
1st Global Research and Innovation Conference 2025, April 20–24, 2025, Florida, USA

AI-ORCHESTRATED CYBER-PHYSICAL SYSTEMS FOR SUSTAINABLE INDUSTRY 5.0 MANUFACTURING AND SUPPLY CHAIN RESILIENCE

Shaikh Shofiullah¹;

- [1]. Master of Engineering Management, College of Engineering, Lamar University, Texas, USA;
Email: s.shofiullah@gmail.com

Doi: [10.63125/jwm2e278](https://doi.org/10.63125/jwm2e278)

Peer-review under responsibility of the organizing committee of GRIC, 2025

Abstract

This study examined the influence of AI-orchestrated cyber-physical systems (CPS) on sustainable Industry 5.0 manufacturing and supply chain resilience through a quantitative, multi-construct analytical model. Using data collected from 412 industrial respondents across manufacturing, logistics, and technology-driven organizations, the study evaluated relationships among CPS integration maturity, AI orchestration capability, sustainability performance, and supply chain resilience. Descriptive analysis showed strong adoption levels, with mean CPS maturity at 4.21, AI orchestration at 4.08, sustainability performance at 4.17, and resilience at 4.11 on a 5-point scale. Correlation results indicated significant positive associations among all major constructs, with AI orchestration exhibiting the strongest correlation with sustainability ($r = 0.71$) and resilience ($r = 0.68$). Reliability and validity tests confirmed strong measurement consistency, with Cronbach's alpha values ranging from 0.89 to 0.94, and AVE values exceeding 0.63. Regression modeling revealed that CPS maturity significantly predicted AI orchestration ($\beta = 0.62, p < 0.001$), which in turn significantly enhanced sustainability ($\beta = 0.58, p < 0.001$) and resilience ($\beta = 0.54, p < 0.001$). Mediation analysis showed that AI orchestration mediated over 64% of the total effect of CPS maturity on sustainability and 59% on resilience. Moderation analysis further demonstrated that organizational readiness strengthened the AI-to-sustainability pathway ($\beta = 0.27, p < 0.01$), while environmental turbulence amplified the AI-to-resilience relationship ($\beta = 0.24, p < 0.01$). Overall, the findings demonstrated that AI-orchestrated CPS functioned as a central mechanism enabling real-time coordination, ecological optimization, and disruption-adaptive behavior, highlighting their essential role in achieving sustainable and resilient Industry 5.0 manufacturing ecosystems.

Keywords

AI Orchestration; Cyber-Physical Systems; Industry 5.0; Sustainable Manufacturing; Supply Chain Resilience.

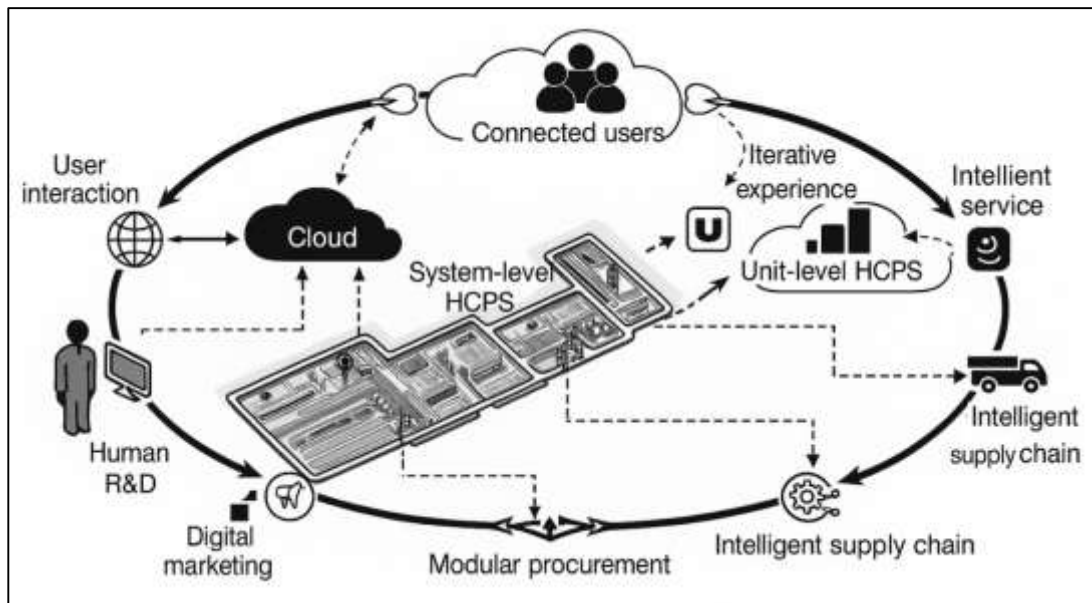
INTRODUCTION

Artificial intelligence and cyber-physical systems have emerged as foundational constructs within contemporary industrial engineering, systems thinking, and operations research (Vahabi et al., 2023). AI is widely recognized as an umbrella term that includes machine learning, deep learning, reinforcement learning, computer vision, natural language processing, and large-scale optimization algorithms that enable machines to analyze data, learn patterns, support decisions, and autonomously coordinate complex processes. Cyber-physical systems, in parallel, refer to deeply integrated networks of computational intelligence, embedded sensors, actuators, communication layers, and physical production assets capable of synchronizing the cyber and physical worlds in real time. The integration of AI and CPS has transformed manufacturing and supply chain ecosystems into dynamic, data-rich environments where physical behaviors, digital representations, and intelligent control mechanisms continuously influence one another. Within this paradigm, international discussions around Industry 5.0 emphasize industrial ecosystems that are sustainable, resilient, and human-centered. This shift builds upon earlier Industry 4.0 advancements by positioning intelligence orchestration, systemic adaptability, ecological responsibility, and worker well-being as essential characteristics of next-generation industrial systems (Lawrance et al., 2022). Global economic forums and regional innovation agendas increasingly recognize that AI-orchestrated CPS enable coordinated decision-making across distributed production networks, accelerating the adoption of clean technologies, optimizing resource efficiency, and strengthening the resilience of globalized supply chains under persistent uncertainty. These concepts have been explored through studies on AI-supported manufacturing optimization, CPS-based real-time monitoring, autonomous robotics, digital control platforms, and integrated data-driven production architectures. Research examining distributed cognition, self-organizing factories, autonomous agents, and digital-to-physical synchronization further reinforces the significance of orchestrated intelligence across industrial infrastructures. Collectively, these strands underscore that AI-orchestrated CPS are not merely collections of smart machines; they are systemic infrastructures capable of managing entire industrial value chains through autonomous reasoning, real-time coordination, and continuous learning (Tofu et al., 2023). As sustainability and resilience become central to national competitiveness and industrial development strategies, AI-orchestrated CPS provide a globally relevant technological foundation for operational alignment with environmental goals, resource circularity, and industrial adaptability.

