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# Enhancing Productivity and Safety in Manufacturing through Cognitive Ergonomics Using AI for Adaptive Systems

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## Abstract

This article presents a theoretical framework for enhancing manufacturing productivity and safety by integrating cognitive ergonomics and artificial intelligence (AI). The framework addresses the critical gap in current research for a holistic approach to managing cognitive workload by proposing an integrated approach to managing cognitive workload and individual differences in modern manufacturing contexts. Despite the growing recognition of cognitive ergonomics, existing frameworks often fail to provide a unified model that incorporates AI and adaptive systems to optimize worker performance without negatively impacting mental workload or well-being. This paper proposes a comprehensive five-step theoretical framework integrating cognitive ergonomics principles, AI, and adaptive systems to optimize worker performance and productivity in manufacturing environments. The framework begins with assessing manufacturing operations and evaluates mental resource allocation to prevent overload. It optimizes cognitive and physical workload through real-time monitoring, integrates AI for dynamic task allocation, and establishes continuous feedback loops to adapt task demands, reduce errors, and enhance safety. This paper aims to contribute to developing predictive models for cognitive workload and tailored technologies for cognitive load reduction, filling a significant gap in existing research. The proposed framework provides a standardized approach to improving manufacturing operations by combining cognitive ergonomics with adaptive automation systems. Ultimately, it aims to promote worker well-being and performance, ensuring that AI and adaptive systems complement, rather than detract from, cognitive capacity while reducing cognitive workload, mental pressure, and performance declines in high-workload environments.

## Keywords
Cognitive-Ergonomics, Adaptive-Systems, Artificial-Intelligence, Cognitive-Workload, Manufacturing-Environment

## 1. Introduction
Integrating cognitive ergonomics in manufacturing systems is a critical strategy to enhance productivity, safety, and efficiency by optimizing work environments and addressing cognitive demands. As manufacturing becomes increasingly complex with the rise of Industry 4.0 technologies, human operators face a heightened cognitive workload, leading to mental pressure, reduced efficiency, and errors. High cognitive workload, which requires individuals to allocate additional resources to task processing, can reduce processing efficiency and ultimately lower performance levels, particularly in high-intensity work environments (Galy, Cariou, and Mélan 2012). Despite the growing recognition of cognitive ergonomics, significant gaps remain in empirical research and practical frameworks that address cognitive workload, decision-making, and task complexity in modern manufacturing contexts (Kim 2016; Badiru et al. 2022). Integrating artificial intelligence (AI) and adaptive automation offers promising solutions to these challenges. However, these technologies must be carefully integrated to avoid exacerbating cognitive overload and ensure they complement human capabilities. This research aims to bridge the gap by proposing a comprehensive framework incorporating cognitive ergonomics with AI and adaptive systems, optimizing worker performance, safety, and well-being in manufacturing environments. The framework will address the need for context-specific approaches that align cognitive ergonomics principles with contemporary industrial practices, thereby reducing cognitive overload, enhancing decision-making, and improving worker performance.

### 1.1 Objective
This research aims to propose a theoretical framework that integrates cognitive ergonomics with AI and adaptive systems to enhance productivity, safety, and employee well-being in manufacturing environments. The key contributions of this study include developing a unified approach to managing cognitive workload, evaluating the role of AI in task allocation and cognitive load reduction, and providing practical insights into human-machine collaboration in adaptive manufacturing systems.

## 2. Literature Review
### 2.1 Artificial Intelligence, Adaptive, and Intelligent Systems
Artificial intelligence (AI) and adaptive systems are pivotal in manufacturing, enhancing efficiency, safety, and productivity. AI simulates human intelligence, enabling problem-solving, decision-making, and pattern recognition tasks. Adaptive systems adjust to environmental or operational changes, improving responsiveness and efficiency (ElMaraghy et al. 2021). Integrating these technologies optimizes processes, alleviates cognitive workload, and enhances worker performance and safety. The importance of focusing on AI and adaptive systems is underscored in this paper. The long-term effects of high cognitive load on worker safety and performance are underexplored, but automation systems can mitigate these impacts, fostering well-being and sustainable practices (Le Guillou et al. 2023). As industries adopt advanced technologies, human-centric design and decision-making become critical. By managing cognitive workload and offering decision support aligned with workers' capacities, AI and adaptive systems create more efficient operational frameworks (Wang et al. 2020). With the shift towards greater automation, ensuring these systems support rather than hinder well-being is essential.

