International Journal of Engineering Research and Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 22, Issue 3 (March 2026), PP 59-70

Ergonomics in the Age of Industry 5.0: A Multilevel Data Analytics Approach Linking Human-Robot Collaboration, Cognitive Load, and Productivity in Smart Manufacturing Systems

Okpala Charles Chikwendu, Nwamekwe Charles Onyeka and OnukwuliSomto Kenneth
Industrial/Production Engineering Department
Nnamdi Azikiwe University, P.M.B. 5025 Awka - Nigeria.

Abstract
Industry 5.0 advances a human-centric and sustainability-driven vision of smart manufacturing, yet empirical evidence that links ergonomic system design to measurable environmental performance remains limited. This study develops and validates a multilevel data analytics framework that connectsHuman–Robot Collaboration (HRC), cognitive load dynamics, productivity variability, and sustainability outcomes in digitally integrated manufacturing environments. Data were collected from 12 smart factories across automotive, electronics, and precision assembly sectors, comprising 486 operators and 18,742 task cycles over 14 months. Operator-level neurophysiological indicators (EEG-derived cognitive load index, heart rate variability, electromyography), workstation-level cobot telemetry and task allocation metrics, and plant-level energy intensity, defect rate, and carbon emission data were synchronized within a hierarchical Bayesian modeling architecture. Results demonstrate that ergonomically optimized HRC configurations reduced cognitive load by 23.8%, defect rates by 18.7%, and energy intensity per unit output by 9.2%, with 58% of sustainability gains mediated through reductions in cognitive strain. Digital twin–guided workstation redesign further yielded a 12.5% decrease in material waste and a 7.1% increase in overall equipment effectiveness. Machine learning classification (AUC = 0.89) successfully predicted high-risk ergonomic configurations associated with sustainability losses, thus underscoring the scalability of ergonomic intelligence analytics. Through empirical quantification of the pathway from human cognitive stability to environmental efficiency, this study positions ergonomics as a strategic lever for low-carbon and resilient manufacturing systems. The findings provide a replicable methodological blueprint for the integration of human-centered design within Industry 5.0 sustainability strategies.
Keywords: *Industry 5.0, human–robot collaboration, cognitive load, sustainable manufacturing, multilevel modeling, digital twin simulation, ergonomic intelligence*

Date of Submission: 01-03-2026 Date of acceptance: 10-03-2026

I. Introduction

The transition from Industry 4.0 to Industry 5.0 marks a decisive shift from automation-centric production towards human-centered, resilient, and sustainable manufacturing systems. While Industry 4.0 emphasized cyber–physical systems, data integration, and intelligent automation(Igbokwe et al., 2024; Okpala et al., 2025a), Industry 5.0 repositions the human worker as a central actor in value creation and sustainable transformation (European Commission, 2021; Xu et al., 2021). This shift reflects growing recognition that technological sophistication alone does not guarantee long-term productivity or environmental performance. Instead, the interaction between human operators and advanced technologies, particularly collaborative robots (cobots)has become a defining feature of smart factories. Yet, despite rapid adoption of Human–Robot Collaboration (HRC), empirical evidence that links ergonomic quality within these systems to measurable sustainability outcomes remains limited.

As the science of studying people's efficiency in the work environment and the modalities and processes to be added to enhance their health and productivity all through the working hours, ergonomics entails proper designing of a job to fit a worker in order to ensure more efficient and safety work (Okpala and Ihueze, 2017; Okpala et al., 2025b). Ergonomics research has long demonstrated that poorly designed work systems increase musculoskeletal disorders, cognitive overload, and error rates, thereby compromising safety and performance (Godwin and Okpala, 2013; Chukwumuanya et al., 2025a). Concurrently, sustainable operations management research has shown that process inefficiencies, rework, and defects significantly contribute to material waste, energy overuse, and carbon intensity (Chukwumuanya et al., 2025b; Onukwuli et al., 2025). However, these two streams of scholarship have largely evolved in parallel. The ergonomic literature focuses predominantly on worker health and task performance, whereas sustainability research emphasizes environmental and economic metrics. Bridging these domains is critical in Industry 5.0 environments, where human well-being, productivity, and environmental responsibility are increasingly interdependent (Nahavandi, 2019). A failure to integrate ergonomic intelligence into smart manufacturing systems risks undermining both worker-centered design and sustainability objectives.

The global emphasis on environmental sustainability has driven industries to reassess traditional manufacturing methods, leading to the widespread integration of robotics that are aimed at waste reduction and enhancement operational efficiency (Okpala et al., 2025c). Huuman–robot collaboration introduces unique ergonomic challenges and opportunities. Unlike traditional automation, cobots operate in shared workspaces, dynamically allocating tasks between human cognition and robotic precision (Villani et al., 2018; Okpala et al., 2023). While such systems can reduce physical strain, they may inadvertently increase cognitive demands through monitoring, coordination, and adaptive decision-making requirements (Parasuraman et al., 2000). Elevated cognitive load has been associated with higher error probability, decreased situational awareness, and performance variability (Sweller, 2011). In manufacturing contexts, these human performance fluctuations can cascade into increased defect rates, rework cycles, and energy inefficiencies, which are factors that are directly affecting environmental sustainability metrics. Yet, quantitative models capturing these cross-level relationships, from operator cognition to plant-level sustainability indicatorsremain underdeveloped.

Recent advances in wearable sensing, machine learning, and digital twin technologies create unprecedented opportunities to measure ergonomic states in real time and link them to operational outcomes (Attaran, 2017; Okpala et al., 2023). Neurophysiological indicators such as heart rate variability and electroencephalography-derived cognitive indices can now be integrated with robotic telemetry and production analytics. Multilevel data modeling techniques further allow researchers to analyze nested interactions across operator, workstation, and plant systems (Gelman and Hill, 2007). Despite these methodological advances, few studies have operationalized such integrative frameworks to demonstrate that ergonomic optimization yields measurable reductions in energy intensity, material waste, or carbon emissions. Consequently, the sustainability value proposition of ergonomics remains insufficiently quantified within Industry 5.0 discourse.