The evolution from Industry 4.0 to Industry 5.0 has encouraged scholars and practitioners to reconsider how digital infrastructures, intelligent automation, and cyber-physical integration support industrial performance (Zhao et al., 2023). In the Industry 4.0 era, studies on smart factories, IIoT ecosystems, embedded sensing, advanced automation, and data-driven production optimization provided a blueprint for technological connectivity. Research explored how machine-to-machine communication, cloud-based manufacturing, flexible robotics, and cyber-physical production systems could enhance mass customization, reduce downtime, and increase process precision. However, more recent discourse extends beyond connectivity to orchestrated intelligence, where AI assumes an active coordinating role across CPS layers, production lines, supply nodes, and human workflows. Studies examining AI-based scheduling, predictive quality control, multi-agent decision systems, autonomous material handling, digital twin-assisted planning, and hybrid human-machine collaboration highlight how intelligence orchestrators integrate tasks across the industrial environment (Kasperson et al., 2022). Similarly, research on system-of-systems engineering, integrated optimization, distributed manufacturing architectures, and dynamic resource allocation illustrates how AI-enabled orchestration reshapes production logic by embedding decision autonomy across physical and digital assets. Scholarship on resilient operations, adaptive manufacturing networks, and intelligent control further demonstrates that distributed AI agents can evaluate operational conditions, allocate workloads, adjust production schedules, and mitigate disturbances in real time. Moreover, studies on collaborative industrial robots, human-centric cyber-physical workplaces, and ergonomic augmentation emphasize that orchestration extends to aligning AI-driven decisions with worker skills, safety requirements, and operational constraints. Collectively, this body of research illustrates a shift toward systems in which AI agents, CPS layers, and human operators interact continuously to manage uncertainties, maintain production continuity, and optimize performance across complex industrial scenarios (Kaftan et al.,

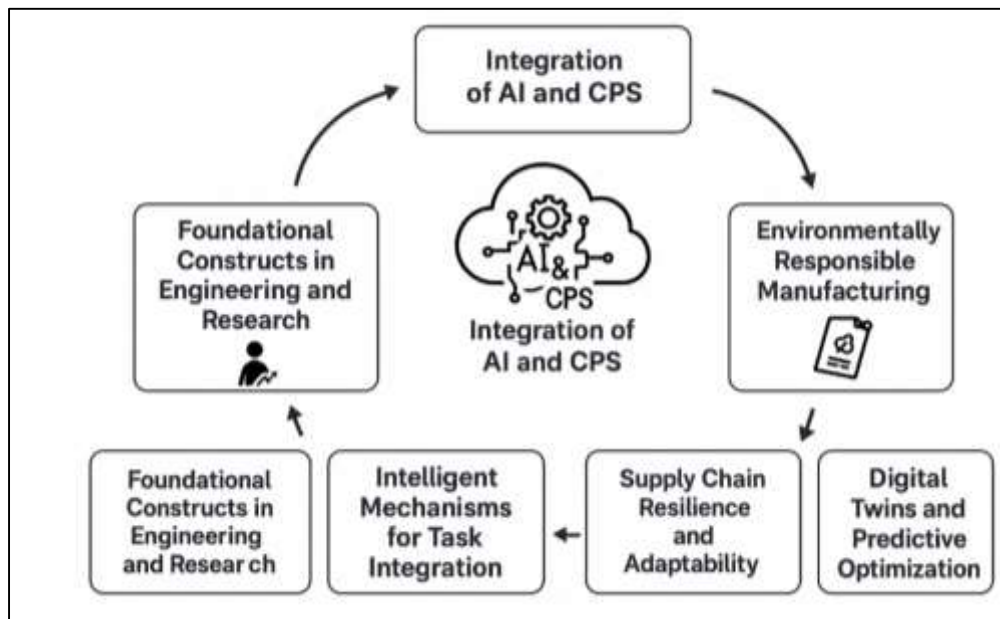
2023). As Industry 5.0 emphasizes sustainability and resilience, these orchestrated AI–CPS interactions lay the theoretical and empirical foundation for understanding how intelligent coordination contributes to environmentally responsible and disruption-ready industrial ecosystems.

Figure 1: Human-Centric Cyber-Physical System Integration



Sustainable manufacturing and environmentally responsible industrial operations have become central priorities for both developed and emerging economies, and extensive research has investigated how digital technologies contribute to ecological performance (Abdulla & Ibne, 2021; Kolade et al., 2022). Scholarly work on sustainable operations, green production systems, industrial ecology, life-cycle management, and resource-efficient manufacturing consistently emphasizes the role of real-time monitoring, intelligent optimization, and data-driven control in reducing environmental impacts (Habibullah & Foysal, 2021; Sanjid & Farabe, 2021). Studies exploring energy-aware machining, emissions reduction, eco-efficiency indicators, and smart resource allocation demonstrate how AI models and CPS-based measurement infrastructures enable continuous tracking of energy consumption, waste generation, process variability, and carbon intensity (Sarwar, 2021; Musfiqur & Saba, 2021). Research on circular manufacturing, product life extension, remanufacturing, and recycling coordination highlights how digital intelligence identifies opportunities for material reuse and supports closed-loop production systems (Dai et al., 2019; Omar & Rashid, 2021; Redwanul et al., 2021). In addition, investigations into sustainable scheduling, multi-objective optimization, process intensification, and cleaner production strategies show that AI algorithms can evaluate trade-offs between throughput, quality, and ecological constraints in real time. Work on digital twins, system modeling, and cyber-physical sustainability platforms further illustrates how virtual replicas of machines and facilities allow simulation-based optimization of environmental performance across the production lifecycle (Tarek & Praveen, 2021; Zaman & Momena, 2021). Similarly, research on sustainable logistics, green supply chain management, reverse logistics coordination, and eco-design connects manufacturing sustainability with broader supply chain responsibilities. Integrated frameworks combining industrial analytics, CPS instrumentation, and sustainability metrics demonstrate how AI-facilitated CPS can align operations with global environmental standards and industrial decarbonization agendas (Romagnoli et al., 2022; Rony, 2021; Shaikh & Aditya, 2021). Across these studies, a consistent theme emerges: sustainable production requires more than isolated clean technologies; it requires continuous orchestration of data, intelligence, and physical assets, which AI-enabled CPS architectures are uniquely positioned to achieve. This theoretical foundation provides a significant conceptual basis for understanding why AI-orchestrated CPS are increasingly viewed as core infrastructures for sustainable Industry 5.0 manufacturing (Sudipto & Mesboul, 2021; Zaki, 2021).

Figure 2: AI-Orchestrated Cyber-Physical Systems Framework



Supply chain resilience has also become a major focus of contemporary research, reflecting the growing vulnerability of globalized networks to disruptions such as pandemics, natural disasters, cyber intrusions, political tensions, logistics breakdowns, and demand shocks (Dorji et al., 2023; Hozyfa, 2022; Amin, 2022). Scholarly work on vulnerability assessment, risk propagation, disruption modeling, and recovery management demonstrates that supply chains must possess visibility, agility, robustness, redundancy, and rapid recovery capabilities to endure operational disturbances (Arman & Kamrul, 2022; Mohaiminul & Muzahidul, 2022). Studies on digital supply chains, real-time logistics tracking, CPS-enabled transport monitoring, and IIoT-based fleet management show how embedded technologies enhance visibility across nodes and flows. Research on AI-enabled risk prediction, disruption detection, inventory reallocation, dynamic routing, and scenario-based decision support illustrates how intelligent systems enable early problem identification and rapid response. Additional studies exploring autonomous planning, multi-agent logistics systems, distributed decision architectures, and intelligent control towers demonstrate the role of AI in coordinating supply-side, production-side, and distribution-side recovery strategies (Torres et al., 2021; Omar & Jobayer Ibne, 2022; Sanjid & Zayadul, 2022). Work on blockchain-enhanced traceability, digital assurance, smart contracts, and trusted data exchange provides further insight into how CPS ecosystems can strengthen resilience by improving information reliability and cross-organizational coordination. Empirical studies on post-disruption performance, response strategies, recovery mechanisms, and structural adaptiveness highlight that resilience is a dynamic capability influenced by both technological and organizational factors (Hasan, 2022; Mominul et al., 2022). Taken together, these strands of research show that resilience depends not only on supply chain design but also on intelligent orchestration mechanisms capable of detecting systemic changes, reallocating resources, optimizing transport flows, and stabilizing operations under stress. AI-orchestrated CPS, when viewed through this literature, represent a comprehensive mechanism capable of integrating detection, assessment, decision-making, and execution across global supply networks (Mani & Goniewicz, 2023; Rabiul & Praveen, 2022; Farabe, 2022). This positioning provides a conceptual basis for quantitative investigation into how orchestrated intelligence supports measurable improvements in supply chain resilience within Industry 5.0 ecosystems (Roy, 2022; Rahman & Abdul, 2022).