Frameworks such as Cyber-Physical Production Systems (CPPS) demonstrate the integration of physical manufacturing elements with digital technologies, enabling real-time monitoring and decision-making. CPPS facilitates information flow between machines, operators, and management, allowing immediate adjustments based on operational needs. Leveraging IoT and cloud computing, CPPS fosters adaptability and resource optimization in manufacturing (ElMaraghy et al. 2021). Similarly, Smart Manufacturing Systems (SMS) emphasize real-time data and predictive analytics to respond to changing demands (ElMaraghy et al. 2021). These frameworks highlight scalability, product customization, and human roles as critical for addressing modern manufacturing complexities. The Flexible Manufacturing Systems (FMS) framework emphasizes customizable flexibility to adapt to varying demands while considering workers' cognitive needs (ElMaraghy et al. 2021). This approach enhances adaptability and sustainability in manufacturing. The Human-Centered Intelligent Manufacturing (HCIM) framework focuses on integrating human factors with AI and adaptive systems to prioritize cognitive ergonomics alongside technological advancements (Wang et al. 2020). Synthesizing principles from CPPS and FMS enables the development of predictive models that integrate cognitive ergonomics into operational strategies, aligning with this research's objective to optimize worker performance, safety, and productivity (Wang et al. 2020). With the shift towards greater automation, ensuring these systems support rather than hinder well-being is essential.

## 2.2 Human Error and Error Prevention in Manufacturing

Human error is a persistent challenge in manufacturing, causing inefficiencies, safety risks, and reduced product quality (Gaboury et al. 2013). Cognitive ergonomics, which studies the interaction between humans and technology, offers a comprehensive approach to addressing these issues. By analyzing how cognitive processes influence task performance, potential sources of error can be identified and mitigated, improving manufacturing outcomes. The detrimental effects of human error on manufacturing are well-documented in the literature (Gaboury et al. 2013). Cognitive ergonomics provides tools to analyze interactions between tasks, tools, and environments, enabling strategies to enhance performance and reduce risks. The Human Performance Model (HPm) compares task complexity and human capabilities on a common scale, identifying mismatches that could contribute to errors (Chiara Leva et al. 2022).

The modified Rasch Model offers a quantitative approach to assessing individual performance and predicting error rates. It models the relationship between a person's capacity and task difficulty, providing insights into factors influencing error rates and identifying individuals prone to errors in specific tasks (Chiara Leva et al. 2022). The NASA Task Load Index (NASA-TLX) measures subjective workload, significantly contributing to human error. By assessing perceived workload, overly demanding tasks or environments can be identified and addressed through task redesign or additional resources (Chiara Leva et al. 2022). Simulation-based approaches also play a vital role. The SHERPA Model predicts human error probability based on task characteristics, performance-shaping factors, and work duration. Simulating scenarios helps identify risks and develop mitigation strategies (Di Pasquale et al. 2016).
Cognitive ergonomics provides a theoretical foundation to create intuitive, efficient systems less prone to error. Applying these principles may involve redesigning workstations, improving task instructions, or incorporating supportive technologies. Integrating these frameworks offers a holistic understanding of human error in manufacturing. This enables empirical data collection, innovative performance assessment, and practical strategies to enhance efficiency and safety.

## 2.3 Mental Models and Cognitive Mapping

Mental models and cognitive mapping are valuable tools for enhancing productivity and safety in manufacturing. Cognitive mapping reveals links between human factors and strategic goals, helping organizations identify hazards and optimize workflows (Village et al. 2013). Understanding how employees perceive and interact with their work enables the design of more intuitive interfaces and automation systems, reducing errors and accidents (Wang et al. 2020). Additionally, cognitive mapping facilitates knowledge transfer and improves human-machine collaboration, contributing to operational excellence (Virmani and Ravindra Salve 2023).

Deep Gated Neural Networks (DGNNs) provide a powerful tool for cognitive mapping. DGNNs can classify cognitive workload levels based on EEG data, creating cognitive maps that reveal relationships between mental states and tasks (Afzal et al. 2024). These insights optimize work environments and enhance human-machine interactions (HMI). Organizational Behavior provides a framework for understanding social and psychological factors influencing cognitive processes. Examining organizational culture, leadership styles, and employee attitudes identifies factors affecting cognitive map formation. For instance, collaborative cultures foster shared mental models, improving teamwork and decision-making.