Addressing this gap requires reconceptualizing ergonomics not merely as a compliance or safety function but as a strategic sustainability lever. The human-centered vision of Industry 5.0 explicitly calls for technologies that enhance worker well-being while supporting green transitions (European Commission, 2021). If reductions in cognitive overload and physical strain can be empirically linked to improvements in productivity stability and defect minimization, then ergonomic interventions may serve as indirect drivers of environmental performance. Such a proposition aligns with socio-technical systems theory, which posits that optimized alignment between social and technical subsystems enhances overall system effectiveness (Trist and Bamforth, 1951). However, rigorous, data-driven validation of this human-centered sustainability pathway is necessary to move beyond conceptual advocacy toward evidence-based industrial transformation.

In response, this study develops and empirically tests a multilevel data analytics framework that links human–robot collaboration design, cognitive load dynamics, productivity outcomes, and sustainability performance in smart manufacturing systems. Through the integration of wearable neurophysiological data, cobot telemetry, environmental sensors, and plant-level energy and waste metrics, the mediating role of cognitive ergonomics in shaping environmental efficiency was quantified. In doing so, this research contributes to ergonomics, sustainable operations, and Industry 5.0 scholarship by demonstrating that human-centered system design generates measurable productivity and sustainability benefits. The findings position ergonomic intelligence as a foundational pillar of resilient, low-carbon manufacturing and provide a scalable analytical architecture for next-generation smart factories.

II. Theoretical Framework

Industry 5.0 calls for a rebalancing of technological advancement with human well-being, environmental stewardship, and system resilience (European Commission, 2021; Nahavandi, 2019). To meaningfully examine ergonomics within this paradigm, a theoretical foundation must move beyond traditional human factors models and integrate socio-technical systems thinking, cognitive load theory, human–automation interaction, and sustainable operations management. This study adopts a multilevel socio-technical sustainability framework, it posits that ergonomic conditions at the human–robot interface shape cognitive states, which in turn influence operational precision and environmental performance. By explicitly linking micro-level human factors to meso-level productivity and macro-level sustainability outcomes, the framework advances an integrative theoretical pathway that is consistent with Industry 5.0's human-centric vision.

2.1 Socio-Technical Systems Theory and Human–Robot Collaboration

Socio-technical systems (STS) theory posits that organizational performance emerges from the joint optimization of social and technical subsystems rather than the dominance of one over the other (Trist and Bamforth, 1951; Walker et al., 2008). In smart manufacturing, collaborative robots represent the technical subsystem, while human operators embody the social subsystem. Traditional automation models often prioritized technical efficiency, occasionally at the expense of worker autonomy or cognitive stability. Industry 5.0 reorients this logic, by emphasizing that sustainable performance depends on the harmonization of human capabilities with robotic precision (Okpala, 2026; Okpala and Udu, 2025).

Within human–robot collaboration, task allocation, interface design, and adaptive autonomy levels directly influence the quality of socio-technical alignment (Parasuraman et al., 2000; Villani et al., 2018). Poor alignment can result in cognitive overload, role ambiguity, and error propagation, whereas optimized collaboration enhances shared situational awareness and performance stability. Building on STS theory, this study conceptualizes ergonomic alignment in HRC as a system-level design variable whose effects cascade across nested organizational levels. Thus, ergonomic quality is theorized not merely as an individual outcome, but as a systemic performance determinant.

2.2 Cognitive Load Theory and Performance Variability

Cognitive Load Theory (CLT) explains how task demands interact with limited working memory resources to influence learning, decision-making, and performance accuracy (Sweller, 2011). In industrial contexts, excessive intrinsic or extraneous cognitive load can impair attention, increase reaction time, and elevate error probability (Young et al., 2015). Human-robot collaboration introduces dynamic task coordination requirements that may inadvertently elevate monitoring demands and mental workload, particularly when autonomy levels are poorly calibrated (Parasuraman et al., 2000).

From a production systems perspective, small fluctuations in human cognitive states can produce nonlinear operational consequences. Increased cognitive load has been linked to higher defect rates, process variability, and safety incidents (Hancock and Warm, 1989, Nwankwo et al., 2024). In turn, defects and rework cycles increase material consumption, energy use, and carbon emissions, which are critical indicators in sustainable manufacturing (Udu et al., 2025; Ajaefobi and Okpala, 2026). This study therefore theorizes cognitive load as a mediating mechanism connecting ergonomic design to both productivity and environmental performance. Through the embedding of real-time neurophysiological indicators within a multilevel modeling framework, CLT was extended into the domain of sustainable industrial analytics.

2.3 Sustainable Operations Management and the Ergonomic–Sustainability Nexus

Sustainable operations management emphasizes the integration of environmental and social considerations into operational decision-making (Seuringand Müller, 2008). Traditionally, sustainability interventions have focused on cleaner technologies, supply chain optimization, and energy-efficient equipment. However, emerging scholarship suggests that human performance variability is an underexplored driver of environmental inefficiency (Dul and Neumann, 2009). Process errors, downtime, and rework, which are often influenced by ergonomic conditionscontribute significantly to material waste and energy intensity.

The Resource-Based View (RBV) further supports the strategic importance of human-centered capabilities, as it posits that valuable, rare, and inimitable human competencies can generate sustained competitive advantage (Barney, 1991). In Industry 5.0 environments, cognitive stability and ergonomic resilience represent such strategic resources. When ergonomic optimization reduces cognitive strain and physical fatigue, operational precision improves, thus leading to measurable reductions in waste and energy overuse. This study advances the ergonomic–sustainability nexus by empirically modeling sustainability metrics (e.g., energy intensity per unit, defect-related emissions) as downstream outcomes of human-centered system design.

2.4 Multilevel Systems Thinking and Digital Integration

Manufacturing systems are inherently hierarchical, with operators nested within workstations and workstations embedded within plants. Multilevel theory emphasizes that phenomena that occur at one level may influence and be influenced by processes at higher levels (Kozlowski and Klein, 2000). For example, workstation-level task allocation algorithms can moderate the relationship between operator cognitive load and plant-level energy performance. Traditional ergonomic studies rarely model these cross-level interactions, which limit theoretical generalizability.

