Cognitive Load Assessment in Maintenance Operations: A Systematic Review in the Context of Industry 5.0

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Abstract: Industry 5.0 emphasizes human-centered manufacturing through a systematic integration of enabling technologies, including Augmented Reality (AR) and Artificial Intelligence (AI). While Industry 4.0 technologies enhance operational efficiency, they also introduce significant cognitive demands on human operators, particularly in maintenance tasks, requiring robust frameworks for mental workload assessment and workplace ergonomics optimization. This study presents a systematic literature review (SLR), updated to May 2025, which allowed to classify cognitive workload assessment methods into three main approaches: subjective, physiological, and behavioural approaches, highlighting the predominant use of one method for each category (NASA-TLX questionnaires, EEG-based monitoring, and eye-tracking techniques respectively). Furthermore, the study examines digital technologies used to support cognitive workload management, such as Virtual Reality (VR) training systems, haptic feedback devices, and Decision Support Systems (DSS). Key findings reveal research gaps in real-time task allocation based on cognitive workload, dynamic decision-making frameworks, and human factors integration in DSS architectures. This review highlights the need for a developing comprehensive, real-time DSS solution that combine physiological and psychological metrics to enhance operator well-being and production efficiency within Industry 4.0 environments.

Keywords: Cognitive workload assessment, Decision Support System, Industry 5.0, Maintenance, Systematic Literature Review.

1. Introduction

The Fifth Industrial Revolution (Industry 5.0) represents a human-centered production model enhancing safety, flexibility, and resilience in industrial ecosystems (European Commission, 2021; Xu et al., 2021). Unlike automation-focused paradigms, Industry 5.0 fosters human–machine collaboration and emphasizes workplace safety through comprehensive risk assessment and adaptive production methods (Yi et al., 2024). Increased flexibility in Industry 4.0 factories imposes higher cognitive demands on operators, especially in maintenance tasks essential for production continuity. These demands require robust safety protocols and real-time monitoring systems to prevent accidents due to mental overload (Afzal et al., 2024; Fang et al., 2024). Maintenance tasks inherently carry high risks, necessitating targeted training and adaptive task allocation based on operators' cognitive states (Di Pasquale et al., 2024). Although technologies such as Augmented Reality (AR) and Artificial Intelligence (AI) aim to support operators, they can also increase task complexity and cognitive load (Longo et al., 2020; Yang et al., 2024). Recent efforts toward adaptive Decision Support Systems (DSS) integrating physiological data show promise (Oliveri et al., 2025, 2024; Anders et al., 2024). However, current frameworks often lack systematic integration of workload assessment into decision-making. This study addresses these gaps through a systematic literature review (SLR) updated to May 2025, aiming to classify cognitive workload assessment methods, identify digital technologies for mental workload management, and evaluate adaptive human-centered DSS in industrial maintenance. Accordingly, the following research questions have been set:

RQ1: What cognitive workload assessment models have been applied in the context of industrial maintenance within Industry 4.0 environments?

RQ2: How are these models integrated with digital technologies to support mental workload management and decision-making in human-centered maintenance systems?

The paper is structured as follows: Section 2 describes the methodology; Section 3 presents the quantitative analysis; Section 4 discusses qualitative findings and emerging trends; Section 5 concludes the study and outlines future directions.

2. Methodology

This study adopts the PRISMA Protocol to execute a Systematic Literature Review (SLR) proposed by (Denyer and Tranfield, 2009), with emphasis on the specific research objective, i.e. to identify and classify cognitive workload assessment models applied to industrial maintenance tasks in Industry 4.0 settings. A comprehensive bibliometric search was executed through the Scopus database, using a query which incorporates terminological variants related to cognitive load, assessment, maintenance operations, and digital technologies integration, to search in titles, abstracts, and keywords. The search, limited to English-language documents returned 900 records (on May 12, 2025). The Scopus search was executed as part of the DESDEMONA project, which started in December 2023 The selection process, shown in Figure 1, implemented rigorous inclusion and exclusion criteria: only studies related to human operators in industrial maintenance contexts, and presenting models, tools, or digital solutions specifically designed for cognitive workload evaluation, were retained.

