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PERSPECTIVE

Extension of HAAS for the Management of Cognitive Load

ABDULRAHMAN K. EESSE^{1,2}, SZILÁRD JASKÓ³,
GYÖRGY EIGNER^{4,5}, (Senior Member, IEEE), JÁNOS ABONYI¹, (Member, IEEE),
AND TAMÁS RUPPERT¹, (Member, IEEE)

¹HUN-REN-PE Complex Systems Monitoring Research Group, Department of Process Engineering, University of Pannonia, 8200 Veszprém, Hungary

²Department of Medical Instrumentation Technology Engineering, Northern Technical University, Mosul 41001, Iraq

³Department of Applied Informatics, University of Pannonia Nagykanizsa—University Center for Circular Economy, University of Pannonia, 8200 Veszprém, Hungary

⁴Biomaterials and Applied Artificial Intelligence Institute, John von Neumann Faculty of Informatics, Óbuda University, 1034 Budapest, Hungary

⁵Physiological Control Research Center, University Research and Innovation Center, 1034 Budapest, Hungary

Corresponding author: Tamás Ruppert (ruppert@abonyilab.com)

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ABSTRACT The rapid advancement of technology related to Industry 4.0 has brought about a paradigm shift in the way we interact with assets across various domains. This progress has led to the emergence of the concept of a Human Digital Twin (HDT), a virtual representation of an individual's cognitive, psychological, and behavioral characteristics. The HDT has demonstrated potential as a strategic tool for enhancing productivity, safety, and collaboration within the framework of Industry 5.0. In response to this challenge, this paper outlines a process for tracking human cognitive load using the galvanic skin response as a physiological marker and proposes a novel method for managing cognitive load based on the extended Human Asset Administration Shell (HAAS). The proposed HAAS framework integrates real-time data streams from wearable sensors, user skills, contextual information, task specifics, and environmental and surrounding conditions to deliver a comprehensive understanding of an individual's cognitive state, physical wellness, and skill set. Through the incorporation of skills set, physical, physiological, and psychological variables, and task parameters, the developed HAAS framework enables the identification, management, and development of individual capabilities, thereby facilitating individualized training and knowledge exchange. The applicability of the developed framework is proved by an experiments in the Operator 4.0 laboratory with the detailed HAAS parameters.

INDEX TERMS Cognitive load, GSR, human asset administration shell.

I. INTRODUCTION

Nowadays, it is becoming more vital to include workers throughout the design phase of systems. The inclusion of workers is accomplished through expanding the standard of industrial engineering concepts and making them more personalized and customized work fields [1], [2], [3], [4]. The forthcoming 5th Industrial Revolution, Industry 5.0 (I5.0), aims to integrate human intellect into autonomous or

semi-autonomous production processes, thereby mitigating the drawbacks of Industry 4.0 (I4.0) by embracing human centricity [5], [6], [7]. Contrary to I4.0, the human operator, known as Operator 4.0 [8] or 5.0 [9], is central in the production system and leverages technology to enhance the production quality [6]. This strategic approach emphasizes human involvement in the production processes, prioritizing operator well-being, and promoting sustainability and resilience in manufacturing systems.

Despite the growing interest in I5.0, current studies are still nascent, and their findings are not substantial [10].

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However, it is clear that the focus of I5.0 on human-centricity marks a departure from the limitations of I4.0. Pivoting to a human-centric approach in I5.0 not only signifies a paradigm shift but is a necessity for fostering truly symbiotic environments. To design an efficient human-centered system, it is principal to consider human factors like emotion, personality, workload, fatigue, and aging. This will lead to enhanced system quality and efficiency and improved working environments. Numerous studies have proved that integrating this strategy provides win-win outcomes [1], [2], [3], [4]. The goal should be to develop intelligent, age-friendly workplaces where modern technology cooperates with human employees and augments their potential, not replace them. [4].

Implementing I4.0 and incorporating human-in-the-loop control systems showed that the cognitive load on operators in work environments has significantly increased, primarily due to the increased volume of data requiring advanced mental processing [11], [12]. According to the research of some academics, some physiological markers are highly responsive to cognitive processing and exhibit significant fluctuations in response to changes in the task's demands. This finding provides evidence in favor of the hypothesis that tasks requiring higher levels of executive and sustained attention elicit more marked alterations in physiological parameters. Compared to cognitive components such as working memory and perceptual processing, these alterations are more pronounced [13].

Cognitive load is described as a multi-dimensional structure expressing the burden that a given task exerts on the worker. It also indicates the perceived effort required for learning, reasoning, and thinking as a measure of working memory pressure during the execution of the task [14]. The cognitive load brought on by an abundance of complicated knowledge has developed into a potential problem. Despite this, structured knowledge systems are still extensively employed, irrespective of the fact that individuals have varying rates of information intake [15]. For more efficient management of mental workload during crucial decision-making, there is an immediate need to design a smart data system that can adjust to the information-processing capacity of each individual [15]. The goal that the researchers are looking for is to decrease the cognitive load, which will be reflected in production efficiency. A numerical simulation study suggests that the adoption of I4.0 technologies alleviates this load by decreasing the amount of information an operator needs to manage for a task, subsequently lowering cognitive effort. This increased processing capacity enables operators to handle more complex tasks involving multiple actions [12].

Technologies in I4.0 enable the creation of digital representations of industrial entities, supporting production systems with considerable advantages and capabilities [16]. To achieve resilient, sustainable manufacturing systems, researchers have started making digital twin models (DT)

that represent the physical assets in the virtual world [17]. Asset Administration Shell (AAS) is the only DT definition that explicitly supports industry-standard protocols and data formats, according to Michael et al. [18]. AAS is an I4.0 architecture that specifies the technical characteristics of an asset. It was designed to convey information as well as data in an organized way, hence facilitating interoperability between DTs models [19].

Humans are increasingly being digitalized in the cyber field through the principle of human centricity. However, most studies in this field, according to Du et al. [15], focus on the system level in modeling information processing rather than modeling behaviors at the personal level. As a result, the Human Digital Twin (HDT) was proposed to integrate human workers in the I4.0 field, which supported data collection, scheduling, communication handling, and so on [20], [21]. HDT is the cyberphase of the human entity, which is fed by dynamic real-time parameters to represent the human in the physical phase. These parameters include but are not limited to workers' characteristics, behaviors [22], geospatial and psychophysical conditions, contextual parameters, intentions, cognitions, emotional state, food income [23], motion recognition [10], and other biological parameters such as electromyogram (EMG), heart rate, heart rhythm, respiration, blood pressure, Galvanic Skin Response (GSR) [20], [21], [24], [25]. Despite the rising number of papers that talk about HDTs and the possible influence they might have in the future, there is no existing agreement on exactly how to design these kinds of systems [26].

Our research is centered on addressing two primary areas of concern that arise during the transition toward industrial digitization and suggesting solutions for them: "What is the cognitive load level that a specific task may induce on an operator, and what is the limit of cognition that the operator should not exceed to tackle that task's load with the best performance?"", factoring in the individual skills and "Based on the outcomes of the first question, is there a need to control the cognitive load of that task, and if so, how?". In the graphical abstract (Figure 1), we identified seven main modules: the task, worker skills, environmental conditions, psychological state, kinematic parameters, anthropometric parameters, and physiological metrics. This paper will contribute its novelty depending on four of these modules (green-colored boxes): the physiological metrics (GSR and HRV) to evaluate the worker's cognitive load and classify it as low, medium, or high, while the other three modules, the task, the worker's skills, and the environmental conditions surrounding the worker, will be used to estimate the required cognitive load and also classify it as low, medium, or high to compare it with the evaluated cognitive load of the worker. Based on these loads, the extended HAAS will make task and surrounding condition manipulations. The other three modules in the graphical abstract colored blue are beyond the scope of this paper, and we may take them into consideration in future works.

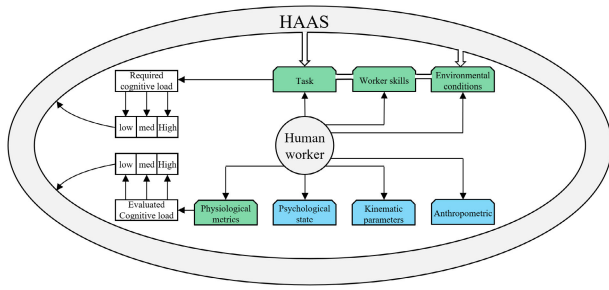


FIGURE 1. Graphical abstract of the proposed HAAS extension with the main elements.

The rest of the paper will cover the following sides: Section II includes several subsections to describe the extended HAAS, cognitive loads, and their analyses and measurements, in addition to the description of the use of the GSR as an indicator of cognitive load. Section III describes the developed framework of the extended HAAS for managing the cognitive load. Section IV presents both the methods of designing the tasks and their surrounding conditions and assets implementation, while Section V presents the conclusion and future work.

II. HAAS EXTENSION TO MANAGE COGNITIVE LOAD

Building an accurate HDT requires collecting data about diverse assets, such as machines, instructions for achieving the tasks, like physical movements, physiological and psychological data, the awareness and cognitive load of the worker, necessary skills, etc. HAAS will collect these parameters and provide the interconnecting process between these different assets for efficient interoperability within assets and external systems. To make an effective HAAS, it is necessary to find a wide range of standards and classifications that describe assets and tasks.

In this section, we will explore the Extended HAAS's capacity to effectively manage cognitive load. The next subsections will define the principle of the HAAS (Section II-A) in the field of cognitive load management (Section II-B) and the GSR applicability to measure cognitive load (Section II-C).