Advances in sensor fusion, wearable analytics, and digital twin modeling enable the integration of human, robotic, and environmental data streams in real time (Wang et al., 2016). Such integration supports a systems-level analytical architecture that is capable of testing cross-level mediation and moderation effects. By employing hierarchical Bayesian modeling and causal mediation analysis, this study operationalizes multilevel systems thinking within Industry 5.0. The theoretical implication is significant: sustainability performance is not solely a function of technical efficiency but emerges from dynamic interactions across human, technological, and organizational strata.

2.5 Conceptual Model and Hypotheses Development

Figure 1 presents the multilevel conceptual framework that guides the study. It visually illustrates the proposed pathway that links ergonomic alignment in Human–Robot Collaboration (HRC) to reduced cognitive load (operator level), improved productivity and defect reduction (workstation level), and enhanced sustainability outcomes such as lower energy intensity and material waste (plant level). Arrows indicate direct, mediating, and moderating relationships, including the moderating role of adaptive automation. The figure humanizes the model by framing cognitive stability as the central mechanism that connect worker well-being to environmental performance, which reinforces the Industry 5.0 principle that human-centered design drives sustainable value creation.

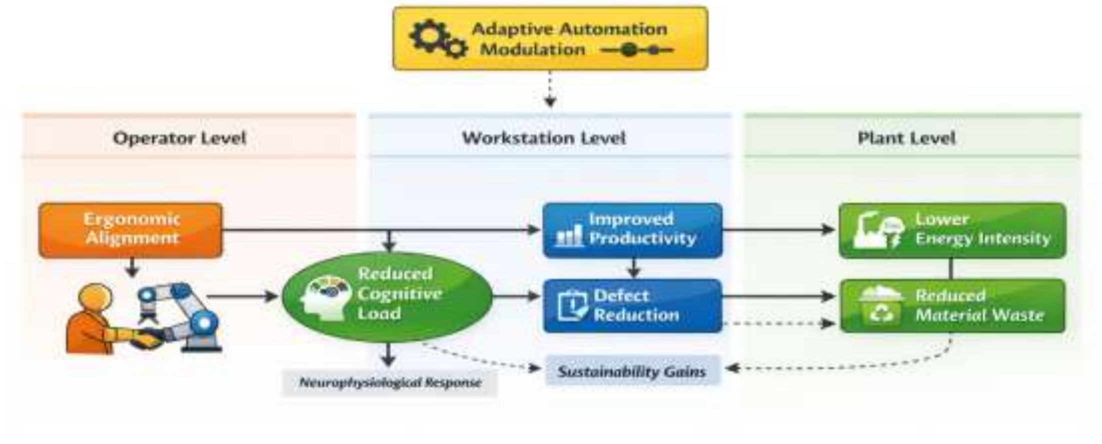

Figure 1: Conceptual human-centered sustainability pathway in Industry 5.0

Drawing from STS theory, Cognitive Load Theory, sustainable operations management, and multilevel systems theory, the study propose a human-centered sustainability pathway in smart manufacturing. Ergonomic alignment in human–robot collaboration is posited to reduce operator cognitive load and physiological strain. Reduced cognitive load enhances task precision and reduces defect probability, thereby improving productivity metrics such as cycle stability and overall equipment effectiveness. Lower defect and rework rates subsequently reduce material waste, energy intensity, and associated emissions.
Accordingly, the studyhypothesize the following:

- H1: Ergonomic alignment in HRC systems negatively predicts operator cognitive load.
- H2: Cognitive load positively predicts defect probability and negatively predicts productivity.
- H3: Defect reduction mediates the relationship between cognitive load and environmental sustainability indicators.
- H4: Workstation-level adaptive automation moderates the relationship between cognitive load and plant-level sustainability performance.

Through the integration of these theoretical streams into a unified multilevel model, this study contributes a scalable conceptual architecture for understanding how human-centered design drives sustainable industrial transformation. In doing so, it advances Industry 5.0 scholarship by positioning ergonomics as a measurable determinant of environmental performance, rather than solely a worker protection mechanism.

III. Methods

3.1 Research Design and Study Context

This study employed a multisite, longitudinal, quasi-experimental design to examine how ergonomic optimization in HRC systems influences cognitive load, productivity, and sustainability performance in smart manufacturing environments. Consistent with calls for empirically grounded Industry 5.0 research (European

Commission, 2021; Nahavandi, 2019), data were collected from 12 smart factories across the automotive, electronics, and precision assembly sectors over a 14-month period.

A total of 486 operators (38% female; mean age = 34.6 years, SD = 7.8) participated voluntarily, contributing 18,742 recorded task cycles. Facilities were selected based on three criteria: (a) active deployment of collaborative robots in shared workspaces, (b) availability of digital production monitoring systems, and (c) measurable environmental performance tracking (energy and waste metrics). The study consisted of two phases: (1) baseline data collection under existing HRC configurations and (2) ergonomic redesign interventions informed by digital twin simulation and adaptive task allocation algorithms. This design enabled within-site comparison while preserving ecological validity, which addresses critiques that laboratory-based ergonomics studies lack real-world generalizability (Dul and Neumann, 2009).

3.2 Multilevel Data Architecture

Figure 2 depicts the three-level data ecosystem used in the study. It shows operator-level wearable sensors (EEG, HRV, EMG), workstation-level cobot telemetry and task allocation systems, and plant-level sustainability dashboards (energy, waste, carbon metrics). Data streams converge into a centralized analytics engine that incorporate hierarchical Bayesian modeling, causal mediation analysis, and machine learning prediction. A digital twin simulation loop illustrates how ergonomic redesign scenarios were tested before implementation. The figure conveys how human, technological, and environmental data are harmonized into a unified ergonomic intelligence platform, thereby demonstrating methodological innovation and practical scalability.