Digital twins and extended cyber-physical environments have gained significant scholarly attention in manufacturing and supply chain systems due to their capabilities in simulation, synchronization, and predictive optimization. Research on digital twin modeling, virtual commissioning, asset lifecycle analytics, and multi-scale system representation demonstrates that digital twins serve as computational mirrors of real physical systems, enabling continuous feedback and iterative improvement (Aina et al.,

2023; Razia, 2022; Zaki, 2022). Studies on intelligent planning, virtual testing, scenario simulation, and real-time process alignment illustrate how digital twins support optimization of production lines, equipment configurations, and material flows (Maniruzzaman et al., 2023; Kanti & Shaikat, 2022). Work on cyber-physical fusion platforms, integrated analytics pipelines, and immersive visualization environments further extends the role of digital twins into broader ecosystems where AI agents learn from real-time data and refine control strategies. In supply chain contexts, studies on network digital twins, logistics simulation, inventory dynamics modeling, and transportation alignment show how virtual representations of supply networks enable evaluation of disruption scenarios and resilience strategies (Egamberdiev et al., 2023; Arif Uz & Elmoon, 2023; Sanjid, 2023). Research on multi-agent orchestration, autonomous control loops, real-time synchronization, and self-adjusting systems highlights how AI algorithms embedded in digital twins coordinate with CPS layers to maintain operational stability and resource efficiency. Investigations into human-digital interaction, augmented visualization, and decision support interfaces demonstrate how digital twins also enhance cognitive accessibility for workers and managers (Sanjid & Sudipto, 2023; Tarek, 2023). Collectively, this literature positions digital twins as pivotal components of Industry 5.0 environments, enabling operational transparency, intelligent planning, and data-driven coordination across highly interconnected industrial systems (Cañizares et al., 2021; Shahrin & Samia, 2023; Muhammad & Redwanul, 2023). When digital twins operate as part of AI-orchestrated CPS architectures, they facilitate multilevel synchronization between physical processes, digital intelligence, and organizational decision-making, thereby strengthening both sustainability and resilience objectives (Muhammad & Redwanul, 2023; Razia, 2023).

Scholarly discourse on international industrial policy further amplifies the importance of AI-orchestrated CPS in enabling sustainable, resilient, and inclusive industrial systems (Cheshmehzangi et al., 2023; Srinivas & Manish, 2023; Sudipto, 2023). Studies examining global manufacturing competitiveness, digital transformation policy, human-centered industrial design, knowledge-driven production, and socio-technical alignment indicate that nations are increasingly adopting strategies that integrate intelligent automation with environmental stewardship and social well-being (Mesbaul, 2024; Zayadul, 2023). Research exploring the conceptual foundations of human-machine collaboration, participatory industrial ecosystems, skill augmentation, and ethical technology deployment highlights that advanced CPS must operate in ways that enhance worker capabilities rather than replace them. Additional studies investigating regional manufacturing ecosystems, economic upgrading, technology transfer, and value chain integration show that intelligent CPS architectures support the development of advanced capabilities in emerging economies (Tarek & Kamrul, 2024; Prabowo et al., 2023; Sudipto & Hasan, 2024). Work on sustainability regulations, industrial decarbonization frameworks, digital governance, and global cooperation emphasizes the growing expectation that manufacturing ecosystems contribute to climate goals, circular resource use, and risk-resilient infrastructures. Across these strands, scholars consistently identify AI-orchestrated CPS as strategic enablers that allow industries to align operational performance with environmental, social, and economic priorities (Abdul, 2025; Hozyfa, 2025). This convergence of technological capability and policy vision indicates that orchestrated intelligence is not only a matter of technical coordination but also an essential component of globally relevant industrial development strategies (Alaie et al., 2022; Alam, 2025; Masud, 2025). The widespread theoretical and empirical emphasis on sustainability, resilience, and human-centricity provides a broader international rationale for analyzing how AI-orchestrated CPS influence performance across diverse industrial contexts.

Despite extensive research on AI, CPS, sustainability, supply chain resilience, and digital twins, the literature exhibits a notable fragmentation that limits integrated understanding of how these constructs interact within Industry 5.0 ecosystems (Allioui & Mourdi, 2023; Arman, 2025; Mohaiminul, 2025). Studies on industrial AI often focus on predictive maintenance, scheduling, robotics, or optimization without examining cross-layer interactions with supply chains or sustainability outcomes (Md Mominul, 2025; Hasan, 2025). Research on CPS integration frequently explores automation, connectivity, or safety but tends to examine isolated machines or production cells rather than orchestrated system-wide behaviors (Milon, 2025; Farabe, 2025). Sustainability research typically

addresses energy efficiency, emissions reduction, green logistics, or circularity but treats digital technologies as auxiliary tools rather than core orchestration mechanisms (Tarek & Ishtiaque, 2025; Momena, 2025). Supply chain resilience literature commonly analyzes risk propagation, recovery strategies, or resilience capabilities without fully incorporating AI-driven decision architectures or cyber-physical coordination. Similarly, digital twin research emphasizes modeling precision, simulation capabilities, or system alignment but does not always connect virtual orchestration to wider industrial resilience or sustainability indicators (Muhammad, 2025; Pankaz Roy, 2025). Only a limited number of studies investigate how autonomous multi-agent orchestration, AI-enabled decision pipelines, CPS integration maturity, and closed-loop digital-physical feedback collectively shape performance across manufacturing and supply chain boundaries (Baloch et al., 2022; Rahman, 2025; Rakibul, 2025). Moreover, empirical research investigating the combined effects of AI orchestration, CPS coordination, sustainability performance, and resilience capabilities remains underdeveloped (Rebeka, 2025; Reduanul, 2025). Quantitative evidence capturing these interdependencies across international industrial contexts is particularly limited. These gaps underscore the need for robust empirical designs capable of operationalizing AI orchestration, CPS integration, sustainability indicators, and resilience metrics within coherent analytical frameworks (Praveen, 2025; Shaikat, 2025). The present study responds directly to these needs by investigating how AI-orchestrated cyber-physical systems support sustainable Industry 5.0 manufacturing while enhancing supply chain resilience across diverse operational environments (Darjee et al., 2023; Rony, 2025; Saba, 2025). Through rigorous quantitative modeling and construct-based measurement, the study provides an integrated examination of how orchestrated intelligence across digital and physical layers contributes to ecological performance and disruption-readiness in contemporary industrial ecosystems (Kanti, 2025; Zayadul, 2025).

The primary objective of a study on AI-orchestrated cyber-physical systems for sustainable Industry 5.0 manufacturing and supply chain resilience is to systematically examine how coordinated intelligence across digital and physical layers contributes to sustainability performance and disruption endurance within modern industrial ecosystems. This objective centers on evaluating the extent to which AI-driven orchestration mechanisms—such as autonomous decision engines, multi-agent control architectures, predictive analytics pipelines, intelligent sensing platforms, and real-time synchronization frameworks—enhance the efficiency, ecological responsibility, and adaptive capabilities of manufacturing and supply chain operations. It involves quantifying how integrated cyber-physical environments support continuous monitoring of energy use, emissions levels, material flows, process variability, and resource utilization to align industrial activities with sustainability goals. The objective also includes assessing how AI-based orchestration influences system robustness by enabling early disruption detection, dynamic resource reallocation, adaptive scheduling, and coordinated recovery responses that maintain operational continuity during supply chain shocks. Another core aspect involves determining how cyber-physical integration maturity influences the effectiveness of AI-based decisions by examining data interoperability, physical-digital alignment, system feedback quality, and the responsiveness of interconnected assets. The objective extends to evaluating how these orchestration mechanisms function across different industrial contexts, organizational scales, and operational complexities to identify structural, technological, and managerial conditions that either strengthen or constrain sustainable and resilient performance outcomes. Furthermore, the study seeks to provide an integrated analytical basis for understanding the interplay between sustainability indicators and resilience capabilities when AI orchestrates manufacturing lines, logistics networks, and material flows within Industry 5.0 environments. By focusing on quantifiable relationships among AI orchestration, CPS coordination, environmental performance, and resilience metrics, this objective supports the development of empirically grounded insights into how intelligent, cyber-physically integrated systems transform the operational, ecological, and protective capacities of advanced industrial value chains.

