

DEcision Support system for the Diagnosis and Evaluation of the Maintenance OperatioNs Activities (DESDEMONA)

SUMMARY REPORT

M2. GAP ANALYSIS OF COGNITIVE ERGONOMIC ASSESSMENT











1. INTRODUCTION

The transition from Industry 4.0 (I4.0) to Industry 5.0 (I5.0) shifts the focus from solely technology-driven improvements in production efficiency to a more human-centric approach, emphasizing worker well-being, sustainability, and collaboration between humans and machines. I4.0 introduced advanced technologies to improve production but had limitations, particularly concerning worker welfare and industrial sustainability. I5.0 seeks to address these issues by promoting social sustainability, talent development, and workforce diversity, restructuring jobs to be more cognitive than manual.

A key challenge in I4.0 is managing complex human-machine systems, with workers facing cognitive overload. To counter this, I5.0 supports a balanced cognitive workload (CWL) for workers. Maintenance, a costly area for industries, is being revolutionized through predictive technologies like Augmented Reality (AR), which supports workers in maintenance tasks. However, AR and other innovations can increase CWL, leading to performance issues.

The DESDEMONA project aims to develop a decision support system (DSS) to assign maintenance tasks based on both the CWL associated with the tasks and that of the worker, ensuring well-being and productivity. The research outlines a need for methods to assess CWL in maintenance, especially when advanced technologies are involved, and suggests future research directions in this area.

2. DISCUSSIONS AND RESULTS

The study explored the impact of I4.0 technologies on operator CWL, with a common research question being how these technologies can enhance operator performance. Technologies such as Augmented Reality (AR) and Virtual Reality (VR) were frequently evaluated for their role in reducing CWL during maintenance tasks. Although these technologies have shown promise in alleviating CWL, the findings were not conclusive, and more extensive experimentation across varied scenarios is needed. Furthermore, while some studies have employed physiological parameters to measure CWL objectively, these experiments often yielded relative results, relying on comparisons between different setups rather than producing generalizable insights.

Another significant finding from the review is the use of CWL as a design driver in developing production and information systems to reduce cognitive overload. Many studies have proposed solutions based on AR and VR to enhance cognitive ergonomics in industrial settings. These approaches commonly relied on physiological measurements like heart rate, eye tracking, and skin responses to gauge operator CWL. However, the lack of predictive models for operator behaviour poses a challenge, as this impedes the ability to generalize the effects of design solutions on CWL.

In summary, while CWL is a critical factor in designing and evaluating industrial systems, current approaches are still largely centred around technology rather than the human-centric principles of I5.0. The development of more objective CWL assessment methods, alongside predictive models for operator behaviour, will be essential for aligning industrial design practices with the goals of I5.0, which prioritize human well-being over mere performance enhancement.



3. GAP ANALYSIS AND RESEARCH AGENDA

The SLIP methodology applied in the gap analysis identified two major types of research gaps: theoretical and application-oriented gaps, each with distinct sub-categories.

Theoretical research gaps highlight several critical issues. The first sub-category focuses on the lack of methodologies that consider the operator's well-being in the design of automation systems. Studies by Lee and Seppelt (2023) and Illankoon and Tretten (2021) emphasize the need for methodologies that integrate the psychophysical well-being of operators and better manage their knowledge when interacting with advanced technologies like AI. Similarly, Madonna et al. (2019) argue that in complex industrial settings, knowledge management is strategic for successful system operations. The second sub-category addresses the absence of models to predict operator behaviour and well-being, including the challenge of interpreting brain signals to associate them with cognitive workload (CWL). Sun et al. (2023) and Du et al. (2020) highlight the difficulty in reliably interpreting brain data and linking it to operator performance. Liu et al. (2022) stress the need for objective measures of CWL, criticizing the subjectivity of post-task questionnaires used in current studies. Furthermore, Lucchese et al. (2022b) note the absence of models to estimate cognitive resources for effective task assignment, while Ciccarelli et al. (2023) emphasize the importance of developing objective CWL metrics using physiological data.

The application-oriented research gaps focus on practical implementation challenges. The first subcategory calls for more comprehensive testing of proposed solutions, particularly expanding experimental setups to improve the reliability of findings. Studies like those by Xu et al. (2024), Sermarini et al. (2023), and others identify limitations in sample sizes, tested activities, and scenarios. The second sub-category stresses the need for better technological integration, such as tracking mental engagement during maintenance tasks (Randeniya et al., 2019) and wearable devices monitoring operator conditions (Belletier et al., 2021). The third sub-category, related to technological limitations, points out issues like the high costs of technologies (Grandi et al., 2024) and hardware limitations of the devices used (Park et al., 2020). The fourth sub-category calls for validating these solutions in real industrial contexts, as emphasized by works like those of Carvalho et al. (2020) and Brunzini et al. (2021). This final gap indicates the need to test experimental setups and solutions in practical, real-world scenarios to ensure their feasibility and effectiveness.

In conclusion, it shows that most studies used CWL primarily as a performance measure rather than focusing on the operator's well-being, indicating that the I5.0 human-centric paradigm has not yet been widely adopted. Instead, research continues to emphasize technology effectiveness over the well-being of operators. Despite consolidating knowledge on the subject, the study faced limitations, including a small sample size and the lack of specific focus on maintenance activities. Future research could address these gaps by incorporating more diverse sources and exploring CWL assessment across different dimensions.

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