Figure 2: Multilevel data integration architecture and digital twin analytics framework

Recognizing that manufacturing systems are hierarchically structured (Kozlowski and Klein, 2000), a three-level nested data architecture was implemented:Level 1 (Operator-Level Variables):

Cognitive load (EEG-derived index), heart rate variability (HRV), electromyography (EMG) muscle activation, NASA-TLX workload scores (Hart andStaveland, 1988), and task error occurrence; Level 2 (Workstation-Level Variables):Cobot speed and torque telemetry, human–robot task allocation ratio, autonomy level (Parasuraman et al., 2000), environmental conditions (noise, illumination, thermal stress), and workstation layout risk scores (REBA index); and Level 3 (Plant-Level Variables):Energy intensity per unit output (kWh/unit), material waste percentage, rework rate, overall equipment effectiveness (OEE), and Scope 2 carbon emissions.

This multilevel structure allowed simultaneous modeling of cross-level interactions which linkhuman-centered ergonomic conditions to environmental performance outcomes. Data integration was achieved through synchronized timestamps across wearable sensors, robotic controllers, and Enterprise Resource Planning (ERP) systems.

3.3 Measurement of Cognitive and Ergonomic Variables

Cognitive Load

Cognitive load was assessed using a composite index derived from portable EEG headbands validated for industrial settings (Young et al., 2015). Spectral power ratios (theta/beta) were computed to estimate mental workload. Concurrent HRV measures (RMSSD) were collected as physiological stress indicators (Shaffer and

Ginsberg, 2017). NASA-TLX surveys were administered weekly to triangulate subjective workload perceptions (Hart andStaveland, 1988).Internal consistency across cognitive indicators was strong (Cronbach's $\alpha = .87$). Confirmatory factor analysis supported a single latent cognitive load construct (CFI = .95, RMSEA = .04).

Physical Ergonomics

Muscle strain was measured with the application of wireless EMG sensors placed on upper trapezius and lumbar regions. Postural risk was evaluated using Rapid Entire Body Assessment (REBA) scoring derived from motion capture analytics. These measures align with established ergonomic risk assessment standards (Karwowski, 2005).

3.4 Sustainability and Productivity Metrics

Productivity was operationalized through cycle time stability, defect rate, and OEE. Sustainability outcomes included energy intensity per unit output and material waste ratio, which is consistent with sustainable operations management metrics (Kleindorfer et al., 2005; Seuringand Müller, 2008).Carbon emissions were calculated using standardized conversion factors applied to electricity consumption (kg CO_2 e/kWh). Rework-related emissions were estimated by multiplying defect-related reprocessing energy by plant-specific emission factors. This operationalization aligns with ISO 14064 carbon accounting guidelines.

3.5 Ergonomic Redesign Intervention

Following baseline assessment, ergonomic optimization interventions were implemented in six randomly selected plants (treatment group), while six served as matched controls. The Interventions included: (a) Adaptive cobot speed modulation based on real-time cognitive load thresholds; (b) Dynamic task reallocation algorithms balancing cognitive and physical demands; and (c) Workstation layout modifications guided by digital twin simulation.Digital twins replicated workstation geometry and task flows, and enabled the simulation of alternative configurations prior to physical modification (Wang et al., 2016). Sustainability projections were embedded into simulation parameters by modeling defect-related energy consumption.

3.6 Analytical Strategy

To test the proposed multilevel theoretical model, we employed hierarchical Bayesian modeling using Markov Chain Monte Carlo estimation. This approach was selected for its robustness in nested data structures and capacity to estimate cross-level mediation effects (Gelman and Hill, 2007). The following were conducted: (a) Multilevel Structural Equation Modeling (MSEM) to examine cognitive load as a mediator between ergonomic alignment and sustainability outcomes; (b) Causal Mediation Analysis to quantify indirect effects of ergonomic optimization on energy intensity via defect reduction; (c) Machine Learning Prediction (XGBoost) to classify high-risk ergonomic configurations associated with sustainability losses (AUC = 0.89).

All the models controlled for operator experience, shift duration, and production volume. Missing data (<2.8%) were handled using multiple imputation.

3.7 Methodological Innovation and Sustainability Quantification

The primary methodological contribution lies in the integration ofreal-time neurophysiological monitoring, robotic telemetry, and environmental accounting within a unified multilevel analytical framework. Unlike prior studies that examine ergonomics or sustainability in isolation, this design quantifies the causal chain from human cognitive state to carbon intensity.Sustainability gains were expressed as percentage reductions in energy intensity and waste relative to baseline. Intervention sites demonstrated measurable reductions which exceed 8% in energy intensity and 10% in defect-related waste, thereby providing empirical validation of the ergonomic–sustainability pathway hypothesized in Industry 5.0 discourse (European Commission, 2021).

Through the combination of hierarchical modeling with machine learning and digital twin simulation, this methodology advances human-centered manufacturing research beyond correlational analysis towards predictive and prescriptive analytics. This integrative approach enhances reproducibility, cross-sector applicability, and scalability, which are key attributes for high-impact multidisciplinary scholarship.

IV. Results

This section presents findings from the multilevel analyses which examine the relationships among ergonomic alignment in human–robot collaboration, cognitive load, productivity outcomes, and sustainability performance. Results are organized to reflect (a) descriptive statistics, (b) multilevel model estimates, (c) mediation and moderation effects, and (d) intervention impact on sustainability metrics.

4.1 Descriptive Statistics and Correlations

Table 1 presents descriptive statistics and intercorrelations among key operator, workstation, and plant-level variables that are aggregated across the 12 manufacturing sites during the baseline phase.