A. DEFINITION OF HAAS

I4.0 uses information and communication technologies to connect the actors in industrial processes in an intelligent network. The AAS has an important role in this process because it helps to implement the I4.0 digital twins and creates (communication) interoperability between solutions from different vendors. All in all, the AAS is a digital representation of an asset. In the case of I4.0, the AAS of machines and certain software components was clear from the start, but the emergence of humans as manufacturing entities was not nearly as obvious. The worker can be divided into two major groups in terms of AAS/digitized data. The first is psychophysical data (e.g., heart rate, galvanic skin response), while the second is static data (e.g., height, weight, smoking

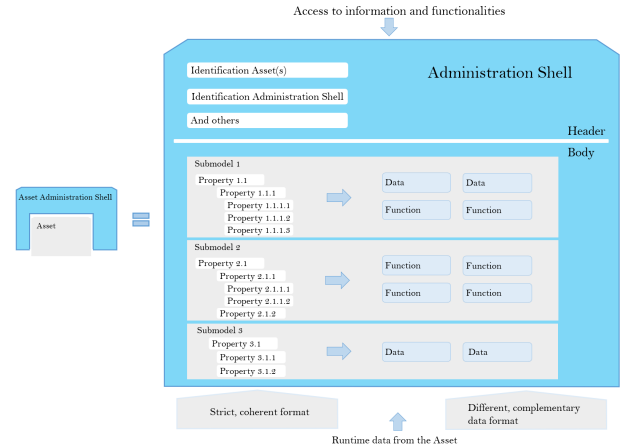


FIGURE 2. General structure of an AAS .

habits). An important requirement of AAS is to provide a minimal but sufficient description of the device according to its use cases. In parallel, it is also expected that existing standards can be mapped to the definition of an AAS.

Existing research shows a tendency to integrate humans into the production environment through the HDT approach, where the Human-AAS (HAAS) is an extension of the AAS concept. The current findings indicate that this process is not yet well-defined and that several inquiries have to be addressed. Some examples of such problems may be “How should a human sub-module be designed?” or “Should a generic AAS include a HAAS, or should these two entities be separated?”. There are works that show that this integration process can realistically be achieved. Some of these are the theses of Niko Bonomi Niko [27] and Sparrow Dale Eric [28] which highlight that humans can be integrated standard way into AAS with additional standard component involvement.

The AAS consists of two main components: header and body, as shown in Figure 2. The header contains basic information about the asset, such as identification, while the body handles the different submodels within the AAS. The single submodel is a hierarchical structure of properties, which refers to the information and functions associated with an asset in a given domain. This approach allows the collection of standard and fixed information. Examples are the bar code or the serial number. In parallel, it is possible to collect dynamic data such as the temperature of a probe or the current value of a pressure sensor. In addition, the submodel has functional properties that allow a program or routine to be started and stopped directly on the asset. The requirements define the structure, parameters, and properties of the AAS [29]. These requirements and compliance with them allow for the design of fully functional and I4.0-compatible AAS. There are 22 requirements, which can be divided into three major groups:

- General requirements (R1-R5)
- Requirements regarding the Administration Shell (R6 and R7)

- Requirements regarding identifiers (R8-R22)

Prior to delving into the HAAS, it is important to establish the nature of the data produced in HDT and the specific standards that include it. International standards are essential to achieving a high level of interoperability between different systems. AAS standardizes the way of data representation and how such data can be related to others. In addition, it allows each piece of data to be expressed in a wide variety of sub-structures. Crucially, the AAS does not dictate the specific sorts of data that should be published or the manner in which they should be published. However, it is the responsibility of the implementer to handle this task. In fact, it may be that each submodel or property refers to a specific standard that specifies the details. While relatively well-defined standards are available in this area for machinery (e.g. ecl@ss [30]), references in human-related standards are lacking for industrial production. Taxonomies of human capabilities refer to for example:

- O*Net: Occupational Information Network, is a database that is containing hundreds of job definitions, sponsored by the US Department of Labor/Employment and Training Administration (USDOL/ETA)
- AS. Chuilef et al. proposed a hierarchical taxonomy for human goals [31].
- ESCO: Classification of European Skills, Competences, Qualifications, and Occupations
- Xiao et al. researched a cryptosporidium taxonomy in the field of human public health [32]
- P.A. David also represented a human taxonomy structure [33]

For the sake of simplicity and clarity, we will utilize P.A. David's grouping as an illustrative example (refer to Figure 3) [33]. According to this classification, human capital can be divided into two main categories: tangible assets and intangible assets. Tangible assets are, for example, health or physiological conditions, and intangible assets should be cognitive capacity or problem-solving capability. A new layer of abstraction is created in the human data - using the insights about human by Bettoni et al. [34] - and each of those can be categorized into tangible or intangible categories. Based on this, the characteristic, parameter, and condition of the worker can be as follows:

- **Characteristic:** an intrinsic or extrinsic quality of the worker, such as height, amount of experience, etc. In general, these characteristics are quasi-static. It means that they do not change very often or at all.
- **Parameter:** a value that can change several times during the day, so these values are automatically collected by some data collection technique and continuously monitored. Examples include GSR, Heart Rate Variability (HRV), or position within a room.
- **Condition:** This defines a worker's actual condition; this can be an intangible state such as current emotion, current level of exertion, or even a health condition, for example, irritability or physical disability. In many

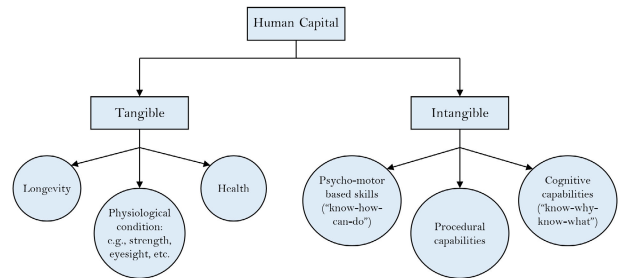


FIGURE 3. Human capital classification .

cases, these parameters can only be determined indirectly.

As Marcon et al. [35] have shown, ideally each production component has an AAS in the I4.0 approach. Human is one of these components too. In this research, the operator wears a unique smart jacket that can measure certain parameters (e.g., temperature) of the wearer and his environment through sensors. The concept uses several technologies, such as human-machine interfaces (HMIs) and industry-standard communication interfaces. A good and forward-looking concept has been developed but lacks formalization of the human in the AAS.

The research of Al Assadi et al. [36] has created a Human Administration Shell (HAS) that uses smart devices (e.g., smart watches, smartphones) to collect and provide information. This solution distinguished between two main categories: condition monitoring (real-time data such as heart rate, location, and accessing data) and service provider (e.g., personal skills and knowledge). This division was aligned with the grouping proposed by David [33], in which human capital was divided into tangible (condition monitoring) and intangible (service provider). The experiment has proved useful in several practical areas, such as automatic adjustment of ergonomic workstations, authentication, and automatic adjustment of HMIs. This research takes into account Human AAS, but lacks some additional components to consider humans as a general component in the I4.0 environment. In this form, it can be considered as a separate entity rather than a fully integrated entity in the production system.

Based on Sparrow in 2021 [28], the main HAAS responsibilities can be as follows:

- **Delegation representing the human:** Even though human operators can respond to various commands or instructions from other surrounding assets in different ways, like touch screens, keyboards, etc., this has consequently made the human operator a stumbling block in the communication process. To avoid this effect, HAAS can take the initiative and work as a representative of human operators by monitoring and recording their activities, behaviors, and working schedules. In this way, humans will have more opportunities to respond to more nuanced inquiries about their work or themselves.

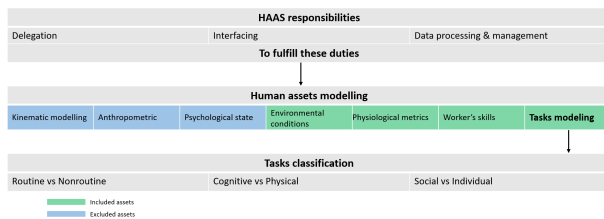


FIGURE 4. Responsibilities and requirements of the extended HAAS.

- **Facilitate Human Interfacing:** HAAS needs bi-directional communication for data flowing with human workers; this will allow for collecting the required data from workers such as body position, motions, eye-tracking, physiological data, etc.
- **Enhancement of digital processing and information management:** Information processing in humans' brains involves a combination of abstraction, pattern matching, heuristics, creativity, and more. These processes are time-consuming in the order of 200 milliseconds and increase much more during decision-making. On the other hand, digital assets in the HAAS may calculate and transfer data with floating-point accuracy, transmit events with statistics, and operate in milliseconds.

In order to provide a concise overview of the requirements and responsibilities associated with the HAAS, Figure 4 presents a tabular representation of them. This figure categorizes the modules that will be modeled for the construction of the extended HAAS, as well as those that are excluded due to their scope falling beyond the purview of this paper.

HAAS does not receive as much attention in industrial processes as conventional equipment, as can be seen from numerous examples in the literature. There are many reasons for this, but perhaps one of the most important is that humans contain far more uncertainty than an artificial element of production.

