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# Towards Industry 5.0 - A Neuroergonomic Workstation for Human-Centered Cobot-Supported Manual Assembly Process

Nikola Knežević<sup>1</sup>, Andrej Savić<sup>1</sup>, Zaviša Gordić<sup>1</sup>, Arash Ajoudani<sup>2</sup> and Kosta Jovanović<sup>1</sup>

**Abstract**— This paper brings the concept of neuroergonomic workcell with its essential components (psychological and physical assessment, non-physical, physical and strategic support) for improving the well-being and productivity of workers at their workplaces. A proof-of-concept neuroergonomic human-centered workstation is demonstrated in a real factory environment for a typical industrial laborious task - assembly. The pilot workstation introduces a fully portable, non-invasive electroencephalogram-based (EEG-based) users' mental workload assessment, a non-obtrusive human-machine interface, illustrative graphical assembly guidelines, a cobot assistant, and an intelligent task scheduler. The subjects' performance and workload were assessed using a NASA-TLX questionnaire, three EEG workload indices, hand gesture detection accuracy, number of errors, and task duration. We identified a notable correlation between multiple EEG indices of workload and NASA score results. The new workstation boosts productivity with better performance and fewer errors on the assembly line while reducing mental demand. Its modular design ensures easy integration and adaptation into factory settings, optimizing manual assembly processes.

## I. INTRODUCTION

Over the past decade, the focus of industrial development has been on increasing productivity and efficiency, relying on technological progress in areas such as artificial intelligence, robotics, automation, and the Internet of Things (IoT). Although the deployment of the concept of Industry 4.0 has yielded significant results, some tasks that demand a high combined physical and cognitive load cannot be adequately automated and still require the engagement of human workers [1]. This necessity has led to the development of a human-centered industry concept, the main pillar of Industry 5.0. In addition to efficiency and productivity, Industry 5.0 needs to prioritize human well-being, encompassing safety, health, and satisfaction. Proposals and initial scientific explorations of the Industry 5.0 concept signal a growing interest in this paradigm shift; however, comprehensive studies and extensive literature on this topic are still in their infancy [2].

Considering current technological advancements in the field of robotics, the use of collaborative robots presents an opportunity for the development and integration of a human-centered industry in various application areas [3]. Moreover,

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there is a growing interest among researchers in assessing the cognitive aspects and effects of human-robot collaboration, in line with Industry 5.0 requirements. While the use of collaborative robots may often be directed to offload work from the operator onto the robot, the introduction of cobots can increase the cognitive load on the user due to heightened task complexity and the requirements for situation awareness [4].

Such challenges can be tackled by applying principles derived from the field of neuroergonomics, an emerging interdisciplinary domain that explores human brain function and its correlation with everyday behavior in real-world contexts [5]. Concerning applications in the human-centered industry, neuroergonomic research aims to utilize brain signals, such as electroencephalographic (EEG) measures or eye gaze tracking, to identify workers' mental states and estimate mental workload levels [6]. Additionally, significant efforts have been made to create a "wearable EEG," allowing long-term recording of brain activity in out-of-lab contexts and during dynamic real-life activities [7]. This has resulted in the development of wireless and miniaturized EEG acquisition systems and fast-mounting EEG sensors integrated into various types of garments and accessories, such as caps, headphones, or hairbands. Such hardware developments, along with advances in signal processing and machine learning, further facilitate neuroergonomic research and practices.

In summary, Industry 5.0 envisions a harmonious integration of human skills with advanced technologies, emphasizing collaboration, efficiency, and well-being, while taking into consideration both physical ergonomic concepts focusing on human physical activity and cognitive ergonomics addressing mental state processes, such as cognitive workload and decision-making [8]. This approach is particularly well-suited for advancing manual assembly labor, which plays a crucial role in the industry, particularly in manufacturing and production operations [9]. A manual assembly task involves workers assembling as many products as they can in one work shift, with one worker assigned to one type of product for an extended period. Manual assembly tasks can lead to specific musculoskeletal strain and harm, saturation in motivation, and decreasing focus while increasing mental workload due to monotonous and repetitive operations. Numerous previous studies have highlighted the benefits of transforming manual workstations into human-robot collaborative environments [10], [11].

Various methods have been employed in such scenarios to measure cognitive workload, including subjective ques-

tionnaires like the NASA Task Load Index (TLX) [12]. Objective methods to capture cognitive workload include bio-instrumentation, specifically EEG brain monitoring. While many EEG studies have been conducted to estimate indices of workload in various conditions, there is a very limited number of studies exploring human-cobot interaction using EEG measurements, particularly in realistic, out-of-lab contexts [13].

The aim of this paper is to present a novel concept of a scalable and adaptable neuroergonomic workstation design to support the manual assembly process, aiming to bridge the gap between Industry 4.0 and the human-centric approaches of Industry 5.0 by focusing on supported assembly tasks through neuroergonomics and collaborative robots. The integration of neuroergonomics concepts and collaborative robots in these workstations promises to revolutionize not only the assembly process and its efficiency but also to endorse human well-being—the fundamental pillar of Industry 5.0. The proposed neuroergonomic workstation adapts the modular design for users' psychological assessment, physical assessment, non-physical support, physical support, and strategic support.

The novelty of this paper is reflected in newly developed or adapted reusable modules of the neuroergonomic workstation which are fully open to the industrial and research community as well as demonstration of easily deployable and scalable neuroergonomic workstation real industrial settings. Therefore, modules of the presented workstation incorporate the state-of-the-art key components and neuroergonomic design principles: sensors (wireless and wearable EEG system, gesture recognition system), actuator (collaborative robot), intelligent decision-making algorithms for real-time sensor data analysis, software and interface (user interface, integration to IoT infrastructure), scalability and adaptability and safety features.

The impact of the paper is reflected in the proposed methodology and concept with the potential for widespread applicability across diverse industries that rely on manual human labor in their production processes. Unlike conventional approaches, the proposed system leverages the unprecedented capability to monitor workers' cognitive states during dynamic, real-world assembly tasks, providing a solution that addresses the intricate cooperation between human cognitive abilities and robotic physical capabilities in industrial settings.