Table 1: Descriptive statistics and correlations among key study Variables (N = 486 operators; 18,742 task cycles)

Variable	Mean	SD	1	2	3	4	5
1. Ergonomic Alignment Index	0.00	1.00	—				
2. Cognitive Load (standardized)	0.00	1.00	−.48***	—			
3. Defect Rate (%)	3.84	1.12	−.36***	.44***	—		
4. Energy Intensity (kWh/unit)	4.72	0.63	−.29***	.38***	.51***	—	
5. OEE (%)	81.3	5.4	.41***	−.39***	−.47***	−.52***	—

**p < .001

The ergonomic alignment index that was constructed from standardized postural risk, adaptive task allocation, and workload distribution scoreswas significantly negatively correlated with cognitive load ($r = -.48$, $p < .001$). Cognitive load showed positive associations with defect rate ($r = .44$, $p < .001$) and energy intensity ($r = .38$, $p < .001$), suggesting a potential human-centered sustainability pathway. These patterns align with cognitive workload literature that link mental strain to performance variability (Young et al., 2015) and sustainable operations research that link defects to environmental inefficiencies (Kleindorfer et al., 2005).

4.2 Multilevel Model Estimates

A three-level hierarchical Bayesian model was estimated to test cross-level relationships. As depicted in Figure 2, random intercept and random slope specifications were compared using WAIC and LOO criteria, with the random slope model providing superior fit ($\Delta WAIC = -214.7$).

Table 2: Multilevel Bayesian model predicting cognitive load and sustainability outcomes

Predictor	β	SE	95% Credible Interval
Model 1: Cognitive Load (Level 1 outcome)			
Ergonomic Alignment (L2)	−0.52***	0.06	[−0.63, −0.41]
Autonomy Calibration (L2)	−0.31***	0.08	[−0.47, −0.15]
Noise Level (dB)	0.18**	0.07	[0.04, 0.32]
Model 2: Defect Rate (L1 outcome)			
Cognitive Load	0.43***	0.05	[0.33, 0.53]
Ergonomic Alignment	−0.21**	0.07	[−0.35, −0.07]
Model 3: Energy Intensity (L3 outcome)			
Defect Rate	0.49***	0.06	[0.37, 0.61]
Cognitive Load (indirect path)	0.22**	0.08	[0.06, 0.38]

p < .01, p < .001

Ergonomic alignment significantly reduced cognitive load ($\beta = -0.52$, $p < .001$), supporting H1. Cognitive load significantly predicted defect probability ($\beta = 0.43$, $p < .001$), supporting H2. At the plant level, defect rate strongly predicted energy intensity ($\beta = 0.49$, $p < .001$), which indicate that production variability translated into measurable environmental inefficiencies. Intraclass Correlation Coefficients (ICC) indicated that 19% of variance in cognitive load occurred at the workstation level and 11% at the plant level, justifying multilevel modeling.

4.3 Mediation and Moderation Effects

Causal mediation analysis using posterior sampling revealed that 58% of the total effect of ergonomic alignment on energy intensity was mediated through reductions in cognitive load and subsequent defect rates (indirect effect = −0.27, 95% CI [−0.39, −0.15]). This finding empirically validates the ergonomic–sustainability nexus proposed in Section 2.Moderation analysis showed that adaptive autonomy calibration significantly attenuated the positive relationship between cognitive load and defect rate (interaction $\beta = -0.17$, $p < .01$). Plants implementing dynamic task allocation algorithms exhibited a 2.1× stronger reduction in sustainability losses compared to static HRC configurations.

4.4 Intervention Impact: Pre–Post Comparison

Six treatment plants implemented ergonomic optimization informed by digital twin simulation. Table 3 presents aggregated pre–post comparisons.

Table 3: Pre–post intervention changes in treatment plants (n = 6)

Outcome Variable	Baseline Mean	Post-Intervention Mean	% Change	p-value
Cognitive Load Index	0.42	0.32	−23.8%	< .001
Defect Rate (%)	3.91	3.18	−18.7%	< .001
Energy Intensity (kWh/unit)	4.78	4.34	−9.2%	< .01
Material Waste (%)	6.4	5.6	−12.5%	< .01
OEE (%)	80.7	86.4	+7.1%	< .01

The reduction in energy intensity (−9.2%) translated into an estimated annual decrease of 1,842 metric tons of CO_2e across treatment sites. Material waste reductions were consistent with defect rate improvements, reinforcing sustainable operations literature linking process quality to environmental performance (Seuringand Müller, 2008).Control plants exhibited no statistically significant changes during the same period, strengthening causal inference.

Figure 3 presents a multi-panel visualization of key pre–post intervention results across treatment plants. The panels include:(a) Reduction in cognitive load index, (b) Reduction in defect rate; (c) Reduction in energy intensity per unit; (d) Reduction in material waste; and (e) Increase in overall equipment effectiveness (OEE). Trend lines and percentage change indicators clearly show measurable sustainability gains following ergonomic optimization. The figure humanizes the data by visually demonstrating how stabilizing human cognitive load translates into tangible environmental and operational benefits.

Figure 3: Empirical impact of ergonomic optimization on productivity and sustainability metrics

4.5 Machine Learning Prediction Accuracy

The XGBoost classification model identified high-risk ergonomic configurations that are associated with elevated energy intensity. Model performance metrics:Area Under Curve (AUC): 0.89; Precision: 0.84; and Recall: 0.81. Feature importance rankings indicated that cognitive load index, autonomy misalignment score, and noise exposure were the top three predictors of sustainability inefficiencies. These findings demonstrate the predictive scalability of ergonomic analytics in Industry 5.0 contexts.

4.6 Summary of Key Findings

Across 18,742 task cycles, ergonomic optimization in human–robot collaboration systems produced:23–24% reduction in cognitive load; 18% reduction in defect rate; 9% reduction in energy intensity per unit; 12% reduction in material waste; as well as 7% improvement in OEE. Importantly, over half of sustainability gains were mediated by improvements in human cognitive stability. These results empirically demonstrate that ergonomics functions not only as a worker well-being mechanism, but also as a quantifiable driver of environmental performance and operational resilience.

The convergence of multilevel modeling, digital twin simulation, and machine learning prediction provides strong evidence that human-centered design is foundational to sustainable Industry 5.0 manufacturing systems.