Systems Engineering offers a holistic perspective on human-machine systems. Cognitive mapping can visualize information flow and decision-making within manufacturing systems, identifying bottlenecks, inefficiencies, or areas of cognitive overload. Engineers can propose improvements to enhance performance by analyzing interactions between system components. Integrating these frameworks broadens the understanding of cognitive mapping and its applications. For example, combining DGNNs with Organizational Behavior explores how organizational factors influence team cognitive maps. Similarly, integrating DGNNs with Systems Engineering identifies cognitive factors affecting system performance, enabling strategies to optimize human-machine interactions. Cognitive mapping is increasingly recognized as a critical tool for understanding and improving complex systems. By combining frameworks like DGNNs, Organizational Behavior, and Systems Engineering, researchers can develop innovative strategies to enhance performance, efficiency, and collaboration in manufacturing environments.

## 2.4 Cognitive Workload

Cognitive Load Theory (CLT) posits that the human cognitive system has limited capacity, and exceeding this capacity leads to cognitive overload, resulting in decreased performance, increased errors, and even physical fatigue (Dadashi et al. 2022). In manufacturing, CLT can be applied to analyze task demands, identify bottlenecks, and develop strategies to reduce cognitive load by examining factors like task complexity, information overload, and time pressure. Sociotechnical Systems Theory emphasizes the interdependence of social and technical systems, highlighting the interplay between human operators, technology, and organizational structures (Thorvald et al. 2019). This framework helps identify bottlenecks and inefficiencies within the manufacturing environment. The Task Complexity Model focuses on quantifying the cognitive demands of specific tasks by considering factors such as the number of steps, decision-making requirements, and information-processing complexity. By understanding task complexity, we can identify those that place a high cognitive load on workers and develop strategies to mitigate these demands. The frameworks of CLT, Sociotechnical Systems Theory, and the Task Complexity Model provide a comprehensive approach to understanding and addressing cognitive workload in manufacturing environments (Dadashi et al. 2022). These frameworks offer valuable insights into the factors that influence human performance, identify potential areas for improvement, and guide the development of strategies to enhance productivity and safety in manufacturing settings.

## 2.5 Human-Machine Interface (HMI) Design

HMI design is crucial in modern manufacturing, especially with AI-powered systems and adaptive automation. Effective HMIs bridge the gap between human cognition and machine functions, enabling clear communication and informed decision-making while minimizing cognitive overload (Badiru et al. 2022). In environments with distributed tasks among humans, engineers, and AI, HMI must support multi-human interactions, catering to diverse cognitive abilities and ensuring seamless collaboration (Johannsen 1997). Integrating cognitive workload monitoring systems (CWMS) within HMI frameworks is crucial. Systems incorporating IIoT, neural networks, and EEG data can track cognitive parameters in real-time, providing feedback to prevent overload (Afzal et al. 2024). The Deep Gated Neural Network (DGNN) framework, utilizing Bi-directional Long Short-Term Memory (Bi-LSTM) and Gated Recurrent Unit (GRU) architectures, effectively classifies cognitive workloads from EEG signals. This enables dynamic adjustments in HMI designs based on real-time cognitive state assessments, enhancing operator performance (Afzal et al. 2024).

HMI design is also critical in human-robot collaboration (HRC). Intuitive interfaces and real-time feedback on robot actions significantly reduce stress and improve trust in the system (Gualtieri et al. 2022). To enhance HMI design, various frameworks can be leveraged. The Knowledge Modules Framework structures knowledge around user requirements, visualizing interactions with information flow diagrams. (Johannsen, 1997). The Design Stages Framework emphasizes iterative user participation, combining systems engineering lifecycle procedures with rapid prototyping and user evaluations (Johannsen 1997). Developing comprehensive, context-specific frameworks that integrate cognitive ergonomics with industrial practices and emerging technologies like AI is crucial. By advancing HMI design methodologies, we can ensure that emerging technologies enhance, rather than hinder, human-machine collaboration in complex manufacturing settings (Badiru et al. 2022)

## 2.6 Situation Awareness

Situation awareness (SA) is defined as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status into the near future" (Adams et al. 1995), is crucial for effective human-robot collaboration (HRC) in manufacturing. Lapses in SA can lead to accidents and reduced productivity, especially in complex environments with increasing automation and AI (Hopko et al. 2021). This research focuses on SA due to the cognitive challenges operators face in these environments, such as information overload and frequent task shifts. While automation enhances performance, it can also reduce operator attentiveness, negatively impacting SA. This study aims to investigate how AI and adaptive automation can alleviate cognitive load and maintain optimal SA.

