further system optimization, which assists managers in monitoring their system, or in further optimization and enhancement of human-machine activity cooperation.

5.2 Application of Kinect sensor for real-time human performance assessment in an electrical product assembly line

The approach of pattern mining the Kinect sensor skeleton data to assess human worker performance was proposed to complement the fact that on-the-shelf production management softwares are not incorporated with a Machine learning model to recognize patterns of human action. A Python package for post-processing the skeleton data from the Kinect sensor is developed, specialized for Industry 5.0-related human-centric improvement projects for manufacturing processes. The assessment result can be utilized for performance enhancement and individual and systematic human-centric improvement in the short and long term.

The overall initiative is depicted in Fig. 2 with a PDCA framework established around the organizational database of movement records from workers. The induced details from the result help understand the work ergonomics, thus contributing to the Healthy Operator pillar of the O4.0 concept. 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.

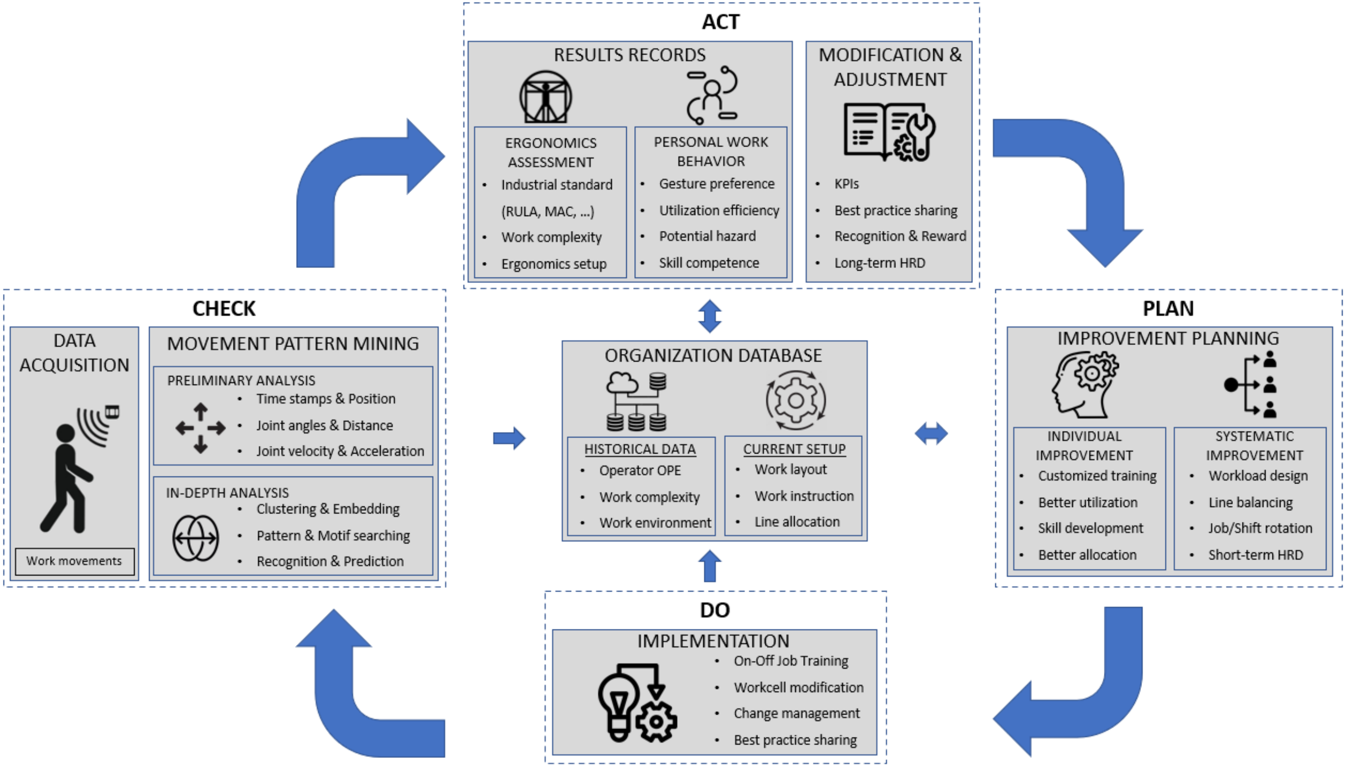

Figure 2: The proposed PDCA circle with pattern mining framework.

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