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NEUROCOGNITIVE INDICATORS OF AUTOMATION READINESS IN INDUSTRY FOUR POINT ZERO

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Abstract
The evolution of technologies within Industry 4.0, which includes intelligent automation and cyber-physical systems, calls for a shift in human cognitive flexibility. Pre-existing models centered on automation readiness often focus on a singular, technical form of automation competence. This overlooks critical human-machine dimension collaboration, neurocognitive factors. This study presents a new model of cognitive readiness incorporating real-time neurocognitive evaluation with EEG, fNIRS, HRV, and eye-tracking during industrial simulations. From human factors and workforce neuroscience perspectives, automation readiness is redefined and framed within neurophysiological variables, neurophysiological adaptability, and contextual factors such as age, training, and digital literacy. Employing a mixed-method experimental approach, industry practitioners were assessed in conditions of varying automation levels. Findings indicated that heightened automation complexity increases cognitive load, particularly for older workers and digitally less proficient individuals. From a neurocognitive standpoint, cognitive stressors were EEG alpha desynchronization and fNIRS-driven prefrontal cortical oxygenation increases. Assisted cognitive strategies markedly improved these neurocognitive stressors. The study highlights the need for industrial practices to incorporate cognitive readiness, suggesting adaptive training, assessment, interfaces, and real-time evaluation as applications. Notwithstanding the challenges posed by sample diversity and ecological validity, the study provides a starting point for neuro-industrial engineering, where technology is anthropocentrically calibrated to a human's cognitive skills for safety, performance, and ecological sustainability in the advancing industries of the future.
Keywords: Neurocognitive readiness, Industry 4.0, Automation adaptation, Human-machine interaction, EEG/fNIRS, Cognitive workload, Neuro-AI integration.

INTRODUCTION

The changing face of automation and technologies like intelligent automation, IoT, AI, and cyber-physical systems has completely reshaped how industries work [2]. When these technologies are adopted, the tasks of humans shift from manual-centered to higher-order interpretation and decision making. Every such automation necessitates workers to possess cognitive agility and novel adaptive learning. In this regard, the old concept of "automation readiness" has now transformed to include far more advanced neurocognitive dimensions. While automation metrics have tracked over-focused automation-centered metrics like machine efficiency or uptime, they ignore entirely the employee aspect. In this scenario, how ready the employee is for advanced automation is the central question to deal with. To solve this issue, the approach needs to shift from superficial, face-value automation assessments and transition to neuroscience and neuroergonomics-based evaluations that delve deep into understanding the mental workload, stress limits, and focus limits of employees interfacing with intelligent systems.This study presents a biometric EEG, fNIRS, HRV, and eye-tracking-based assessment of automation readiness employing a neurocognitive automation paradigm. These modalities permit non-invasive and real-time measurement of brain processes, attention, and the interplay between the autonomic nervous system and industrial tasks. Coupling these measurements with social and contextual information like age, skill level, and training history aims to assess the automation adaptability of workers' cognitive flexibility [14].To inform the design of human-centered interfaces, adaptive training systems, and ethical workforce policies, this study seeks to accomplish the following objectives: (1) define automation readiness neurocognitive markers, (2) assess age and skill-based differences for automation adaptability, and (3) design cognitive training strategies for the workforce.This study, alongside other neuro-industrial research, highlights the importance of human factors in the functioning of industrial systems [6][11]. The shift to Industry 5.0 with deeper human AI collaboration will hinge on the ability to neurocognitively assess and proactively manage workforce readiness and sustain operational agility [3][4][5][7][8].

1.1 Industry 4.0 and Cognitive Demands

- Industry 4.0 has transformed human work into interpretive and analytic supervision, which is more demanding and incurs higher mental flexibility and adaptability compared to previous manual and routine work.
- Executive functions such as working memory, attention, and situational awareness are critical in the performance of tasks in the modern workplace.
- For persons with low levels of digital fluency, complexity in HMIs such as dashboards, predictive alerts, and augmented reality interfaces increases the mental burden [8][12].
- These cognitive difficulties are not addressed in traditional assessments of the workforce. For this reason, neurocognitive techniques such as EEG and fNIRS are needed to capture mental load, attention shifts, and adaptive changes as they happen during a task.