Existing frameworks provide valuable insights. Neisser's Perceptual Cycle explains how mental models guide perception and anticipation, aiding SA (Adams et al. 1995). The Situation Awareness-based Agent Transparency (SAT) model focuses on how transparent artificial agents can support team-level SA in human-autonomy collaboration (Le Guillou et al. 2023). These models highlight cognitive strategies to help manage complex tasks and maintain SA. Various measurement techniques can assess SA in manufacturing environments. The Situation Awareness Rating

Technique (SART) measures SA subjectively (Hopko et al. 2021). The NASA Task Load Index (NASA-TLX) measures operator workload. Objective physiological measures, such as heart rate variability (HRV), provide real-time insights into cognitive states like fatigue, impacting SA and task performance (Le Guillou et al. 2023).

This research proposes a new framework for SA that integrates cognitive ergonomics with AI and adaptive automation. By leveraging the strengths of existing frameworks, such as Neisser's Perceptual Cycle and the SAT model, this framework will enable the development of cognitive load management strategies tailored to the complexities of modern manufacturing environments. AI and intelligent systems can continuously monitor the operator's cognitive state, adjusting the level of automation and task support based on real-time data, such as HRV metrics. This will ensure that the cognitive workload remains manageable, maintaining high SA and optimizing both worker performance and safety (Hopko et al. 2021; Adams et al. 1995).

## 2.7 Task Complexity and Multitasking

Task complexity, influenced by factors like the number of steps, task variety, and interdependencies, significantly impacts manufacturing operations. Though necessary in complex environments, multitasking increases cognitive workload and can degrade performance. Researching these intertwined elements is crucial for improving cognitive ergonomics and operational efficiency. Modern manufacturing systems present intricate challenges due to complex products and configurations, exceeding the limitations of current human performance models. This necessitates a unified approach that integrates task complexity, multitasking, and cognitive workload within diverse manufacturing contexts.

Several frameworks offer valuable insights. The Task-Component-Factor-Dimension Framework systematically categorizes task complexity through literature review and conceptual modeling (Liu et al. 2012). The Manufacturing Complexity Model evaluates complexity at three levels (product, process, and operational) using a matrix methodology, providing objective measures (EImaraghy and Urbanic 2004). The Operational Complexity Index emphasizes both physical and cognitive aspects of operational complexity, aiding in developing cognitive load reduction technologies. Signal Detection Theory and Multiple Resource Theory provide crucial insights into the effects of multitasking on operator performance (Bommer and Fendley 2018). These foundational models can be leveraged to develop a new framework that integrates cognitive ergonomics with AI and adaptive systems. A comprehensive understanding of task complexity considering cognitive workload and operational demands can be achieved by adopting a systematic approach. Integrating AI and adaptive automation allows for dynamic adjustments to cognitive workload, enhancing operator engagement and performance while mitigating the adverse effects of multitasking. This combined approach will provide a solid foundation for developing innovative solutions to address the challenges of modern manufacturing environments.

The frameworks in Table 1 are closely linked to key concepts in cognitive ergonomics, human error prevention, and situation awareness. They emphasize integrating AI, adaptive systems, and human-centered design into modern manufacturing. These frameworks guide our research and are used to develop a comprehensive approach for optimizing manufacturing systems, and improving worker safety, performance, and efficiency.