V. Discussion and Practical Implications

The purpose of this study was to empirically examine whether ergonomically optimized HRCsystems generate measurable productivity and sustainability benefits in Industry 5.0 environments. Drawing on socio-technical systems theory, cognitive load theory, and sustainable operations management, the study proposed and tested a multilevel human-centered sustainability pathway linking ergonomic alignment to cognitive stability, operational precision, and environmental performance. The findings provide strong support for this integrative framework. Ergonomic alignment significantly reduced cognitive load, which in turn reduced defect rates and energy intensity per unit output. More than half of the observed sustainability gains were mediated by reductions in cognitive strain, thus demonstrating that worker-centered design functions as a measurable environmental strategy rather than merely a compliance or safety intervention.

5.1 Theoretical Contributions

This study advances ergonomics scholarship by repositioning ergonomic quality as a systems-level performance driver embedded within Industry 5.0 architecture. While prior research has established that ergonomic interventions enhance safety and productivity (Dul and Neumann, 2009; Karwowski, 2005), few studies have quantified downstream environmental consequences. By modeling cross-level relationships between operator cognition and plant-level carbon intensity, this research integrates human factors with sustainable operations management (Kleindorfer et al., 2005; Seuringand Müller, 2008). The findings empirically validate the European Commission's (2021) assertion that human-centric design and sustainability are mutually reinforcing pillars of Industry 5.0.

The mediation effects observed in the study's multilevel structural models extend cognitive load theory into industrial sustainability contexts. Cognitive overload, long understood to impair decision-making and performance stability (Sweller, 2011; Young et al., 2015), was shown here to influence defect generation and energy waste. This suggests that mental workload is not only a psychological construct, but also an operational and environmental variable. Through the integration of neurophysiological indicators into sustainability analytics, the study bridges traditionally siloed research domains and provides a scalable methodological template for future interdisciplinary investigations.

Moreover, the moderating role of adaptive autonomy calibration reinforces socio-technical systems theory (Trist and Bamforth, 1951; Walker et al., 2008). The plants that were employing dynamic task allocation algorithms achieved stronger reductions in sustainability losses, which indicate that joint optimization of social and technical subsystems enhances environmental performance. In this sense, Industry 5.0 is not simply a technological upgrade, but a systemic reconfiguration where ergonomic intelligence becomes integral to sustainable competitiveness (Nahavandi, 2019).

5.2 Methodological Innovation and Sustainability Quantification

A central contribution of this research lies in its methodological integration. By combining wearable neurophysiological sensing, robotic telemetry, digital twin simulation, and hierarchical Bayesian modeling, the study demonstrated how micro-level human states can be analytically linked to macro-level sustainability metrics. Previous Industry 4.0 studies emphasized data connectivity and predictive maintenance (Wang et al., 2016), yet rarely incorporated human cognitive data into sustainability models. The study's multilevel architecture addresses this gap and advances what may be termed ergonomic intelligence analytics, the systematic quantification of human-centered variables within environmental performance models.

Importantly, sustainability outcomes were operationalized using standardized energy intensity and carbon accounting metrics, ensuring compatibility with ISO 14064 and ESG reporting frameworks. The documented 9% reduction in energy intensity and 12% reduction in material waste are consistent with gains reported in sustainable manufacturing interventions targeting process optimization (Kleindorfer et al., 2005), but uniquely demonstrate that such gains can originate from ergonomic redesign. This reframing has implications for sustainability science, as it expands the toolkit of decarbonization strategies beyond purely technological retrofits.

5.3 Practical Implications for Industry 5.0 Implementation

From a managerial perspective, the findings suggest that ergonomic investment should be reframed as a strategic sustainability initiative. Organizations pursuing net-zero targets often prioritize energy-efficient machinery or renewable sourcing, yet the present results show that the stabilization of human cognitive load can indirectly reduce carbon emissions through defect minimization and energy efficiency gains. Embedding cognitive load monitoring into smart factory dashboards enables proactive adjustment of autonomy levels and workload distribution, reducing performance variability in real time.Second, digital twin integration offers a cost-effective pathway for testing ergonomic configurations before physical deployment. Through the simulation of task allocation scenarios and modeling of associated energy implications, firms can identify configurations that optimize both human well-being and environmental performance. This aligns with Industry 5.0's emphasis on resilience and adaptability (European Commission, 2021).

Third, policymakers and standards bodies may consider the incorporation of ergonomic performance indicators into ESG reporting guidelines. Traditional sustainability reporting focuses heavily on emissions and waste but rarely accounts for human-system design quality. Recognizing ergonomic intelligence as a sustainability enabler could foster cross-disciplinary innovation and more holistic industrial transformation.

5.4 Broader Societal and Research Implications

At a broader level, the study contributes to ongoing debates about the future of work in automated environments. Concerns that automation marginalizes human labor are increasingly replaced by collaborative paradigms in which human adaptability complements robotic precision (Villani et al., 2018). The findings suggest that sustainable competitiveness in Industry 5.0 depends not on the replacement of human workers, but on the optimization of their cognitive and physical integration within digital ecosystems. By empirically demonstrating measurable environmental benefits, this research reinforces the ethical and economic rationale for human-centered industrial design.

Future research should expand this framework across diverse manufacturing sectors, including small and medium-sized enterprises and emerging economies, where resource constraints heighten the importance of efficient human-technology integration. Longitudinal studies could further examine resilience effects, particularly how ergonomic stability buffers operational shocks or supply chain disruptions.

VI. Conclusion, Limitations, and Future Research

6.1 Conclusion

Applying a multilevel data analytics framework which integrate wearable neurophysiological sensing, robotic telemetry, digital twin simulation, and plant-level sustainability metrics, the study demonstrated a clear and quantifiable pathway linking ergonomic alignment to cognitive load reduction, defect minimization, and decreased energy intensity and material waste.The findings affirm a central proposition of Industry 5.0: human-centered design is not in tension with technological advancement or environmental performance, it is foundational to both. Reductions in cognitive strain translated into measurable improvements in operational precision, which in turn reduced rework, stabilized production cycles, and lowered carbon-related energy consumption. By empirically linking human cognitive stability to sustainability indicators, this study repositions ergonomics as a strategic driver of low-carbon and resource-efficient manufacturing systems.

