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COGNITIVE WORKLOAD AND FATIGUE IN A HUMAN-ROBOT COLLABORATIVE ASSEMBLY WORKSTATION: A PILOT STUDY

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Abstract

Background: Industry 5.0 represents a novel approach that builds upon the advancements of Industry 4.0 and is aimed at fostering a more harmonious relationship between humans and machines to prioritize resource efficiency and user-centered manufacturing. **Objective**: This paper presents a study, integrated in the COBOSHe project, for assessing and analyzing the cognitive workload and fatigue, using heart rate (HR) and a perceived scale related to fatigue, in a car engine assembly in which a robot and a human operator are performing tasks in a shared workspace. **Method**: For this purpose, a sample of 30 subjects were divided into two groups, with group A having read the assembly instructions before the usage of the assembly workstation and group B without having any previous knowledge about the car engine. The data analysis was carried out using descriptive and inferential statistics (Kruskal-Wallis's test and Spearman's correlation test) in the IBM SPSS Statistics software, version 28.0. **Results**: The results showed that HR and perceived fatigue didn't had statistical differences between groups ($p=0.380$). There is insufficient statistical evidence, to state that the subscales of SOFI are not identical between the two groups ($p > 0.05$). **Conclusion:** Therefore, we conclude that the usage of the augmented reality system in the assembly workstation for providing on demand instructions was intuitive and allowed the operators to learn how to assemble the car engine without requiring any previous knowledge about the assembly process. **Application**: this type of study allows to improve collaborative workstations, as it increases the efficiency and productivity of production lines.

Keywords: Mental Workload, Industry 5.0, Assembly Work, Human-Robot Interaction

Introduction

Manufacturing companies are increasing their resilience and accelerating the transition to sustainable industry. As such, companies are improving the workers wellbeing and quality of working conditions by relying on the adoption of technologies that complement and assist the human capabilities (Renda et al., 2022). Therefore, this shift of focus from technology-driven progress to a human-centric approach is one of the most important characteristics of Industry 5.0. Considering culture values, respecting the human rights and valuing the skills of the workers are crucial ideals for designing a safe and beneficial working environment (Breque et al., 2021).

The adoption of collaborative robots (or cobots) is growing in manufacturing since they offer an opportunity for the human and robots to exchange information and share tasks. In order to improve this interactive experience and maximize efficiency, it is necessary that the robot understands the human actions and the human understands the robot tasks (Losey & O'Malley, 2019). In a collaborative workplace, where humans and cobots interact to accomplish the defined objectives, there are many factors that influence this interaction and that need to be explored in an integrated and multidisciplinary way, not only to maximize human involvement in the decision chain but also to promote human health, well-being and quality of life.

Therefore, the development of research in this field should be performed by multidisciplinary teams, with expertise in the engineering fields along with human ergonomics and phycology, in order to create realistic and sustainable studies that analyze the impact that can be caused on humans when working alongside robots. Namely, in Human-Robot Collaboration (HRC) workstations, the human contributes with extensive cognitive and sensorimotor skills and the robot excels at tasks that require strength, accuracy, and endurance (Faber et al., 2016).

In the current literature on intelligent cobot design, the balance between human situational awareness, workload optimization, and production efficiency must be considered (Gombolay et al., 2017). The interaction style and task design may also affect how the collaboration is perceived by the human with respect to efficiency, comfort, safety, and fluency (Gombolay et al., 2017). The influence of task design on muscle fatigue and performance is not completely understood during low-load repetitive work, such as small parts assembly tasks (Schulz et al., 2018). On the other hand, assembly-line workers perceived a lack of energy and physical discomfort during a workday (Santos et al., 2017). Concerning human cognitive performance, researchers referred that it reduces over time, if the complexity of the task or the probability of robot error increases (Rabby et al., 2019). Robot acceptance and trust (cognitive and affective) are also key predictive factors of the success of the human robot interaction (Cameron et al., 2016; Wang et al., 2019). Assembly work is characterized by strictly standardized procedures, where workers have short cycle times (less than 30s), little task variation, repetitive wrist motions and reduced breaks and pauses. Therefore, they suffer from physical and psychological stress (Colombini & Occhipinti, 2006; Rajabalipour Cheshmehgaz et al., 2012). As such, HRC can be a good option for assembly tasks, since it can improve physical and mental health of the human operators. However, there are many factors related to the internal logistics of companies and their supply chains, along with the engineering challenges associated with the deployment of cobots in manufacturing (Simões et al., 2020).

