Materials Research Proceedings 35 (2023) 53-61 https://doi.org/10.21741/9781644902714-7

Workload and stress evaluation in advanced manufacturing systems

Graziana Blandino[1,a *], Francesca Montagna[1,b] and Marco Cantamessa[1,c]

[1]Department of Management and Production Engineering, Politecnico di Torino,10129 Torino, Italy

[a]graziana.blandino@polito.it, [b]francesca.montagna@polito.it, [c]marco.cantamessa@polito.it

Keywords: Ergonomics, Smart Manufacturing, Industry 4.0/5.0

Abstract. Industry 5.0 emphasizes the development of human-centred work environments, shifting the focus from technologies embedded in manufacturing systems to workers. Efforts in the literature focus on operators' well-being for workstation configuration or on stress in collaborative environments, but few papers consider stress induced by management practices in advanced manufacturing contexts, although "lean" or "agile" for instance could in principle lead to more stressful workplaces. This paper reviews the literature, evaluating the mental and physical workload of production line operators who perform mentally demanding tasks and experience stress in advanced manufacturing systems. The goal is to design and to perform a pilot test on an innovative and rigorous research protocol, to be adopted in 'non-fictional' experiments, and able to compare push vs pull settings and their effects on workers' workload and stress (WLS). The results will highlight new sources of stress, contributing to the development of human-centred and socially sustainable manufacturing systems.

Introduction

The fifth industrial revolution, Industry 5.0, defines a new paradigm of efficient and productive cooperation between autonomous machines, robots and human workers in advanced manufacturing systems. Automation and digitalization of processes have ensured efficiency and system optimization, but have had several consequences on workers that have acquired new roles [1,2] and had to develop new competencies, with possible impact on their safety and health [3]. Learning new skills, as well as changing roles, have been found to contribute to workers' discomfort, stress and fatigue [3]. In view of that, detecting signs of workload and stress (WLS) experienced by workers while executing work tasks at these contemporary manufacturing workplaces can contribute to developing new strategies aimed at preserving their well-being [4].
The literature on advanced manufacturing systems presents some limits. On the one hand, WLS phenomena are sometimes confused or considered as synonyms, and only few contributions [5,6] attempt to define them properly. On the other hand, contributions tend to explore only physical factors such as workload, fatigue and ergonomics and neglect the stress phenomenon. Some current contributions focus on human factors, such as cognitive load in manufacturing [7–9] and especially in assembly tasks [10,11] or push/pull tasks [12,13], though without assessing the phenomenon of stress.

The present work reviews the human factors measurement methods and the experimental protocols used in the literature, focusing on the analysis of WLS assessment. It then proposes a protocol to be adopted in 'non-fictional' experiments, along with a pilot study conducted to validate it and to assess if the measurements are suitable to compare effectively push vs pull settings.

The first section of the paper reviews the literature on human factors in advanced manufacturing systems and on experimental protocols. The following sections illustrate the aim of the paper, the research methodology and the designed protocol, followed by the discussion. Finally, the conclusions and limitations are shown.

Materials Research Proceedings 35 (2023) 53-61 https://doi.org/10.21741/9781644902714-7

Literature review

Workload is defined as the cost of performing a task and depends on several factors, such as the requirements of the task, the context in which the task is performed, and the skills of the worker [6]. Stress at work, on the other hand, is the phenomenon that occurs when the demand for work exceeds the worker's ability to perform it [14].

Three main categories of measurements, as in Table 1, exist in the literature: physiological, physical and psychological. The physiological and physical categories are defined as objective since they measure data that are not influenced by the perceptions of participants to experiments. Psychological measurements are subjective, and focus on workers' emotional state of WLS.

The physical methods measure stress and physical workload through the analysis of body posture and the ergonomics of workstations. In this regard, studies focus on postural measurements [15], body motion indicators [9,15,16], body language [9] or workers' performance [11,13,17].

Physiological measurements record the unconscious physiological and cognitive processes of workers while executing tasks. A number of studies focus on heart rate [18], or on associated composite indicators [15,17,19,20], measuring the distance between two heartbeats on the cardiac signal [6,17,21]. Besides, electrodermal activity (EDA) is investigated [5] by examining skin conductance (SC), in reaction to external stimuli e.g. [17,20,21]. Finally, other measures are possible: the breath rate [22], even if not so diffusely [15,19]; the electroencephalographic (EEG) signal [23], especially for stress measurements; and face temperature [24]. Finally, workload can be evaluated through the blink rate and the pupil size indicators of the ocular activity [25].