Table 1. Frameworks Reviewed to Define Research Gap and Study Aim

| Framework Title | Purpose | Methods | Tools and analysis |
|---|---|---|---|
| Human-Centered Intelligent Manufacturing (HCIM) (Wang et al. 2020) | Key development approach and direction for intelligent manufacturing, considering human factors throughout the lifecycle | Applies human-centered principles and uses advanced digital, networked, and intelligent technologies | Presents a three-tiered reference architecture (unit-level, system-level, system-of-systems-level) and key technologies |
| Deep Gated Neural Network (DGNN) (Afzal et al. 2024) | The DGNN is a hybrid neural network architecture that combines Bi-LSTM and GRU layers to classify cognitive workload levels effectively based on EEG data. | The DGNN model is trained on the STEW EEG dataset, which contains EEG data from subjects performing various cognitive tasks. | Python, Jupyter Lab, and deep learning libraries (e.g., TensorFlow, Keras) are used. DGNN model's performance is assessed with accuracy, precision, recall, and F1-score. |
| Industrial Internet of Things (IIoT) (Afzal et al. 2024) | The IIoT framework provides the infrastructure for real-time data collection, transmission, and analysis. | Raspberry Pi Zero W modules are used as gateways to collect EEG data from virtual users. The data is transmitted to a central server using the CoAP protocol. | Raspberry Pi Zero W, CoAP, Things Board, and PostgreSQL enable the IIoT framework for real-time monitoring of latency, processing time, and cognitive workload levels. |
| Cognitive Load Theory (Dadashi et al. 2022) | This theory examines cognitive load, the mental effort needed for information processing and task performance, and identifies factors that affect it. | Experimental studies, cognitive task analysis, and workload measurement techniques. | Cognitive load measurement tools, such as NASA-TLX, and data analysis techniques |
| Cognitive Workload Model (Ma et al. 2024) | To conceptualize the relationship between task demands, cognitive workload, and operator performance. | The model is based on the theory of demands and strain, with additional consideration of non-attentional factors like expertise. | The model is used to guide the experimental design and analysis. |
| SHERPA Model (Di Pasquale et al. 2016) | This framework predicts the likelihood of human error based on the task, performance shaping factors (PSFs), and worked time. | Uses a Weibull probability distribution to model human reliability as a function of worked time. | Software simulator (SHERPA) considers task characteristics, PSFs, and worked time to calculate nominal HEP. |
| Hierarchical Task Analysis (HTA) (Gualtieri et al. 2022) | Analyzes the hierarchical structure of tasks, breaking them down into subtasks and operations. | Decomposing a task into a hierarchy of goals, operations, and plans. | Task decomposition diagrams and task analysis worksheets to represent task structure. |
| NASA Task Load Index (NASA-TLX) (Chiara Leva 2022) | To quantify the operator's workload | NASA-TLX includes six subscales: mental, physical, temporal demand, performance, effort, and frustration. The overall workload is the sum of these subscales. | Participants completed the NASA-TLX questionnaire after each experimental condition. Provides a subjective measure of the operator's perceived workload. |

| | | | |
|---|---|---|---|
| Operational Complexity Index (EIMaraghy et al. 2004) | To assess operational complexity in manufacturing systems, considering physical and cognitive aspects. | Defines the operational complexity index as a function of the diversity ratio, complexity coefficient, and effort factor. | A detailed effort analysis that considers physical and cognitive elements as part of the operational complexity coefficient is presented. |
| Multiple Resource Theory (MRT) (Bommer and Fendley 2018) | To understand the relationship between resources and demands while multitasking in a complex environment. | Uses four dimensions to justify variance in the time-sharing of performance: processing stages, perceptual modalities, visual channels, and processing codes. | MRT ratings are used as inputs in the IMPRINT simulation tool to predict mental workload. |
| Shared Mental Models (SMM) and Team Situation Awareness (TSA) (Le Guillou et al. 2023) | To highlight the importance of a shared understanding between team members for effective coordination and performance | Common mental models and situation awareness within teams | Measurement tools developed to assess SMM and TSA; demonstrated in various studies for team performance |
| Human-Centered Design ((Dadashi et al. 2022) | HCD designs user-centered products, systems, and services, tailoring manufacturing tasks to human cognitive capabilities and limits. | HCD typically involves user research, prototyping, testing, and iteration. | Observation, interviews, surveys, usability testing, and design thinking tools. |

## 3. Research question and Aim

Current research in manufacturing often isolates cognitive workload, decision-making, and individual differences. This fragmented approach hinders the development of unified solutions for optimizing worker performance and well-being, especially in AI-driven environments. This research aims to address this gap by developing a comprehensive framework that integrates cognitive ergonomics principles while explicitly addressing the potential negative impacts of AI on worker cognitive workload, individual differences, and overall well-being. How can an integrated framework of cognitive ergonomics be developed to optimize worker performance, safety, and productivity in manufacturing environments while ensuring that the integration of artificial intelligence (AI) and adaptive automation systems does not negatively impact cognitive workload, individual differences, and overall well-being?

## 4. Results

### 4.1 Assess Current Manufacturing Operations (Step 1)

Step 1 of the AI-Enhanced Cognitive Ergonomics Framework evaluates current manufacturing operations to understand how workers perform their daily tasks and where AI could help improve their work. This assessment uses three main methods to gather comprehensive information. This assessment uses three main methods to gather comprehensive information, utilizing the frameworks from Table 1. The first method, Hierarchical Task Analysis (HTA), breaks manufacturing processes into smaller, manageable parts to understand how different tasks connect and flow together. The second method, Applied Cognitive Task Analysis (ACTA), examines the mental demands of each task by identifying when workers need to make crucial decisions and what thinking skills they use. The third method, Cognitive Load Theory (CLT), helps measure how mentally demanding each task is by looking at different types of mental workload that workers experience. The result of Step 1 is a detailed map of all work processes that shows where AI could be added to help workers perform better and more safely.