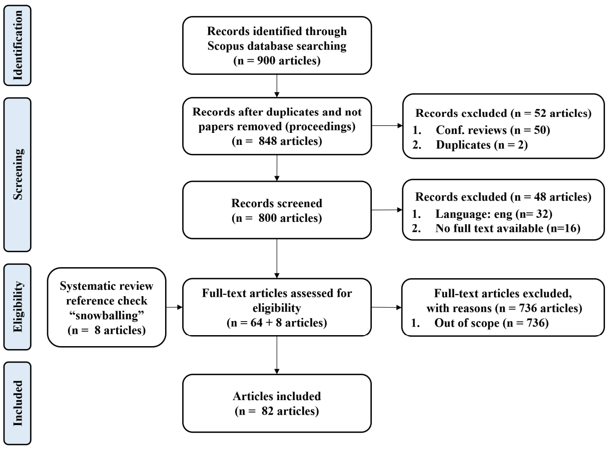

Figure 1. PRISMA Protocol

After the exclusions made on the topic based on abstract screening, a backward snowballing was performed reaching the final number of 82 relevant papers, which were included for full-text reading. Key information was extracted and organized to document multiple dimension of investigation: assessment model types (e.g., subjective evaluation, physiological measurement, behavioural observation), technological implementation (e.g., sensor-based monitoring, AI-based systems, data acquisition platforms), research methodological approaches (e.g. research design frameworks, data collection, analytical procedures), and key findings (e.g. theoretical contributions, empirical outcomes, case studies, implementation challenges). These elements formed the basis for both quantitative and qualitative analysis in the subsequent sections.

3. Quantitative analysis

The bibliometric analysis highlights a steady growth in research interest on cognitive workload in industrial maintenance, with publications accelerating markedly over the past decade (Figure 2). Early works (1994–2010) were sporadic, while post-2015 contributions increased exponentially, aligning with the transition from automation-centered Industry 4.0 to the human-centered paradigm of Industry 5.0.

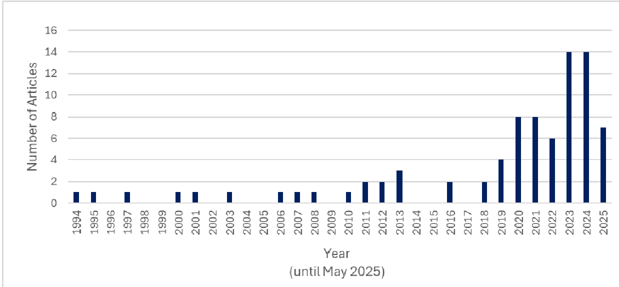

Figure 2. Distribution of Papers per year

Regarding publication types, journal articles dominate (55%, n=45), followed by conference proceedings (40%, n=33) and book chapters (5%, n=4), reflecting a shift toward more consolidated, peer-reviewed research outputs. Geographically, the United States leads with 21 publications, followed by Italy (13), Germany (8), and China (7), highlighting strong engagement from North America and Europe, with growing involvement from Asia and Latin America (Figures 3-4). Methodologically, two main categories emerge: t heoretical assessments (26 papers) including literature reviews and conceptual frameworks, and analytical assessments (23 papers) focused on model development and empirical evaluations. Fewer studies address technology development (14), case studies (5), surveys (5), and real-world application cases (9), revealing a gap between conceptualization and practical implementation. Overall, the distribution shows robust conceptual development but a limited number of empirical validations, indicating challenges in integrating cognitive workload assessments into dynamic industrial environments.