1.2 Automation Readiness in the Workplace

- Preparation for automation involves digital skills, automation readiness, and automation readiness, alongside flexibility, cognitive resilience, and adaptability to rapid change. Automation irrefutably shifts core demands, and most traditional evaluations continue to ignore real-time cognitive benchmarks, for instance, concentration, mental weariness, and problem-solving progress.
- Cognition and automation-strain can be monitored continuously and non-invasively through EEG, fNIRS, HRV, and eye-tracking. These reveal the automation-strain appropriate for informing role assignment, customized training, and the development of ergonomic interfaces whose calibration enhances work and reduces cognitive burden.

1.3 Neurocognitive Approach: A Rationale

- Standard approaches, such as surveys and skill assessments, do not effectively measure neurocognitive automation processes vital for automation-centric environments. EEG and fNIRS monitoring reveal brain engagement and workload, HRV measures stress regulation, and eye tracking reveals attention and mental strategy.
- The automation-technology development and human factors integration automation systems design shift facilitates the development of performance and safety-inclusive and human-centered systems that adapt, not just respond, by actively minimizing cognitive workload.

2. RELATED WORK AND THEORETICAL BACKGROUND

Exploring automation readiness through the neurocognitive approach synthesizes work in cognitive psychology, neuroscience, human factors, and industrial automation [15]. Assessed alongside cognitive flexibility, gaps in traditional models focus only on technical skills. NASA-TLX and SWAT were developed to measure workload, but more recently, EEG, fNIRS, and HRV are being used to measure mental workload and stress actively. While human factors engineering has led to or improved user-centered interface design, the integration of cognitive state monitoring and readiness for complex automation is largely unexplored. The introduction of neurorobotics by Parasuraman and Rizzo allows for the evaluation of real-world systems and brain activity. Adaptable automation research shows that including human physiological responses to systems design increases efficiency and decreases overload. The understanding of neurocognitive automation and its variance with age, skill level, and other factors is still emerging. This work seeks to fill that void by applying cognitive load theory and experimental biometric data to devise a practical framework for assessing and improving workforce preparedness in the context of Industry 4.0.

2.1. Neurocognitive Foundations of Automation Readiness

- The traditional evaluation approach does not capture the cognitive workload stress and strain accuracy that Industry 4.0 imposes. Neurocognitive measures, including EEG and eye-tracking, along with human factors engineering, provide optimization opportunities for design, instruction, and occupational health and safety in real time.
- The responsiveness of the brain and body to the degree of automation's intricacy in innovative industrial systems offers automation-tailored responsiveness evaluation for proactive job-role alignment, sustainable human-machine teamwork, and automation-guided interventional profiling, thus enabling bespoke readiness profiling.

METHODOLOGY

This study used a neurocognitive evaluation framework to assess automation readiness in industrial workers under varying automation levels. Conducted in a simulated Industry 4.0 lab, the methodology integrated biometric tools like EEG and HRV with task performance data to capture real-time cognitive responses. Participants performed escalating automation tasks in environments featuring HMI terminals, robotic cells, and digital twins. Metrics such as accuracy, error rates, and decision latency were recorded alongside video observations. Data were segmented by demographics and task type to build individualized readiness profiles, offering objective insights into cognitive adaptability within high-tech industrial settings.

4.1 Participant Profile and Context

Manufacturing, logistics, and innovative infrastructure sectors were represented in the study by 60 participants, evenly split across gender and age (22–58), as well as level of automation exposure. The participants also differed in their education, digital literacy, and work experience, which provided an opportunity to analyze cognitive diversity. A pre-screening questionnaire in self-assessed milestones verified familiarity with Industry 4.0. The tasks simulation took place in a smart factory boasting AI dashboards, robotic work cells, and digital twins. Every participant underwent three 45-minute sessions: manual, semi-automated, and fully automated. Stressful conditions included multitasking and anomaly detection. Ethical safeguards included informed consent, breaks, and anonymized data. The outcome focused on experience-specific neurocognitive profiles aimed at more effective automated systems and training development.

4.2 Neurocognitive Tools (EEG, fNIRS, Eye-Tracking, HRV)

For a more objective evaluation of cognitive readiness, the research utilized four non-invasive neurocognitive techniques—EEG, fNIRS, Eye-Tracking, and HRV—while participants interacted with automated interfaces. EEG scanning captured real-time cortical α, β, and θ wave activity for mental effort and engagement, and fNIRS captured cortical oxygenated hemoglobin associated with cognitive control, signaling oxygenation of the prefrontal cortex. Eye-tracking captured gaze, fixation duration, and scan paths to measure attention and interaction with the interface engagement behavior. HRV captures balance in the autonomic nervous system, reflecting conditions of stress and adaptability as high or low frequency variability. These methods were integrated and provided a more comprehensive picture of each participant's cognitive and emotional engagement. With the integrated data, researchers were able to pinpoint specific neurocognitive reactions and automation stimuli, establishing intervals of stress, distraction, or adaptation. This added biometrics as a basis for automation and systems interface evaluations, ensuring cognitive assessments could be more objective and moved beyond the subjective perception, yielding clear steps to be taken for automation and systems interface recalibrations, ergonomicinterface redesign, and tailored cognitive coaching and training.

