Safety-Critical Systems in the Automotive Sector: Pros and Cons in the Current State-of-the-Art of Human Performance Assessment

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Carlos Albarrán Morillo

Department of Applied Science and Technology, Politecnico di Torino, Italy.
E-mail: carlos.albarran@polito.it

Devesh Jawla

Technological University Dublin, Ireland. E-mail: Devesh.Jawla@tudublin.ie

John D. Kelleher

Technological University Dublin, Ireland. E-mail: john.d.kelleher@tudublin.ie

Micaela Demichela

Department of Applied Science and Technology, Politecnico di Torino, Italy.
E-mail: micaela.demichela@polito.it

Even though the possible replacement of workers with automation or robots seems to indicate a future loss in human workforce needs, most manufacturing lines still require human interaction, e.g., for maintenance, inspections, and operations. Due to this interaction, the human-machine interface and human reliability are critical performance factors for identifying and dealing with safety-critical scenarios and business continuity. This paper is based on a literature review on human performance assessment in the automotive sector. This review reports the pros and cons of the current human performance assessment and deployment methods and data at the current state-of-the-art.
In the automotive sector, production systems are based on assembly lines where the automation process is becoming increasingly complex, which calls for additional capabilities for the workers' operations and for analyzing safety-critical operations and making decisions. Artificial intelligence that made massive progress in science and technology can play a relevant role. Artificial intelligence is expected to support the decision-making for the management of safety-critical systems in an always more rapid and effective way, exploiting data from the shopfloor, both from equipment and operators' monitoring. Moreover, independent artificial intelligence decisions, even in critical scenarios, will be the future target of the research. This work is an initial step in our research activity within the Collaborative Intelligence for Safety-Critical Systems (CISC) project. https://www.ciscproject.eu/

Keywords: Human Capability, human performance, safety-critical systems, Task Complexity.

1. Motivation and context

The manufacturing sector is still widely based on human operations, despite increasing automation. The automotive sector, for instance, is based on assembly lines, where the automation process is becoming more and more complex. Different operators contribute to assembly products, which require different operational capabilities and a multi-faceted approach for analyzing critical-safety procedures and making technological decisions. The Human Factor (HF) is a critical factor for employers' safety. A practical way to assess human performance modelling as the reliability of individuals to perform a specific duty can help identify critical scenarios in manufacturing plants. When an operator has enough capabilities to perform a complex task, the probability of accident or error is reduced (Lin et al. (2001)).
In more detail, human performance (HP) modelling can be described as the result of an interaction between the skill level demanded to achieve a given job in a workplace and the capabilities of the employees assigned to it. In particular, Leva et al. (2017) showed that human performance could be represented as directly dependent on two macro-factors:

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- Task Complexity (TC): assessed through Mental Workload (MW) and Physical Workload (PW), both associated with each task identified and analyzed in the assembly line.
- Human Capability (HC): it represents the workers' skills under the actual working states, including each employee's physical, mental and cognitive abilities.

Leva et al. (2020) applied this framework to assembly line work. The HC component can be grounded in three quantifiable capabilities: Memory, Manual and Physical skills. In order to assess these skills, a set of practical tests were designed (Comberti et al. (2020)), the so-called "ability corners". The TC was estimated by assessing the observable variables related to Mental and Physical Workload and expressed in terms of indices harmonized in a Likert scale. The HP model results were addressed using a matching index matrix that compared the required aptitudes for each workstation with the harmonized recorded skillsets of each worker.

The recent technological advances in various fields, including artificial intelligence (AI), allow enriching human performance modelling. Since the dawn of the era of modern computers, some tasks, particularly repetitive ones, are best performed by machines. However, nowadays, more than that is demanded. The emerging technologies aim to improve operator safety, performance, and well-being and enhance the capabilities of the work-station-operator interaction. As a result, operators will have to acquire a broader range of specific skills. They will have more and more often to combine traditional task-associated expertise with computer science.