The conceptual overview of a neuroergonomic workstation is introduced in Section II, followed by a pilot realization of a neuroergonomic workstation for the concept validation in Section III. The experimental protocol to distinguish neuroergonomic workstations and regular working routine outputs is defined in Section IV. The methodology for assessing the impact of the pilot is described in Section V, while the results are presented in Section VI. The effectiveness of improving work productivity while improving worker satisfaction is discussed in Section VI.

## II. NEUROERGONOMIC WORKSTATION - CONCEPTUAL OVERVIEW

In general, the architecture of a neuroergonomic workstation system is tailored to optimize worker satisfaction, productivity, and safety in real-world work environments. The general architecture of such workstations incorporates five core components (type of modules):

- 1) Modules for assessment of workers' physical states (monitoring or prediction of worker s' motion and/or ergonomics) which encounter motion sensors (e.g. cameras, IMU, infrared);
- 2) Modules for assessment of workers' psychological (mental) states including brain-computer interfaces or gaze tracking systems;
- 3) Modules for physical support (protecting musculoskeletal structure or augmenting physical capabilities – power or precision) including collaborative robots or exoskeletons;
- 4) Modules for non-physical support (visual or audio) such as novel user interfaces, augmented or mixed reality;
- 5) Modules for strategic support based on domain expert systems, data analytics and IoT technologies for reliable and efficient data exchange among modules, thereby serving as a foundation for intelligent workstation planning.

The first two types of modules represent Human-Machine Interfaces (HMI), whose neuroergonomic design prioritizes non-invasiveness and non-obtrusiveness, minimizing disruptions to workers' established routines. They play crucial roles in understanding human factors within an industrial workstation. The next two types of modules facilitate interactive engagement with workers, thereby augmenting efficiency and improving ergonomic conditions. Additionally, strategic modules play a pivotal role in enhancing task allocation, promoting both worker satisfaction and overall production performance.

The shift from Industry 4.0, which is performance-centered, to Industry 5.0, which is human-centered, presents challenges that must be addressed, particularly in relation to human factors [1], [8]. In this paper, we propose five core components to facilitate the human-centered, neuroergonomic design of workplaces. These components aim to enhance human well-being while improving process performance. In this new paradigm of Industry 5.0, process performance must consider not only production metrics such as task execution time or device assembly rates but also factors like human satisfaction, the time required to onboard newcomers (including unskilled workers) to a production process, and the reduction of mental workload for individual workers.

To address these newly raised challenges, it is essential to conduct proper assessments of human psychological and physical states by developing modules capable of providing more meaningful insights into human workload and actions. Subsequently, by providing appropriate physical and non-physical support to human workers, the new core components

of Industry 5.0 aim to address these challenges by introducing a neuroergonomic workplace that will enhance process performance in Industry 5.0.

### III. NEUROERGONOMIC WORKSTATION - PILOT REALIZATION

The goal of the experimental part of this study was to provide proof-of-concept validation of the developed workstation. Our primary objective was to assess the performance of each module of the workstation and the system as a whole. Moreover, we assessed its deployment potential within a real factory environment, with a trained professional in manual assembly as well as workers naive to the system.

The task considered in this paper is a typical assembly task of devices assembled manually due to their design, which is not suitable for automated assembly. All necessary components are stored in boxes in front of the worker. The worker needed to pick the correct pieces that were to be assembled, in the exact order and use appropriate tools (screwdriver, glue, soldering iron, etc.) and operations to perform the assembly task. A worker was usually assigned a specific type of device that had to be assembled over the course of one or more workdays. Any product complaints and related economic and reputation losses of the company are directly related to assembly errors, putting additional pressure on assembly line workers. This type of task can sometimes be monotonous and repetitive, which can cause the worker to lose focus and not be engaged enough to execute assembly tasks properly. However, assigning different assembly tasks to one worker may lead to another set of challenges, related to a lack of assembly routine, difficulties remembering the exact assembly procedure, required parts, and order of operations, etc.

The objective of the proposed neuroergonomic workstation is to enable cobot-assisted manual assembly of various products, which is a widespread industrial task. To ensure the safe execution of assembly tasks, the design of the system must take into account the optimal position of the worker, the cobot, and accompanying HMI displays and sensors for estimating vital worker parameters and intentions. The design needs to minimize non-ergonomic worker positions to enable the work process to be carried out in a manner that maximally reduces the risk of injuries and unwanted incidents. This approach involves creating an environment that is tailored to the worker, enabling task execution with minimal physical strain and reducing the risk of occupational diseases, as well as decreasing the cognitive workload. With that in mind, the proposed system was designed so that workers perform assembly tasks in the so-called golden zone [14]. This means that the need for stretching and twisting is minimized. The cobot is placed in a position that will minimally occupy the worker's personal space. Also, the adaptive interface and sensor for hand gesture recognition are placed in an ergonomic position.

The assembly process starts when a product type that needs to be assembled is assigned to the worker by the Smart Task Scheduler acting as a Strategical Support Module.

Throughout the assembly process, the worker can follow the assembly instructions provided by the adaptive user interface, including the necessary parts and tools to be used as well as a description of actions to be taken. The assembly instructions are followed using the Adaptive Interface (ADIN)<sup>1</sup> - Non-physical Support Module. This module enables the creation of a new set of instructions, including text and pictures, and it can easily be modified by authorized users to add product assembly instructions in the future. At the beginning of each assembly step, a collaborative Franka Emika Panda robot, acting as a Physical Support Module, takes the necessary parts from storage and brings them to the human worker in a convenient position. In case of need, stocks can be replenished with new components while assembly is ongoing. After picking the necessary parts from a bin held by the robotic gripper, the human worker signals with a hand gesture that the parts were taken, and the robot moves to pick parts for the next step. Multi-Modal Offline and Online Programming – Leap Motion (M202P-L)<sup>2</sup> Physical Assessment Module, is used to classify the hand gestures of the user based on the Leap Motion sensor. The outputs from this module are used to synchronize ADIN-powered instructions and robot assistance with the progress of assembly by the worker. Throughout the assembly, wireless EEG sensors integrated within mBrainTrain Smartphones, based on semi-dry signal recording technology, measure electrical brain activity used by the BrainWatch<sup>3</sup> Psychological Assessment Module to extract indicators of worker's engagement and mental workload. The information from the BrainWatch module is used to make decisions regarding the optimized assignment of the next product type assembly to the human worker.