The more recent conceptual models or methodological approaches to optimize the design of HRC includes a holistic perspective of collaboration, that integrates multiple key parameters, such as legal, technical and psychological requirements as well as the technological complexity, HRC relevance, benefits/costs indicators, ergonomics, safety and logistic interfaces (Simões et al., 2021; Zanella et al., 2017). Despite the promising results of the ongoing research, a completely human-centered collaborative workstation, which satisfies all the physical and cognitive ergonomic principles, was not yet possible to design, due to the diversity of knowledge fields involved in this process (Marvel et al., 2020). Considering this gap, it was designed a research project, named COBOSHe project, that had a multidisciplinary approach for collaborative workspaces with the intention of designing an HRC workstation that was human-centered, which satisfies all physical and cognitive ergonomics principles. This project aims to respond to the new vision introduced by the Industry 5.0, that complements the existing Industry 4.0 approach by specifically putting research and innovation at the service of the transition to a more sustainable, human-centric and resilient industry. The experimental scenario integrated in this project was the development of a collaborative workstation for the assembly of a car engine, in which a robotic arm and a human operator helped each for performing the assembly tasks.

This article presents the preliminary results of a cognitive workload assessment performed in a human-robot collaborative workstation. This pilot study aimed to assess and analyze the cognitive workload and fatigue of a human operator, using heart rate (HR) and fatigue perceived scale, during a car engine assembly.

Material and Methods

A randomized cross-sectional study was developed in a collaborative workstation dedicated to the assembly of a car engine, which was designed for demonstrating a scalable and flexible approach to production, that can be integrated with factory planning, optimization and maintenance systems for further improving productivity and efficiency. This transversal approach included the use of collaborative robots along with production management and simulation systems, in order to dynamically adapt the automation levels to the production needs.

A) Description of the collaborative workstation

The augmented reality workstation (shown in Figure 1) relies on a video projector along with a 3D sensor for providing an immersive environment in which the instructions are displayed on demand and directly in the target objects. This way, the operator receives concise and intuitive information for each active task, such as the working zones assigned to the operator (with green highlight) and the robot (with red highlight), along with a text summary and a video showing how to perform the tasks. All partipants performed an assembly task, sharing tasks with the robot at the same time and in the same space.

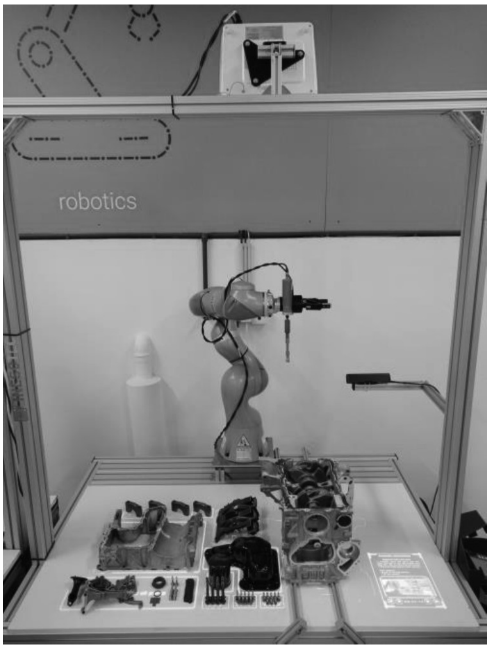

Figure 1. *Augmented reality workstation with projected instructions and work zones for the assembly of a car engine.*

B) Characteristics of the participants

Thirty university students (63% female and 37% male) aged between 22 and 26 years, without any cobots experience participated in this study. None of the subjects reported any pain or musculoskeletal disorders. Table 1 shows the demographics characteristics of the sample. This sample was divided into two groups, in which group A had read the assembly instructions before using the workstation and group B having no previous knowledge about the car engine assembly tasks.