Some initial research questions can be formulated that may feed the paradigm transformation. What technological advances could be added to analyze the human performance in safety-critical scenarios, and how? Which are the pros and cons of these ongoing advances from the human performance point of view? Are all the devices or methods suitable to apply to the automotive sector? How can the data for assessing the operator's abilities and task complexity be collected? How could this approach be improved? Exploring the literature will be the first step to comprehending how the human performance model could be enhanced and deployed within safety-critical systems.

2. Methodology

This paper provides an overview of human performance assessment and deployment literature. It also includes the current potential technologies, devices, and methods in the human performance assessment that could be exploited to improve the monitoring and adaptation of work environments and operators, above all in safety-critical domains.

2.1. *Steps of the review*

The first phase of the review consisted of a systematic examination of publications recorded in Scopus database according to the following keywords: *"automotive sector", "assembly line", "manufacturing", "safety", "critical", "human performance"* and *"human factor"*. The year of publication is limited from 2013 to 2022; the most current state-of-the-art was searched. In this phase, 273 papers were selected.

Stage two consisted of initial filtering of titles and abstracts to identify the papers most relevant to the topic. In this phase, 20 papers were selected.

Finally, the full text of selected papers has been reviewed to determine the explicit inclusion in the search analysis. In this stage, 9 papers were selected.

After eliminating irrelevant articles, we proceed with a "snowball" approach in each step to select more relevant papers by looking at the references and citations.

3. Results

Despite the increase in the number of scientific publications dealing with human performance in manufacturing, we note that few of these were related or can be related to safety issues. The nine papers of interest are listed in Table1 (see Table 1).

Reniers (2017) studied the safety trends in the manufacturing industry. Some innovations would make the evolutionary trends a revolutionary field; the dynamic risk assessment methods are used

Table 1. Articles reviewed.

Article	Type of article
Badri et al. (2018)	Review article
Bai and Wicaksono (2020)	Conference article
Cohen et al. (2018)	Journal article
Faramondi et al. (2019)	Conference article
Gazzaneo et al. (2020)	Conference article
Golan et al. (2019)	Journal article
Grazia et al. (2020)	Conference article
Peruzzini et al. (2020)	Journal article
Reniers (2017)	Conference article

to advance real-time knowledge and decision-making within manufacturing factories.

A model was suggested by Golan et al. (2019) and Cohen et al. (2018) to describe the interaction between the operator and the workstation in the contemporary Industry 4.0 era. The framework is composed of three subsystems: (1) Observation, (2) Analysis, and (3) Reaction. The integration of AI permits intelligent, ongoing interactions between an operator and his/her workstation that strives to enhance operator safety, performance, and other production indicators.

Bai and Wicaksono (2020) explore the relevance of environmental measures of noise, temperature, light, humidity, ventilation, and cleanness to the assembly staffers. The outcomes and assessments of their study show how these conditions impact human performance.

Grazia et al. (2020) presented a tool to coordinate, maintain, control, and examine unsafe equipment and working conditions. They developed an algorithm to estimate the status of degradation of the equipment and a method to monitor actual time operator and workstation status. Faramondi et al. (2019) proposed a similar design, able to detect abnormal conditions and provide data about the status directly to the worker and only in case of a critical situation to the supervisor.

Recent technologies associated with smart production offer chances to enhance the operator's cognitive, sensorial, physical, and interaction abilities Gazzaneo et al. (2020). The potential effect of these relevant technologies is discussed by Badri et al. (2018).

Peruzzini et al. (2020) proposed a case study based on human physiological reaction monitoring to evaluate physical ergonomics and mental workload through a structured examination.

The model mentioned by Leva et al. (2017), which compares operators' capabilities with the task complexity associated with the workstation, is the starting point for this work. Some current tools and potential technologies are explored in the next section discussing if and how they can be adopted to improve the initial human performance model.