Psychological measurements examine the subjective perceptions of workers through the submission of questionnaires and tests, as in Table 1. The main advantage of these measurements relies on the fact that questionnaires and tests can be proposed during different stages of the experimental activities, or some days after, allowing different comparisons e.g. [6,20]. Moreover, these methods enable a better calibration of measurement methods, reducing the misinterpretation of data [26], but they require large samples of respondents to provide reliable results [27].

Table 1. Physical, Physiological and Psychological measurements and indicators

Physical measurement	**Indicators**	**Workload**	**Stress**	**Reference**
Postural	Ovako Working Posture Analysis System (OWAS)		X	[15]
	Rapid Entire Body Assessment (REBA)		X	[15]
	Rapid Upper Limb Assessment (RULA)		X	[15]
Body motion	Assembly line speed		X	[16]
	Occupational Repetitive Action (OCRA)	X		[8]
	Vector Magnitude Units (VMU)		X	[15]
	Hyperactivity		X	[9]
Body language/Behavioural	Self-touching		X	
	Reaction time	X		[11]
	Error rate	X		[17]
	Completion time	X		[13]
	Accuracy	X		
Physiological measurement	**Indicator**	**Workload**	**Stress**	**Reference**
Cardiac activity	Inter-beat intervals	X	X	e.g.[17,21]
	Heart Rate (HR), HR Variability (HRV)	X	X	e.g.[15,28]
EDA	Skin Conductance (SC)	X	X	e.g.[20,21]
Breathing activity	Breathing rate	X	X	[15,19]
Facial activity	Face temperature	X		[24]
Cerebral activity	High Beta frequency	X	X	[23,29]
Ocular activity	Pupil size changes	X		[25]
	Blink rate	X		[25]
	Eyes movement	X		[29]

Materials Research Proceedings 35 (2023) 53-61 https://doi.org/10.21741/9781644902714-7

Psychological data collection Method	Workload	Stress	Reference
Cognitive Load Assessment for Manufacturing (CLAM)	X		[7]
National Aeronautics Space Administration-Task Load Index (NASA-TLX)	X	X	e.g.[19,30]
Rating Scale Mental Effort (RSME)	X		[30]
Subjective workload assessment technique (SWAT)	X	X	[24,31]
Workload profile (WP)	X		[31]
Instantaneous Self-Assessment (ISA)	X		[17]
Modified Cooper-Harper Scale (MCH)	X		[24]
State-Trait Anxiety Inventory (STAI)		X	[20]
Depression Anxiety Stress Scales (DASS)		X	[12]
Valence-Arousal Test		X	[23]
Numeric Analog Scale (NAS)		X	[6]
Body Part Discomfort (BDP) scale		X	[32]
Perceived Stress scale (PSS)		X	[33]
Short Stress State Questionnaire (SSSQ)		X	[27]

The comparison of methods shows an overlap of measurements and indicators for WLS and suggests combining multiple types of measurements to avoid incomplete analyses. The experimental tasks usually include motor and cognitive activities. As in Table 2, motor tasks consist of manual assembly activities [9,15,32] that, in some studies, are executed by using collaborative robots [21,23] or augmented reality glasses [10], or working in different operational (e.g., push vs. pull) contexts [12,19]. In other cases, the task type involves other activities, such as crimping [8] or replacement of spare parts [6]. On the other hand, cognitive tasks aim to replicate high levels of attention and mental concentration in real manufacturing contexts. Examples are the N-back task [13,19], [28,29], the auditory stimulus detection task [11], or the visual search task [17]. Motor tasks are instead proposed to measure physical workload, while cognitive tasks are usually related to mental workload; however, standard tasks have still not emerged. Experimental activities can be carried out in laboratories and in real industrial environments. In laboratory experiments, augmented and virtual reality are adopted to simulate manufacturing contexts while executing tasks, and sensitive and fragile measurement equipment [15], difficult to integrate in real manufacturing environments, is used. In a real context [11, 12, 21], such as an automotive assembling line [32], wearable technologies for measurements aim to not interfere with the tasks.