B. COGNITIVE LOAD AND COGNITIVE WORK ANALYSES

It is very individual how a person receives the information that is presented to them; some people may have difficulty processing visual-spatial information, whereas others may be resistant to being instructed verbally [15]. The same person's information-intake attitude can also change dramatically depending on their cognitive status, such as a preference for visual-spatial content during times of emotional disturbance [15], [37]. This implies that approaches to reducing cognitive load caused by information intake should be tailored to the individual and the situation [15]. Based on this criterion, three approaches under what is known as the "Cognitive Load Theory" (CLT) have been presented to answer the following questions: "What is the information that should be presented to the worker?" "And how exactly ought it to be presented to decrease the cognitive load?". The CLT assumes that the capacity of our working memory is limited,

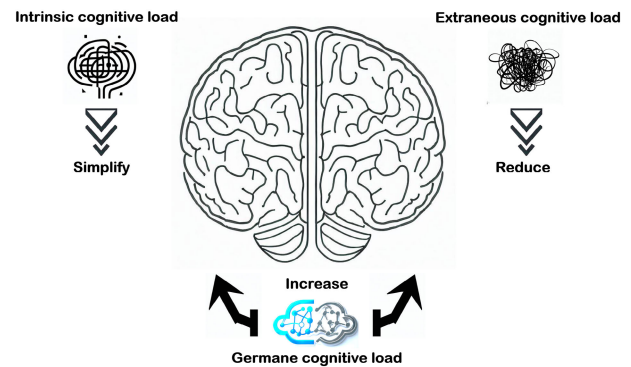


FIGURE 5. Cognitive load theory.

unlike the long-term memory capacity, which is considered to be unlimited [38].

The first approach of the CLT is dealing with the level of sophistication of the new information that is being obtained [39]. Building a worker's prior knowledge represented by their long-term memory will help in this case, or it is possible to modify the level of task difficulty; for example, sequential processing does not place as much of a load on the working memory as simultaneous processing does [38]. This approach is referred to as "*intrinsic cognitive load*" [38], [39].

The second approach is known as "*extraneous cognitive load*." This load is caused by the manner in which the instructions are delivered as well as the system's design. As a result, anything that diverts workers' attention from their goals must be avoided. Extraneous cognitive load is something that can be controlled by trainers, and as a result, the interacting aspects that are caused by extraneous cognitive load may be minimized or removed entirely by modifying the way that strategies or instructions are delivered. The extraneous cognitive load needs to be decreased at all times, and there should be no circumstances in which it may be raised. The final approach of the CLT is called the "*Germane cognitive load*." It is unlike the previous cognitive loads in its positive impacts on the workers through processing and constructing schemas. It focuses on learners' or workers' cognitive processes in order to motivate them to put forth effort in the learning process and facilitates the process of acquiring knowledge [38], [39]. Figure 5, shows the CLT principle and depicts the three components of CLT positioned around the brain, symbolizing their interaction area. The left side of the figure depicts the intrinsic cognitive load with a downward-pointing symbol, signifying the need for task simplification in order to reduce this particular kind of cognitive load. The right side of the figure represents the second element of the CLT: extraneous cognitive load; there is also a downward-pointing symbol that depicts the importance of decreasing this kind of load at all times. The third component, positioned at the bottom, has upward arrows, signifying the importance of increasing this element to counter the other two elements.

To monitor and measure the cognitive load, it is crucial to do these processes in real-time to provide feedback that can be used to decrease the cognitive load, which leads to an increase in the workers' performance and supports their decision-making. Hence, using psychological measurements (eg., the NASA Task Load Index) is not the best choice, as they provide feedback after the tasks are finished. On the other hand, several physiological parameters can be utilized for providing better cognitive load comprehension, such as "Galvanic Skin Response" (GSR), "Heart Rate Variability" (HRV), blood pressure, electroencephalogram (EEG), etc. [15]. However, while monitoring real-time cognitive load is essential for understanding and managing the demands placed on workers, it is equally important to understand how the work environment and system design can be structured to accommodate these demands. This is where the Cognitive Work Analysis (CWA) becomes essential.

Cognitive Work Analysis (CWA) is a framework used to analyze and design work systems in which human operators interact with complex technological systems [40]. It is based on the idea that in order to design effective work systems, it is necessary to understand the cognitive processes that humans use to perform their tasks [40], [41]. CWA consists of a set of principles and methods for analyzing and designing work systems in order to optimize the fit between the demands of the system and the capabilities of the human operators [40]. It is concerned with how people perceive, think, and act in the context of their work, and how the design of the work environment can support or hinder these processes [15]. Wearable sensors have been used in CWA studies to gather data on the physical and cognitive demands of a task [42].

Since the commencement of the I4.0 movement, the industrial shop floor has been undergoing a transformation brought on by smart and digital technology. However, to achieve efficient smart and digital representation of the diverse assets by HAAS, it is crucial to effectively understand the human operators' tasks and classify them based on specific characteristics that support their digitization processes efficiently. Based on these criteria, three-dimensional task classification was suggested by Cimini et al. [43] as follows:

- **Routine and Nonroutine tasks:** The routine tasks represent the activities that can be achieved based on preprogrammed rules. In the manufacturing fields, these kinds of tasks are characterized by their repetition, such as loading, unloading, assembling, packaging, etc. These kinds of tasks are characterized by the fact that they are easily codable, as the steps are already known. On the other hand, nonroutine tasks are not properly defined if compared with routine tasks, making these kinds of tasks hardly codable. Nonroutine activities are abstract tasks, such as those connected to management, technical, and creative roles, that demand problem-solving talents, anticipation, analytical skills, etc.
- **Cognitive and Physical tasks:** The cognitive tasks are concerned with cognitive activities, whereas the

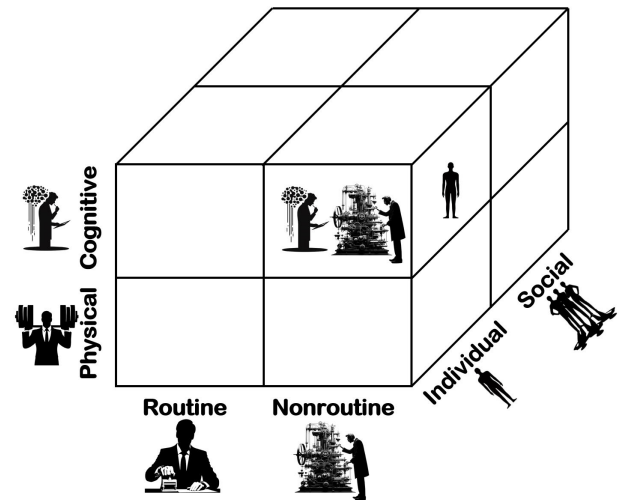


FIGURE 6. Task classification model, which has been adapted from cimini et al.,2023 [43].

physical or manual tasks are the activities that may be characterized in terms of a series of actions and involve sensory skills.

- **Individual and Social Tasks:** The level of interactions in any activity defines the category of the task as either an individual or social task. Duties that can be performed independently by a single person are primarily characterized by a lack of or minimal social interaction. Whereas duties that require a higher level of interaction with others require more mediation. Based on the study conducted by (Frey and Osborne, 2017), the lower the sociality tasks (lower interactions), the easier the digitization process [44].

Based on this three-dimensional classification, Figure 6 represents the general model that can be used to map any kind of task. Any task can be a combination of these dimensions. For instance, assembling tasks can be categorized as routine/physical tasks, whereas maintenance tasks can be categorized as nonroutine/physical tasks. On the other hand, cognitive tasks like data collection can also be routine or nonroutine based on the characteristics of the duty. Simultaneously, the third dimension of the task can take the form of either individualistic or sociocentric, depending on the presence of collaborative elements such as operators, robots, or other assets.

In light of the task characterization framework discussed, the following sections will delve into the HAAS. This will involve exploring how the HAAS, as a crucial component of the HDT, incorporates and utilizes these task classifications to optimize cognitive load tracking and administration.

C. GSR AS AN INDICATOR OF COGNITIVE LOAD

As mentioned in the previous sections, multiple and complicated technologies are aimed at improving the capabilities of workers in the working field. Yet, these technologies might potentially raise stress and workload [45]. In 2003, [46] it

was observed that utilizing diagnostic automation with an accuracy of less than 80 percent to help unmanned aircraft users led to increased stress and workload in comparison to not using automation [45]. As a result of the increase in technologies, especially with the advent of I4.0 and 5.0 and the inclusion of the human-in-the-loop, it has become important to search for technical methods to estimate the value of the workload on workers and increase their capabilities through tracking their intentions.

Recent research has shown that GSR can be a reliable physiological indicator of cognitive load [47]. GSR or what is known as “Electrodermal Activity” (EDA) is the name given to the electrical events in the skin, covering both passive and active electrical aspects related to the skin [48]. GSR denotes fluctuations in endocrine gland activities that reflect the degree of human emotional state; it is also referred to as “emotional arousal” [49]. The activities of the endocrine glands are directly controlled by the sympathetic nervous system [50]. The intensity of emotional arousal varies according to the surroundings, based on whether something is terrifying, dangerous, pleasant, or anything associated with emotions. These surrounding events (stimuli) will alter the secretion of sweat in the endocrine glands, which in turn will change the GSR value. However, regardless of the kind of stimulus, the skin conductance will be changed and increased, hence the GSR does not indicate the kind of emotion, but instead its intensity [49].

GSR consists of two essential features: (1) “skin conductance level” (SCL) which represents the tonic level of the skin conductance, and (2) “skin conductance response” (SCR), which represents the phasic change in the skin conductance [51]. According to the recommendations issued in 2012 by the “Society for Psychophysiological Research Ad Hoc Committee on Electrodermal Measures,” recording the electrical aspects of the skin can be achieved in one of three ways: (1) endosomatically without applying external electrical current; (2) exosomatically through applying direct electrical current DC; and finally, (3) exosomatically through using alternating electrical current AC [48], [52]. The range of studies outlined in these tables encompass a broad spectrum of methodologies, research aims, tracked features, stimuli types, and participant numbers. This richness highlights the multifaceted nature of research into cognitive load, offering several different perspectives for assessment and measurement.