4.3 Experimental Design and Data Collection

The experimental framework utilized a within-subject repeated measures approach in which all participants went through three automation phases in an innovative factory simulation: a baseline manual phase, a semi-automated phase, and a fully automated environment. Tasks involved interpreting alerts generated by AI, AI-guided workflow management, and executing decisions within a varying and complex automation landscape. Increasing automation in each phase added cognitive load. Biometric tools captured real-time EEG, fNIRS, HRV, and eye-movement data. Along with subjective workload and emotional ratings (NASA-TLX and SAM scale), behavioral data included error rates, time to complete tasks, and decision latency. Video data was recorded and analyzed in MATLAB and Python scripts for artifact filtering, epoch segmentation, and spectral analysis. EEG-derived power spectra and eye movement tracking produced heat maps. HRV was analyzed with respect to stress recovery and decomposed for stress profiling. The combined dataset permitted calculating neurocognitive readiness, which computed automation adaptability for assessed tailored interface and training recommendations through predictive models.

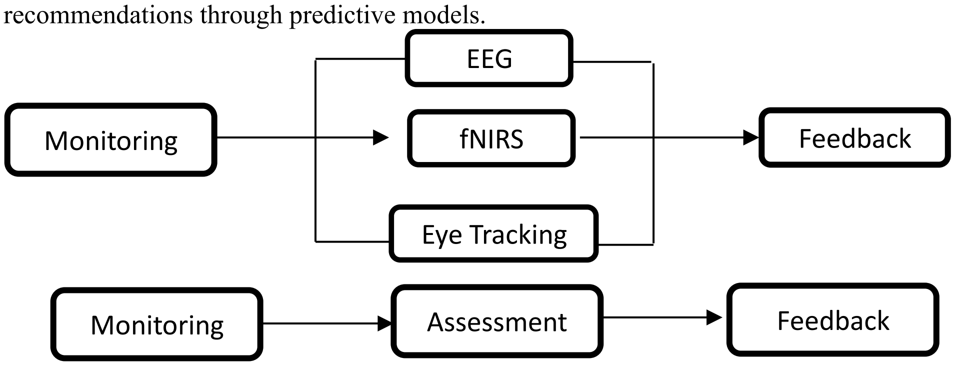

Figure 1: Neurocognitive Monitoring Framework

Figure 1 shows how automation readiness was assessed with the aid of neurocognitive automation data using a mixed-method approach. Participants from the manufacturing sector, logistics, and infrastructure, aged 30-55, with a certain level of automation exposure and specialized work history, made up a sample of 60. Each of the participants performed in a manually driven smart factory first as individual workers and progressed as a team in semi-automated and highly automated stages. In order to assess one's cognitive and physiological response, the EEG (brain activity), fNIRS (prefrontal oxygenation), Eye-Tracking (visual engagement), and HRV (stress and strain) were applied. The smart factory tasks were performed within the increasing complexity of automation. The flow of neurocognitive assessment in the automation readiness evaluation is illustrated in Figure 1 with the application of each of the tools in the respective phases of monitoring, assessment, and feedback. All biometric measures were collected continuously and integrated to assess the participant's mental load, stress level, and decision-making efficiency in real time. Automated evaluation of these metrics together with advanced signal processing methods, and correlating with metrics of behavioral performance yielded, among other feedback, individual readiness scores.

5. RESULTS AND DISCUSSION

The findings illustrate notable patterns connecting the complexity of automation with neurocognitive preparedness for all of the study's subjects. Higher automation levels corresponded with distinct EEG, fNIRS, and HRV changes, indicating different degrees of responsiveness. Readiness scores in the three task environments demonstrated a performance plateau or regression at advanced automation levels for some participant clusters. This suggests a paradox whereby automation improves effectiveness, but cognitive load increases in a way that becomes impossible for some users to cope with.