Table 2. Experimental tasks and contexts

References	Experimental task				Experimental environment	
	Motor task			Cognitive task		
	Assembly	Push vs Pull	Other		Laboratory	In-field
[10,32]	X					X
[11]	X			X		X
[6,8]			X		X	
[28]			X	X	X	
[9,15,21,23]	X				X	
[13,29]	X			X	X	
[12]		X				X
[19]		X		X	X	
[17]				X	X	

As a general comment about human factors measurements and these experimental protocols, one can observe the little attention paid to demographic variables, such as workers' age and gender [34] or to environmental factors, such as noise and temperature levels, which instead have been demonstrated to influence humans' stress and workload [35].

Aim of the paper and research questions

This paper describes the protocol design and validation phase of a research aimed at comparing push vs pull settings and their effects on workers' WLS indicators. The first research question to be answered is: what are the most appropriate WLS measurement methods to be employed in the case of in-field experiments? The ensuing research question is: how do WLS indicators change when working in push vs. pull operational settings?

The literature review suggests adopting a combination of methods for measuring WLS. In line with this, the research methodology implements cardiac, electrodermal and breathing activity data collection to calculate physiological indicators, and NASA-TLX and PSS-10 questionnaires for psychological indicators.

The originality of the research is due to the possibility of:

- conducting these complementary measures through professional biomedical devices recording the integral physiological signal in a real industrial environment, with levels of accuracy and detail in the parameters that would be impossible to achieve by using widely-diffused consumer-grade wearable devices;
- conducting the measures in a real industrial environment, to consider environmental factors.

The validation process of the experimental protocol consisted of physiological and psychological signals analyses firstly to prove their suitability for in-field WLS measurements and, subsequently, to verify changes in the associated indicators according the experimental conditions.

The designed protocol and the adopted methodology of analysis

The protocol designed for the pilot experiment consists of three consecutive phases (i.e. before, during and after the task execution), as in Fig. 1. Before the task execution, the consent form and the sociodemographic questionnaire are filled; health status is certified, and gender and age data are collected to allow further investigations that are now neglected in the literature. Moreover, the participant wears the non-invasive biomedical devices to test functionality and for calibration; physiological data are collected for 5 minutes in rest condition and the subject is then instructed on the procedure details. Each data collection session consists of almost 15 minutes of physiological signals recording while the participant performs assembly tasks. Then, the biomedical devices are removed and a rest pause is ensured for the subject. Finally, WLS questionnaires are anonymously filled in by the participant referring to the task executed.

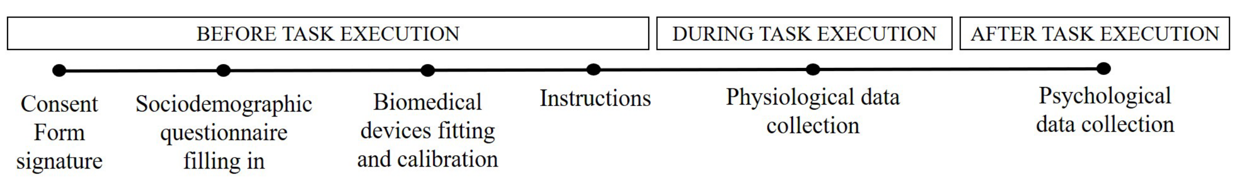

Figure 1. Experimental protocol

The device to be used for data collection are Encephalan Mini ABP-10, connected to ECG, EDA and thorax/abdominal breath sensor, in combination with Encephalan-EEGR Elite software. The ECG is recorded through three electrodes (Fig. 2.a), placed one for each wrist and the third on the left forearm. The sensor for respiratory activity is a band positioned on the participant's abdomen (Fig. 2.b), while EDA device comprehends ring sensors in the index and middle fingers of the left hand (Fig. 2.c). Electrodes and sensors are connected to the central data collection unit (Fig. 2.d), which in turn is connected to the SW for data storage. HR for the ECG technique, SC for EDA, and finally breathing rate for respiratory activity are the chosen WLS indicators.