4. Qualitative analysis

The qualitative analysis of the literature reveals heterogeneous methodological paradigms and theoretical frameworks addressing cognitive load management, decision support systems (DSS), and maintenance operations within Industry 5.0 contexts (Illankoon and Tretten, 2021; van Oudenhoven B. et al., 2023). While each contribution has advanced specific domains understanding, from cognitive ergonomics to immersive training and organizational fit models, none of them suggests integrated solutions that synthesize real-time cognitive workload assessment with dynamic allocation of maintenance tasks. Despite an extensive exploration of technologies implementations and evaluation methods, the literature still lacks a comprehensive framework able to supports decision-making based on cognitive conditions of human operators during operational activities. However, recent studies have increasingly converged toward integrated ecosystems that combine physiological monitoring, predictive analytics, and decision-making interfaces, particularly in uncontrolled or realistic industrial environments (Anders et al., 2024; Oliveri et al., 2024).

Correlation between Type of research and country of origin of the first author																								
Type of research	Australia	Brazil	Canada	China	Finland	France	Germany	Greece	India	Iran	Israel	Italy	Japan	Korea	Mexico	Netherlands	Portugal	Russian Federation	Spain	Sweden	Taiwan	United Kingdom	United States	Total
Action Research/Application Case			1	1			1							1	1						1		3	9
Analytical assessment				3			2			2		8	2						1		1		4	23
Case Study	1	1														1						1	1	5
Survey			1				1													1			2	5
Technology development	1	1	1	2	1				1			2	1				1			1			2	14
Theoretical assessment		2		1		1	4	1	1		1	3				1		1				1	9	26
Total	2	4	3	7	1	1	8	1	2	2	1	13	3	1	1	2	1	1	1	2	2	2	21	82

Figure 3. Correlation between type of research and country of origin of the first author

Correlation between year of publication and country of origin of the first author																								
Year	Finland	France	Greece	Israel	Russian Federation	Spain	Korea	Mexico	Portugal	Australia	India	Iran	Netherlands	Sweden	Taiwan	United Kingdom	Japan	Canada	Brazil	China	Germany	Italy	United States	TOTAL
2025 - until May									1											1	1	3	1	7
2024						1					1				1		1			2	2	4	2	14
2023										1	1		1			1				2	2	1	5	14
2022			1									1								1		2	1	6
2021	1											1		1		1					1	1	2	8
2020					1		1												1	1		1	3	8
2019								1		1								1					1	4
2018																						1	1	2
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TOTAL	1	1	1	1	1	1	1	1	1	2	2	2	2	2	2	2	3	3	4	7	8	13	21	82

Figure 4. Correlation between year of publication and country of origin of the first author.

4.1 Methodological approach for cognitive workload assessment

A range of methodological approaches is used across the selected papers for evaluating operators' cognitive load in industrial environments (Shin et al., 2024). Most interesting are three frameworks: self-reporting assessment methods, physiological monitoring systems, and behavioural analysis through eye-tracking. The NASA Task Load Index (NASA-TLX) is the predominant self-report instrument for capturing operators' subjective perceptions of workload dimensions. This instrument obtained a widespread adoption due to its recognized capability of systematically capturing the perceived mental effort, the established validation across different industrial contexts (Abbas et al., 2020; Barajas-Bustillos et al., 2020; Ghalenoei et al., 2022; Yang et al., 2012). which demonstrates its robustness, and the integration capability with other assessment methodologies. Advanced physiological monitoring techniques, including electroencephalography (EEG) and cardiovascular (e.g. heart rate) monitoring, provide objective quantification of autonomic responses to cognitive stimuli (Du et al., 2020). These methods offer real-time monitoring of neural activity patterns, objective measurement of psychophysiological states, continuous assessment of autonomic responses, and temporal resolution in data acquisition (Illankoon and Tretten, 2021; Peruzzini et al., 2018; Van der Grinten M.P. and Houtman I.I.D., 2000). Eye-tracking methodologies enable detailed analysis of visual attention and cognitive processing mechanisms by the systematic monitoring of oculomotor behaviour patterns (Shi et al., 2020; Zyrianov et al., 2020). This approach provides high-precision tracking of gaze patterns, quantitative analysis of visual attention distribution, temporal mapping of cognitive processing sequences, and integration with advanced visualization technologies. Collectively, these approaches offer robust data on mental workload and operator performance. In addition to these, recent studies emphasize the use of wearable multimodal sensing (EEG, EDA, BVP, skin temperature, accelerometers) for real-time cognitive load detection in both controlled and uncontrolled environments (Apraiz et al., 2024; Hou et al., 2025). These approaches represent a methodological leap, allowing for continuous, ecologically valid assessment integrated with industrial activities.