Table 1. *Participant characteristics (N=30).*

Characteristic	**Group A (M±SD)**	**Group B (M±SD)**
Age (years)	22.4 (±1.06)	22.4 (±0.74)
Weight (Kg)	68.6 (±16.50)	63.1 (±7.63)
Height (cm)	170.0 (±8.60)	168.0 (±8.00)
Body Mass Index (Kg/m2)	23.5 (±4.60)	22.3 (±2.00)

C) Equipment for measuring HR and fatigue

Cognitive workload and fatigue were assessed through HR and perceived scales of fatigue. A Polar H10 HR monitor with a Pro Strap was used to measure HR at rest and during the assembly tasks. According to a previous study (Gilgen-Ammann et al., 2019), Polar H10 has been found to be valid when compared with

ECG, with a correlation of r=0.997. The Portuguese version of the Swedish Occupational Fatigue Inventory (SOFI) was also applied to all participants after the work tasks. SOFI is a self-report instrument developed for occupational assessment of fatigue with 5 dimensions and 20 expressions (4 items per dimension), namely, lack of energy (worn out, spent, drained, overworked), physical exertion (palpitations, sweaty, out of breath, breathing heavily), physical discomfort (tense muscles, numbness, stiff joints, aching), lack of motivation (lack of concern, passive, indifferent, uninterested) and sleepiness (falling asleep, drowsy, yawning, sleepy). It has a 7-grade response scale, where the extreme values were verbally labeled, 0 "not at all" and 6 "to a very high degree" (Santos et al., 2017).

D) Data analysis

The statistical treatment of the research data was carried out using the IBM SPSS Statistics software, version 28.0, for analyzing and processing the statistical data. The descriptive analysis was performed to describe and synthesize the data obtained. Two descriptive measures were calculated, namely, the mean and the standard deviation. For analyzing and verifying whether the results were reliable and stable, a 95% confidence interval was used, which means, a significant level of 5% (α=0,05). Regarding inferential statistics, we used the Kruskal-Wallis, a nonparametric test, and the Spearman's correlation test to compare the subscales of the questionnaires with each other and with HR.

Results and Discussion

A) Heart Rate (HR)

Mental workload and fatigue, as we said earlier, can be assessed via physiological data. In mental workload the heart rate is considered to be a good correlate of mental activity (Gilgen-Ammann et al., 2019), easy to acquire, and sensitive to changes in mental workload. In fatigue, the heart rate of the operator under stress condition is very useful. The stress may give influence to the heart rate which is caused by an autonomic nerve when the operator gets the stress.

Table 2 shows the means and standard deviations obtained for HR at rest, during the collaborative task and the maximum HR in the two groups.

Table 2. *Means and standard deviations of HR by groups (N=30).*

Parameters	Group A (n=15) (M±SD)	Group B (n=15) (M±SD)	*p*-value
HR at rest	78.9 (±9.6)	86.5 (±13.3)	0.120
HR during task	94.8 (±12.2)	100.1 (±16.7)	0.380
Maximum HR	102.6 (±12.0)	109.8 (±16.6)	0.610

As can be seen in Table 2, there were no significant differences in HR during the assembly tasks between the 2 groups (p=0.380), which demonstrated that the previous knowledge about the operations with the cobot did not have a large influence. HR is directly linked to physical activity; however, it is also a measure of both the sympathetic and parasympathetic autonomic nervous system activity (Vanneste et al., 2020). The results about HR during assembly tasks were similar between groups, which can be explained by the participants inexperience and by the anxiety and nervousness caused due the proximity with robot and the lack of knowledge of the robot's actions. The study of Solhjoo et al. (2019) showed that when the subjects did not have time to sit down and think about the activity performed, stress levels increased and consequently, the HR. Participants reported that the augmented reality system facilitated the assembly of the car engine. In fact, this type of solution, when compared with instructions through a manual, is more intuitive and less time-consuming.

B) Perceived Fatigue

Although objective measures (e.g., HR) remain the most desirable measures to evaluate workload and fatigue the use of subjective measures (those brought back by the questioned individuals) still a good complement. In the five subscales that are part of the fatigue questionnaire (lack of energy, physical exertion, physical discomfort, lack of motivation and sleepiness), the fact that the subjects had been previously instructed on the assembly tasks did not lead to statistically significant differences between group A and group B ($p > 0.05$), as can be observed in Table 3.

Despite the disadvantages, self-reporting assessment scales (subjective measures) has been used as a gold standard to evaluate cognitive load (Vanneste et al., 2020). Research using SOFI has proven to be able to determine the level of workload (Yuliani & Tambunan, 2018). In this study, it was used a multidimensional questionnaire (Portuguese version of SOFI), where each dimension was defined by the content of 5 expressions related to physiological, cognitive, motor and emotional responses (Åhsberg et al., 2000). According to Fan and Smith (Fan & Smith, 2020), the organizations should be identified and manage cognitive workload and fatigue to promote safety in their workplaces. Lack of motivation was the sub-scale that had the item with the highest score (1.13) (Group A).