LITERATURE REVIEW

The rapid convergence of artificial intelligence and cyber-physical systems has reshaped the foundations of modern industrial ecosystems and created new pathways for optimizing production systems, strengthening supply chain reliability, and advancing global sustainability agendas (Trakadas

et al., 2020). Literature across manufacturing engineering, operations research, and systems science consistently highlights that Industry 5.0 introduces a transformative shift toward intelligent, adaptive, and purpose-driven industrial architectures that extend beyond the automation focus of Industry 4.0. Within this evolution, AI-orchestrated CPS represent a core technological configuration in which digital intelligence governs the behavior of physical machinery, data streams, human-machine interactions, and multi-tier supply networks (De Alwis et al., 2021). The scholarly landscape examining this domain is expansive but highly fragmented. Research streams on industrial AI emphasize the role of machine learning, autonomous decision systems, and predictive optimization; CPS literature focuses on real-time sensing, interconnectivity, and embedded control; sustainability research investigates energy efficiency, emissions reduction, circular material flows, and resource-intensive operations; supply chain resilience studies analyze risk propagation, adaptive capability, and recovery speed (Grzesiak & Sulich, 2023). While each domain provides valuable insights, few studies integrate these constructs within a unified empirical framework capable of quantifying how orchestrated intelligence across CPS layers contributes simultaneously to manufacturing sustainability and supply chain resilience. Therefore, a structured literature review is essential for synthesizing existing theoretical, technological, and empirical contributions, clarifying conceptual boundaries, identifying gaps, and developing measurable constructs appropriate for quantitative analysis (Andronie, Lăzăroiu, Ștefănescu, et al., 2021). The following outline presents an extended, in-depth structure for mapping the existing knowledge landscape and informing the theoretical grounding for this quantitative study.

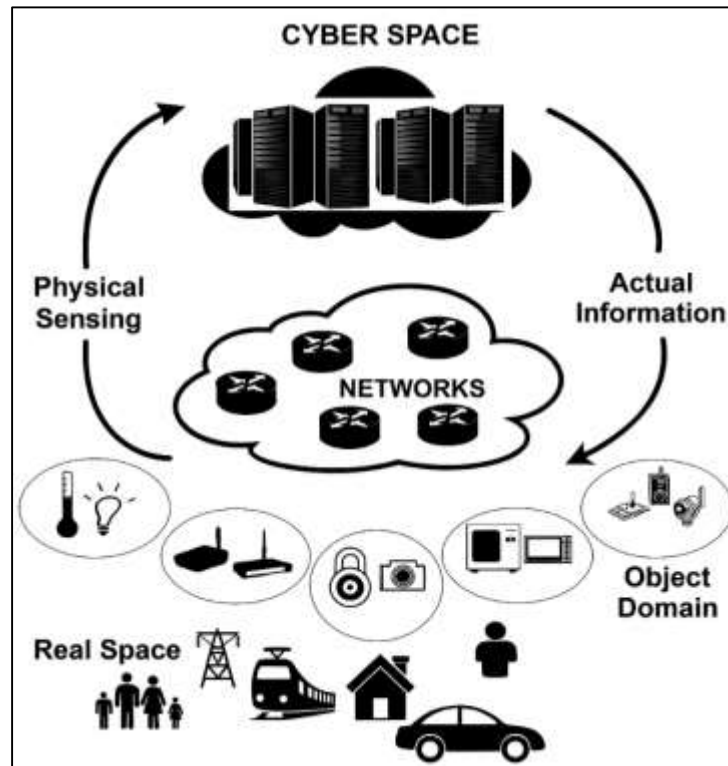
Foundations of AI-Orchestrated Cyber-Physical Systems

Cyber-physical systems have been consistently characterized in the scholarly literature as integrated technological environments in which sensing, embedded computing, actuation, and advanced communication layers operate together to synchronize digital intelligence with physical processes (Tao et al., 2019). Researchers examining CPS architecture describe these systems as tightly coupled networks where sensors capture high-resolution data, embedded processors interpret contextual information, actuators execute physical responses, and communication networks ensure reliable data movement across interconnected devices. Multiple studies emphasize that CPS operate through continuous feedback loops that allow instantaneous recognition of machine states, environmental variations, or process fluctuations. Scholars consistently note that real-time responsiveness is a core attribute of CPS, enabling systems to adapt their behavior based on dynamic operational inputs. Interoperability across heterogeneous devices, platforms, and industrial protocols is also identified as essential, as CPS rarely function in isolation but instead operate across distributed manufacturing and supply environments (Yao et al., 2019). From a structural perspective, research frequently frames CPS using a layered functional model: the perception layer collects sensory data; the control layer interprets conditions and initiates responses; the integration layer coordinates commands and cross-device communication; and the execution layer enacts the system's physical decisions. The literature on industrial systems engineering expands upon these foundations by illustrating how CPS support automation, precision control, synchronized machine operations, and embedded intelligence throughout advanced manufacturing environments. As industrial systems evolve toward increased digitalization, CPS form the backbone enabling real-time visibility, autonomous response patterns, and integrated process flows (Radanliev et al., 2021). These conceptual foundations reflect a broad scholarly consensus that CPS represent a central technological paradigm driving contemporary industrial transformation, providing the structural and functional basis that allows advanced analytics, robotics, and machine coordination to operate cohesively across complex industrial infrastructures.

Across the growing body of research on industrial automation and systems intelligence, artificial intelligence is frequently positioned as the orchestration layer that elevates cyber-physical systems from automated infrastructures into adaptive, decision-driven ecosystems (Conrad et al., 2023). Scholars describe AI-enabled CPS as systems in which data processing, pattern learning, predictive reasoning, and decision algorithms are interwoven into the physical machinery and digital communication pathways of industrial operations. Machine learning models, including supervised and unsupervised learning techniques, allow CPS to detect anomalies, anticipate process deviations, and refine operational parameters based on historical and real-time data patterns. Reinforcement learning studies demonstrate how agents continuously learn optimal control strategies by evaluating system

feedback, while optimization models contribute to minimizing waste, balancing workloads, and allocating resources under complex constraints. Multi-agent system research highlights how distributed AI agents can concurrently manage machine behavior, line scheduling, and transport activities, creating coordinated interactions that enhance overall system efficiency (Groshev et al., 2021). AI-based perception models support the integration of visual inspection, acoustic sensing, vibration analysis, and thermal monitoring within CPS, enabling finer-grained interpretation of physical environments. Equally important is the role of AI in decision-making processes where algorithms can evaluate numerous operating alternatives and select the most efficient or stable actions without constant human intervention. This orchestration capability extends to autonomous control functions, where AI agents adjust machine settings, initiate recovery actions, or reconfigure workflows based on real-time conditions. Literature across industrial robotics, automated quality control, and intelligent manufacturing consistently emphasizes that AI transforms CPS from reactive systems into proactively managed industrial environments (Panetto et al., 2019). In this sense, the orchestration function of AI is not limited to enhancing computational capacity but rather involves governing how physical assets interact, adapt, and collaboratively sustain system performance. This body of research consistently reinforces the view that AI serves as the coordinating mechanism that integrates distributed CPS components into cohesive, intelligent, and operationally aligned industrial architectures.