The high-level architectural diagram of the deployed technical solution is illustrated in Fig. 1. The BrainWatch, M202P-L, Cobot, and Smart Task Scheduler modules were custom-developed for this study. Nevertheless, the ADIN module, as a component available for the SHOP4CF<sup>4</sup> portfolio, was adopted to project to fully meet all requirements of a neuroergonomic cobot-supported assembly workstation.

The pilot workstation and individual modules developed within the scope of the project SHOP4CF are open-source and available on the project platform.

All components of the solution use FIWARE as middleware [15]. FIWARE is an open-source technology, used for creating smart solutions, digital twins, and data spaces in various domains of digital transformation. By utilizing Smart Data Models and FIWARE, the integration of various systems with different communication protocols is ensured through data-driven approaches. The main benefit of FIWARE middleware is that the FIWARE is interoperable

<sup>1</sup>Adaptive Interface Module available on: <https://ramp.eu/#/component/6491a34c-221e-4c0a-84f1-a71ab09294d9>

<sup>2</sup>Multi-Modal Offline and Online Programming Solutions – Leap Motion available on: <https://ramp.eu/#/component/f642a89a-08b4-458d-be98-33f0fa613a92>

<sup>3</sup>BrainWatch Module available on: <https://ramp.eu/#/component/2bc9443a-fa9d-4ab9-a822-65681754b8c7>

<sup>4</sup>SHOP4CF: Smart Human Oriented Platform for Connected Factories: <https://shop4cf.eu/>

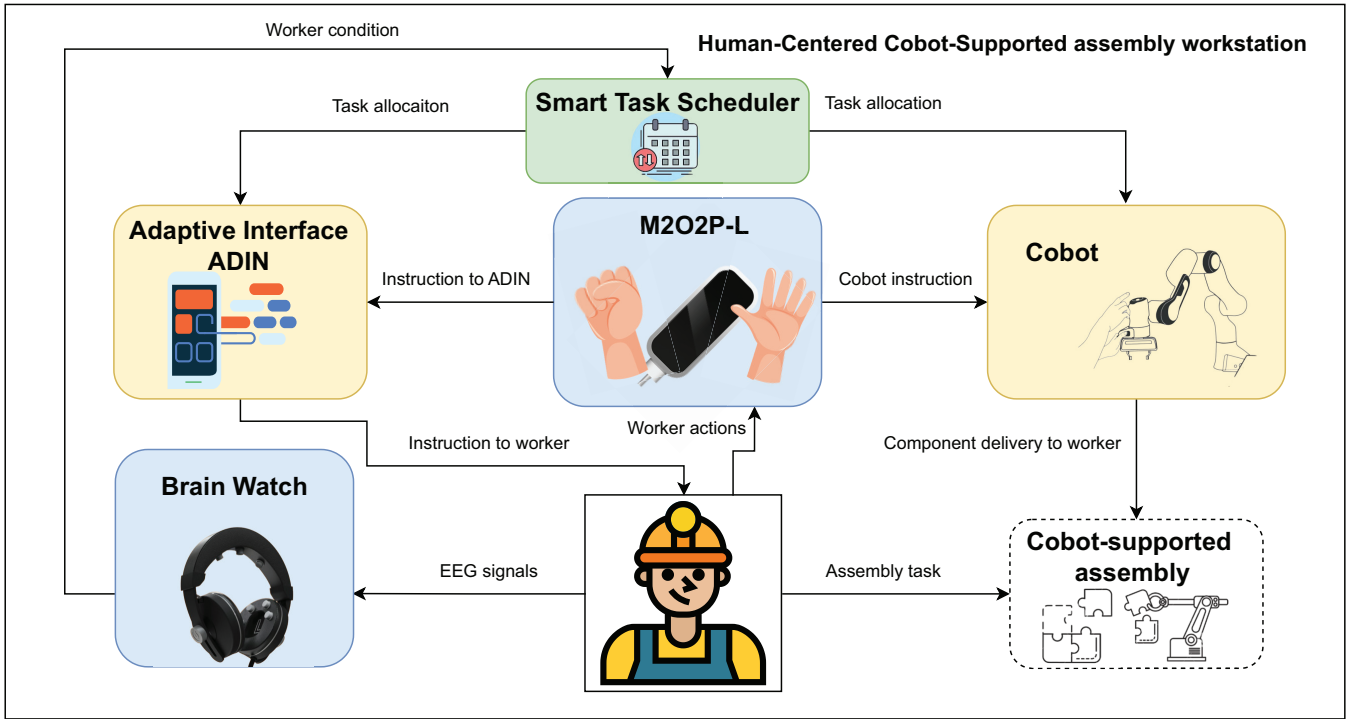


Fig. 1. Typical human-centered system architecture diagram: blue denotes input modules for mental (BrainWatch) and physical (M2O2P-L) worker assessment; yellow signifies output modules for physical (Cobot) and visual (ADIN) assistance to the worker; and green is the intelligent module (Smart Task Scheduler) for input-output mapping.

and vendor-agnostic. Also, using additional plugins available in the FIWARE portfolio, it is possible to integrate different, third-party systems (databases, robotics systems, IoT devices, sensors). FIWARE uses its Orion context broker (OCB) to receive, send, and process all data. Furthermore, in comparison to other available middleware using its unique context management can be exploited to dynamically handle and process data. All of this provides the possibility for greater flexibility and scalability of the proposed solution to promote ergonomic factors within neuroergonomic workstations. Enabling users with intuitive and fail-safe solutions for assessment of all above-mentioned human factors and promoting the well-being of workers.