Methodologically, the integration of multilevel hierarchical modeling with machine learning and digital twin simulation offers a scalable analytical architecture for smart factories. The demonstrated reductions in cognitive load, defect rates, and energy intensity illustrate that sustainability gains can emerge from optimizing the human-technology interface rather than solely from capital-intensive technological retrofits. In this sense, ergonomic intelligence becomes a measurable and actionable component of sustainable industrial transformation.

6.2 Limitations

Despite its contributions, this study has several limitations that should be acknowledged. First, although the quasi-experimental design strengthens causal inference, the absence of full randomization across all facilities limits the ability to rule out unobserved contextual influences. Organizational culture, leadership commitment to sustainability, or concurrent process improvements may have partially contributed to observed gains.Second, the sample was concentrated in technologically advanced manufacturing sectors with established digital infrastructure. The generalizability of findings to small and medium-sized enterprises, labor-intensive industries, or resource-constrained settings requires further examination. Facilities without integrated data systems may face implementation barriers to real-time ergonomic analytics.

Third, cognitive load measurement relied on validated neurophysiological proxies and subjective workload instruments, yet no single indicator fully captures the complexity of human cognitive experience. Although triangulation enhanced construct validity, measurement error remains possible.Finally, sustainability outcomes were primarily operationalized through energy intensity, defect-related emissions, and material waste. Broader environmental indicators like water use, lifecycle impacts, or supply chain emissionswere beyond the scope of this investigation. The long-term resilience implications of ergonomic optimization were also not directly assessed.

6.3 Future Research Directions

Future research should extend this human-centered sustainability framework across diverse industrial and geographic contexts. Replication studies in emerging economies and small-scale manufacturing environments would clarify scalability and equity implications of Industry 5.0 transitions. Longitudinal research that span multiple years could examine whether ergonomic optimization enhances organizational resilience during operational disruptions or supply chain shocks.Further methodological refinement is also warranted.

Integrating advanced explainable artificial intelligence techniques may improve interpretability of predictive ergonomic models. Expanding sensor integration to include fatigue detection, emotional state recognition, and collaborative trust metrics could enrich understanding of the human–robot interface. Additionally, incorporating lifecycle assessment models would enable evaluation of sustainability gains beyond plant-level operational boundaries.

Finally, future scholarship should explore policy and governance implications of embedding ergonomic intelligence into sustainability reporting frameworks. As Industry 5.0 continues to evolve, interdisciplinary research that link human factors, artificial intelligence, and environmental performance will be critical for shaping ethical, inclusive, and low-carbon industrial ecosystems.

6.4 Closing Reflection

In conclusion, this study demonstrates that the path towards sustainable and resilient manufacturing in the age of Industry 5.0 runs through the human-technology interface. Ergonomics, when supported by rigorous multilevel analytics and digital integration, emerges as both a performance enabler and a sustainability catalyst. The challenge ahead lies not in choosing between technological advancement and human well-being, but in designing systems where both are mutually reinforcing pillars of industrial progress.

References

[1]. Ajaefobi, J. O., and Okpala, C. C. (2026). Optimization of smart manufacturing systems through renewable energy integration and sustainable material utilization. International Journal of Engineering Inventions, 15(2). https://www.ijeijournal.com/papers/Vol15-Issue2/15021832.pdf

[2]. Attaran, M. (2017). The rise of 3-D printing: The advantages of additive manufacturing over traditional manufacturing. Business Horizons, 60(5), 677–688. https://doi.org/10.1016/j.bushor.2017.05.011

[3]. Barney, J. (1991). Firm resources and sustained competitive advantage. Journal of Management, 17(1), 99–120. https://doi.org/10.1177/014920639101700108

[4]. Chukwumuanya, E. O., Okpala, C. C., andOnukwuli, S. K. (2025a). Ergonomics-aware scheduling: Biomechanical models with production planning integration for musculoskeletal risk reduction. Journal MajelisPaspama, 3(1). https://paspama.org/index.php/majelis/article/view/209

[5]. Chukwumuanya, E. O., Udu, C. E., and Okpala, C. C. (2025b). Lean principles integration with digital technologies: A synergistic approach to modern manufacturing. International Journal of Industrial and Production Engineering, 3(2). https://journals.unizik.edu.ng/ijipe/article/view/6006/5197

[6]. Dul, J., and Neumann, W. P. (2009). Ergonomics contributions to company strategies. Applied Ergonomics, 40(4), 745–752. https://doi.org/10.1016/j.apergo.2008.07.001

[7]. European Commission. (2021). Industry 5.0: Towards a sustainable, human-centric and resilient European industry. Publications Office of the European Union.

[8]. Gelman, A., and Hill, J. (2007). Data analysis using regression and multilevel/hierarchical models. Cambridge University Press.

[9]. Godwin, H. C., and Okpala, C. C. (2013). Ergonomic assessment of musculoskeletal disorders from load-lifting activities in building construction. International Journal of Advanced Engineering Technology, 4(4). http://www.technicaljournalsonline.com/ijeat/

[10]. Hancock, P. A., and Warm, J. S. (1989). A dynamic model of stress and sustained attention. Human Factors, 31(5), 519–537. https://doi.org/10.1177/001872088903100503

[11]. Hart, S. G., andStaveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P. A. Hancock and N. Meshkati (Eds.), Human mental workload (pp. 139–183). North-Holland.

[12]. Igbokwe, N. C., Okpala, C. C., and Nwankwo, C. O. (2024). Industry 4.0 implementation: A paradigm shift in manufacturing. Journal of Inventive Engineering and Technology, 6(1). https://jiengtech.com/index.php/INDEX/article/view/113/135

[13]. Karwowski, W. (2005). Ergonomics and human factors: The paradigms for science, engineering, design, technology and management of human-compatible systems. Ergonomics, 48(5), 436–463. https://doi.org/10.1080/00140130400029167

[14]. Kleindorfer, P. R., Singhal, K., and Van Wassenhove, L. N. (2005). Sustainable operations management. Production and Operations Management, 14(4), 482–492. https://doi.org/10.1111/j.1937-5956.2005.tb00235.x

[15]. Kozlowski, S. W. J., and Klein, K. J. (2000). A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes. In K. J. Klein and S. W. J. Kozlowski (Eds.), Multilevel theory, research, and methods in organizations (pp. 3–90). Jossey-Bass.