Figure 3: Cyber-Physical Systems Interaction Framework



Studies exploring the integration of AI-driven CPS within industrial ecosystems reveal a significant shift from traditional automation toward intelligence-centric operational structures. Scholars analyzing digital transformation in manufacturing emphasize that earlier automation primarily focused on mechanizing tasks and enhancing machine-level precision, whereas new industrial architectures embed decision intelligence throughout production lines, logistics infrastructures, and organizational workflows (Khujamatov et al., 2021). Research on robotics integration illustrates how industrial robots equipped with AI-enabled controllers coordinate movements, collaborate with workers, and adjust operations in synchronization with CPS data streams. Literature addressing industrial Internet of Things integration shows that sensor-rich eliot networks create a digital substrate that supports AI-based learning models, enabling CPS to achieve real-time situational awareness across materials,

equipment, and environmental conditions. Studies on digital platforms demonstrate how cloud-based and edge-based computing environments facilitate seamless CPS data circulation, allowing distributed systems to exchange operational information quickly and reliably. Smart infrastructure research further highlights the importance of connected devices, embedded analytics, and digital-physical alignment in creating unified industrial environments where decision-making processes span multiple levels of the production hierarchy (Leitão et al., 2022). In addition, scholarship on industrial organizational structure identifies multi-level orchestration as a critical aspect of modern CPS integration. At the machine level, CPS manage local sensing and actuation; at the line level, coordination aligns machine sequences and production flows; at the plant level, CPS integrate with scheduling systems and resource management; and at the network level, AI-orchestrated CPS synchronize interactions among suppliers, manufacturers, and distribution nodes. Research on manufacturing ecosystems repeatedly shows that this layered integration supports operational consistency, minimizes variability, and enhances system adaptability across distributed industrial environments (Napoleone et al., 2023). Studies within systems engineering, production operations, and industrial cybernetics collectively reinforce that AI-orchestrated CPS create an interconnected industrial landscape in which machines, systems, and decision agents operate with shared intelligence and collaborative synchronization.

Research examining industrial evolution consistently identifies the movement toward intelligence-centric architectures as a defining characteristic of contemporary manufacturing and supply chain systems. Earlier industrial models prioritized mechanization, digitization, and automation, but recent literature highlights a conceptual transition toward architectures that embed adaptive intelligence, systemic coordination, and continuous learning capabilities (Leng et al., 2019). Scholars in industrial systems management observe that AI-orchestrated CPS support this transition by integrating sensing, analytics, and control mechanisms into cohesive operating structures that function across organizational and technological boundaries. Studies on distributed manufacturing illustrate how intelligence-centric systems rely on CPS coordination to manage geographically dispersed assets, ensuring consistent performance across multiple facilities. Research on smart factories demonstrates how AI-orchestrated CPS facilitate real-time alignment between production capacities, material flows, and environmental conditions, thereby supporting more flexible and efficient manufacturing. Literature in smart logistics and autonomous warehousing describes how CPS-enabled navigation, AI-driven routing systems, and synchronized transport networks extend intelligence from production floors into supply chain environments (Puliafito et al., 2021). Additionally, investigations into industrial decision architectures show that intelligence-centric systems depend on multi-level decision alignment, where machine-level decisions are synchronized with organizational scheduling, inventory control, and cross-facility planning. Studies focusing on human-machine interaction in CPS environments suggest that intelligence-centric architectures improve operational clarity by enabling transparent interfaces through which workers and AI systems share situational understanding. Research in industrial analytics and system optimization indicates that intelligence-centric architectures enable continuous calibration of performance by harmonizing digital models, physical behaviors, and operational parameters (Hlophe & Maharaj, 2023). Across these various lines of scholarship, the central theme is that AI-orchestrated CPS do not merely enhance automation but transform industrial systems into interdependent networks where intelligence is distributed, shared, and operationally embedded at multiple levels. This scholarly consensus highlights that the transition toward intelligence-centric industrial architectures rests on the maturation of AI-orchestrated CPS as the fundamental organizational, technological, and analytical infrastructure shaping contemporary industrial capabilities.

Theoretical Links Between AI-Orchestrated CPS and Industry 5.0

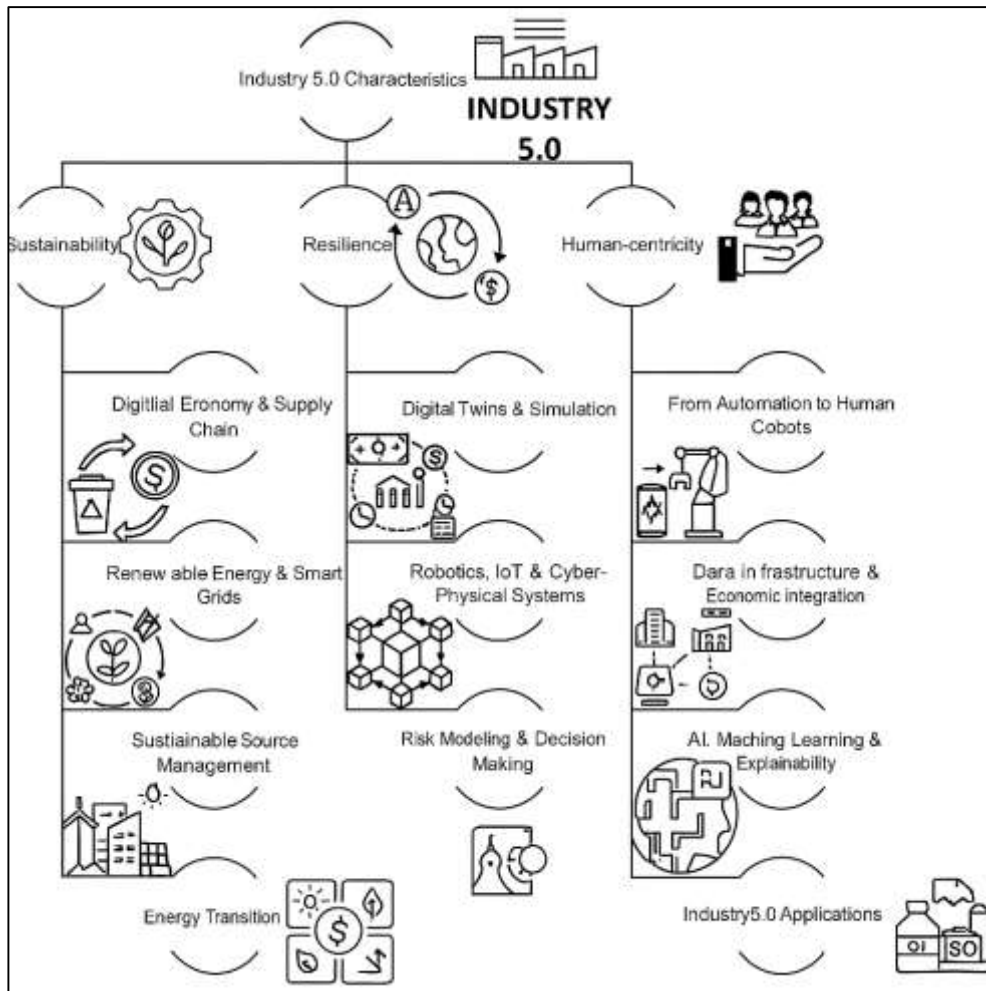
The shift from Industry 4.0 to Industry 5.0 is characterized by a conceptual broadening in which technological advancement is linked with human-centricity, resilience, and sustainability (Ivanov, 2023). Industry 4.0 emphasizes digital connectivity, automation, and data-driven control, prioritizing efficiency and precision through integrated cyber-physical infrastructures. In contrast, Industry 5.0 extends these technological foundations by integrating social, environmental, and organizational dimensions into industrial performance. Human-centricity is emphasized in the industry 5.0 discourse as systems are designed to support worker well-being, ergonomic task distribution, and collaborative

interaction between humans and intelligent machines. Resilience becomes a defining principle in which industrial processes are structured to maintain stability during disruptions, absorb shocks, and restore function under challenging conditions. Sustainability further expands industrial expectations by encouraging resource-efficient practices, reduced environmental burdens, and alignment of production with ecological preservation (Carayannis et al., 2023). These distinctive orientations differentiate Industry 5.0 as a socio-technical paradigm where technological development coexists with human value systems. AI-orchestrated cyber-physical systems are increasingly recognized as the mechanism through which these expanded expectations become operational. Through coordinated sensing, analytics, and control, AI-driven CPS harmonize digital intelligence with human contributions and environmental constraints. Scholars describe this transition as the emergence of adaptive intelligence within industrial architectures, enabling systems to exhibit greater flexibility, contextual awareness, and alignment with broader societal priorities. The evolution from Industry 4.0 to Industry 5.0 therefore reflects an expansion from connected automation to human-aware, ecologically grounded, and resilient operational ecosystems (Pereira & dos Santos, 2023).