Perceived mental workload and Mental Workload (MWL) and Task-Technology Fit (TTF) can significantly influence user acceptance (Dang et al., 2020). The results demonstrated no difference between groups which can be explain by the similar sociodemographic characteristics of the sample studied. Czaja et al. (2006) suggested that adoption of technology is influenced by a variety of factors, including sociodemographic factors, attitudinal variables, and cognitive abilities.

Table 3. *Ratings of fatigue on the Portuguese version of SOFI by group (N=30).*

	Group A (n=15) (M±SD)	Group B (n=15) (M±SD)	*p*
Lack of energy			
Worn out	0.27 ± 0.59	0.07 ± 0.26	
Spent	0.60 ± 0.83	0.27 ± 0.46	0.483
Drained	0.33 ± 0.72	0.06 ± 0.26	
Overworked	0.20 ± 0.41	0.40 ± 1.30	
Physical exertion			
Palpitations	0.73 ± 0.96	0.93 ± 1.10	
Sweaty	0.53 ± 0.74	0.20 ± 0.56	0.934
Out of breath	0.20 ± 0.41	0.00 ± 0.00	
Breathing heavily	0.07 ± 0.26	0.13 ± 0.52	
Physical discomfort			
Tense muscles	0.93 ± 1.16	0.27 ± 0.59	
Numbness	0.53 ± 0.99	0.00 ± 0.00	0.300
Stiff joints	0.33 ± 0.82	0.13 ± 0.35	
Aching	0.27 ± 0.59	0.00 ± 0.00	
Lack of motivation			
Lack of concern	1.13 ± 1.77	0.60 ± 0.98	
Passive	0.47 ± 0.74	0.27 ± 0.80	0.509
Indifferent	0.33 ± 0.62	0.53 ± 1.36	
Uninterested	0.33 ± 1.05	0.33 ± 0.72	
Sleepiness			
Falling asleep	0.33 ± 0.72	0.00 ± 0.00	
Sleepy	0.47 ±0.92	0.53 ± 0.83	0.934
Drowsy	0.60 ± 1.12	0.27 ± 0.80	
Yawning	0.20 ± 0.56	0.40 ± 0.74	

Some studies show that if the internal, external and initial conditions are kept constant, HR demonstrated a very high correlation with questionnaires and behavioral tasks (Grossman et al., 1991; Pagani et al., 1991), in our case it was not what was verified. The correlations among the subscales of the Portuguese version of SOFI and HR (see Table 4), are not statistically significant (p>0.05) (see Table 4). These results might take us think that some variables in our study (internal, external and initial conditions) needs to be better controlled.

Table 4. *Correlations among the subscales of the Portuguese Version of SOFI and HR*

	Lack of Energy	Physical Exertion	Physical Discomfort	Lack of Motivation	Sleepiness	HR during task
Lack of Energy						
Correlation Coefficient Sig. (2-tailed)	1.000 ---					
Physical Exertion						
Correlation Coefficient Sig. (2-tailed)	0.052 (0.786)	1.000 ---				
Physical Discomfort						
Correlation Coefficient Sig. (2-tailed)	0.375 (0.041)	0.474 (0.008)	1.000 ---			
Lack of Motivation						
Correlation Coefficient Sig. (2-tailed)	0.406 (0.026)	0.293 (0.117)	0.210 (0.265)	1.000 ---		
Sleepiness						
Correlation Coefficient Sig. (2-tailed)	0.746 (< 0.001)	0.110 (0.562)	0.232 (0.217)	0.665 (< 0.001)	1.000 ---	
HR during task						
Correlation Coefficient Sig. (2-tailed)	0.044 (0.818)	0.230 (0.221)	0.154 (0.417)	- 0.108 (0.572)	0.006 (0.975)	1.000 —

Limitations

Although all participants did not have previous experience with collaborative robots or experience in manufacturing operations, the small sample of participants without similar gender representation (63% female and 37% male) was a limitation of this current study. As such, our results cannot be generalized. Furthermore, the experiment referred to a specific set of tasks that aims to reproduce a common, but not unique, industrial workstation with collaboration between humans and robots.