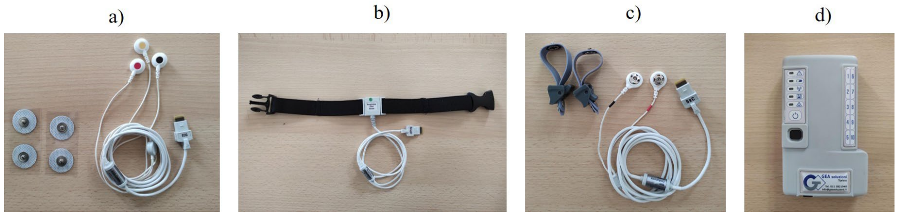

Figure 2. a) ECG device. b) Respiratory sensor. c) EDA device. d) Central data collection unit

The experimental protocol is aimed at tasks typical of an assembly environment and includes picking components, carrying out pre-assembly processes, assembly and storing the finished good. In the “push” setting, the order follows the production cycle, without restrictions on working times and unlimited buffers between stations. In the pull setting, production follows a Kanban system that defines limited buffers, and tack time defines the production pace. All physiological signals are analysed by MATLAB. The power spectral density of the noise is plotted, as well as the appropriate filters are applied to clean the signal. The physiological WLS indicators are calculated for each session, both in task execution and rest condition, in order to validate the difference among the experimental conditions. Then, statistical analyses of the WLS questionnaires for the assessment of correlation with the physiological results are conducted on MINITAB.

Validation of the protocol

The validation experiment was conducted in cooperation with a company operating in the plastic components industry, which has both “push” and “pull” operations. The company is a small-to-medium-sized enterprise with high Technology Readiness Level and medium-high maturity and leadership levels, according to ISO 9004:2018 standard. Since time constraints have been identified as a source of stress [36], one would expect to find physical and psychological stress levels to be higher under pull than push conditions. Therefore, in view of the validation, if the protocol works in push settings, it could work in the pull condition as well. Among the push sections of the company’s operations, we have chosen the assembly process (Fig 3.a) for customized heating radiator covers (Fig. 3.b).

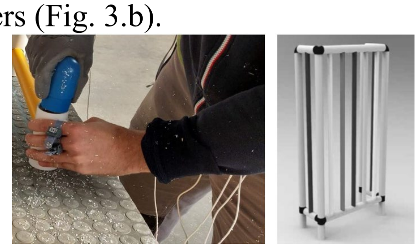

Figure 3. a) Assembly process. b) Heating radiator cover

The process consists in analysing the specific customer order and picking the required plastic tubes, cutting the tubes to measure, drilling holes in tubes, assembling and delivering to outgoing port. These steps are carried out by a single operator, who is free to organize his work, since the process is not rigid, and who moves along the workstations dedicated to each step. Cycle time depends on the customer order and averages 5 minutes per part. After set-up and calibration, physiological data were collected for 5 minutes in rest condition, followed by a working session of 15 minutes. A total of 4 sessions were carried out at different times. The breathing rate indicator was calculated for each step and for the entire session and was compared between the rest and the working conditions, as in Fig 4.a. By using research-grade equipment, the indicator recorded changes significantly for each session between the rest and the push task execution, coherently with the literature [17], and showed differences in WLS between the process steps, as in Fig 4.b, indicating the effectiveness of the protocol in detecting WLS differences. After each session, the NASA-TLX and PSS-10 questionnaires were compiled; the responses were examined, but not statistically analysed due to the limited sample of responses.

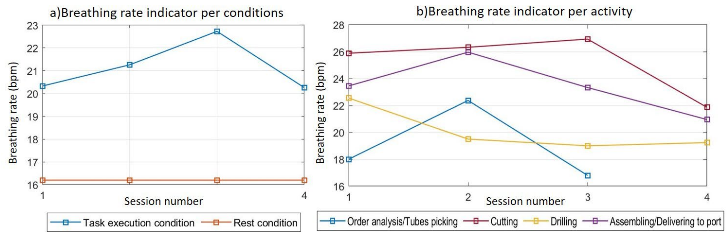

Figure 4. a) Breathing rate vs task conditions. b) Breathing rate vs task activities

The NASA-TLX responses for the 4 sessions (S1-S4) in Fig. 5.a, revealed that the mental demand (item 1) is higher than physical and temporal demand (items 2, 3). In general, the task was successfully performed (item 4) in each session at an intermediate level of effort and frustration (items 5, 6). Finally, from the PSS-10 assessments, in Fig. 5.b, intermediate scores were registered and negative emotions (items 1,2,3,6,9,10) were never perceived, while positive ones (items 4,5,7,8) occurred at times. The capability to appreciate differences in mental, physical and temporal demand, and also to capture the intensity and the nature of the perceived emotions of the workers, allowed the validation of both the two proposed questionnaires.