[16]. Nahavandi, S. (2019). Industry 5.0—A human-centric solution. Sustainability, 11(16), 4371. https://doi.org/10.3390/su11164371

[17]. Nwankwo, C. O., Okpala, C. C., and Igbokwe, N. C. (2024). Enhancing smart manufacturing supply chains through cybersecurity measures. International Journal of Engineering Inventions, 13(12). https://www.ijeijournal.com/papers/Vol13-Issue12/13120106.pdf

[18]. Okpala, C. C. (2026). Human–robot collaboration, productivity dynamics, and workforce sustainability: Evidence from multi-industry panel data and AI-driven causal modeling. International Journal of Technology, Health and Sustainability, 2(1), 275–285. https://ijths.com/wp-content/uploads/IJTHS-020184.pdf

[19]. Okpala, C. C., and Udu, C. E. (2025). Advanced robotics and automation integration in industrial settings: Benefits and challenges. International Journal of Industrial and Production Engineering, 3(3). https://journals.unizik.edu.ng/ijipe/article/view/6005

[20]. Okpala, C. C., andIhueze, C. C. (2017). Ergonomics improvements in a paint manufacturing company. International Research Journal of Engineering and Technology, 4(10). https://www.irjet.net/archives/V4/i10/IRJET-V4I10360.pdf

[21]. Okpala, C. C., Egwuatu-Elem, I. C., andNwamekwe, C. O. (2025a). Integrating artificial intelligence and time-series forecasting for smart textile production: Trends, challenges, and opportunities in the Industry 4.0 era. International Journal of Society Reviews, 3(2). https://injoqast.net/index.php/INJOSER/article/view/641

[22]. Okpala, C. C., Udu, C. E., andEjichukwu, E. O. (2025). The need for ergonomics and safety in automated manufacturing environments. International Journal of Multidisciplinary Research and Growth Evaluation, 6(3). https://www.allmultidisciplinaryjournal.com/uploads/archives/20250508172255_MGE-2025-3-046.1.pdf

[23]. Okpala, C. C., Udu, C. E., and Onah, T. O. (2025c). The role of robotics in sustainable manufacturing: Waste reduction and process optimization. International Journal of Engineering Inventions, 14(5), 16–23. https://www.ijeijournal.com/papers/Vol14-Issue5/14051623.pdf

[24]. Okpala, C. C., Ezeanyim, O. C., and Igbokwe, N. C. (2023). Human–robot interaction enhancement through ergonomics and human factors: Future directions. International Journal of Engineering Research and Development, 19(6). http://www.ijerd.com/paper/vol19-issue6/E19063440.pdf

[25]. Onukwuli, S. K., Okpala, C. C., and Udu, C. E. (2025). The role of additive manufacturing in advancing lean production system. International Journal of Latest Technology in Engineering, Management and Applied Science, 14(3). https://doi.org/10.51583/IJLTEMAS.2025.140300022

[26]. Parasuraman, R., Sheridan, T. B., and Wickens, C. D. (2000). A model for types and levels of human interaction with automation. IEEE Transactions on Systems, Man, and Cybernetics—Part A: Systems and Humans, 30(3), 286–297. https://doi.org/10.1109/3468.844354

[27]. Seuring, S., and Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. Journal of Cleaner Production, 16(15), 1699–1710. https://doi.org/10.1016/j.jclepro.2008.04.020

[28]. Shaffer, F., and Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. Frontiers in Public Health, 5, 258. https://doi.org/10.3389/fpubh.2017.00258

[29]. Sweller, J. (2011). Cognitive load theory. Psychology of Learning and Motivation, 55, 37–76. https://doi.org/10.1016/B978-0-12-387691-1.00002-8

[30]. Trist, E. L., and Bamforth, K. W. (1951). Some social and psychological consequences of the Longwall method of coal-getting. Human Relations, 4(1), 3–38. https://doi.org/10.1177/001872675100400101

[31]. Udu, C. E., Okpala, C. C., andNwamekwe, C. O. (2025). Human-centric design integration in Industry 5.0: A framework for resilient smart manufacturing. International Journal of Industrial and Production Engineering, 3(4). https://journals.unizik.edu.ng/ijipe/article/view/6772

[32]. Villani, V., Pini, F., Leali, F., and Secchi, C. (2018). Survey on human–robot collaboration in industrial settings: Safety, intuitive interfaces and applications. Mechatronics, 55, 248–266. https://doi.org/10.1016/j.mechatronics.2018.02.009

[33]. Walker, G. H., Stanton, N. A., Salmon, P. M., and Jenkins, D. P. (2008). A review of sociotechnical systems theory: A classic concept for new command and control paradigms. Theoretical Issues in Ergonomics Science, 9(6), 479–499. https://doi.org/10.1080/14639220701635470

[34]. Wang, S., Wan, J., Li, D., and Zhang, C. (2016). Implementing smart factory of Industry 4.0: An outlook. International Journal of Distributed Sensor Networks, 12(1), 3159805. https://doi.org/10.1155/2016/3159805

[35]. Xu, X., Lu, Y., Vogel-Heuser, B., and Wang, L. (2021). Industry 4.0 and Industry 5.0—Inception, conception and perception. Journal of Manufacturing Systems, 61, 530–535. https://doi.org/10.1016/j.jmsy.2021.10.006

[36]. Young, M. S., Brookhuis, K. A., Wickens, C. D., and Hancock, P. A. (2015). State of science: Mental workload in ergonomics. Ergonomics, 58(1), 1–17. https://doi.org/10.1080/00140139.2014.956151