4. Discussion and challenges

Hazard identification, risk analysis, and risk assessment are the founding steps of industrial risk management (Demichela et al. (2021),Comberti et al. (2019)). Safety training, training on the job, emergency response and planning, learning for maintenance and inspections, and more (Djapan et al. (2019)) are strictly related to the outcomes of risk assessment and are a part of the risk management domain. One trend concerns making risk assessment less static and more dynamic. Dynamic risk analyses contain advanced mathematical methods, including Markov chains, Event Sequence Diagrams, Petri-nets, and Bayesian networks. In the same line, real-time data, Big Data, and the Internet of Things have begun to be included within manufacturing plants for creating risk knowledge and supporting safety decision-making (Comberti et al. (2015)). By integrating digital production systems with analysis and communication of all data collected within an intelligent domain, Industry 4.0 promises increases in safety. The most relevant technologies classification related to the human performance and safety is the following:

- Health Monitoring Sensors provide continuous monitoring of the health-related data of the operator, thus enabling a quick intervention in case of irregularities, proper to identify critical scenarios, and precise analysis of the workers' health.
- Personal Activity Trackers, monitor the operator activity status, place, and task advancement,

thus providing a clear view of the work improvement and permitting quick real-time adjustments.

- Posture Sensors provide continuous monitoring of the workers during a given duty, thus allowing the operator to adjust the posture in real-time and examine the worker's wellness.
- Internet of things (IoT) Sensors monitor relevant parameters within the production system and enhance the operator capabilities. New devices are evaluated for adoption in new application areas, like safety at work, especially to manage safety levels at complex workstations dynamically. Several projects have been developed using IoT technologies to dynamically address safety levels at complex workplaces (Wu et al. (2010),Yang et al. (2012)). Therefore, IoT enhances the interaction between equipment/machinery, flexibility and accessibility, process monitoring and management, and detection of irregularities. On the other hand, every IoT device processes and communicates data that need apps, services, and protocols for transmission, and many IoT security patches arise from unconfident interfaces. The most typical interface issues are lack of insufficient device authentication and inadequate or no encryption.
- Big Data Analytics; indeed, IoT sensor generates extensive datasets about the operator itself or about the conditions that can be computationally analyzed only by artificial intelligence/machine learning (ML) to reveal patterns, trends, associations, learning, and quick recognition of risks and timely decision-making. The potential benefits of Big Data are reduced uncertainty and improved capacity for analysis of behaviour and expectation of errors. There are also issues associated with personal data confidentiality and data selection measures. Privacy is an essential point in applying Big Data technologies for analytics. As more and more data is being collected, this data collection and analytics could result in user privacy breaches. An untrusted third-party employee can infer users' personal information if the data analytics is outsourced.

The understanding of the environmental aspects is rising in the assembly systems. The previous human performance model Leva et al. (2017) compares operators' capabilities with the risk related to the equipment or workstation, exclusively focused on the effects of assembly tasks' physical and mental workload to assess the task complexity and the external environment was considered but in a static way. For example, we can monitor the proper temperature, ventilation, and humidity to include them in a runtime task complexity assessment. Adequate lighting can decrease workers' efforts to read work instructions and carry out high-precision duties. In addition, a clean environmental avoid health issues and improves production quality. The high relevance may further researches to integrate environmental benchmarks into the assessment methods.

Other further developments of the HP model are discussed in the followings paragraphs:

4.1. *Development of the human performance rules*

The first approach is about a more exhaustive evaluation of the human performance model from a theoretical point of view. Firstly, the number of tests assessing the operator's capabilities is relatively tiny. Even if participants are interested in performing the tests, a larger size will enhance the data quality for a better assessment and definition of the indicators. For example, we can change the way to collect data from the operators to assess their capabilities with some of the technologies mentioned previously. Secondly, all the adapted indicators have the same influence on the human performance definition. Promoting a more detailed analysis of the importance of the single index concerning the human error probability of occurrence would make the model more accurate. The analysis could be done at a single task level, identifying which variables are more stressed and less solicited. This model is highly sensible and depends on the tasks and sub-tasks carried out in the assembly line.