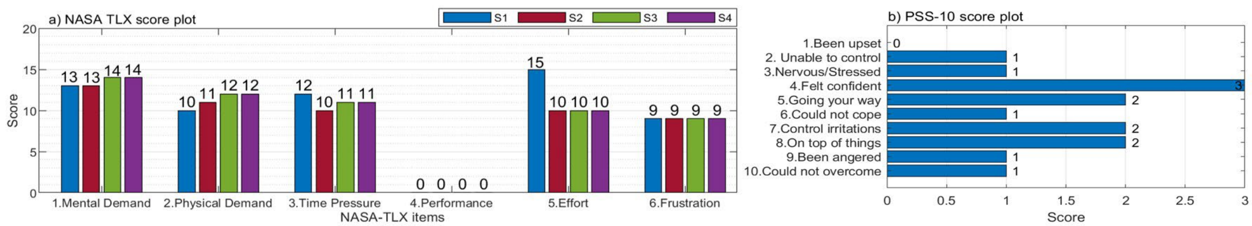

Figure 5. a) NASA-TLX responses. b) PSS-10 responses

Conclusion and limitations

The paper describes the design and validation of an experimental protocol for the evaluation of WLS indicators in push vs pull conditions in real industrial environments, using research-grade physiological equipment. The experiment was conducted in a plastics component company in a push condition. Cardiac, breathing, electrodermal activities data and NASA-TLX and PSS-10 answers have been collected, even if by way of example only the breathing rate data is reported. The indicators, among which here the respiration rate is discussed, have proved to be appropriate for WLS detection, and the two questionnaires confirmed that the protocol is suitable to study WLS in real push/pull industrial contexts. Furthermore, the results suggest that the analysed push task is demanding. The task variety and schedule flexibility balanced the stress due to medium-high time pressure, effort, mental and physical demand, according to the International Labour Organisation [37]. Consequently, it will be interesting to compare with pull situation. A larger number of participants and longer sessions will characterise the next experiments to monitor the evolution of WLS indicators and establish robust evidence under various work conditions.

References

[1] J. Alves, T. M. Lima, P. D. Gaspar, Is Industry 5.0 a Human-Centred Approach? A Systematic Review, Processes, 11.1 (2023) 193. https://doi.org/10.3390/pr11010193

[2] M. C. Zizic, M. Mladineo, N. Gjeldum, and L. Celent, From Industry 4.0 towards Industry 5.0: A Review and Analysis of Paradigm Shift for the People, Organization and Technology, Energies, 15.14 (2022) 5221. https://doi.org/10.3390/en15145221

[3] J. Leng, W. Sha, B. Wang, P. Zheng, C. Zhuang, Q. Liu, L. Wang, Industry 5.0: Prospect and retrospect, J Manuf Syst, 65 (2022) 279-295. https://doi.org/10.1016/j.jmsy.2022.09.017

[4] V. Villani, M. Gabbi, L. Sabattini, Promoting operator's wellbeing in Industry 5.0: detecting mental and physical fatigue, in Conference Proceedings - IEEE International Conference on

Systems, Man and Cybernetics, 2022 (2022), 2030-2036. https://doi.org/10.1109/SMC53654.2022.9945324

[5] C. Setz, B. Arnrich, J. Schumm, R. la Marca, G. Tröster, U. Ehlert, Discriminating stress from cognitive load using a wearable eda device, IEEE Transactions on Information Technology in Biomedicine, 14.2 (2010) 410-417. https://doi.org/10.1109/TITB.2009.2036164

[6] A. Brunzini, M. Peruzzini, F. Grandi, R. K. Khamaisi, M. Pellicciari, A preliminary experimental study on the workers' workload assessment to design industrial products and processes, Applied Sciences, 11.24 (2021) 12066. https://doi.org/10.3390/app112412066

[7] P. Thorvald, J. Lindblom, R. Andreasson, On the development of a method for cognitive load assessment in manufacturing, Robot Comput Integr Manuf, 59 (2019) 252-266. https://doi.org/10.1016/j.rcim.2019.04.012