A remarkable variety of analysis methods have been employed across these studies. Among the most common are statistical tests such as ANOVAs, paired t-tests, and pairwise analyses. At the same time, a number of studies have utilized decomposition methods like continuous and discrete deconvolution, largely facilitated by toolboxes like Ledalab. Notably, there is a growing reliance on machine learning techniques, with methods like Support Vector Machines, Naive Bayes, and Random Forest featuring prominently in many investigations. Moving to the central aims of these

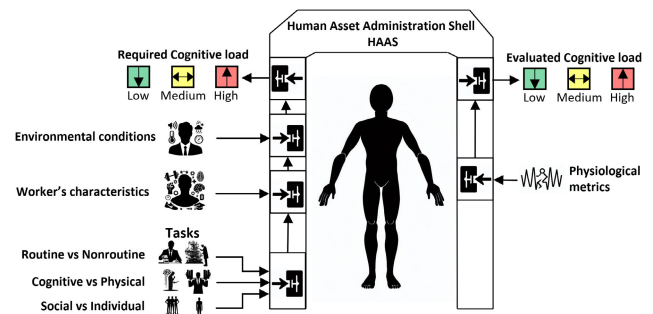


FIGURE 7. Extended HAAS proposed diagram.

studies, a significant majority aimed to estimate and classify cognitive load, with the stimuli varying extensively across research. These stimuli range from more traditional cognitive tasks like arithmetic exercises, memory tasks, and listening tasks, to more complex assignments such as Stroop tests, puzzles, and tasks based on virtual reality. While most studies aimed at the broad estimation of cognitive load, several were designed with a more nuanced focus, delving into aspects like frustration, trust, and cognitive fatigue.

In terms of tracked features, these largely depended on the physiological signals used in the research. For studies that leveraged GSR signals, some extracted features directly from the noise-removed GSR signals, while others decomposed GSR signals into their basic components (SCL and SCR) before extracting features. Commonly tracked features included signal intensity, peak intensity, mean, standard deviation, and the number of peaks.

Based on our analysis of several studies, it is clear that GSR has been successfully utilized to measure cognitive load in various surroundings and work settings. These results provide strong evidence for our claim that GSR is a suitable measure for inclusion in the HAAS.

III. THE DEVELOPED FRAMEWORK TO MANAGING COGNITIVE LOAD BASED ON THE EXTENDED HAAS

The HAAS model we propose is built around four fundamental modules that serve as the basis for its structure and operation. These modules include physiological parameters, workers' characteristics, task type and level, and environmental conditions. As seen in Figure 7 located on the right side, the physiological metrics focus on the GSR and HRV data, which are acquired using sensors placed on the individuals doing the tasks. This crucial module records these parameters and subsequently evaluates and categorizes the cognitive load into three discernible categories: low, medium, and high, as shown on the upper right side under the “Evaluated Cognitive load”.

On the left side of Figure 7 are three modules, the workers' characteristics module, which is designed to effectively capture the distinct skills and proficiencies possessed by each worker and recognizes that individual capabilities can

vary widely. This module is updated based on a preliminary assessment of each worker's abilities prior to engaging in specific tasks. Task type and level is the other module in the developed model, as seen in Figure 6. It takes into account not just the categorical nature of a task but also integrates the worker's innate skills and capacities into its analysis. As an example, a task with cognitive demands might be perceived differently by two workers of varying physical strengths, illustrating that the complexity of a task is multifaceted. The final module in our model is the environmental condition, which acknowledges that external factors play a crucial role in determining cognitive load. This module continuously monitors and adjusts the changes in the environment, such as noise, temperature, etc. These modules on the left side will estimate the required cognitive load based on their inputs into three levels: low, medium, and high, as shown on the upper left side under "Required Cognitive load". With these four modules in place, the extended HAAS model establishes a dynamic interplay. By comparing the evaluated and required cognitive loads, it aims to modulate tasks and surrounding conditions, ensuring a balance between optimal worker comfort and heightened productivity.

Given the comprehensive nature of the study, which encompasses four modules across diverse disciplines, it became vital to engage these modules inside a management system in order to augment flexibility and improve decision-making capacities. We integrated our developed HAAS with the OODA Loop framework. The OODA loop, established by military strategist John Boyd, is a decision-making process that consists of four sequential steps: Observe, Orient, Decide, and Act [53]. The primary objective of this fusion is to maximize productivity, ensure safety, and promote general well-being.

For simplification purposes, we have segmented the developed model into five methodical phases within the loop of the OODA, as seen in Figure 8. Starting with the first step, "observe," which includes both Phase 1 for establishing the cognitive load thresholds and Phase 2 for operational monitoring and cognitive load assessment. The second step is "Orient," which represents the other modules for contextual information in Phase 3. The third step is "Decide," which reflects the evaluation and comparison processes within Phase 4, and finally, the "Act" step within the OODA loop is represented by Phase 5 for adjusting and looping purposes.

Each phase serves a distinct purpose and systematically builds upon the knowledge and results obtained in the preceding phase. The core of this concept is centered upon the implementation of a responsive feedback loop that continuously monitors, assesses, and adapts using up-to-date data, with the primary objective of effectively regulating and managing cognitive load. This dynamic approach paves the way for creating optimal working conditions, leading to enhanced performance and reduced worker fatigue. The following sections provide a comprehensive analysis of each stage:

• OODA Step 1: Observe

This step includes two phases for observing both the baseline and operational conditions from the physiological characteristics, as follows:

Phase 1 - Establishing the Cognitive Load Thresholds

- 1) Neutral Condition Monitoring Phase: The objective of this phase is to consistently observe and analyze the physiological characteristics of the worker (HRV and GSR) in a neutral situation devoid of any tasks, noise, or distractions. The signals need to be processed in order to derive the cognitive load, which is an intangible factor.
- 2) Low Cognitive Load Threshold: The calculated cognitive load from this phase represents a low cognitive load. Consider this value as the threshold for low cognitive load. Any measured cognitive load that falls below or equals this threshold means the worker is operating under a low cognitive load.
- 3) Medium and High Cognitive Load Thresholds: Determining thresholds for medium and high cognitive load depending on the previously established threshold for low cognitive load in (Phase 1 / 2). The medium cognitive load threshold can be operationally defined as twice the value of the low threshold. Any cognitive load measurement over this threshold would signify a high level of cognitive load.

Phase 2 - Operational Monitoring and Cognitive Load Assessment

- 1) Operational Condition Monitoring Phase: The worker starts the execution of different tasks amid probable auditory disturbances and interruptions. Throughout this period, it is important to consistently record the worker's physiological metrics (HRV and GSR).
- 2) Cognitive Load Calculation: The acquired physiological data will be processed in a continuous manner in order to compute the cognitive load experienced during the execution of a task in these circumstances.

• OODA Step 2: Orient

This step of the loop is not just about collecting the data as the observation step but also understanding its context with respect to workers' characteristics, task difficulty, and environmental conditions to understand the cognitive load. This step is represented by Phase 3 as follows:

Phase 3 - Other modules for Contextual Information

- 1) Worker's Characteristic module: This module will include the intrinsic characteristics and talents originating from the worker as well as the extrinsic elements and effects originating from outside the worker.

Some of the intrinsic Qualities:

- *Physical Strength and Stamina:* Numerous tasks within the industrial sector require a considerable degree of physical exertion, necessitating a commendable level of strength and stamina.

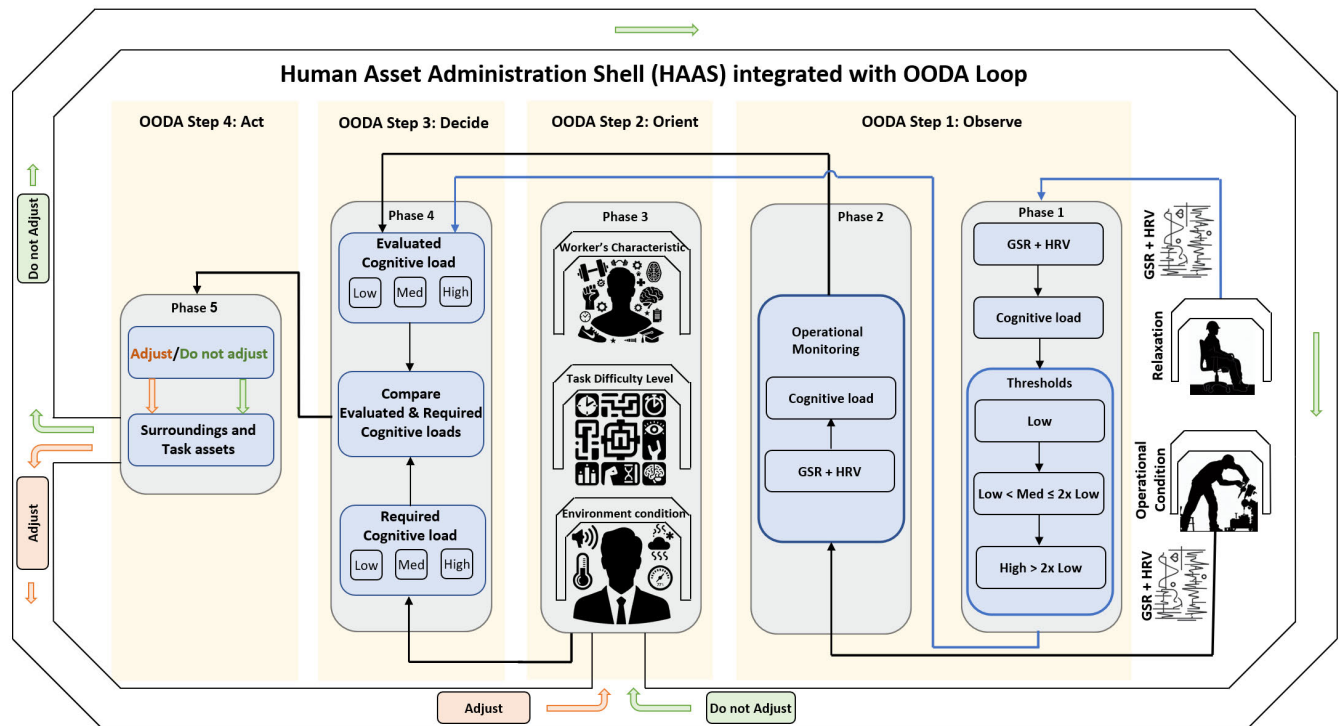


FIGURE 8. The developed concept for tracking and managing cognitive load based on the extended HAAS model integrated with the OODA loop .