4.2 Digital technologies

The systematic literature review shows a comprehensive ecosystem of advanced digital technologies to support cognitive load assessment and operator training enhancement (Johannsen, 1997). These technologies can be classified into distinct functional domains: immersive visualization systems, haptic feedback systems, visual attention monitoring systems, physiological monitoring systems, and integration architectures. Augmented Reality (AR) and Virtual Reality (VR) are widely applied to create immersive learning environments that enhance spatial understanding and performance optimization through simulation-based training (Grandi F. et al., 2024; Liu et al., 2022; Park et al., 2020; Quandt and Freitag, 2021; Randeniya et al., 2019; Sermarini et al., 2023; Webel et al., 2013; Xu et al., 2024). They also could allow real-time feedback mechanisms for skill development and risk-free experimentation in complex maintenance scenarios (Bi and Jia, 2024; Byvaltsev, 2020; Eswaran and Bahubalendruni, 2024; Park et al., 2020). Tactile feedback devices, particularly haptic gloves, provide sensorial augmentation, improving both perception and motor control precision during maintenance tasks (Maddahi et al., 2013; Shanmugam et al., 2023). They also could allow simulation of tactile responses for training purpose and integration with immersive environments for skill development. High-speed eye-tracking systems are used to monitor real-time attention patterns, while semantics-aware replay tools analyze interaction data to support cognitive process interpretation (Xu et al., 2025; Zyrianov et al., 2020). Additionally, to capture stress responses and motion patterns a set of physiological sensing technologies are employed: EEG for brain activity assessment, skin temperature for physiological state assessment, Blood Volume Pulse (BVP) for stress evaluation, Electrodermal Activity (EDA) for monitoring stress reaction, and accelerometers for behavioural pattern recognition (Grandi F. et al., 2024; Knisely et al., 2021; Miyake, 2001; Thomas Kosch et al., 2023). When integrated into a DSS, these technologies could significantly improve the accuracy and adaptability of real-time cognitive load assessment, task allocation based on operator state, dynamic workflow optimization (Illankoon and Tretten, 2021; Xu et al., 2021; Yang et al., 2024). A recent trend is the integration of these technologies into wearable and mobile formats, enabling unobtrusive data collection and use in live operational contexts (Anders et al., 2024). Some systems now embed biometric feedback directly into adaptive DSS platforms, with Digital Twin architectures (Villani et al., 2025) serving as cognitive-aware control layers.

4.3 Mathematical models

Some papers introduce mathematical models aimed at evaluating cognitive load and predicting operator performance (Blood et al., 2023). Cognitive Task Analysis and Workload Classification models are used to identify key variables influencing task execution, e.g. task-related cognitive demands, hierarchical classification of cognitive complexity, quantitative assessment of mental workload parameters (Barajas-Bustillos et al., 2020; Cavallo et al., 2021; Johannsen, 1997; Lee and Seppelt, 2023; Lucchese, A. et al., 2022). Machine learning algorithms are also employed to analyze large datasets and predict cognitive load under varying operational conditions (Li et al., 2023; Rousopoulou et al., 2022). Recent contributions include the use of deep learning architectures, such as Transformer-based classifiers, for real-time cognitive state inference from multimodal signals (Hou et al., 2025) Other models focus on wearable-sensor driven cognitive load regression (Anders et al., 2024), expanding the potential for dynamic, predictive, and user-specific workload management. Despite these methodological advancements, significant limitations persist in current research: limited development of dynamic mathematical models, insufficient integration with operational DSS, inadequate validation in industrial maintenance contexts, absence of real-time cognitive workload quantification frameworks, limited implementation of dynamic task allocation algorithms, insufficient adaptation mechanisms for varying operational conditions. However, a growing body of research is actively addressing these gaps with real-time, context-aware modelling and early-stage deployment of predictive DSS in Industry 5.0 scenarios (Oliveri et al., 2025, 2024).