5.1 Automation Level vs. Readiness Scores

- Performance Divergence Across Levels: The group of participants showed proficiency in both manual and semi-automated tasks; however, in fully automated contexts, 40% exhibited a lack of mental control, as demonstrated by heightened theta EEG and decreased HRV. For participants unacquainted with AI, their comprehension of systems and readiness scores showed a sharp decline.
- Neurocognitive Threshold Effect: A limit effect was detected whereby users with intermediate experience sustained their output in fully automated tasks. Automation beyond a specific level incited mental fatigue, as indicated by fNIRS showing overactivation of the prefrontal cortex.

5.2 Cognitive-Behavioral Correlates

- Link Between Attention and Accuracy: Eye-tracking showed that participants with stable fixation maintained on task-relevant areas achieved higher task accuracy and lower EEG theta activity, suggesting automated cognitive efficiency.
- Stress and Delay in Decision-Making: Increased fNIRS oxygenation and reduced HRV on decision points were correlated with inaction and decision-making error, reflecting a cognitive stress and decision delay relationship.

5.3 Role of Age, Skill, and Training

- Cognitive Load: Older adults had a greater cognitive load—measured through EEG beta activity and HRV suppression—while performing high automation tasks compared to younger peers. This suggests that older adults may be less adaptable than their younger counterparts.
- Cognitive Training: Prior cognitive-based training improved readiness and neurocognitive efficiency, demonstrating the effectiveness of tailored training interventions.

6. INDUSTRY IMPLICATIONS

The integration of neurocognitive insights into industrial environments presents transformative implications for how organizations design, train, and govern human-machine systems in Industry 4.0. As automation advances, understanding the mental workload, attention span, and stress levels of human operators becomes vital to optimizing performance without compromising well-being. The study's findings underscore the need for **human-centric system design**, where user interfaces and automation levels are aligned with cognitive capacities. Such design approaches improve usability, minimize mental fatigue, and ensure operational safety. Furthermore, **cognitive-based training strategies** tailored to individual neurotrophies can significantly enhance workforce adaptability, preparing employees for dynamic, data-driven environments. These programs emphasize mental resilience, attention regulation, and adaptive decision-making skills essential in high-tech settings. However, the implementation of neurocognitive monitoring also raises **ethical and policy concerns**, particularly around data privacy, informed consent, and potential bias. Industry leaders and policymakers must collaborate to create transparent, inclusive frameworks that regulate how neuromata are collected, interpreted, and applied. Overall, the adoption of neurocognitive indicators can lead to more intelligent, responsive, and ethical industrial systems—provided that technology is deployed with a strong commitment to human dignity, diversity, and agency.

6.1 Human-Centric System Design and Cognitive Training

- Human-centered design techniques are particularly critical in avoiding human cognitive overload in highly automated environments. EEG and eye-tracking technology show how flight deck ergonomics and interface design can draw attention, leading to a myriad of safety and performance issues. Stress and cognitive overload are lessened in users by maintaining focus through mental workload responsive adaptive systems that change alert and interface complexity.
- Resilience and attention control can be strengthened by cognitive training and through neurofeedback and virtual or augmented reality simulations. Training workers in realistic situations and monitoring cognitive load customizes and enhances training. In automated industrial environments, cognitive-centered design and adaptive training of this kind strengthen readiness and mental health.

6.2 Ethics and Policy in Neurocognitive Automation

- The use of neurocognitive technologies in the workplace for stress and workload management raises issues of privacy and autonomy since brain and stress monitoring should always adhere to explicit consent and data monetization frameworks, as well as require robust data anonymization measures to prevent surveilled or mishandled feelings.
- They may be treated as less competent than their peers, and as a result, face discrimination because of their age or neurocognitive diversity. To foster fairness, trust, and responsible smart workplace innovation, the data must be used ethically to support and empower the employees, reinforcing and safeguarding responsible workplace practices.

CONCLUSION

This study proposed a neurocognitive framework to assess automation readiness in Industry 4.0, using EEG, fNIRS, HRV, and eye-tracking to capture real-time cognitive responses. Results showed a nonlinear link between automation complexity and performance, with overload risks beyond certain thresholds. Factors like age, skill level, and prior cognitive training influenced readiness, highlighting the need for personalized support. Though insightful, limitations such as sample size and simulation scope suggest future research should explore scalable, adaptive systems. Integrating neurocognitive data with AI could enable smart co-bots and training, but ethical safeguards are essential to protect privacy, consent, and inclusivity.

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