- *Manual Dexterity:* Many industrial tasks require precise motor abilities, such as the aptitude to manipulate tools or assemble small parts.
- *Mental Strength:* This includes qualities such as resilience, determination, problem-solving skills, critical thinking abilities, and the capacity to acquire knowledge and adjust to novel circumstances.
- *Cognitive Abilities:* The capacity to understand instructions, follow procedures, make quick decisions, and maintain attention to detail.

Some of the extrinsic Qualities:

- *Training and Education:* Skills and expertise obtained via systematic training and academic pursuits, including both practical skills and comprehension of apparatus or equipment.
 - *Work Experience:* A worker's performance is significantly affected by their prior experience in comparable positions or sectors [54].
- 2) **Task Difficulty Level module:** This module should be defined based on various parameters and characteristics of the task itself. Some of these parameters can be summarized as follows:
- *Complexity:* Defined by the number of steps, complexity, or the need for high accuracy.
 - *Time pressure:* Determined by the allotted time to complete the task.

- *Familiarity:* Defined by how common or unusual the task is for the worker.
- *Required skill level:* Determined by the necessary skills or qualifications needed to perform the task.
- *Physical demands:* Identified by the physical strength or stamina required to complete the task.
- *Cognitive demands:* Determined by the level of concentration, problem-solving, or decision-making required for a specific task.

- 3) **Environment module:** It is important to consistently observe and assess the prevailing environmental factors, such as temperature, noise levels, humidity, etc.

• OODA Step 3: Decide

This step will decide the next action based on Phase 4. It will either decide to adjust or not adjust Phase 3 modules.

Phase 4 - Evaluation and comparison

- 1) **Cognitive Load Assessment:** Use the data of the cognitive load calculation (**Phase 2 / 2**) to evaluate the worker's cognitive load in the context of the environment based on the threshold values (**Phase 1 / 2, 3**) to get one of the following cognitive load levels (low, medium, high).
- 2) **Required Cognitive Load Assessment:** Use the data from the Worker's Characteristic module, the Task Difficulty Level module, and the Environment module (**Phase 3**) to evaluate the expected cognitive load for a specific task given the worker's skill level and environmental condition.

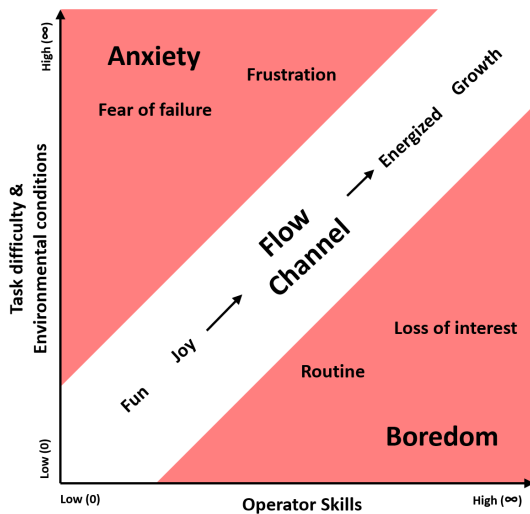


FIGURE 9. Flow channel between the anxiety and boredom zones in the industrial fields.

3) Comparison and Adjustment stage: The purpose of this stage is to compare the cognitive load that was evaluated during (Phase 4 / 1) with the required cognitive load that was assessed in (Phase 4 / 2). The objective of our model is to optimize cognitive load for maximum productivity while maintaining a comfortable work environment. We adopt Csikszentmihalyi's criteria, illustrated in Figure 9 [55], which identify two zones: Anxiety and Boredom, with a "flow channel" between them. The aim is to keep the individual operating within this flow channel. When the skill level is low and the task or environmental conditions are challenging, the individual experiences anxiety. Conversely, if the task is overly simple and the skill level is high, boredom sets in. Accordingly, a decision for adjustments should be made to either the environment or the task's complexity to facilitate entry into the flow channel, thereby maximizing productivity and comfort.

• OODA Step 4: Act

This step includes the implementation of changes based on the decision in the previous step of the OODA; it will either be monitoring the system without alteration or it will include adjusting the surroundings or the task difficulty. Phase 5 can be aligned to represent this step as follows:

Phase 5 - Looping for Continuous Monitoring and Adjustment

- *Do not Adjust*: In this case, the worker will be within the flow channel, and there will be no need for any change in the surroundings or task. The action will be restricted to continuously monitoring the cognitive load.
- *Adjust the surroundings*: In order to optimize the working environment, it is advisable to use

environmental controls to minimize noise levels and eliminate potential distractions.

- *Adjust the Task*: If the provided environmental or surrounding modifications do not prove to be effective, it may be advisable to explore modifying the level of difficulty associated with the activity. This may include modifying the nature of the activity or offering supplementary aids, such as automated tools or extra instructions, to assist the worker in effectively doing the task despite their high cognitive load.
- *Continuously Loop*: Go back to (Phase 2) (Operational Monitoring Phase) and continue through the process. This allows for continuous monitoring and adjustments based on real-time data.

IV. COGNITIVE LOAD EXPERIMENTS AND THE IMPLEMENTATION OF THE EXTENDED HAAS

In this section, we offer comprehensive insight into the methodologies we employed to design the tasks and their surrounding environmental conditions. Subsequently, we will explore the complex procedures for implementing the included assets and the interconnection among them, aiming to provide a thorough understanding of their combined functionality and significance.

A. DESCRIPTION OF THE EXPERIMENTS

This subsection will elucidate the methodologies and sensors that are utilized to design the cognitive load experiments and record the physiological signals and other environmental parameters surrounding the participants. The Operator 4.0 laboratory [56] at the University of Pannonia has been utilized as the place for settling the experiments. The Shimmer3 wearable sensor [57] has been used to capture two principal physiological signals. The first signal is the GSR signal that is recorded from the proximal phalanges of the middle and ring fingers of the participant's non-dominant hand. The second signal is the photoplethysmogram recorded by an optical electrode attached to the earlobe, which will be used later to extract the HRV signal. Another sensor for monitoring the environmental and surrounding conditions of participants has been installed in the laboratory to record the ambient noise, temperature, and humidity. Six cognitive load experiments have been designed by the PsyToolkit online platform [58], [59] to induce and monitor participant cognitive load as follows:

- *Backward-Corsi*: In this test, participants are tracking reversed sequences of a fixed number of flashed boxes. The experiment had two difficulty levels: medium and high (more boxes in the high level) to maintain consistent cognitive load across the levels.
- *Cueing*: Participants react to rapidly presented stimuli preceded by a distracting cue. Difficulty levels (medium or high) were determined by the reaction time and inter-trial intervals.

TABLE 1. Sample of extracted features and environmental parameters.

Sessions	GSR peaks	GSR area	GSR SCR area	GSR rising time	GSR decay time	HRV VLF	HRV (HF/LF)	HRV SD1	HRV SD2	HRV skew	Noise Amplitude	Temperature	Humidity
Baseline	13	102.1177	5.405	1.6385	3.1107	2.5976e+07	0.0041	82.1619	105.0025	0.0043	40.0531	27.6146	40.0171
Medium	12	210.2810	9.8914	1.4618	3.5108	2.9295e+07	0.0042	46.1915	105.1028	-0.5595	38.7592	27.6372	40.1425
High	12	251.6388	16.5215	1.7010	3.2255	2.9006e+07	0.0041	41.3538	72.3754	-0.6276	41.5724	27.6575	40.2312
Baseline	13	915.6148	16.9062	1.5385	2.9518	2.9217e+07	0.0041	41.1147	129.0137	-0.5035	30.7854	27.6661	40.2122
Medium	19	316.9376	19.6286	1.1369	1.7453	3.0649e+07	0.0061	50.7662	163.9415	-0.9902	921.1282	27.8278	39
High	18	329.9550	17.1582	1.2068	2.1546	2.8018e+07	0.0045	30.2529	57.0140	-0.6882	1230	27.8394	38.0278

- **N-back Task (2 back):** In this test, two difficulty levels were established by changing the time allotted for letter presentation and response.
- **Visual Search Task:** In this test, we control the time of presenting and responding to the visual stimulus to get the two difficulty levels.
- **Simon Task:** We also controlled the time of presenting and responding to the visual stimulus to achieve the two difficulty levels.
- **Stroop Task:** The test's difficulty levels were determined by controlling the time given for displaying and reacting to stimuli.

In this research, three recording sessions were conducted under two distinct conditions: a noise-free environment and exposure to ambient noise.