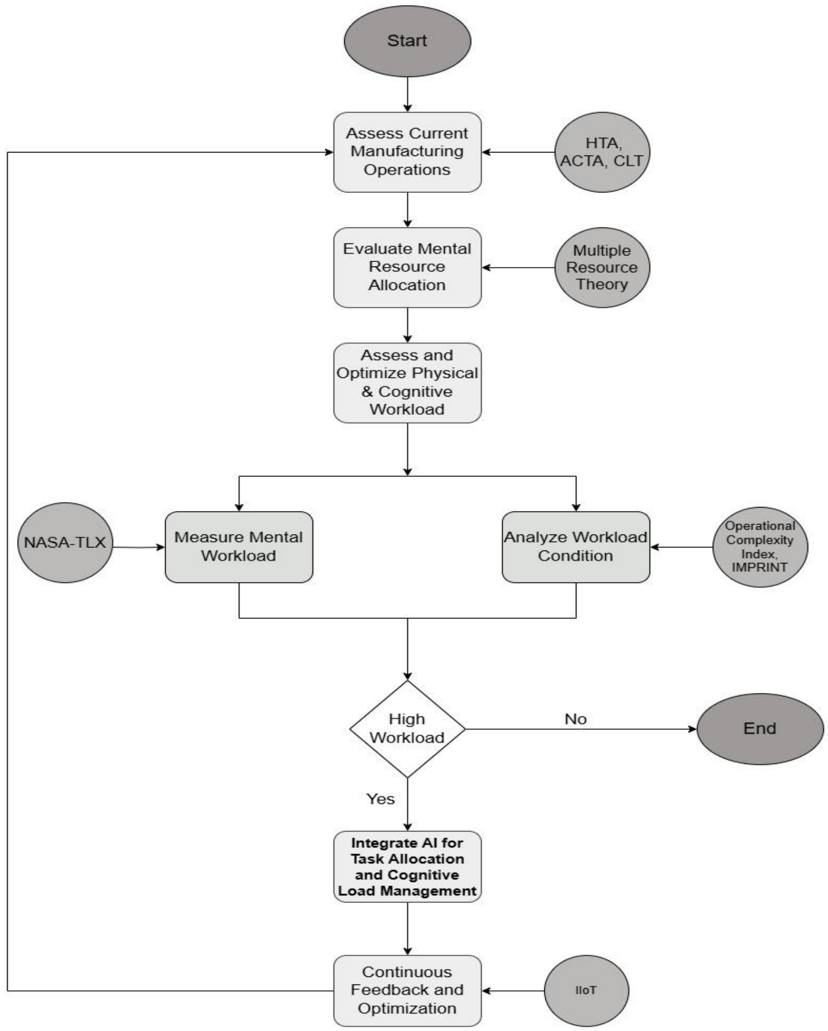


Figure 1. AIDA Framework (AIDA: AI-Driven Assessment for Manufacturing Operations)

### 4.2 Evaluate Mental Resource Allocation (Step 2)

Step 2 of the framework evaluates how workers manage their mental resources during manufacturing tasks to distribute work effectively and prevent mental fatigue. This evaluation primarily uses Multiple Resource Theory (MRT), which examines how workers divide their attention between mental activities - such as seeing, hearing, and physical movement - especially when multitasking is required. The outcome of this step is a flexible model that helps managers assign tasks in ways that prevent mental overload. This step builds upon three important frameworks: Human-Centered Intelligent Manufacturing (HCIM), which ensures that smart systems work in harmony with human mental capabilities; Human-centered design (HCD), which uses direct feedback from workers to identify and fix problems in how mental effort is distributed; and Shared Mental Models (SMM) and Team Situation Awareness (TSA), which examine how team members' shared understanding affects their mental workload during collaborative tasks. These approaches help create a working environment that respects and optimizes workers' mental capabilities.