In the following paragraphs, we will explain the purpose of each module/component within the system and the motivation/need behind introducing it into the manual assembly workstation based on previous knowledge and industrial needs.

#### A. Psychological assessment – BrainWatch module

The BrainWatch module is intended for online estimation of a user's mental workload during manual assembly tasks. This component comprises a commercial EEG device and a custom-developed algorithm for calculations of workload indices in real time. The EEG device used for this component is a portable system with wireless data transfer (Smarting MOBI), in combination with Smartphones with 11 semi-dry electrodes for recording electrical brain activity. This system has recently been validated for neuroergonomics and human-robot interaction research purposes [13].

The main indices of cognitive workload measured by BrainWatch and utilized in this study were theta-alpha ratio (TAR), theta-beta ratio (TBR), and engagement index (EI), calculated according to the following equations:

$$TAR = \frac{P\theta}{P\alpha},$$

$$TBR = \frac{P\theta}{P\beta},$$

$$EI = \frac{P\beta}{P\alpha + P\theta}.$$

where  $P\theta$ ,  $P\alpha$ , and  $P\beta$  represent the spectral powers in theta, alpha, and beta frequency bands, respectively. TAR is an index of workload and mental effort, based on the assumption that an increase in mental load is associated with a decrease in alpha power and an increase in theta power; TBR is associated with working memory, attention, and drowsiness, and assumes that an increase in alertness and task engagement results in an increase in beta power and decrease in theta power; while EI reflects the mental effort, vigilance, attention, alertness, and task engagement [16]. The BrainWatch module output is intended to be used as a decision support tool for the reallocation of tasks between workers, to reduce mental workload and increase overall workers' satisfaction in the process. The BrainWatch module provides output in the form of three values of cognitive workload indices, calculated online every 10 seconds. This output is used as a decision support tool for reallocating tasks among workers, aiming to reduce mental workload and increase overall worker satisfaction. An example of

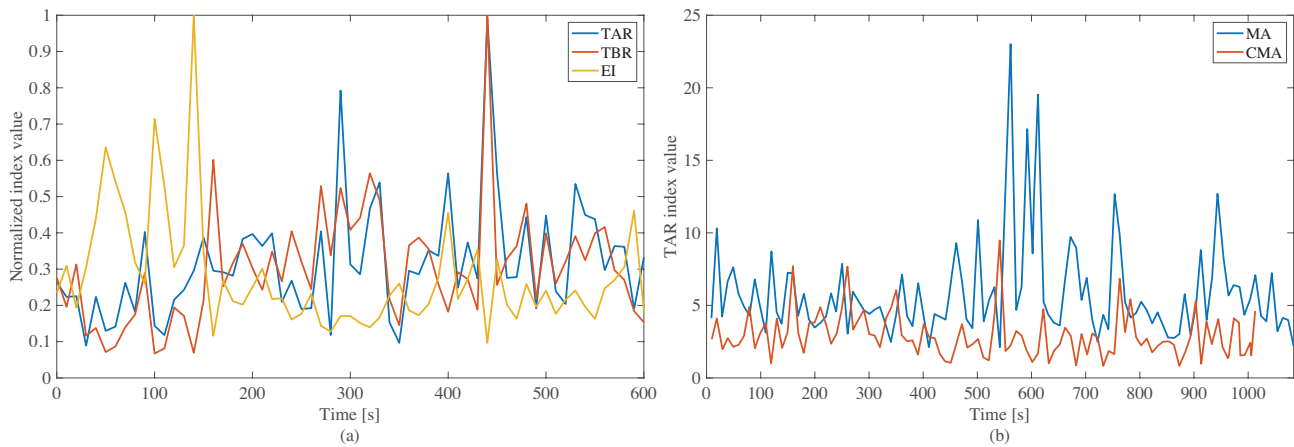


Fig. 2. EEG-based indices calculated inside the BrainWatch module. (a) - Example of all three indices during a task: TAR - blue; TBR - red; EI - orange. (b) - Comparison of TAR index in MA(blue) and CMA(red) scenario.

BrainWatch output during the assembly task is presented in Figure 2(a).

Figure 2(a), shows the BrainWatch module output (TAR, TBR, and EI curves) during the manual assembly task. For visualization and comparison, index values were normalized to 1. The BrainWatch module is configured to provide three index values every 10 seconds in real time during task execution. The Figure 2(b), depicts BrainWatch output of TAR index in two different scenarios (MA - manual assembly, CMA - cobot supported manual assembly). The Figure provides clear evidence of the benefits of using a neuroergonomic workstation in this initial study (smaller TAR index and shorter time in the CMA scenario).

### B. Physical assessment – M202P-L Motion Recognition module

The M202P-L module is based on the existing M202P [17] component from the Smart Human Oriented Platform for Connected Factories (SHOP4CF) project portfolio. Using a Leap Motion sensor, this component can recognize the presence of a human hand and detect hand gestures, in a non-intrusive way. An adequate dataset of different hand gestures needs to be created so that they can be detected properly. Although there are publicly accessible datasets of different hand gestures, a new dataset was formed because the structure of the available datasets was inadequate. In most of the available datasets, the hand was at a fixed height from

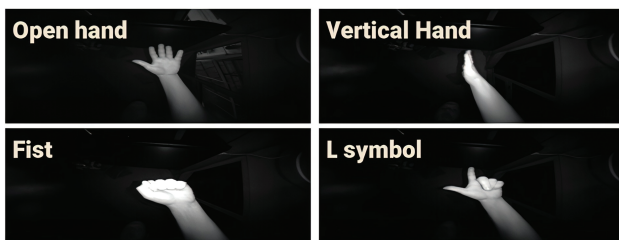


Fig. 3. Typical hand gestures that the M202P-L component can recognize.

the sensor, which will not be the case in real work scenarios. The dataset created for this study consists of four classes of hand gestures, with 5000 images of each. The module utilizes the VGG16 deep convolutional neural network to group hand gestures into four different classes. The classes analyzed are open hand, fist, vertical hand, and L symbol (Fig. 3.). The system outputs good performance on test data of 99.3%, where the recognition of the vertical hand is 100%, the L symbol 98.4%, and the open hand and fist 99.4% [18]. Also, the M202P-L component can be used in real-time applications because the whole process of detecting the hand and recognizing a gesture takes around 0.33 seconds. Different hand gestures can be reconfigured based on the production process needs. In the present case scenario, the open hand gesture was used to notify the system that the worker has finished the current assembly step, the fist gesture to roll back to the previous user guide page within the GUI of the ADIN module, and the other two hand gestures were left unused. Additionally, the M202P-L model can be extended and retrained to classify different hand gestures, if needed.