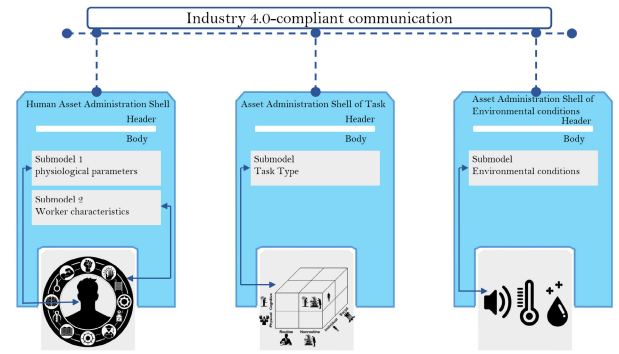
- **Baseline session:** Participants remain calm and seated and avoid any mental or physical effort.
- **Medium-level session:** Participants engage in the medium-level of the tests.
- **High-level session:** Participants engage in the high-level of the tests.

The recorded physiological signals during these sessions and conditions are processed to extract 30 features. However, a feature selection technique called Minimum Redundancy Maximum Relevance (mRMR) has been utilized to choose the most powerful 10 features that are highly relevant to the target. Table 1 presents a sample of extracted features from the physiological signals in addition to the ambient parameters recorded during the three sessions in each of the two conditions.

B. IMPLEMENTATION OF EXTENDED HAAS

In accordance with the previously discussed HAAS framework for managing workers' cognitive load, which encompasses four distinct modules, this section will outline the implementation procedures for the assets associated with each module. The diagram shown in Figure 10 illustrates the interconnection of the three assets, which are integrated through Industry 4.0 compatible communication to form the framework of the developed HAAS. The primary objective of this conceptual framework is to effectively manage the cognitive load of workers.

Given the clear relationship between the physiological signals, which include the GSR and HRV, and worker characteristics, we have created an AAS including two submodels to capture and analyze these data. Table 2 presents the header of the primary components of the first AAS. This contains pertinent information about the asset, such


FIGURE 10. Diagram of interconnecting the assets together through an Industry 4.0-compliant connection to form the developed HAAS.
TABLE 2. Human asset administration shell HAAS header.

Field Name	Type/Example	Description	The internal GUID
HAAS ID	URL, c1@ss	Unique identifier for the HAAS.	
Title	String	Human Asset Administration Shell.	0658d398-d7ca-4197-a6b2-cd0925bdf8e
Date	Date	Date of creation or last modification.	
Contact	Email, Phone	Worker contact details	
Submodel 1	String	The Worker physiological parameter submodel.	9aba4948-8000-412d-b365-54084c5d8163
Submodel 2	String	The Worker characteristics submodel.	c290d893-66be-453a-9a8d-3f5b2c649445
Manifest	Link/Reference	A directory of key information derived from the properties of the submodels.	

TABLE 3. Worker physiological parameters submodel.

Name	Submodel 1		
GUID	9aba4948-8000-412d-b365-54084c5d8163		
Properties			
GUID	Name	Type	Description
35cd4db0-24a0-47a2-bb61-dea37c34b166	GSR peaks	Numeric stream	The number of peaks in the skin conductivity signal
b5d5635d-c59f-448f-bd7c-472b09c12c73	GSR area	Numeric stream	The area under the skin conductivity signal
2c25d961-170e-48e9-a5e0-7a0d5e80f27a	GSR SCR area	Numeric stream	The area under the Skin Conductance Response SCR
b660589-a3a6-4c3e-843e-739b607ca51f	GSR rising time	Numeric stream	The average time from the baseline to the peak after the stimulus
a4dfc715-b4d6-42fe-98d0-80d39f2d61ff	GSR decay time	Numeric stream	The average time from the peak to the baseline
5c34cda8-b1f0-42ae-b0a3-327cb9a6ef68	HRV VLF	Numeric stream	Very Low Frequency power of HRV in the band (0.003-0.04) Hz
f7e01fc3-9ed4-467e-a588-60113bf7874	HRV (HF/LF)	Numeric stream	Ratio of High-Frequency power (0.15-0.4) Hz to the Low-Frequency power (0.04-0.15) Hz
fb355df1-951e-4d08-9439-a656959e7166	HRV SD1	Numeric stream	Poincaré plot descriptor (short-term HRV)
00806cd2-d88d-4d47-a1a1-5d988817a06	HRV SD2	Numeric stream	Poincaré plot descriptor (long-term HRV)
9c2ae141-8ccf-43b5-b714-e4469432921e	HRV Skew	Numeric stream	Skewness of RR intervals in the HRV

TABLE 4. Worker characteristics submodel.

Name	Submodel 2			
GUID	c290d893-66be-453a-9a8d-3f5b2c649445			
Properties				
GUID	name	type	description	
54da3d25-a63d-4924-9f1c-35d9d46f5b0	Sex	Options	Biological classification	
878660fc-9252-4900-a989-36f290503d73	Birthdate	Date	Date of birth	
95e85567-cdd5-4247-b37b-23d0b9985222	Date	Date	Hiring date.	
de85ab37-bd07-413c-8b47-33457e39109	Job Experience	Options	Selection from Entry-level, Mid-level, Senior.	
021817ec-cf00-4c1b-9652-580cedad6d5	Worker condition	Options	Nervous, exhausted, happy, sad, etc.	
33fdabdd-a6d3-47c1-a71f-4c5476f75533	Physical strength	Options	Selection from Low, Medium, High	
7eb7941-62b2-4cd6-9503-a6aed5d9eb	Stamina	Options	Selection from Low, Medium, High	
d2741bc0-0971-4206-b9fb-3cdfda8875e7	Manual dexterity	Options	Selection from Basic, Intermediate, Advanced	
85b40d59-bb17-48fe-92a8-d5b0f1d39915	Mental strength	Options	Selection from Low, Moderate, High	
7f0013e7-f18b-450e-9eb9-cf727e0cfed5	Cognitive abilities	Options	Selection from Basic, Intermediate, Advanced	
2e43e074-b2ab-4745-864a-cf94c4bec7b7	Training and education	List	List of formal education, courses, certifications, and training programs	

as its title, unique identifier, and the submodels included inside it. The specifics of the two submodels, namely the worker physiological parameters submodel and the worker characteristics submodel, are shown in Tables 3 and 4, respectively. The first submodel pertains to physiological features derived from the GSR and HRV signals. Every individual feature has its own distinct guide code that is utilized for later processing using the AAS. The second submodel refers to worker characteristics, whereby we have identified the key characteristics that may delineate each person and provide a distinct sense of their identity. These attributes included a range of factors, including gender, age, educational attainment, etc.

TABLE 5. Asset administration shell header of the task types and characteristics.

Field Name	Type/Example	Description	The internal GUID
AAS ID	URI, cCI@ss	Unique identifier for the AAS.	
Title	String	Task Asset Administration Shell.	76fe9622-2868-43f0-854f-0b9f91f13950
Date	Date	Date of creation or last modification.	
Task submodel	String	Task types and characteristics submodel	c8825b55-54c9-4137-ac61-273dc4ff4ca4
Manifest	Link/Reference	A directory of key information derived from the properties of the submodel.	

TABLE 6. Task types and characteristics submodel.

Name	Task submodel		
GUID	c8825b55-54c9-4137-ac61-273dc4ff4ca4		
Properties			
GUID	name	type	description
8ed7a8c-27ba-47ff-81fc-6299fa68913	Routine Aspect	Options	Select between Routine, Non-routine
c2ef0564-96ff-4866-9ff6d-a66833ee8524	Nature of Task	Options	Select between Cognitive, Physical
ae84b07f-af41-4a52-958e-6da5e7ed7c5d	Social Aspect	Options	Select between Social, Individual
4c2fd17-1f66-4a16-886c-b5ce51fc633	Task Complexity	Options	Select between Low, Medium, High
9b056d18-8abc-4ca1-b3bc-97d1e13b63b2	Time pressure of Task	Time	Specific duration or deadline for task completion
22dc1ba6-723c-4e8a-9527-816dd100bdc	Familiarity of Task	Numeric	Frequency of encountering the task (e.g., number of times per month)
b712cb3d-0564-4db5-b326-74cfa78d7ed1	Required skills level of Task	Options	The level of expertise needed (Beginner, Intermediate, Expert)
d5d58276-bd77-4bb2-9913-d7a8395aa682	Task Physical demands	Options	The level of physical exertion required (Light, Moderate, Heavy, Very Heavy)
6ef34463-196c-4445-9832-668dce3bcd4c	Task Cognitive demands	Options	The level of cognitive exertion required (Simple, Moderate, Complex, Highly Complex)

TABLE 7. Asset administration shell header of the environmental conditions.

Field Name	Type/Example	Description	The internal GUID
AAS ID	URI, cCI@ss	Unique identifier for the AAS.	
Title	String	Environmental condition	01adf4f2-2f32-472f-b893-6781f2a2cf8e
Date	Date	Asset Administration Shell.	
Environmental conditions submodel	String	Date of creation or last modification.	
Manifest	Link/Reference	Monitoring the worker's surrounding conditions	d8d345bf-2b1c-4491-abaa-b2087d3ac5ee
		A directory of key information derived from the properties of the submodel.	

TABLE 8. Environmental conditions submodel.

Name	Environmental conditions submodel		
GUID	d8d345bf-2b1c-4491-abaa-b2087d3ac5ee		
Properties			
GUID	name	type	description
3848608a-1e9d-40af-aad2-d2a362abc2ce	Noise level	Numeric	Ambient noise level
cd5bfff0a-7dad-4963-a483-a77e58f07676	Temperature	Numeric	Ambient temperature measured in degrees (°C or °F)
d2da3eb8-e527-498f-9b4e-0df652eb0116	Humidity	Numeric	Ambient relative humidity measured in percentage (%)

Tables 5 and 6 depict the header and body of the second AAS for task types and characteristics, respectively, providing a comprehensive description of each job. There will be an opportunity to define a certain activity using the Task Classification Model shown in Figure 6. Additionally, we established a set of requirements for each task, including factors such as time constraints, physical and cognitive demands, required skills, and other relevant considerations.