[8] E. Giagloglou, P. Mijovic, S. Brankovic, P. Antoniou, I. Macuzic, Cognitive status and repetitive working tasks of low risk, Saf Sci, 119 (2019) 292-299. https://doi.org/10.1016/j.ssci.2017.10.004

[9] M. Lagomarsino, M. Lorenzini, E. de Momi, A. Ajoudani, An Online Framework for Cognitive Load Assessment in Industrial Tasks, Robot Comput Integr Manuf, 78 (2022). https://doi.org/10.1016/j.rcim.2022.102380

[10] H. Atici-Ulusu, Y. D. Ikiz, O. Taskapilioglu, T. Gunduz, Effects of augmented reality glasses on the cognitive load of assembly operators in the automotive industry, Int J Comput Integr Manuf, 34.5 (2021) 487-499. https://doi.org/10.1080/0951192X.2021.1901314

[11] M. Drouot, N. le Bigot, E. Bricard, J. L. de Bougrenet, V. Nourrit, Augmented reality on industrial assembly line: Impact on effectiveness and mental workload, Appl Ergon, 103 (2022) 103793. https://doi.org/10.1016/j.apergo.2022.103793

[12] M. Petrovic, A. M. Vukicevic, M. Djapan, A. Peulic, M. Jovicic, N. Mijailovic, K. Jovanovic, Experimental Analysis of Handcart Pushing and Pulling Safety in an Industrial Environment by Using IoT Force and EMG Sensors: Relationship with Operators' Psychological Status and Pain Syndromes, Sensors, 22.19 (2022) 7467. https://doi.org/10.3390/s22197467

[13] F. N. Biondi, A. Cacanindin, C. Douglas, J. Cort, Overloaded and at Work: Investigating the Effect of Cognitive Workload on Assembly Task Performance, 63.5 (2021) 813-820. https://doi.org/10.1177/0018720820929928

[14] D. M. Wegner, Stress and Mental Control'. Stress and mental control. Handbook of life stress, cognition and health, In S. Fisher & J. Reason (Eds.), 1988, 683-697.

[15] M. Peruzzini, F. Grandi, M. Pellicciari, Exploring the potential of Operator 4.0 interface and monitoring, Comput Ind Eng, 139 (2020) 105600. https://doi.org/10.1016/j.cie.2018.12.047

[16] V. K. Rao Pabolu, D. Shrivastava, M. S. Kulkarni, A Dynamic System to Predict an Assembly Line Worker's Comfortable Work-Duration Time by Using the Machine Learning Technique, in Procedia CIRP, 106 (2022) 270-275. https://doi.org/10.1016/j.procir.2022.02.190

[17] E. M. Argyle, A. Marinescu, M. L. Wilson, G. Lawson, S. Sharples, Physiological indicators of task demand, fatigue, and cognition in future digital manufacturing environments, International Journal of Human Computer Studies, 145 (2021) 102522. https://doi.org/10.1016/j.ijhcs.2020.102522

[18] R. Castaldo, P. Melillo, U. Bracale, M. Caserta, M. Triassi, L. Pecchia, Acute mental stress assessment via short term HRV analysis in healthy adults: A systematic review with meta-

analysis, Biomedical Signal Processing and Control, 18 (2015) 370-377. https://doi.org/10.1016/j.bspc.2015.02.012

[19] F. N. Biondi, B. Saberi, F. Graf, J. Cort, P. Pillai, B. Balasingam, Distracted worker: Using pupil size and blink rate to detect cognitive load during manufacturing tasks, Appl Ergon, 106 (2023) 103867. https://doi.org/10.1016/j.apergo.2022.103867

[20] M. Ciccarelli, A. Papetti, M. Germani, A. Leone, G. Rescio, Human work sustainability tool, J Manuf Syst, 62 (2022) 76-86. https://doi.org/10.1016/j.jmsy.2021.11.011

[21] R. Gervasi, K. Aliev, L. Mastrogiacomo, F. Franceschini, User Experience and Physiological Response in Human-Robot Collaboration: A Preliminary Investigation, Journal of Intelligent and Robotic Systems: Theory and Applications, 106.2 (2022) 36. https://doi.org/10.1007/s10846-022-01744-8