4.2. *Development of the Human Capability assessment*

The second line of development is the way to gather and evaluate the operator's capabilities through constant observation. Measuring operators' physiological responses allows for knowledge about how they interact with the workplace, thanks to objective data. According to the literature review, the primary set of physiological parameters is: heart rate (HR), heart rate variability (HRV), breathing rate (BR), pupil dilatation (PD), eye gaze (EG), and eye blinks. In particular, the measures regarding the heart rate and heart rate variability. In addition, the number of detectors to be worn has to be minimized to limit the intrusiveness and not interfere with activity execution.

Heart monitoring is relatively straightforward because of the simplicity and low-cost sensors. In particular, the measurement regards HR and HRV. Also, the BR is a reasonable stress indicator in meeting other physiological measures (Labbé et al. (2007)).

Regarding eye-tracking, the most frequent parameters used are EG and PD, which provide details on an individual's attention source and stress (Sharma and Gedeon (2012)). In addition, several investigations focused on the eye-tracking application for human workload analysis and the correlation between eye-based signals and human factors. Marquart et al. (2015) found that the human workload rises with the increase of the blink latency and drops with the increase of blink duration and gaze variability. In addition, outcomes demonstrated that eye tracking is a powerful tool for studying mental workload while executing a complex task.

Other indicators could include electroencephalography (EEG) based on brain activity measurement. An innovative device to measure workload could be EEG-based (Mijović et al. (2014)). However, due to its complexity, it has been found that subjective stress can be investigated more precisely by the combined measurements of multiple parameters to complete a reliable evaluation of both physical and mental stress objectively.

Unfortunately, many of the solutions proposed in the literature have difficulties being accepted because they implicitly have instruments that can monitor the workers' activities. With the scope to overcome such drawbacks, different approaches are presented. A complete solution Faramondi et al. (2019) where all the detailed information is managed in order to avoid any potential abuse of the data. The worker gathers the information directly and exclusively using an architecture based on deployed and wearable sensors. The information shared to manage the crisis is only in case of an abnormal or unsafe condition. The control room must require the key to access the report contents. Then the worker can permit sending the key. An automatic key is performed in case of particular health conditions.
The control of privacy and data protection is crucial in our project. The indirect exchange of data between workers must ensure the respect of the privacy policy. Also included is the data retrieved from the industrial machines and devices to improve the effectiveness of the early alert system.

4.3. *Development of operator's state into the HP model*

This line of development should focus on including personal psychological aspects into the model. The model focuses the assessment on physical, memory, and dexterity skills and neglects, for example, the motivational factors relevant in terms of performance. In the remainder of the paper, it is firstly included relevant literature regarding operators' states and different technologies that have been proposed for identifying these states. The term 'operator's state' refers to psychological, physiological, and cognitive elements likely to influence a worker's performance. It is suggested to classify the operator's state based on the following descriptors:

- Motivation describes the amount of effort a worker is keen to invest in his/her work and can be estimated using the Motivational Trait Questionnaire (MTQ) (Kanfer and Ackerman (2018)).
- Learning represents the change in conduct caused by re-experiencing a situation. Learn-

ing is measured via knowledge or skill tests; however, future technologies based on brain imaging may deliver physiological proof of the learning process (Draganski et al. (2006)).

- Fatigue denotes a lack of attention, a desire for rest, and dizziness. It is known that it increases the possibility of human error and may lower safety levels. Bio-sensor technologies for measuring fatigue are already widely used in, for example, driving contexts (Gate et al. (2015)).
- Emotions are regarding how they influence job satisfaction. Pekrun and Frese (2016) suggests that enjoyment, hope, and relief are positive feelings that improve performance. In contrast, boredom, anxiety, and unhappiness are negative sentiments that reduce performance. Thus researchers (Shen et al. (2009)) have recently designed technology to detect various emotions automatically, such as the EEG device (Zheng et al. (2019)).
- Attentiveness refers to concentrating on a specific task without being distracted by outside information. Lack of attention reduces performance and should therefore take into account. Novel technologies are attempting to achieve this as in Mijović et al. (2017) simulated a manual assembly operation to assess the level of attention during a monotonous task and a more heterogeneous duty using a wearable EEG device.