Human-machine collaboration within cyber-physical environments has become a central theme within Industry 5.0 scholarship, where hybrid intelligence models combine the strengths of artificial intelligence with human judgment and experiential knowledge. Hybrid intelligence frameworks describe collaborative systems in which humans and AI agents share responsibility for perception, interpretation, and decision-making, enabling operational outcomes that neither can achieve independently (Mourtzis, 2023). Cyber-physical interfaces serve as the intermediary platforms through which this collaboration unfolds, integrating sensor outputs, machine states, and analytical insights with human situational awareness and contextual interpretation. These interfaces include augmented dashboards, adaptive visualizations, wearable decision support systems, voice-guided controls, and immersive interactive environments. They provide workers with real-time feedback, predictive indicators, and environmental cues that enhance their ability to supervise, coordinate, or redirect automated actions (Crnobrnja et al., 2023). Augmented decision environments expand this collaboration by creating information-rich contexts where humans interact with system behavior in transparent and intelligible ways. Within these settings, AI algorithms manage routine tasks, detect anomalies, and adjust machine parameters, while workers intervene at strategic points, monitor system trajectories, and evaluate complex trade-offs. The literature consistently emphasizes that such collaborative environments strengthen system reliability, increase ergonomic comfort, and support organizational learning by enabling humans to work alongside intelligent CPS rather than being displaced by them (Carayannis & Morawska, 2023). As a result, human-machine collaboration becomes an essential dimension of AI-orchestrated CPS within the Industry 5.0 framework.

Industry 5.0 introduces system-level characteristics that redefine how cyber-physical systems are conceptualized and integrated into industrial ecosystems. Resource-conscious manufacturing is among the defining attributes, emphasizing controlled energy use, reduced waste generation, and efficient material throughput. CPS enable these outcomes by monitoring machine behavior, regulating operating conditions, and adjusting process variables through embedded feedback mechanisms (Madsen & Slåtten, 2023). Circularity is another essential characteristic, highlighting the importance of regenerating resources, extending product lifecycles, and recapturing value through material loops. Cyber-physical tracking, embedded sensors, and AI-driven analytics contribute to these efforts by documenting product histories, material compositions, and usage behaviors. Operational robustness complements these environmental and resource-oriented characteristics by reinforcing system capacity to maintain performance under disturbances (Tran et al., 2022). Robustness is supported by distributed sensing, synchronized machine coordination, and modular system design—elements that enable CPS to regulate process flows when disruptions arise. A defining conceptual shift in Industry 5.0 literature is the treatment of CPS as socio-technical systems rather than isolated technological constructs. This framing emphasizes the interaction between technical components, organizational practices, human involvement, and environmental priorities (Le Jeune et al., 2023). Industry 5.0 therefore situates CPS within a broader ecological and social context, integrating technological efficiency with values of responsibility, adaptability, and collective well-being.

Figure 4: Industry 5.0 Systems Framework



AI-orchestrated CPS play a pivotal role in aligning industrial systems with the core principles of Industry 5.0 by connecting intelligent automation with human-centered design and sustainable practices. Research portrays AI orchestration as a structured mechanism that integrates perception, prediction, decision, and action across cyber-physical layers (Aydin et al., 2023). Within Industry 5.0 environments, this orchestration supports adaptive intelligence, where systems learn from historical and real-time data to regulate machine behavior, adjust operations, and maintain stability. AI-driven orchestration enhances human-centricity by enabling safe interactions between workers and automated equipment, facilitating ergonomic task distribution, and supporting supervisory control. It also contributes to sustainable manufacturing through continuous monitoring of resource use, identification of inefficiencies, and coordination of environmentally aligned operational strategies (Ystgaard & De Moor, 2023). For resilience, AI orchestrators detect anomalies, adjust system trajectories, and synchronize recovery actions across interconnected assets. At the ecosystem level, AI-orchestrated CPS align system performance with Industry 5.0 values by balancing productivity with social and environmental considerations. This integration demonstrates how AI-based coordination serves as both a technological and conceptual anchor for establishing Industry 5.0 as a multi-dimensional, value-driven industrial paradigm (Vaezinejad & Schniederjans, 2022).

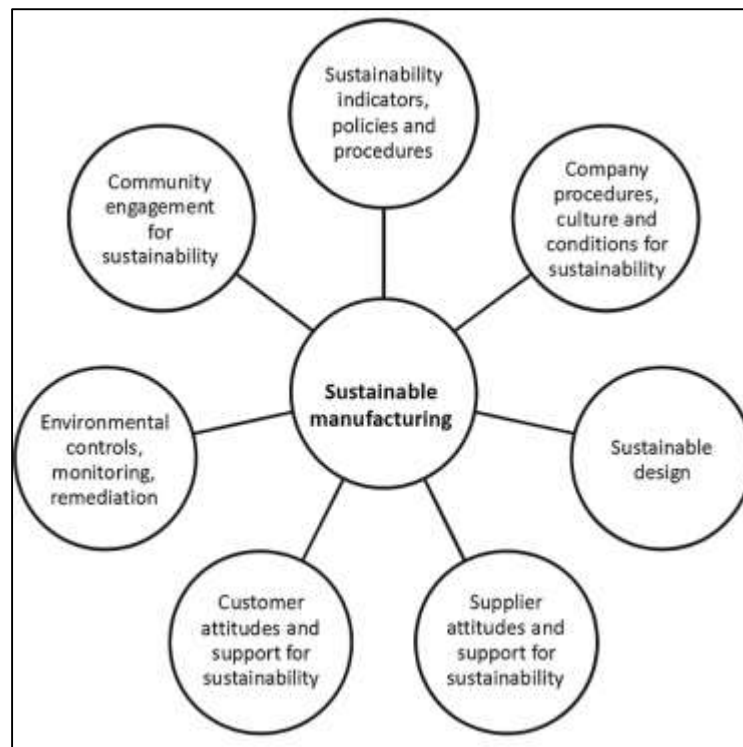
AI-Orchestrated CPS for Sustainable Manufacturing

Sustainability has evolved from a conceptual aspiration into a quantifiable performance dimension within manufacturing systems. Scholars emphasize measurable indicators such as energy intensity, emissions rates, waste volumes, and material utilization as the basis for evaluating environmental performance (Taddese et al., 2020). Energy intensity assesses how much energy is required for each stage of production; emissions metrics capture pollutant outputs; waste indicators quantify

inefficiencies; and resource utilization reflects the effectiveness of input use. Cyber-physical systems enable continuous monitoring of these metrics through embedded sensors, multi-sensor fusion platforms, and integrated data nodes that track real-time environmental conditions. AI techniques refine this monitoring by interpreting patterns, identifying deviations, and evaluating relationships between operational parameters and environmental outcomes (Pham et al., 2020). Process transparency becomes a defining feature of sustainable operations, as CPS provide stakeholders with visibility into environmental impacts across machines, lines, and facilities. Ecological footprints are no longer estimated at aggregated levels but are captured at fine-grained scales, enabling precise evaluation of each contributing process. Research consistently shows that sustainability becomes more actionable when grounded in quantifiable measures supported by cyber-physical data infrastructures and AI-driven analytical mechanisms (Lütje & Wohlgemuth, 2020).