[22] A. Nicolò, C. Massaroni, E. Schena, M. Sacchetti, The importance of respiratory rate monitoring: From healthcare to sport and exercise, Sensors, 20.21 (2020) 1-45. https://doi.org/10.3390/s20216396

[23] A. T. Eyam, W. M. Mohammed, J. L. Martinez Lastra, Emotion-driven analysis and control of human-robot interactions in collaborative applications, Sensors, 21(2021) 4626. https://doi.org/10.3390/s21144626

[24] J. Kang, K. Babski-Reeves, (2009). Evaluation of methods for determining optimal mental workload levels. In IIE Annual Conference. Proceedings, Institute of Industrial and Systems Engineers (IISE) (2009) 913.

[25] S. Chen, J. Epps, Using task-induced pupil diameter and blink rate to infer cognitive load, Hum Comput Interact, 29. 4 (2014) 390-413. https://doi.org/10.1080/07370024.2014.892428

[26] Y. Z. Abd Elgawad, M. I. Youssef, T. M. Nasser, New methodology to detect the effects of emotions on different biometrics in real time, International Journal of Electrical and Computer Engineering, 13.2 (2023) 1358-1366. https://doi.org/10.11591/ijece.v13i2.pp1358-1366

[27] L. Gualtieri, F. Fraboni, M. de Marchi, E. Rauch, Development and evaluation of design guidelines for cognitive ergonomics in human-robot collaborative assembly systems, Appl Ergon, 104 (2022) 103807. https://doi.org/10.1016/j.apergo.2022.103807

[28] D. Cavallo, F. Facchini, G. Mossa, Information-based processing time affected by human age: An objective parameters-based model, in IFAC-PapersOnLine, 54.1 (2021) 7-12. https://doi.org/10.1016/j.ifacol.2021.08.001

[29] J. Morton, A. Zheleva, B.B. Van Acker, W. Durnez, P. Vanneste, C. Larmuseau, K. Bombeke, 'Danger, high voltage! Using EEG and EOG measurements for cognitive overload detection in a simulated industrial context', Appl Ergon, 102 (2022) 103763. https://doi.org/10.1016/j.apergo.2022.103763

[30] A. Widyanti, W. Larutama, The relation between performance of lean Manufacturing and employee' mental workload, in IEEE International Conference on Industrial Engineering and Engineering Management, 2016 (2016) 252-256. https://doi.org/10.1109/IEEM.2016.7797875

[31] S. Rubio, E. Díaz, J. Martín, J. M. Puente, Evaluation of Subjective Mental Workload: A Comparison of SWAT, NASA-TLX, and Workload Profile Methods, Applied Psychology, 53.1 (2004) 61-86. https://doi.org/10.1111/j.1464-0597.2004.00161.x

[32] V. Kopp, M. Holl, M. Schalk, U. Daub, E. Bances, B. Garcia, U. Schneider, Exoworkathlon: A prospective study approach for the evaluation of industrial exoskeletons, Wearable Technologies, 3 (2022) e22. https://doi.org/10.1017/wtc.2022.17

[33] M. Mailliez, S. Hosseini, O. Battaiä, R. N. Roy, Decision Support System-like Task to Investigate Operators' Performance in Manufacturing Environments, in IFAC-PapersOnLine, 53 (2020) 324-329. https://doi.org/10.1016/j.ifacol.2021.04.110

[34] V. di Pasquale, S. Miranda, W. P. Neumann, Ageing and human-system errors in manufacturing: a scoping review, International Journal of Production Research, 58.15 (2020) 4716-4740. https://doi.org/10.1080/00207543.2020.1773561

[35] A. M. Abbasi, M. Motamedzade, M. Aliabadi, R. Golmohammadi, L. Tapak, Combined effects of noise and air temperature on human neurophysiological responses in a simulated indoor environment, Appl Ergon, 88 (2020) 103189. https://doi.org/10.1016/j.apergo.2020.103189

[36] J. R. Kelly, J. E. Mcgrath, Effects of Time Limits and Task Types on Task Performance and Interaction of Four-Person Groups, 49.2 (1985) 395. https://doi.org/10.1037/0022-3514.49.2.395

[37] International Labour Organization. Workplace Stress: A Collective Challenge. International Labour Office: Geneva, Switzerland (2016).