### C. Non-physical support – ADIN module

The ADIN module is connected to the FIWARE and SQL database as a visualization tool, also available in the SHOP4CF component marketplace. The database stores all information about each assembly sequence. Through FIWARE, based on input from M202P-L, ADIN changes the information that needs to be displayed on-screen. The component provides very useful information in an illustrative manner, so it supports more experienced workers to do an assembly task with less responsibility due to a fully guided procedure. On the other hand, the component provides very useful information for newcomers in their learning process and especially reduces challenges when a worker is reassigned from the assembly of one device to another. Figure 4. shows an ADIN instruction panel where all information about the current assembly step is presented (including the components and tools needed, essential comments, and illustrations). As the data about all the tasks





Fig. 4. ADIN instruction panel.

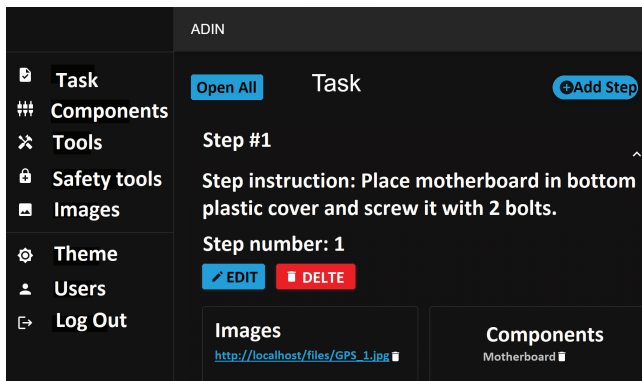


Fig. 5. Application for task creation and editing.

need to be provided to the SQL database, the application for seamlessly generating new tasks into the database was designed for the purpose of the current workstation and future use. Users can log into the application and access information according to their designated access rights. With this application, users can define new components, tools, and safety measures, and create new tasks and subtasks. Then the new tasks can be shown on the ADIN module. Also, using this application, users can modify already generated task sequences to introduce changes to the system. The application allows the writing of SQL queries to be avoided, enabling people who do not have a background in SQL databases to create new tasks. This component is essential for easier adoption of the system and higher flexibility in industrial settings with limited programming skills. Figure 5. presents some functionalities of the application for task creation/editing.

#### D. Physical support – Cobot module

The Cobot module was developed to control the Franka Emika Panda robot in a synchronized way to meet the user's requirements and deliver to the worker right on time all the necessary parts for the assembly process. First, the cobot was provided with the locations of all storage compartments in which all the components for all the defined tasks are stored. All cobot movements need to also consider the ergonomics of

the worker. For a human to adopt the cobot in the workspace, the cobot needs to have predictable movements, to ensure that the human worker does not have unpleasant reactions like fear, shock, or surprise [19]. To that end, the Cobot module used in the proposed system minimally interrupts the human workspace. Also, the dynamics of the cobot's movements and task execution are directly correlated with the worker's progress because the robot will interact with the user only upon receiving a command from the M2O2P-L module.

#### E. Strategic support – Smart Task Scheduler module

The Smart Task Scheduler can monitor performance on different workstations (production parameters and mental workload indices) and allocate resources to workstations and workers. Resources can be planned manually (by a production manager) or automatically (by an intelligent software application), based on production management needs. Smart Task Scheduler makes it possible for production management to manually schedule tasks between workstations and workers and set up the workstation for the allocated task. This module can be further utilized to automatically reschedule workers and the tasks between them in the most optimized way to increase productivity and worker satisfaction by setting the reallocation rules based on workers' performance, workload levels, and production needs.

## IV. EXPERIMENTAL SETUP AND PROTOCOL

The proposed human-centered neuroergonomic workstation for assembly tasks was set up on the premises of the Galeb Electronics factory in Šabac, Serbia. Galeb Electronics is a regional leader in the production of a broad portfolio of fiscal devices and GPS modules characterized by intensive manual assembly tasks. Experiments were conducted with employees of the company working on manual assembly of different electronic devices. The subjects who volunteered for the tests had a day off from their usual activities. All the participants were informed about study procedures and signed a written informed consent form before participation. The study was approved by the local ethics committee and was in accordance with ethical guidelines defined by the Declaration of Helsinki. The subjects were seated in a chair at a workbench on which they performed the assembly task. A computer screen displaying the graphical user interface of the ADIN application was in the left part of the workspace. The M2O2P-L module for commanding gestures was positioned to the left of the subject. The cobot and a shelf with assembly parts were placed near the bench, across from the subject. The experimental setup is presented in Fig. 6. EEG headphones were mounted on the subject's head and the electrode impedance was inspected and lowered as necessary, in order to reach values below  $1k\Omega$ . The purpose and procedure of the experiment were explained to the subject. The task was to assemble two fiscal devices comprising different steps coinciding with appropriate ADIN instruction screens. Two tasks were treated separately and there was a five-minute break between them. The tools used



Fig. 6. Experimental setup of the assisted assembly line with the example of one assembly task. 1 – BrainWatch module interpreting brain activity indicators, 2 – Smartphones used to acquire EEG signals for BrainWatch module, 3 – ADIN module used to display instructions, 4 – Collaborative robot passing necessary components to the worker, 5 – Leap Motion sensor that supports interaction with the system using M2O2P-L module. Task 1 - Place the motherboard on the plastic cover. Task 2 - Assemble the front cover of the fiscal device. Task 3 - Screw the motherboard to the fiscal device. Task 4 - Assemble the thermal printer. Task 5 - Connect the GSM module to the motherboard. Task 6 - Assemble the top and bottom parts of the fiscal device.

were a screwdriver (in five steps) and a soldering iron (one step). No tools were needed for the other steps. The actions of the worker involved attaching different parts with screws, manual positioning of electronic parts in predefined places on the printed circuit boards, soldering, etc. An illustrative demonstration of the system in the given industrial setting is provided in the supplementary video material.