### 4.3 Assess and optimize cognitive and physical workload (Step 3)

This step involves two steps. The mental workload measurement focuses on measuring mental workload through a comprehensive assessment system designed to evaluate cognitive strain in manufacturing environments. The core of this component relies on traditional assessment tools, particularly NASA-TLX, to gather workers' subjective ratings of their mental workload. The mental workload measurement is supported by three key frameworks: Joint Action and Intentional Stance, which helps understand cognitive demands during team collaboration; Deep Gated Neural Network (DGNN),

which analyzes brain activity data to classify mental workload levels; and the Task-Component-Factor-Dimension Framework, which evaluates how task complexity impacts mental strain to optimize resource allocation. The primary goal remains to enable proactive task adjustments based on identified cognitive demands and potential errors.
The analysis of workload conditions, running parallel to the mental workload assessment, analyzes overall workload conditions through a continuous feedback system that monitors real-time operator performance. At its core, this component utilizes an Operational Complexity Index to evaluate manufacturing tasks by considering three crucial factors: the diversity ratio (task variety), complexity coefficient (task difficulty), and effort factor (physical and mental energy requirements). Simultaneously executing this workload analysis alongside the mental workload assessment creates a complete picture of worker demands, resulting in an updated performance and workload analysis system that optimizes task management while strengthening operator engagement.

After measuring mental workload and analyzing workload conditions, the workflow reaches a critical decision point labeled "High Workload." This decision node is a gateway for determining whether additional intervention is needed based on the combined assessments from both measurement streams. If the workload is determined to be "High" (Yes path), the workflow proceeds to Step 4 to integrate AI-based task allocation and cognitive load management solutions. Suppose the workload is evaluated as manageable (No path). In that case, the process terminates at the "End" node, suggesting that the current operational conditions are within acceptable limits and do not require additional technological support.

## 4.4 Integrate AI for Task Allocation and Cognitive Load Management (Step 4)

Following Step 3, the decision node determines whether the workload intensity is high or low. If the decision is yes, indicating a high-workload environment, Step 4 is initiated, as such environments benefit significantly from integrating AI and adaptive systems for task allocation. Step 4 of the framework aims to develop a dynamic task allocation system that uses AI to optimize workload distribution based on assessments of cognitive load and real-time performance metrics, ensuring that tasks match individual capabilities and cognitive states. By doing this, the system can improve safety in manufacturing settings, increase productivity, and minimize errors (Le Guillou et al. 2023). Dynamic task allocation using machine learning algorithms minimizes overload. It maintains an ideal workload balance by enabling responsive job assignments depending on workers' cognitive workload and task complexity in real time (Yu et al. 2024).

AI integration improves task execution and reduces human error in smart manufacturing settings by enabling adaptive systems to manage work allocation based on cognitive states (Gao et al. 2024). By ensuring that task demands match cognitive capacity, integrating AI with cognitive ergonomics frameworks such as Cognitive Load Theory (CLT) and Cognitive Workload Models (CWM) provides a basis for controlling cognitive load (Bommer and Fendley 2018). Cognitive Workload Monitoring permits real-time workload modifications based on cognitive state information obtained from IIoT devices, like EEG tests, which tell AI systems about the available mental resources and allow task modifications to correspond with present worker capacities (Johannsen 1997).

This procedure considers a variety of workforce elements that can affect performance and safety, such as individual differences and age-related cognitive changes (Stedmon et al. 2012).
Through analyzing task characteristics, performance-shaping factors, and real-time data, the responsive system, driven by models such as SHERPA, can forecast the likelihood of human error (Di Pasquale et al. 2016). By proactively assigning tasks that reduce cognitive overload and error risk, SHERPA empowers AI to improve safety and efficiency. For instance, safety results can be improved by reassigning tasks with a higher calculated error likelihood to employees with lower cognitive loads. By including feedback loops in the task allocation process, this method guarantees that the cognitive burden is balanced over time, preventing extended high demand that might cause errors or fatigue. The dynamic application of cognitive ergonomics principles through AI-driven changes enables the manufacturing system to become flexible and adaptive to the intricacies of a modern industrial environment.

## 4.5 Continuous Feedback and Optimization (Step 5)

Step 5 creates a continuous feedback loop following Step 4's implementation of AI-driven dynamic task allocation, guaranteeing that the system continues to adapt to the demands of operators' cognitive abilities. AI may dynamically modify job distribution based on operator performance and input due to this continuous improvement, backed by real-time data, improving efficiency and safety (Yu et al. 2024). Continuous data streams (such as EEG evaluations) and operator input are fed into machine learning algorithms, which learn over time, adjust task distributions to minimize errors, and balance the cognitive load in real time. A reliable foundation for responsive, agile optimization is ensured by utilizing IIoT technologies for data transfer and EEG monitoring (Afzal et al. 2024). Using frameworks such as the Industrial Internet of Things (IIoT) (Johannsen 1997) for ongoing monitoring and alignment with cognitive requirements, the system becomes more sensitive to individual operators' workload and task complexity. This method ensures operators are neither overloaded nor underutilized by establishing a human-centered, adaptive environment in which the AI continuously learns and adapts. The system aims to promote steady improvements in safety, productivity, and cognitive load management as it iteratively adapts to operator feedback. It also fits in well with new developments in cognitive ergonomics and AI integration trends in manufacturing.