In addition, the Industry 4.0 era is expected to determine operator's confidence and stress levels (Healey and Picard (2005)).

Data collection can be based on cameras and sensors to produce measures related to the operator's mental condition. Some studies have employed mathematics methods such as neuronal networks (Shehu et al. (2021)) and Markov models for identifying emotions. For example, it is possible to accomplish emotion analysis through facial expressions using any version of the convolutional neuronal network (CNN), depending on the target features need to assess the operator's mental states. Future interfaces may allow the machine to react to the operator's state smartly and effectively, not only to identify emotions. A similar view is discussed by Baraglia et al. (2017), who claims that emotionally intelligent machines will decide when and how to intervene.

4.4. *Predictive maintenance and anomaly detection*

The information about the workstation counts for understanding human performance. Machinery downtime and servicing could be reduced considerably if intelligent systems predicted maintenance needs. There are two relevant concerns for the automotive industry that could be addressed using ML/AI techniques, namely, predictive maintenance and anomaly detection:

- Predictive maintenance: Predictive maintenance monitors the condition of equipment (Martínez-Arellano and Ratchev (2019)) and uses machine learning to define the actual state and forecast future states. This approach offers cost savings over preventive maintenance because maintenance is performed only when warranted. Reinforcement learning (RL) and active learning (AL) can be used to perform predictive maintenance (Casanova et al. (2020)). RL is based on the concept of training a model by rewarding correct predictions and penalizing incorrect predictions (Silver et al. (2017)). We can use RL and AL to incorporate a human in the loop for predictive maintenance. The RL algorithm predicts that a specific part of a machine needs replacement; then the system can alert an operator that a part needs a replacement; however, in the other case, if the part in question does not need a replacement, then the AL algorithm can query the human and improve the RL agent from this feedback (Fang et al. (2017)).
- Anomaly detection: This technique deals with the identification of abnormal data points which deviate significantly from the usual data. Its applications are numerous, and in the context of industry and IoT, it is used to identify safety-critical scenarios, for example, detecting the malfunction of equipment in production assembly or detecting faulty products coming out of an assembly. For IoT (Gudur et al. (2019))

and Sensor Time-Series Data, anomaly detection uses AL through uncertainty sampling (Van Amersfoort et al. (2020)). For example, suppose a highly imbalanced data with 999 regular events and only one abnormal event. In that case, the algorithm provides a label for this one abnormal event. There are usually only very few key events that require human attention in a long-time series. Here, AL and anomaly detection detect anomalies and learn about these critical events rather than the complete time series.

Predictive maintenance and anomaly detection can help study the risk related to the equipment and thereby contribute to the assessment of the Task Complexity of each workstation.

5. Conclusion and future works

The present review is an initial stage in our research activity within the Collaborative Intelligence for Safety-Critical Systems project. Ongoing technological developments in the human performance assessment and deployment are proposed with pros and cons to enrich the human performance model that compares the operator's capabilities with the task complexity. One open research challenge is to align both. A critical step in this alignment task is to assess human performance on a task. We find that human performance assessment is a complex, multi-faceted task and point to the potential for artificial intelligence to help with this assessment process. Future outcomes will focus on developments in the human performance context, such as determining the technologies proposed to be tested on an assembly line in the industrial vehicle sector in collaboration with IVECO and validating the results regarding enhancement in safety.

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References

Badri, A., B. Boudreau-trudel, and A. Saâdeddine (2018). Occupational health and safety in the industry 4.0 era : A cause for major concern?. *Safety Science 109*(August 2017), 403–411.

Bai, X. and H. Wicaksono (2020). How Relevant Are Environmental Factors in The Ergonomic Performance Assessments?. *Procedia Manufacturing 52*(2019), 325–330.