AI-driven optimization models enhance resource efficiency within CPS-enabled manufacturing by improving energy use, refining operational sequences, and minimizing environmental burdens. Predictive energy management algorithms identify temporal patterns in consumption and detect inefficient modes of operation, guiding adjustments that stabilize production energy profiles (Mengistu & Panizzolo, 2023). Intelligent scheduling approaches reduce environmental impact by distributing workloads in ways that avoid peak demand, prevent extended idling, and synchronize high-energy tasks with favorable process conditions. Thermal, mechanical, and electrical efficiency modeling further demonstrates the capabilities of machine learning techniques in identifying subtle correlations among process parameters and environmental outcomes (Peças et al., 2023). These models contribute to optimized control decisions by recommending machine settings, material flow adjustments, and production configurations that minimize waste. CPS sensing infrastructures support these optimization efforts by providing detailed real-time inputs about equipment conditions, process states, and resource flows (Han et al., 2023). Through this integration of sensing, learning, and control, AI-orchestrated CPS convert resource efficiency into a continuously managed and systematically improved operational dimension.

Figure 5: Sustainable Manufacturing System Framework



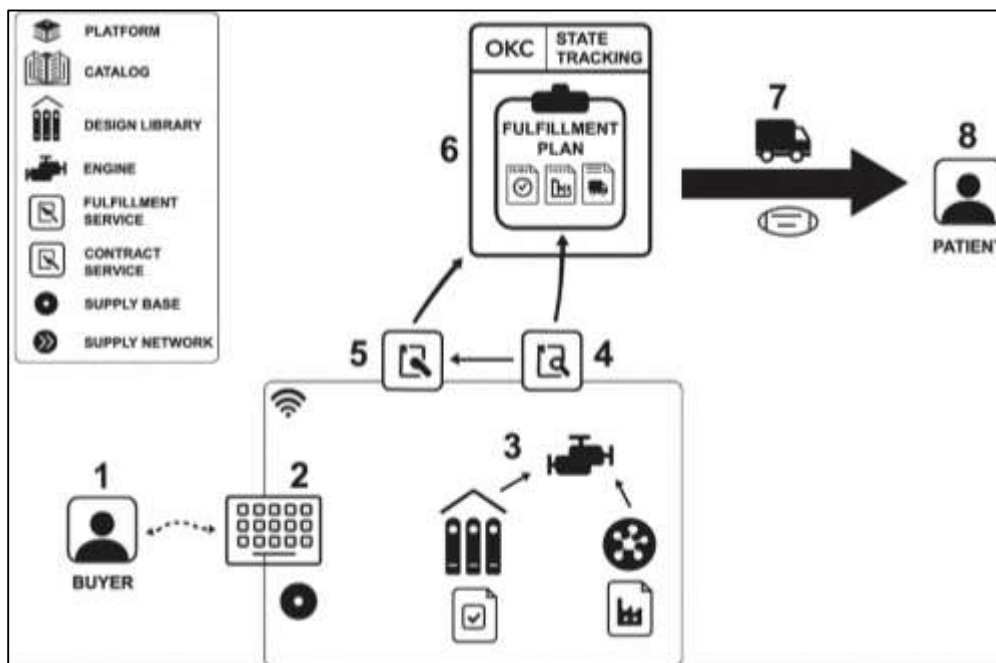
Circular manufacturing practices rely on cyber-physical infrastructures to enable resource recirculation, remanufacturing, and life-cycle optimization (Vega-Muñoz et al., 2021). Predictive

analytics identify which components are suitable for remanufacturing by assessing wear patterns, performance trajectories, and expected remaining life. AI-driven tracking systems monitor material locations, usage histories, and degradation states, facilitating closed-loop material flows that minimize resource losses. Embedded sensors within products and equipment allow CPS to capture real-time data that informs decisions across repair, refurbishing, and recycling pathways (Moghayedi & Awuzie, 2023). Life-cycle assessment becomes more precise as CPS record environmental impacts across stages such as sourcing, production, use, and recovery. These data-rich records support design adjustments, process improvements, and material substitutions aligned with circularity principles. As a result, circular manufacturing becomes a coordinated process in which CPS automate tracking, AI models interpret recovery potential, and industrial systems enact decisions based on integrated environmental information (Gonçalves et al., 2022).

AI-Orchestrated CPS and Supply Chain Resilience

Supply chain resilience is conceptualized through quantifiable dimensions that reflect a system’s capacity to absorb, withstand, and respond to disruptions (Hosseini et al., 2020). Disruption frequency captures how often disturbances occur within operations; recovery time measures the duration required to restore baseline functionality; continuity rate evaluates the ability to sustain material flows during turbulence; and response precision reflects the accuracy and efficiency of reactive measures. These metrics allow resilience to be understood as an operational capability rather than an abstract attribute. The literature highlights robustness, redundancy, flexibility, and visibility as underlying constructs shaping resilience performance (Han et al., 2020). Cyber-physical systems and AI analytics enhance quantification by generating continuous data streams on logistics movements, machine states, inventory levels, and external conditions. Scholars emphasize that resilience assessment benefits from these integrated sensing and analytics capabilities because they provide empirical foundations for evaluating vulnerabilities and performance under stress (Cheng et al., 2022). Through structured measurement, organizations gain insight into the stability and adaptability of their supply networks.

Figure 6: Digital Fulfillment and Supply Workflow



The ability to detect and anticipate disruptions is enhanced by AI-enabled predictive analytics embedded within CPS infrastructures. Machine learning models analyze historical behavior, real-time signals, and contextual factors to identify deviations in transportation, inventory movement, supplier performance, and demand patterns (Abourokbah et al., 2023). Anomaly detection mechanisms uncover irregularities that signal potential system instability, while predictive risk assessments estimate the

likelihood and potential impact of disruptions. These analytical processes form early warning systems that notify decision-makers of emerging issues before they escalate (Katsaliaki et al., 2022). CPS sensing layers supply the real-time data required for such models, enabling continual evaluation of conditions across supply chain nodes. Research indicates that early detection improves operational stability by allowing timely adjustments to schedules, route allocations, and inventory strategies (Mackay et al., 2020).