The ultimate asset deals with the surrounding conditions encompassing the human workers engaged in shop floor duties. Similarly, there are two tables, 7 and 8, which correspond to the header and body of this asset, respectively. This asset incorporates three aspects, namely noise, temperature, and humidity.

V. CONCLUSION AND FURTHER WORK

Significant changes have been made to the design and functioning of industrial processes as a direct result of I4.0 and the associated digitalization. These changes have led to an increase in the amount of automation utilized. With the advent of Industry 5.0, which focused on human centricity, the working environments associated with manufacturing and logistics systems have become more detailed and complex, which has in turn led to an increase in the mental workload that is placed on human operators. Cognitive load is a

multi-dimensional structure that shows how hard a task is for a worker. In addition, it provides an indication of the perceived effort necessary for learning, reasoning, and general thinking as a measurement of the pressure placed on the working memory while the activity is being carried out. In this paper, we develop a new way of managing cognitive load based on the Human Asset Administration Shell (HAAS) via gathering real-time data from a variety of assets.

The proposed HAAS is not restricted to the conventional role of AAS in providing interoperability between assets; it extends its function toward the manipulation of tasks and surrounding events based on multivariate parameters. Four modules have been covered in the extended HAAS: the physiological module represented by GSR and HRV signals, the workers' characteristics module to make the HAAS personally dependent, the task module, and the final module, which is the environmental condition surrounding the operator.

REFERENCES

- [1] D. Battini, M. Faccio, A. Persona, and F. Sgarbossa, "New methodological framework to improve productivity and ergonomics in assembly system design," *Int. J. Ind. Ergonom.*, vol. 41, no. 1, pp. 30–42, Jan. 2011.
- [2] C. H. Glock, E. H. Grosse, H. Abedinnia, and S. Emde, "An integrated model to improve ergonomic and economic performance in order picking by rotating pallets," *Eur. J. Oper. Res.*, vol. 273, no. 2, pp. 516–534, Mar. 2019.
- [3] W. P. Neumann and J. Dul, "Human factors: Spanning the gap between OM and HRM," *Int. J. Oper. Prod. Manage.*, vol. 30, no. 9, pp. 923–950, Aug. 2010.
- [4] F. Sgarbossa, E. H. Grosse, W. P. Neumann, D. Battini, and C. H. Glock, "Human factors in production and logistics systems of the future," *Annu. Rev. Control.*, vol. 4, pp. 295–305, Apr. 2020.
- [5] S. Huang, B. Wang, X. Li, P. Zheng, D. Mourtzis, and L. Wang, "Industry 5.0 and Society 5.0—Comparison, complementation and co-evolution," *J. Manuf. Syst.*, vol. 64, pp. 424–428, Jul. 2022.
- [6] J. Alves, T. M. Lima, and P. D. Gaspar, "Is Industry 5.0 a human-centred approach? A systematic review," *Processes*, vol. 11, no. 1, p. 193, Jan. 2023.
- [7] B. Wang, H. Zhou, X. Li, G. Yang, P. Zheng, C. Song, Y. Yuan, T. Wuest, H. Yang, and L. Wang, "Human digital twin in the context of Industry 5.0," *Robot. Comput.-Integr. Manuf.*, vol. 85, Feb. 2024, Art. no. 102626.
- [8] T. Ruppert, S. Jaskó, T. Holczinger, and J. Abonyi, "Enabling technologies for Operator 4.0: A survey," *Appl. Sci.*, vol. 8, no. 9, p. 1650, Sep. 2018.
- [9] J. Müller, "Enabling technologies for Industry 5.0," Eur. Commission, Brussels, Belgium, Tech. Rep., 2020, pp. 8–10.
- [10] P. K. R. Maddikunta, Q.-V. Pham, B. Prabadevi, N. Deepa, K. Dev, T. R. Gadekallu, R. Ruby, and M. Liyanage, "Industry 5.0: A survey on enabling technologies and potential applications," *J. Ind. Inf. Integr.*, vol. 26, Mar. 2022, Art. no. 100257.
- [11] M. Madonna, L. Monica, S. Anastasi, and M. Di Nardo, "Evolution of cognitive demand in the human-machine interaction integrated with Industry 4.0 technologies," *WIT Trans. Built Environ.*, vol. 189, pp. 13–19, Nov. 2019.
- [12] A. Lucchese, F. Facchini, G. Mossa, G. Mummolo, and F. P. Sisto, "A numerical assessment of the influence of Industry 4.0 technologies on the cognitive complexity of procedure-guided tasks," *Int. J. Simul. Process Model.*, vol. 18, no. 2, p. 112, 2022.
- [13] A. Luque-Casado, J. C. Perales, D. Cárdenas, and D. Sanabria, "Heart rate variability and cognitive processing: The autonomic response to task demands," *Biol. Psychol.*, vol. 113, pp. 83–90, Jan. 2016.
- [14] E. Haapalainen, S. Kim, J. F. Forlizzi, and A. K. Dey, "Psychophysiological measures for assessing cognitive load," in *Proc. 12th ACM Int. Conf. Ubiquitous Comput.*, Sep. 2010, pp. 301–310.