Baraglia, J., M. Cakmak, Y. Nagai, R. P. Rao, and M. Asada (2017). Efficient human-robot collaboration: When should a robot take initiative?. *International Journal of Robotics Research 36*(5-7), 563–579.

Casanova, A., P. O. Pinheiro, N. Rostamzadeh, and C. J. Pal (2020). Reinforced active learning for image segmentation. *arXiv preprint arXiv:2002.06583*.

Cohen, Y., M. Golan, G. Singer, and M. Faccio (2018). Workstation–Operator Interaction in 4.0 Era: WOI 4.0. *IFAC-PapersOnLine 51*(11), 399–404.

Comberti, L., G. Baldissone, and M. Demichela (2015). Workplace accidents analysis with a coupled clustering methods: S.O.M. and K-means algorithms. *Chemical Engineering Transactions 43*, 1261–1266.

Comberti, L., G. Baldissone, and M. Demichela (2019, 10). Risk awareness versus risk assessment in manufacturing: a field study. *Conference: ESREL 2019*.

Comberti, L., M. Demichela, and M. C. Leva (2020). Human skills assessment as a support to human factor management. *30th European Safety and Reliability Conference, ESREL 2020 and 15th Probabilistic Safety Assessment and Management Conference, PSAM 2020*, 2650–2655.

Demichela, M., L. Comberti, and G. Baldissone (2021). Operators' risk awareness towards operations' risk assessment: a field study in the motor vehicle field. *Journal of Quality in Maintenance Engineering*.

Djapan, M., I. Macuzic, D. Tadic, and G. Baldissone (2019). An innovative prognostic risk assessment tool for manufacturing sector based on the management of the human, organizational and technical/technological factors. *Safety Science 119*(February 2018), 280–291.

Draganski, B., C. Gaser, G. Kempermann, H. G. Kuhn, and C. Bu (2006). Temporal and Spatial Dynamics of Brain Structure Changes during Extensive Learning. *26*(23), 6314–6317.

Fang, M., Y. Li, and T. Cohn (2017). Learning how to active learn: A deep reinforcement learning approach. *arXiv preprint arXiv:1708.02383*.

Faramondi, L., P. Bragatto, C. Fioravanti, M. G. Gnoni, S. Guarino, and R. Setola (2019). A Wearable Platform to Identify Workers Unsafety Situations. *2019 IEEE International Workshop on Metrology for Industry 4.0 and IoT, MetroInd 4.0 and IoT 2019-Proceedings*, 339–343.

Gate, S., T. Brummett, J. B. Turner, and C. Browning (2015). (12) Patent Application Publication (10) Pub.

No.: US 2015/0015400 A1. *1*(19).

Gazzaneo, L., A. Padovano, and S. Umbrello (2020). Designing Smart Operator for Human Values: A Value Sensitive Design Approach. *Procedia Manufacturing 42*(2019), 219–226.

Golan, M., Y. Cohen, and G. Singer (2019). A framework for operator-workstation interaction in Industry 4.0. (July).

Grazia, M., P. Angelo, M. Francesca, and R. Setola (2020). Integrating IoT technologies for an " intelligent " safety management in the process industry. *Procedia Manufacturing 42*(2019), 511–515.

Gudur, G. K., P. Sundaramoorthy, and V. Umaashankar (2019). Activeharnet: Towards on-device deep bayesian active learning for human activity recognition. *CoRR abs/1906.00108*.

Healey, J. A. and R. W. Picard (2005). Detecting Stress During Real-World Driving Tasks Using Physiological Sensors. *6*(2), 156–166.

Kanfer, R. and P. L. Ackerman (2018). Individual Differences in Work Motivation: Further Explorations of a Trait Framework Individual Differences in Work Motivation: Further Explorations of a Trait Framework. (February).

Labbé, E., N. Schmidt, J. Babin, and M. Pharr (2007). Coping with stress: The effectiveness of different types of music. *Applied Psychophysiology Biofeedback 32*(3-4), 163–168.