The subjects were instructed to perform each manual assembly task in two experimental scenarios:

- Standard manual assembly (MA);
- Cobot-supported manual assembly (CMA).

In the first scenario, the subject did not interact with any component of the system except for the EEG, which recorded the subject's brainwaves. In the second scenario, the subject performed the manual assembly task assisted by the cobot, while using the ADIN, M2O2P-L, and BrainWatch modules. The order of assembly and the order of scenarios within the same assembly task were randomized over the subjects.

In the MA scenario, all the tools and parts necessary to execute the task were sorted and placed on the workbench in front of the subject, along with printed assembly instructions. The MA task was conducted in a way to completely replicates the daily routine of manual assembly workers. The subjects were skilled factory workers already familiar with

the assembly process of the targeted electronic devices.

In the CMA scenario, the task started with the first instruction page displayed on the screen via the ADIN interface and the cobot taking the necessary parts from storage for the first step and bringing them to the human worker at a convenient position in front of him in a plastic container. After reading the instructions and taking the necessary parts from the plastic container held by the cobot, the test subject could initiate the next instruction slide and cobot movement by making the open hand gesture to M2O2P-L. In that way, he could perform the first step of the assembly task using the parts and tools provided, while the cobot left the empty container in its place and reached for the next container with the set of parts needed for the next step. In the CMA scenario, *TAR*, *TBR*, and *EI* were calculated every 10 seconds online, and raw EEG data was stored. The time required to complete the manual assembly in each scenario was recorded by the experimenter. Also, the experimenter observed the process and noted any errors made by the subjects, such as mixing the order of operations that resulted in the need to repeat a certain step in the manual assembly procedure.

The sensor data (EEG and Leap Motion) were automatically collected, processed, and stored through the proposed



framework. After completing one task, a subjective assessment was made via the NASA task load index questionnaire (NASA-TLX) [12] to evaluate the perceived workload and task performance. NASA-TLX uses six subscales, ranging from 1 to 21, to estimate the overall mental workload. The first questionnaire subscale was “mental demand”, or the amount of mental and perceptual activity required to execute the task (e.g., thinking, deciding, calculating, remembering, looking, searching, etc.). The second subscale was “physical demand”, or the amount of physical activity required. The third subscale was “temporal demand”, or the amount of time pressure felt due to the pace at which the tasks or task elements occurred. The fourth subscale was “overall performance”, or the subjective estimate of success in performing the task. The fifth was the “effort” subscale, or the amount of mental and physical work required for the achieved level of performance. The sixth subscale was “frustration level”, i.e., the amount of irritation, stress, or annoyance felt during the task.

## V. VALIDATION MEASURES

To obtain the results required for offline analysis of EEG indices, stored raw EEG data were processed in the following manner. The EEG signal of channel Cz was used for analysis. EEG was first filtered in the 1-45 Hz range using a 4<sup>th</sup> order Butterworth filter. The signal was segmented into 5 s intervals, and intervals containing high amplitude drifts exceeding  $\pm 100 \mu\text{V}$  were excluded from further analysis. The remaining signals were filtered in theta (4-7 Hz), alpha (8-13 Hz), and beta (14-45 Hz) ranges using a 4<sup>th</sup>-order Butterworth filter, squared, and averaged to obtain bandpower time courses. The median band power for each band, task, and scenario was then calculated, and the *TAR*, *TBR*, and *EI* indices were extracted.

The goal of the data analysis was to validate each component of the novel workstation in a real factory environment and to compare the performance measures of each component between two experimental scenarios (CMA vs. MA).

The measures of human performance and workload analyzed and compared between the scenarios included:

- NASA-TLX results: values in the 1-21 range for 6 scales of the questionnaire;
- EEG indices: *TAR*, *TBR* and *EI*;
- M2O2P-L module classification accuracy;
- Number of errors during task execution; and
- Assembly duration (time needed to complete the task).

Each subject completed two tasks in two experimental scenarios, so we adopted an 8 (measurements) x 2 (scenarios) design for comparative analysis between scenarios using the Wilcoxon signed-rank test with a significance threshold of 0.05.

The results are reported as median  $\{Q_1-Q_3\}$ , where  $Q_1$  and  $Q_3$  are the first and third quartiles.

A correlation analysis of three EEG indices and NASA-TLX values of each scale was conducted. The aim was to determine EEG indices sensitive to changes in specific

workload aspects measured by NASA-TLX. Pearson’s correlation coefficient ( $r$ ) and significance value ( $p$ ) were obtained between each of the EEG indices and NASA-TLX values of each of the six scales. The significance threshold for the  $p$ -value was 0.05. Each correlation test included 16 values of EEG indices (8 tasks x 2 scenarios) and 16 NASA scores of a single scale.

## VI. RESULTS

Four right-handed male participants aged 29 to 45 took part in the experiment. They were all skilled workers employed at positions that required manual assembly of fiscal devices. None of the participants had prior experience working with industrial robots or any other component of the system.

Statistical analysis of NASA-TLX scores between CMA and MA scenarios revealed a significant decrease in the “mental demand” score for the CMA scenario and a significant increase in the performance score for the CMA scenario ( $p = 0.016$ ).

Statistical comparison of EEG indices between the scenarios (CMA vs. MA) revealed a statistically significant difference ( $p = 0.008$ ) only for *TAR*, where the median *TAR* values (median  $\{Q_1, Q_3\}$ ) for CMA and MA were 2  $\{1.3, 3.2\}$  and 3  $\{1.5, 4.9\}$ , respectively.