- [15] J. Du, Q. Zhu, Y. Shi, Q. Wang, Y. Lin, and D. Zhao, "Cognition digital twins for personalized information systems of smart cities: Proof of concept," *J. Manage. Eng.*, vol. 36, no. 2, pp. 04019052-1–04019052-17, Mar. 2020.
- [16] E. Montini, V. Cutrona, N. Bonomi, G. Landolfi, A. Bettoni, P. Rocco, and E. Carpanzano, "An IIoT platform for human-aware factory digital twins," *Proc. CIRP*, vol. 107, pp. 661–667, Jul. 2022.
- [17] X. Zheng, J. Lu, and D. Kiritsis, "The emergence of cognitive digital twin: Vision, challenges and opportunities," *Int. J. Prod. Res.*, vol. 60, no. 24, pp. 7610–7632, Dec. 2022.
- [18] M. Jacoby, B. Jovicic, L. Stojanovic, and N. Stojanović, "An approach for realizing hybrid digital twins using asset administration shells and apache StreamPipes," *Information*, vol. 12, no. 6, p. 217, May 2021.
- [19] T. A. Abdel-Aty, E. Negri, and S. Galparoli, "Asset administration shell in manufacturing: Applications and relationship with digital twin," *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 2533–2538, 2022.
- [20] E. Montini, N. Bonomi, F. Daniele, A. Bettoni, P. Pedrazzoli, E. Carpanzano, and P. Rocco, "The human-digital twin in the manufacturing industry: Current perspectives and a glimpse of future," in *Trusted Artificial Intelligence in Manufacturing: A Review of the Emerging Wave of Ethical and Human Centric AI Technologies for Smart Production*. Hanover, Germany: Now Publishers, 2021, pp. 132–147.
- [21] D. Sparrow, K. Kruger, and A. Basson, "Human digital twin for integrating human workers in Industry 4.0," in *Proc. Int. Conf. Competitive Manuf.*, Stellenbosch, South Africa, 2019, pp. 259–265.
- [22] I. Graessler and A. Poehler, "Integration of a digital twin as human representation in a scheduling procedure of a cyber-physical production system," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage. (IEEM)*, Dec. 2017, pp. 289–293.
- [23] B. R. Baricelli, E. Casiraghi, J. Gliozzo, A. Petrini, and S. Valtolina, "Human digital twin for fitness management," *IEEE Access*, vol. 8, pp. 26637–26664, 2020.
- [24] T. Erol, A. F. Mendi, and D. Dogan, "The digital twin revolution in healthcare," in *Proc. 4th Int. Symp. Multidisciplinary Stud. Innov. Technol. (ISMSIT)*, Oct. 2020, pp. 1–7.
- [25] P. Saariluoma, J. Cañas, and A. Karvonen, "Human digital twins and cognitive mimetic," in *Proc. Int. Conf. Human Interact. Emerg. Technol.*, Paris, France: Springer, 2020, pp. 97–102.
- [26] M. W. Lauer-Schmaltz, P. Cash, J. P. Hansen, and A. Maier, "Designing human digital twins for behaviour-changing therapy and rehabilitation: A systematic review," *Proc. Design Soc.*, vol. 2, pp. 1303–1312, May 2022.
- [27] N. Bonomi, "Exploiting human-in-the-loop characterization applied to aas in the field of Industry 4.0," Ph.D. dissertation, Dept. Innov. Technol., Univ. Appl. Sci. Arts Southern Switzerland (SUPSI), Manno, Switzerland, 2022.
- [28] D. E. Sparrow, "An architecture for the integration of human workers into an Industry 4.0 manufacturing environment," Ph.D. dissertation, Dept. Mech. Mechatronic Eng., Stellenbosch Univ., Stellenbosch, South Africa, 2021.
- [29] P. Adolphs, S. Auer, and H. Bedenbender, "The structure of the administration shell: Trilateral perspectives from France, Italy and Germany," Ministry of Economy, Federal Ministry for Economic Affairs Finances and Ministero dello Sviluppo Economico Energy (BMWi), Berlin, Germany, Tech. Rep., 2018. [Online]. Available: https://industrialdigitaltwin.org/en/wp-content/uploads/2021/09/01b_structure_of_the_administration_shell_en_trilat_2018.pdf
- [30] (2023). *Ecl@SS*. Accessed: Feb. 14, 2023. [Online]. Available: <https://eclass.eu/>
- [31] A. Chulef, S. Read, and D. Walsh, "A hierarchical taxonomy of human goals," *Motivat. Emotion*, vol. 25, pp. 191–232, Sep. 2001.
- [32] L. Xiao, R. Fayer, U. Ryan, and S. J. Upton, "Cryptosporidium taxonomy: Recent advances and implications for public health," *Clin. Microbiol. Rev.*, vol. 17, no. 1, pp. 72–97, Jan. 2004.
- [33] P. A. David, "Knowledge, capabilities and human capital formation in economic growth," New Zealand Treasury, Wellington, New Zealand, Working Paper 01/13, 2000.
- [34] A. Bettoni, E. Montini, M. Righi, V. Villani, R. Tsvetanov, S. Borgia, C. Secchi, and E. Carpanzano, "Mutualistic and adaptive human-machine collaboration based on machine learning in an injection moulding manufacturing line," *Proc. CIRP*, vol. 93, pp. 395–400, Jul. 2020.
- [35] P. Marcon, C. Diedrich, F. Zezulka, T. Schröder, A. Belyaev, J. Arm, T. Benesl, Z. Bradac, and I. Vesely, "The asset administration shell of operator in the platform of Industry 4.0," in *Proc. 18th Int. Conf. Mechatronics Mechatronika (ME)*, Dec. 2018, pp. 1–5.
- [36] A. A. Assadi, C. Fries, M. Fechter, B. Maschler, D. Ewert, H.-G. Schnauffer, M. Zürn, and M. Reichenbach, "User-friendly, requirement based assistance for production workforce using an asset administration shell design," *Proc. CIRP*, vol. 91, pp. 402–406, May 2020.
- [37] E. A. Holmes and C. Bourne, "Inducing and modulating intrusive emotional memories: A review of the trauma film paradigm," *Acta Psychologica*, vol. 127, no. 3, pp. 553–566, Mar. 2008.
- [38] M. Klepsch and T. Seufert, "Understanding instructional design effects by differentiated measurement of intrinsic, extraneous, and germane cognitive load," *Instructional Sci.*, vol. 48, no. 1, pp. 45–77, Feb. 2020.
- [39] J. Sweller, *Cognitive Load Theory* (Psychology of learning and motivation), vol. 55. Amsterdam, The Netherlands: Elsevier, 2011, pp. 37–76.
- [40] E. M. Roth and A. M. Bisantz, "Cognitive work analysis," in *The Oxford Handbook of Cognitive Engineering*. U.K.: Oxford Univ. Press, 2013, pp. 240–260.
- [41] R. Fidel and A. M. Pejtersen, "From information behaviour research to the design of information systems: The cognitive work analysis framework," *Inf. Res., Int. Electron. J.*, vol. 10, no. 1, pp. 1–15, Oct. 2004.
- [42] D. Romero, J. Stahre, T. Wuest, O. Noran, P. Bernus, Å. Fast-Berglund, and D. Gorecky, "Towards an Operator 4.0 typology: A human-centric perspective on the fourth industrial revolution technologies," in *Proc. Int. Conf. Comput. Ind. Eng.*, Tianjin, China, 2016, pp. 29–31.
- [43] C. Cimini, D. Romero, R. Pinto, and S. Cavalieri, "Task classification framework and job-task analysis method for understanding the impact of smart and digital technologies on the operators 4.0 job profiles," *Sustainability*, vol. 15, no. 5, p. 3899, Feb. 2023.
- [44] C. B. Frey and M. A. Osborne, "The future of employment: How susceptible are jobs to computerisation?" *Technol. Forecasting Social Change*, vol. 114, pp. 254–280, Jan. 2017.
- [45] C. H. Perala and B. S. Sterling, "Galvanic skin response as a measure of soldier stress," Army Res. Lab Aberdeen Human Res. Eng., Proving Ground, MD, USA, Tech. Rep. ARL-TR-4114, May 2007.
- [46] S. R. Dixon and C. D. Wickens, "Automation reliability in unmanned aerial vehicle control: A reliance-compliance model of automation dependence in high workload," *Human Factors, J. Human Factors Ergonom. Soc.*, vol. 48, no. 3, pp. 474–486, Sep. 2006.
- [47] W. Romine, N. Schroeder, T. Banerjee, and J. Graft, "Toward mental effort measurement using electrodermal activity features," *Sensors*, vol. 22, no. 19, p. 7363, Sep. 2022.
- [48] W. Boucsein, *Electrodermal Activity*. New York, NY, USA: Springer, 2012.
- [49] R. Gao, A. Islam, T. Gedeon, and M. Z. Hossain, "Identifying real and posed smiles from observers' galvanic skin response and blood volume pulse," in *Proc. Int. Conf. Neural Inf. Process.*, Switzerland: Springer, 2020, pp. 375–386.
- [50] R. Norman, "Galvanic skin response & its neurological correlates," *J. Consciousness Explor. Res.*, vol. 7, no. 7, pp. 553–572, 2016.
- [51] D. M. Alexander, C. Trengove, P. Johnston, T. Cooper, J. P. August, and E. Gordon, "Separating individual skin conductance responses in a short interstimulus-interval paradigm," *J. Neurosci. Methods*, vol. 146, no. 1, pp. 116–123, Jul. 2005.
- [52] W. Boucsein, D. C. Fowles, S. Grimnes, G. Ben-Shakhar, W. T. Roth, M. E. Dawson, and D. L. Filion, "Publication recommendations for electrodermal measurements," *Psychophysiology*, vol. 49, no. 8, pp. 1017–1034, 2012.
- [53] Y. Zhao, P. Wen, L. Bai, X. Liu, Z. Wang, and N. Wu, "Service-oriented intelligent OODA loop," in *Proc. 26th ACIS Int. Winter Conf. Softw. Eng., Artif. Intell., Netw. Parallel/Distrib. Comput. (SNPD-Winter)*, Jul. 2023, pp. 182–187.
- [54] N. Uppal, S. K. Mishra, and N. Vohra, "Prior related work experience and job performance: Role of personality," *Int. J. Selection Assessment*, vol. 22, no. 1, pp. 39–51, Mar. 2014.
- [55] M. Csikszentmihalyi, *Flow: The Psychology of Optimal Experience (P.S.)* (Harper Perennial Modern Classics). New York, NY, USA, 2008.
- [56] T. Ruppert, A. Darányi, T. Medvegy, D. Csereklei, and J. Abonyi, "Demonstration laboratory of Industry 4.0 retrofitting and Operator 4.0 solutions: Education towards Industry 5.0," *Sensors*, vol. 23, no. 1, p. 283, Dec. 2022.
- [57] Shimmer. (2023). *Shimmer Sensing*. Accessed: Oct. 3, 2023. [Online]. Available: <https://shimmersensing.com/>
- [58] G. Stoet, "PsyToolkit: A software package for programming psychological experiments using Linux," *Behav. Res. Methods*, vol. 42, no. 4, pp. 1096–1104, Nov. 2010.
- [59] G. Stoet, "PsyToolkit: A novel web-based method for running online questionnaires and reaction-time experiments," *Teaching Psychol.*, vol. 44, no. 1, pp. 24–31, Jan. 2017.



ABDULRAHMAN K. EESÉE received the bachelor's degree in medical instrumentation technology engineering from Northern Technical University, Iraq, in 2011, and the master's degree in biomedical engineering from the University of Strathclyde, U.K., in 2015. He is currently pursuing the Ph.D. degree with the Department of Processing Engineering, University of Pannonia, Hungary. His research interests include human intention recognition and bio-signal processing.



JÁNOS ABONYI (Member, IEEE) received the M.Eng. and Ph.D. degrees in chemical engineering from the University of Pannonia, Hungary, in 1997 and 2000, respectively, and the Habilitation degree in process engineering and the D.Sc. degree from the Hungarian Academy of Sciences, in 2008 and 2011, respectively. From 1999 to 2000, he was with the Control Laboratory, Delft University of Technology, The Netherlands. He is currently a Full Professor in computer science

and chemical engineering with the Department of Process Engineering, University of Pannonia. He has coauthored more than 250 journal articles and chapters in books and has published five research monographs and one Hungarian textbook about data mining. His research interests include complexity, process engineering, quality engineering, data mining, and business process redesign.



SZILÁRD JASKÓ received the M.Sc. degree in computer engineering and the Ph.D. degree in information technology, in 2002 and 2012, respectively. He is currently the Head of the Department of Applied Informatics, University of Pannonia. He has published over 40 scientific articles and book chapter that received over 390 independent citations. His research interests include the adaptive intelligent systems and the sensor networks in industry 4.0. He is a member

of the Hungarian Scientific Academy–Veszprém Territorial Committee and Communication Working Committee.



GYÖRGY EIGNER (Senior Member, IEEE) is currently the Dean of the John von Neumann Faculty of Informatics and the Head of the Biomatics and Applied Artificial Intelligence Institution, Óbuda University, where he is currently an Associate Professor. His research interests include advanced control methods for physiological relations, biomedical engineering, human-in-the-loop systems, and artificial intelligence-based cyber medical systems.



TAMÁS RUPPERT (Member, IEEE) received the bachelor's degree in mechanical engineering and in engineering information technology, in 2015, the master's degree in mechatronics engineering, in 2016, and the Ph.D. degree, in 2020. He is currently an Assistant Professor in computer science with the Department of Process Engineering, University of Pannonia. His research interests include process mining algorithms, discrete-event simulators, and supply chain management. His

current research interests include industry 4.0 (discrete event simulators, connected factory, and supply chain management) and operator 4.0.

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