Leva, M. C., L. Comberti, and M. Demichela (2017). Human Performance Modelling in Manufacturing: Mental Workload and Task Complexity. pp. 0–4.

Leva, M. C., L. Comberti, M. Demichela, and A. Caimo (2020). Human performance in manufacturing tasks: Optimization and assessment of required workload and capabilities. *Proceedings of the 29th European Safety and Reliability Conference, ESREL 2019*, 277–284.

Lin, L., C. G. Drury, S. Kim, and B. Hall (2001). Ergonomics and Quality in Paced Assembly Lines. *11*(4), 377–382.

Marquart, G., C. Cabrall, and J. D. Winter (2015). Review of eye-related measures of drivers ' mental workload. *Procedia Manufacturing 3*, 2854–2861.

Martínez-Arellano, G. and S. M. Ratchev (2019). Towards an active learning approach to tool condition monitoring with bayesian deep learning. In M. Iacono, F. Palmieri, M. Gribaudo, and M. Ficco (Eds.), *Proceedings of the 33rd International ECMS Conference on Modelling and Simulation, ECMS 2019 Caserta, Italy, June 11-14, 2019*, pp. 223–229. European Council for Modeling and Simulation.

Mijović, P., E. Giagloglou, P. Todorović, I. Mačužić, B. Jeremić, and I. Gligorijević (2014). A Tool for Neuroergonomic Study of Repetitive Operational Tasks.

Mijović, P., M. Milovanović, V. Ković, I. Gligorijević, B. Mijović, and I. Mačužić (2017). Neuroergonomics method for measuring the influence of mental workload modulation on cognitive state of manual assembly worker. In *Communications in Computer and Information Science*, pp. 213–224. Springer International Publishing.

Pekrun, R. and M. Frese (2016). Emotions in work and achievement. (January 1992).

Peruzzini, M., F. Grandi, and M. Pellicciari (2020). Computers Industrial Engineering Exploring the potential of Operator 4.0 interface and monitoring. *Computers Industrial Engineering 139*(December 2018).

Reniers, G. (2017). On the future Society in the manufacturing industry. *Procedia Manufacturing 13*, 1292–1296.

Sharma, N. and T. Gedeon (2012). Objective measures, sensors and computational techniques for stress recognition and classification: A survey. *Computer Methods and Programs in Biomedicine 108*(3), 1287–1301.

Shehu, H. A., H. Sharif, S. Uyaver, J. Shao, Q. Cheng, and T. Shimamura (2021). Deep CNN. *AIP Conference Proceedings 2334*(March), 549–559.

Shen, L., M. Wang, and R. Shen (2009). Affective e-Learning: Using " Emotional " Data to Improve Learning in Pervasive Learning Environment Related Work and the Pervasive e-Learning Platform. *12*, 176–189.

Silver, D., T. Hubert, J. Schrittwieser, I. Antonoglou, M. Lai, A. Guez, M. Lanctot, L. Sifre, D. Kumaran, T. Graepel, et al. (2017). Mastering chess and shogi by self-play with a general reinforcement learning algorithm. *arXiv preprint arXiv:1712.01815*.

Van Amersfoort, J., L. Smith, Y. W. Teh, and Y. Gal (2020). Uncertainty estimation using a single deep deterministic neural network. In *International conference on machine learning*, pp. 9690–9700. PMLR.

Wu, W., H. Yang, D. A. Chew, S. hua Yang, A. G. Gibb, and Q. Li (2010). Towards an autonomous real-time tracking system of near-miss accidents on construction sites. *Automation in Construction 19*(2), 134–141.

Yang, H., D. A. Chew, W. Wu, Z. Zhou, and Q. Li (2012). Design and implementation of an identification system in construction site safety for proactive accident prevention. *Accident Analysis and Prevention 48*, 193–203.

Zheng, W.-l., S. Member, W. Liu, Y. Lu, B.-l. Lu, and S. Member (2019). EmotionMeter: A Multimodal Framework for Recognizing Human Emotions. *49*(3), 1110–1122.