The results of the correlation analysis between the EEG indices and NASA-TLX scores are presented in Fig. 7. The correlation analysis revealed a significant positive correlation between *TAR* and the “mental demand” score ( $r = 0.67$ ,  $p = 0.004$ ), a significant positive correlation between *TBR* and the “mental demand” score ( $r = 0.66$ ,  $p = 0.005$ ), a significant negative correlation between *TAR* and the “overall performance” score ( $r = -0.59$ ,  $p = 0.016$ ), and a significant negative correlation between *EI* and the “effort” score ( $r = -0.54$ ,  $p = 0.029$ ).

No significant differences in assembly duration were identified between the scenarios. Regarding the number of errors, however, none were identified in the CMA scenario, while five were detected in the MA scenario, which required corrective action and/or returning to the previous step.

The results on the M2O2P-L module performance showed a 100% accuracy. More specifically, all open-hand gestures signaling transfer to the next step were detected accurately

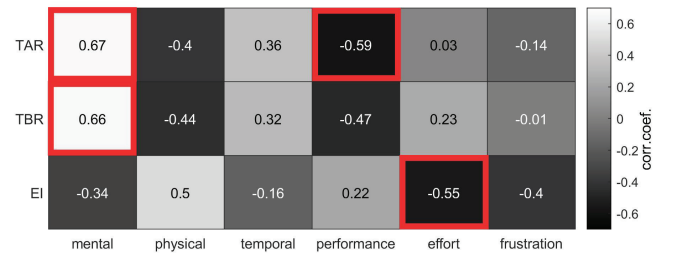


Fig. 7. Pearson’s correlation coefficients between three EEG indices (*TAR*, *TBR*, and *EI*) and six NASA-TLX scales’ values (mental demand, physical demand, temporal demand, overall performance, effort, and frustration level). Significant correlation values are marked in red.

and in a timely manner. Since the number of errors in the CMA scenario was 0, there was no need to use fist gestures during the experiment.

The average NASA-TLX scores in the MA and CMA scenarios are presented in Fig. 8

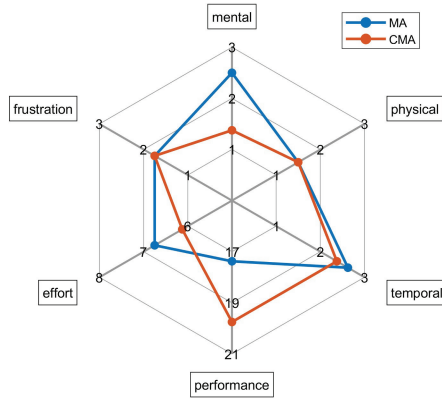


Fig. 8. Averaged NASA-TLX scores for six subscales (“mental demand”, “physical demand”, “temporal demand”, “overall performance”, “effort”, “frustration level”) and for two conditions (MA and CMA).

## VII. DISCUSSION

The overall aim of this paper was to present the methodological concepts and technical architecture of the newly developed neuroergonomic workstation for human-centered cobot-supported manual assembly. The results of system feasibility tests are just an initial indicator of the effectiveness in improving work productivity while decreasing workload during manual assembly tasks. However, broader scope feasibility studies and longitudinal research over a range of subjects and different assembly tasks are needed to confirm current findings. Nevertheless, our findings corroborated the basic functionality of each component individually and of the system as a whole, as well as proved the feasibility of easy integration of the system in a real factory environment.

The results of the NASA-TLX scores analysis revealed that the subjects perceived the same tasks as less mentally demanding in scenarios where task execution was assisted by a collaborative robot. In other words, task execution required less mental and perceptual activity in CMA scenarios. This result is in line with the analysis of EEG workload indices, which revealed significantly lower  $TAR$  values in scenarios involving the collaborative robot (CMA). Also, the subjects’ self-reported performance score was significantly higher when they used the workstation (i.e., the subjective estimate of success in performing the task was higher in the CMA scenario).

Moreover,  $TAR$  as an EEG index of workload and mental effort, based on the assumption that an increase in mental load was associated with a decrease in alpha power and an increase in theta power, was found to be significantly correlated with values of the “mental demand” scale of NASA-TLX. Also, the  $TAR$  index revealed a significant

negative correlation with the “overall performance” scores of the NASA-TLX.

We uncovered other significant correlations between the NASA-TLX results and the EEG indices, but neither of those values was significantly affected by introducing our workstation into the execution of the task, i.e., no significant differences between the scenarios were observed for the EEG indices other than  $TAR$ .

A significant positive correlation between the  $TBR$  index and the “mental demand” scores was noted.  $TBR$  is associated with working memory and attention. An increase in the mental demand scores of our tasks correlated with increases in  $TBR$ . The theta/beta ratio ( $TBR$ ) has been related to different aspects of cognitive control and motivated decision-making [20]. Increased theta and reduced beta power were observed during mind wandering, compared to episodes of focused attention.

Our results confirmed a relationship between  $TBR$  (as an index of reduced attention control) and self-perceived mental demand of the task recorded by the questionnaire. We identified a significant negative correlation between the self-reported effort score and the engagement index ( $EI$ ). A reduction in the engagement index during vigilance tasks demonstrated task engagement deterioration over time.

These results showcase the feasibility of the BrainWatch module in calculating workload indices during task execution, by using state-of-the-art EEG headphones with wireless data transfer and easy and fast mounting semi-dry electrodes, as presented in Figure 2. Where the real impact of BrainWatch output measurements is expected to occur over a sustained period of repetitive work. The intended role of this module within the system architecture is to estimate worker focus and mental workload and to act based on that information to improve productivity and decrease monotonous and repetitive tasks by optimally reallocating workers to a different task, or to provide timely information to reduce the possibility for errors. Therefore, the information from the BrainWatch module (current worker’s workload index) is transferred via OCB to the Smart Task Scheduler module, which decides based on the value whether to call for a break or assign the worker to a different assembly task (i.e., with higher/lower demands).