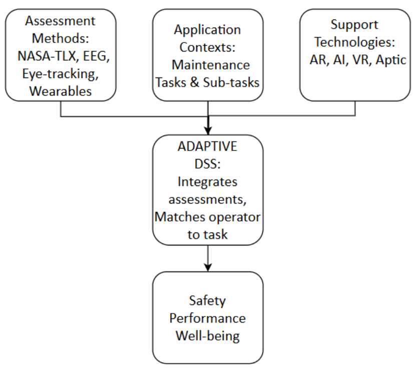

Figure 5. Conceptual framework of an adaptive DSS for cognitive-aware maintenance task allocation

4.4 Psychological aspects

The reviewed studies also shed light on psychological dimensions crucial to understanding and managing cognitive load in industrial settings. Key themes include:

- cognitive overload management, specifically for complex maintenance operations and tasks with high-cognitive demand (Dadashi et al., 2021; Digiesi et al., 2022; Stenfors et al., 2013);
- attentional resources, which focuses on enhancing sustained attention during operational tasks especially in complex industrial environments (Ciccarelli et al., 2023);
- stress response mitigation, which requires systematic intervention strategies, to ensure operational effectiveness and decision-making process quality (Vona et al., 2025);
- anxiety regulation, which addresses psychological barriers to optimal performance; anxiety is influenced by operators' confidence with the task and influence task execution.

Recent literature emphasizes the incorporation of these psychological factors into technical frameworks. DSS platforms now use emotion-aware input, physiological stress markers, and attention-tracking mechanisms to dynamically adapt task allocation, prioritize safety, and mitigate anxiety. These systems aim not only to optimize performance but also to enhance operator well-being and prevent burnout. Many contributions highlight the role of advanced technologies (particularly AR and VR) in providing real-time visual and tactile feedback, helping to redistribute mental workload, prevent fatigue, and improve both accuracy and decision-making speed (Agnisarman et al., 2019; Ávila et al., 2013; Grandi et al., 2025; Sermarini et al., 2023). Enhancing attention and focus is another frequently cited goal (Chu et al., 2024; Roda and Thomas, 2006; Sun, Z. et al., 2023), often pursued through the use of eye-tracking systems that provide operators with immediate feedback (Zyrianov et al., 2020). Furthermore, the assessment of psychosocial environmental factors and their impact on cognitive performance highlights the importance of a supportive work environment for sustaining high operational effectiveness, and ergonomics. These psychological considerations are essential for the development of DSS solutions that not only optimize task allocation but also promote operator well-being, supporting sustainable operational excellence.

5 Conclusions

This review reveals a lack of integrated solutions combining real-time cognitive workload assessment with dynamic task allocation in industrial maintenance. While some studies address cognitive load evaluation and decision support systems, gaps remain, especially regarding real-time frameworks aligning task assignment with operators' cognitive and physical states.

Research on cognitively demanding maintenance tasks is mostly limited to simulations, with few real-world implementations addressing ergonomic and safety challenges. Although early prototypes of adaptive DSS incorporating wearable sensors and digital twins are emerging, these remain at experimental stages and require further validation. Moreover, current approaches insufficiently integrate human factors and emotional states into actionable systems for task assignment, missing the link between cognitive conditions, safety behaviors, and maintenance performance. Future research should focus on developing adaptive, human-aware maintenance systems bridging theory and practice, emphasizing safety awareness, risk perception, and human reliability. While recent contributions indicate a shift toward sensor-driven, cognitively adaptive systems, broader empirical validations and cross-sector applications are needed to establish robust frameworks for real-time, cognitive-aware task allocation.

Acknowledgements

Funded by the European Union NextGenerationEU

This research work is part of the activities carried out in the context of the DESDEMONA project (DEcision Support system for the Diagnosis and Evaluation of the Maintenance OperatioNs Activities) of the Italian Ministry for Universities and Research MUR (Project PRIN – CUP D53D2301836 0001) funded by the European Union – NextGenerationEU, component M4C2, investment 1.1.

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