Conclusions

The primary focus of this study was to compare the cognitive workload differences between participants with and without previous knowledge about the instructions associated with the assembly of a car engine in a collaborative workstation equipped with a cobot. For performing this evaluation, the HR and fatigue of the

participants was collected, and a statistical analysis was performed. According to the literature, HR is related to physical and mental load, however no significant differences were found between the 2 groups under evaluation, when analyzing the HR and fatigue results. This can be explained by the confidence that the participants had on the information projected by the augmented reality system, which made the assembly task intuitive and allowed the human operators to spatially visualize the work zones assigned to them and the cobot.
Future studies are needed to analyze workstations with different cobots and assembly tasks. The statistical analysis may also be extended to include the collection of more biomechanical, physiological and perception data during the tasks at the collaborative workstation and also include the impact that may arise when the operators are cycled between workstations that have different purposes in order to avoid the cognitive and physical fatigue of doing the same operations for a long period of time. COBOSHe project is ongoing, and it will be representing relevant research for the development of more human centered collaborative workstations, that are able to improve the cognitive performance, health, and well-being of the operators.

References

Åhsberg, E., Gamberale, F., & Gustafsson, K. (2000). Perceived fatigue after mental work: An experimental evaluation of a fatigue inventory. *Ergonomics*, *43*(2), 252–268. https://doi.org/10.1080/001401300184594

Breque, M., De Nul, L., & Petridis, A. (2021). Industry 5.0 : towards a sustainable, human-centric and resilient European industry,. *Publications Office of the European Union*. https://data.europa.eu/doi/10.2777/308407

Cameron, D., Collins, E., Cheung, H., Chua, A., Aitken, J. M., & Law, J. (2016). Don't Worry, We'll Get There: Developing Robot Personalities to Maintain User Interaction After Robot Error. In *Lecture Notes in Computer Science* (Vol. 9793, pp. 409–412). https://doi.org/10.1007/978-3-319-42417-0_38

Colombini, D., & Occhipinti, E. (2006). Preventing upper limb work-related musculoskeletal disorders (UL-WMSDS): New approaches in job (re)design and current trends in standardization. *Applied Ergonomics*, *37*(4), 441–450. https://doi.org/10.1016/j.apergo.2006.04.008

Simões, A. C., Soares, A. L., & Barros, A. C. (2020). Factors influencing the intention of managers to adopt collaborative robots (cobots) in manufacturing organizations. *Journal of Engineering and Technology* Management, *57*, 101574. https://doi.org/10.1016/j.jengtecman.2020.101574

Czaja, S. J., Charness, N., Fisk, A. D., Hertzog, C., Nair, S. N., Rogers, W. A., & Sharit, J. (2006). Factors predicting the use of technology: Findings from the center for research and education on aging and technology enhancement (create). *Psychology and Aging*, *21*(2), 333–352. https://doi.org/10.1037/0882-7974.21.2.333

Dang, Y. (Mandy), Zhang, Y. (Gavin), Brown, S. A., & Chen, H. (2020). Examining the impacts of mental workload and task-technology fit on user acceptance of the social media search system. *Information Systems Frontiers*, *22*(3), 697–718. https://doi.org/10.1007/s10796-018-9879-y

Faber, M., Kuz, S., Mertens, A., & Schlick, C. M. (2016). Model-Based Evaluation of Cooperative Assembly Processes in Human-Robot Collaboration. In *Advances in Intelligent Systems and Computing* (Vol. 490).

Fan, J., & Smith, A. P. (2020). Effects of Occupational Fatigue on Cognitive Performance of Staff From a Train Operating Company: A Field Study. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.558520

Gilgen-Ammann, R., Schweizer, T., & Wyss, T. (2019). RR interval signal quality of a heart rate monitor and an ECG Holter at rest and during exercise. *European Journal of Applied Physiology*, *119*(7), 1525–1532. https://doi.org/10.1007/s00421-019-04142-5

Gombolay, M., Bair, A., Huang, C., & Shah, J. (2017). Computational design of mixed-initiative human–robot teaming that considers human factors: situational awareness, workload, and workflow preferences. *The International Journal of Robotics Research*, *36*(5–7), 597–617. https://doi.org/10.1177/0278364916688255

Grossman, P., Karemaker, J., & Wieling, W. (1991). Prediction of Tonic Parasympathetic Cardiac Control Using Respiratory Sinus Arrhythmia: The Need for Respiratory Control. *Psychophysiology*, *28*(2), 201–216. https://doi.org/10.1111/j.1469-8986.1991.tb00412.x

Losey, D. P., & O'Malley, M. K. (2019). Enabling Robots to Infer How End-Users Teach and Learn Through Human-Robot Interaction. IEEE Robotics and Automation Letters, 4(2), 1956–1963. https://doi.org/10.1109/LRA.2019.2898715

Marvel, J. A., Bagchi, S., Zimmerman, M., & Antonishek, B. (2020). Towards Effective Interface Designs for Collaborative HRI in Manufacturing. ACM Transactions on Human-Robot Interaction, 9(4), 1–55. https://doi.org/10.1145/3385009

Pagani, M., Mazzuero, G., Ferrari, A., Liberati, D., Cerutti, S., Vaitl, D., Tavazzi, L., & Malliani, A. (1991). Sympathovagal interaction during mental stress. A study using spectral analysis of heart rate variability in healthy control subjects and patients with a prior myocardial infarction. Circulation Supplement, *83*(4), 43–51.