The M2O2P-L module proved to be very robust throughout the tests. The classification accuracy of open-hand gestures of all subjects was 100%. All open-hand gestures were detected accurately and in a timely manner. Since the subjects made no errors in the scenario with an adaptive user interface, there was no need for a rollback command (i.e., no fist gestures were made during the experiment). In perspective, a natural human-robot interface can help operators improve manipulation performance through guided physical interaction, from robot-assisted assembly to telesurgery. A hand gesture is a convenient, non-invasive, and simple human-robot interaction. With the development of sensing technology, the use of gesture interaction can increase the level of safety and intuitiveness of robot manipulation.

Due to the constantly shifting demands of the market,

current production processes require a high degree of flexibility. HMI interfaces need to provide a full range of potential actions and instructions in order to satisfy the demand. This requires an undesirable cognitive effort that might reduce human operator efficiency and satisfaction. Researchers have created the concept of an adaptive user interface to tackle such issues. Adaptive user interfaces might provide advantageous solutions for a variety of industrial applications. A more customized interaction and increased efficiency of the production process might result from their capacity to adjust to operator interaction patterns. To that end, the ADIN module can be adapted for a variety of tasks in different industries.

As noted in Result section, the duration of assembly did not differ significantly between the scenarios. In CMA scenario, task execution time is also influenced by supply parts organization and logistics due to the use of the collaborative robot, but allowing the supply of spare parts in clusters without interrupting the worker in the assembly process. Moreover, this experiment was a feasibility test of skilled manual assembly workers who were well-practiced in assembling two sets of devices. Also, they did not have prior experience with any system component (ADIN, M2O2P-L, BrainWatch, or Cobot module). However, during the CMA scenario, no error was identified, whereas in the MA scenario, there were five errors. Nevertheless, in the CMA scenario, task execution required less mental and perceptual activity, while we revealed significantly lower TAR (as an index of workload) values in scenarios involving the collaborative robot. Subjects' self-reported performance score was significantly higher when they used the workstation, while the self-perceived mental demand was significantly lower. On the other hand, we believe that the difference in time needed to complete assembly tasks for novice workers will be significant. Also, it is expected that differences in task execution time between the two scenarios will be drastic during the sustained period of repetitive work. This, in turn, leads to increasing overall Industry 5.0 process performances and productivity.

The main goal of the proposed system is to enable production planning or task distribution in laborious work environments based on the worker's condition and disposition, improving product quality and productivity with currently available labor. Equally importantly, the solution proposed in this case opens up completely new possibilities for the optimization of manual manufacturing, while simultaneously increasing the worker's well-being. To achieve both general objectives, the solution relies on monitoring of the brain activity using EEG smart headphones to recognize the engagement and mental load of the human worker. The acquired information may be used to assign the worker to a task that will ensure overall optimized performance, in terms of productivity and the worker's well-being and satisfaction.

The impact of the neuroergonomic workstation concept is reflected in the possibility of easy adaptation to different assembly scenarios or an extension of the setup to other relevant human-centered industrial contexts by introducing

new modules in the presented architecture and its essential components (psychological and physical assessment, non-physical, physical and strategic support).

Although presented use-case scenarios were driven by the specific needs of a company and demonstrate the feasibility of our workstation in environments where human-robot collaboration has the potential to become increasingly common. Still, there are significant prospective applications across a range of assembly tasks. By integrating neuroergonomic human-machine interfaces with robotic platforms or cobots, the utilization of each presented component and overall conceptual framework could enable seamless collaboration on complex assembly tasks, leveraging the strengths of both humans and machines. Using custom-made software for task scheduling, production management can define assembly instructions for arbitrary tasks, which will be consequently presented to workers through the ADIN module as non-physical support. The Cobot module, as a physical support module used for tending to the human worker, can be easily reprogrammed and adjusted to a larger number of working sequences, and drawers, and be able to deliver to workers many more assembly pieces. In the end, both assessment modules can be used regardless of the task complexity to provide insights into human aspects and initiate consequential actions of human-supporting components.

To broaden the usage of our neuroergonomic workstation, we impose core components such as psychological assessment, physical assessment, physical support, non-physical support, and strategic support. In general, one can decide what exact application or use case needs to be implemented by following the proposed concept of five Industry 5.0 core components while making a human central figure in the production process. For example, the usage of exoskeletons can be exploited for physical assistance, augmentation of operator performance, or musculoskeletal injury prevention. For non-physical support exploitation of audio/visual signals and new AR/XR technologies can be introduced to guide the human worker through the production process which would also expand workplace spatial limitations. For extension of physical or physiological assessment modalities, one can use different types of sensors like camera-based mocaps or smart gloves with tactile sensing for physical or eye gaze sensing for assessing human psychological states.

## VIII. CONCLUSION

We presented a newly developed workstation for a human-centered cobot-supported manual assembly process and tested its effects on objective and subjective measures of users' performance and workload in a real factory setting. The presented workstation is a pilot of the general, easily adaptable, and scalable neuroergonomic workstation in human-centered Industry 5.0 concept with its core components/modules for worker assessment (physical and psychological) and support (physical, non-physical, strategic). The pilot demonstrates newly developed essential modules for mental (BrainWatch) and physical (M2O2P-L) worker's assessments as inputs, as well as modules for physical (Cobot)

and visual (ADIN) assistance to the worker. The workstation is deployed in a real industrial setting to demonstrate the anticipated primary benefits of the system including a reduction in the number of faulty products, improving productivity, and increasing worker satisfaction. An open-source software solution for each neuroergonomic workstation module was made publicly available and is reusable in the SHOP4CF component marketplace or robotics and automation marketplace (RAMP). The current system architecture allows a great amount of flexibility in adapting each component to the individual requirements of various tasks. Further research is needed to validate the effectiveness of the system in long-term use.

This work not only addresses current challenges but also lays the foundation for innovation, envisioning a future where human-centered industrial processes are not only technologically advanced but also inherently attuned to the well-being of the workforce. This marks a paradigmatic leap forward in Industry 5.0.

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