## 5. Discussion

The proposed AI-enhanced Cognitive Ergonomics Framework significantly contributes to manufacturing ergonomics by addressing critical workload management and decision-making gaps. Integrating cognitive and physical workload assessments in Step 3 provides a comprehensive understanding of worker demands, surpassing traditional single-focus methods. Combining established tools like NASA-TLX with newer methodologies such as the Operational Complexity Index highlights how traditional principles can be enhanced with contemporary techniques.

A key strength is the framework's flexible AI integration. Unlike existing systems that mandate technological solutions, this framework allows AI integration to be optional in all steps, recognizing the varying needs of different manufacturing contexts. This flexibility addresses concerns about forced AI integration's negative impact on worker cognitive load and well-being. The stepwise structure—starting with operational assessments, mental resource evaluation, workload optimization, AI integration for task allocation, and continuous feedback—offers a clear and gradual implementation pathway, enabling organizations to build robust programs over time.

Despite its strengths, the framework has limitations. Empirical validation across diverse manufacturing contexts is essential to establish its generalizability and effectiveness. Its comprehensive nature may demand significant resources for implementation, and organizational culture and worker attitudes may influence its success. Practical recommendations for implementation include a phased approach, starting with foundational elements before integrating complex components. Early involvement of workers and supervisors is crucial for acceptance and success. Organizations should adapt tools and methods to their contexts while maintaining the framework's core structure.

Future research should focus on standardized metrics for cross-context comparison, the effects of different AI integration levels on worker well-being, and the long-term impacts on productivity, safety, and satisfaction. Additionally, developing industry-specific guidelines, streamlined assessment methods, and exploring cultural factors influencing adoption are critical areas for further investigation.

## 6. Conclusion

The AI-enhanced Cognitive Ergonomics Framework represents a significant advancement in addressing the complex challenges of modern manufacturing environments. This framework offers organizations a practical tool to enhance productivity and worker well-being by providing a structured and flexible approach to cognitive ergonomics integration while prioritizing human-centered principles.

Our framework aims to mitigate the negative impacts of high cognitive workload through a systematic assessment of manufacturing operations, evaluation of mental resource allocation, optimization of cognitive and physical workload, integration of AI for dynamic task allocation, and establishment of continuous feedback loops. Prolonged high cognitive workload can lead to various mental health issues, such as stress, burnout, and decreased cognitive performance. By addressing these challenges, our framework creates more efficient, safer, and worker-friendly manufacturing environments.

Future research and practical implementation will further refine and validate this approach, potentially leading to more efficient and worker-friendly manufacturing environments.

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**Deeksha Kalkatte Laxman** is a Graduate Student in the Department of Engineering Management, Systems & Technology at the University of Dayton, Dayton, Ohio, USA. She holds a Bachelor of Technology in Civil Engineering from the University Visvesvaraya College of Engineering, Bengaluru, India, and is currently pursuing a Master of Science in Engineering Management. Her academic focus includes Lean Six Sigma methodologies, supply chain management, and production engineering, with an emphasis on process optimization and efficiency improvement. She has been actively involved in research, including operations optimization using Lean Six Sigma and supply chain network design using linear programming techniques. Deeksha has presented work addressing diversity and inclusion in STEM and has contributed to multiple publications, including ongoing research on cognitive ergonomics in manufacturing. Her academic and research pursuits reflect a commitment to advancing innovative solutions for industrial and operational challenges.

**Dr. Sharon Claxton Bommer** is an Associate Professor in the Department of Engineering Management, Systems and Technology. She earned a Ph.D. of Engineering in Industrial and Human Systems, specializing in human performance and cognition. Dr. Bommer holds a Bachelor of Science in Mechanical Engineering and two master's degrees: Master of Business Administration and Master of Science in Industrial Engineering. Prior to earning her Ph.D., she had a successful career working for over fifteen years in the automotive manufacturing industry in various engineering and operation roles, whereas her last role was Plant Manager for a Tier 1 parts supplier. In addition, she has served as the Dean of the School of Business and Applied Technologies at Clark State College, providing leadership for business, information technology, agriculture, and engineering technology programs. She enjoys teaching graduate and undergraduate courses relative to operational improvements. Her research is in human systems integration, focusing on human performance and cognition for industrial and military operations.