Rabby, K. M., Khan, M., Karimoddini, A., & Jiang, S. X. (2019). An Effective Model for Human Cognitive Performance within a Human-Robot Collaboration Framework. *2019 IEEE* International Conference on Systems, Man and Cybernetics (SMC), 3872–3877. https://doi.org/10.1109/SMC.2019.8914536

Rajabalipour Cheshmehgaz, H., Haron, H., Kazemipour, F., & Desa, M. I. (2012). Accumulated risk of body postures in assembly line balancing problem and modeling through a multi-criteria fuzzy-genetic algorithm. Computers & Industrial Engineering, 63(2), 503–512. https://doi.org/10.1016/j.cie.2012.03.017

Renda, A., Schwaag Serger, S., Tataj, D., Morlet, A., Isaksson, D., Martins, F., Mir Roca, M., Hidalgo, C., Huang, A., Dixson-Declève, S., Balland, P.-A., Bria, F., Charveriat, C., Dunlop, K., & Giovannini, E. (2022). Industry 5.0, a transformative vision for Europe: governing systemic transformations towards a sustainable industry. Office of the European Union. https://data.europa.eu/doi/10.2777/17322

Santos, J., Carvalhais, C., Ramos, C., Coelho, T., Monteiro, P. R. R., & Vaz, M. A. P. (2017). Portuguese version of the Swedish Occupational Fatigue Inventory (SOFI) among assembly workers: Cultural adaptation, reliability and validity. *International Journal of Occupational Medicine and Environmental Health*, *30*(3), 407–417. https://doi.org/10.13075/ijomeh.1896.00760

Schulz, R., Kratzer, P., & Toussaint, M. (2018). Preferred Interaction Styles for Human-Robot Collaboration Vary Over Tasks With Different Action Types. Frontiers in Neurorobotics, 12. https://doi.org/10.3389/fnbot.2018.00036

Simões, A. C., Pinto, A., Santos, J., Pinheiro, S., & Romero, D. (2021). Designing human-robot collaboration (HRC) workspaces in industrial settings: A systematic literature review. Journal of Manufacturing Systems, 62, 28–43. https://doi.org/https://doi.org/10.1016/j.jmsy.2021.11.007

Solhjoo, S., Haigney, M. C., McBee, E., van Merrienboer, J. J. G., Schuwirth, L., Artino, A. R., Battista, A., Ratcliffe, T. A., Lee, H. D., & Durning, S. J. (2019). Heart Rate and Heart Rate Variability Correlate with Clinical Reasoning Performance and Self-Reported Measures of Cognitive Load. *Scientific Reports*, *9*(1). https://doi.org/10.1038/s41598-019-50280-3

Vanneste, P., Raes, A., Morton, J., Bombeke, K., Van Acker, B. B., Larmuseau, C., Depaepe, F., & Van den Noortgate, W. (2020). Towards measuring cognitive load through multimodal physiological data. Cognition, Technology and Work, 23(3), 567–585. https://doi.org/10.1007/s10111-020-00641-0

Wang, Y., Lematta, G. J., Hsiung, C.-P., Rahm, K. A., Chiou, E. K., & Zhang, W. (2019). Quantitative Modeling and Analysis of Reliance in Physical Human–Machine Coordination. Journal of Mechanisms and Robotics, 11(6). https://doi.org/10.1115/1.4044545

Yuliani, E. N. S., & Tambunan, E. B. M. (2018). Reduce workload of security officers using NASA-LTX, SOFI, Heart Rate and Energy Expenditure Method. IOP Conference Series: Materials Science and Engineering, 453, 012065. https://doi.org/10.1088/1757-899X/453/1/012065

Zanella, A., Cisi, A., Costantino, M., Di Pardo, M., Pasquettaz, G., & Vivo, G. (2017). Criteria Definition for the Identification of HRC Use Cases in Automotive Manufacturing. Procedia Manufacturing, 11, 372–379. https://doi.org/10.1016/j.promfg.2017.07.120