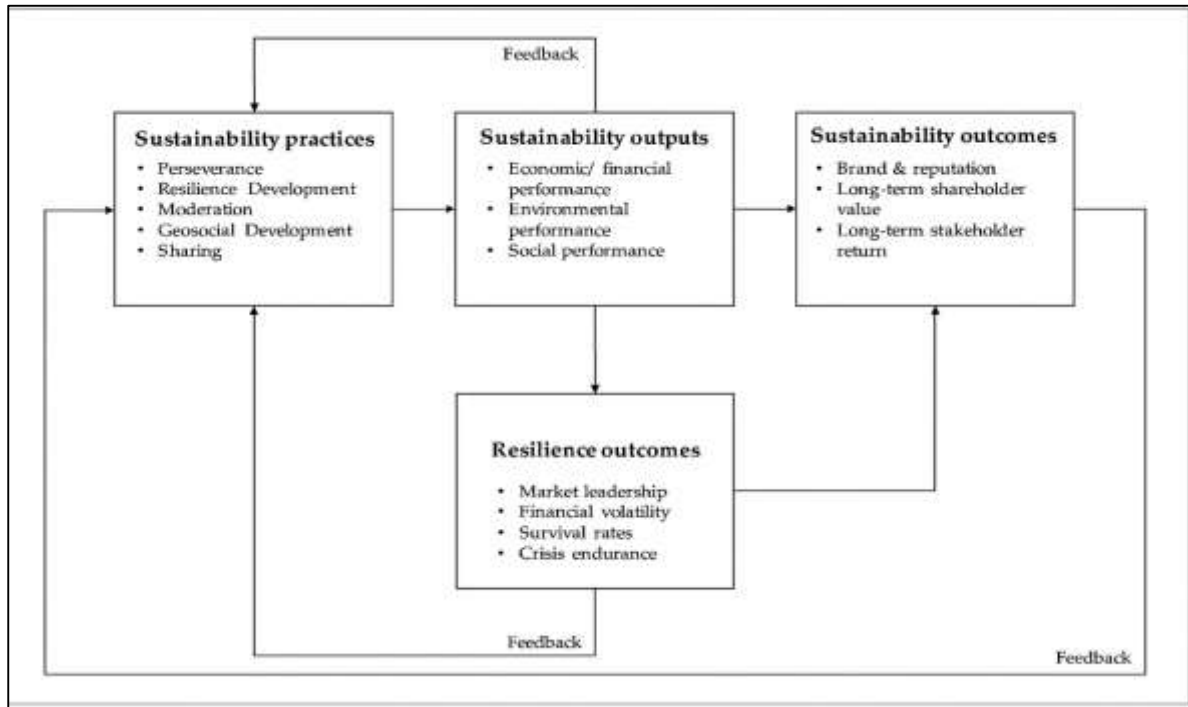
Cyber-physical coordination strengthens supply chain resilience by synchronizing activities among production systems, warehouses, and transportation infrastructures. Embedded CPS devices track the movement of goods, machine conditions, and storage environments, providing continuous updates to logistics systems (Ivanov, 2022). These data flows enable dynamic routing adjustments when disruptions occur and support adaptive scheduling that reallocates workloads in response to unexpected delays. AI-driven optimization models coordinate decisions across distributed nodes, ensuring that material flows remain balanced even under fluctuating conditions (Yang et al., 2023). Autonomous logistics systems—including robotic handling units and CPS-enabled transport vehicles—augment human efforts by executing time-sensitive operations with speed and accuracy. Real-time communication among these elements ensures that operations across the supply chain remain coherent, coordinated, and resilient (Kähkönen et al., 2023). In addition, Digital twin technologies expand supply chain resilience by enabling detailed simulation and analysis of potential disruptions (Golan et al., 2020). A network digital twin represents the structural and functional characteristics of a supply chain, including its suppliers, transportation links, warehouses, and production facilities. This virtual environment allows decision-makers to simulate disruptions, examine their propagation across the network, and analyze system vulnerabilities. Visualization tools embedded in digital twins translate network complexity into interpretable scenarios that assist managers in understanding interdependencies and bottlenecks (Vanany et al., 2021). Twin-based optimization evaluates alternative recovery strategies by simulating rerouting plans, inventory reallocations, or production adjustments. These virtual tests allow organizations to assess the effectiveness of resilience strategies without disrupting real operations. Cyber-physical integration ensures that digital twins reflect real-world conditions, as sensor data continuously update the virtual model (Shandiz et al., 2020). This synchronization strengthens the reliability of disruption simulations and reinforces supply chain stability.

Sustainability and Resilience in CPS-Orchestrated Ecosystems

Sustainability and resilience share conceptual foundations that reinforce each other within industrial ecosystems (Nüchter et al., 2021). Sustainability focuses on responsible resource use, reduced environmental impact, and efficient operational practices. Resilience emphasizes stability under disruptions, rapid recovery, and continuity of operations. These two constructs converge through their mutual dependence on efficiency, adaptability, and systemic robustness. Systems that optimize energy use and material flows often exhibit greater stability during external shocks because they rely on fewer volatile inputs and more controlled processes (Susur et al., 2019). Similarly, resilient systems tend to reduce waste, manage resources effectively, and minimize fluctuations that contribute to ecological inefficiencies. Environmental monitoring supports disruption readiness by providing accurate assessments of operational states, while resilience-oriented design promotes resource-efficient structures that align with sustainability goals (Nyström et al., 2019). The interrelationship between these dimensions reflects the increasing recognition that ecological performance and disruption endurance are intertwined aspects of high-functioning industrial systems (Roostaie et al., 2019). orchestrated cyber-physical systems serve as integrative mechanisms that unify sustainability and resilience. These systems evaluate resource consumption, emissions patterns, and waste accumulation while simultaneously monitoring disruptions, delays, and operational instabilities (Zavala-Alcívar et al., 2020). Multi-objective decision models use these inputs to identify operational strategies that maintain environmental performance without compromising continuity under stress (Rao et al., 2019). Cyber-physical sensing captures environmental and operational states, AI analytics interpret both dimensions, and coordinated control actions align resources, machine behavior, and logistics pathways accordingly (Di Tommaso et al., 2023). Through these interactions, AI-orchestrated CPS establish an operational environment where sustainability and resilience reinforce each other

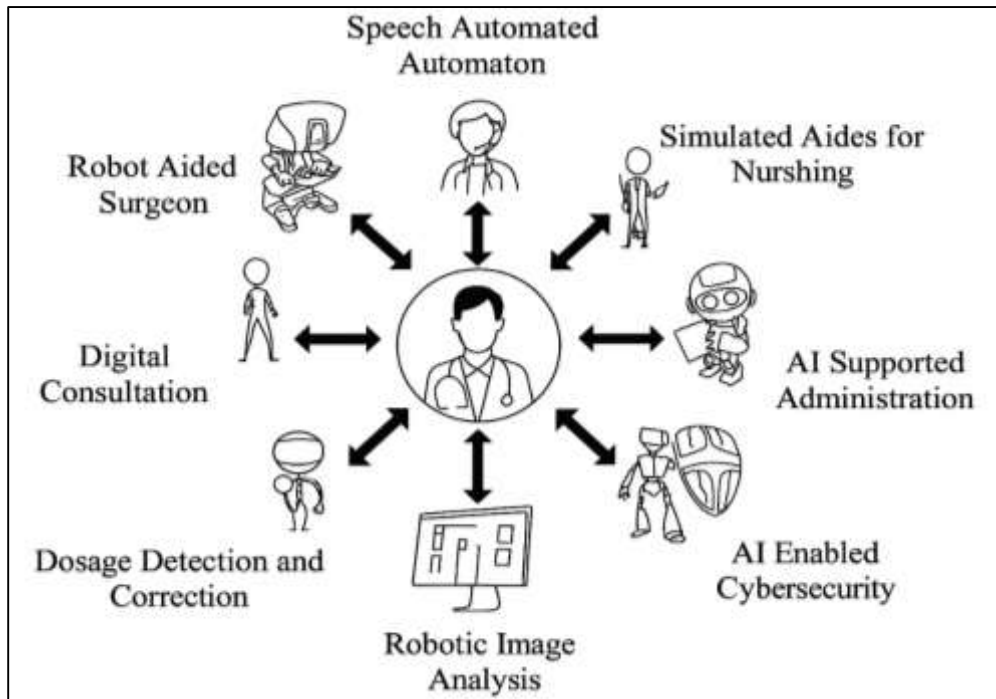
rather than compete (Prayag, 2023).

Figure 7: Sustainability and Resilience Feedback Framework



AI- Technological, Organizational, and Structural Determinants

CPS integration maturity influences the effectiveness of AI-orchestrated industrial systems by shaping how well hardware, communication networks, and sensing infrastructures support system-wide coordination (Chae et al., 2023). Hardware readiness determines whether machines possess sufficient sensing capabilities, processing power, and actuation mechanisms to participate in cyber-physical interactions. Communication density affects the speed and reliability of information exchange, determining how quickly systems detect changes and implement adjustments. Sensor infrastructure quality determines the accuracy and completeness of environmental and operational data, influencing the precision of AI-driven decision-making (Bousdekis et al., 2020). Data availability ensures that AI systems receive consistent and granular information, while interoperability allows devices, platforms, and applications to collaborate without technical barriers. System responsiveness—driven by low-latency communication and stable feedback loops—enables real-time control and adaptive system behavior. High CPS maturity therefore supports efficient orchestration, accurate analytics, and resilient system performance (Radanliev et al., 2021). AI adoption shapes the intelligence capacity of industrial systems and determines how effectively CPS coordinate operations (Nagy et al., 2023). The accuracy of learning models influences the reliability of predictions, anomaly detection, and performance assessments. Decision autonomy determines how independently AI agents can manage tasks, adjust system parameters, or supervise machine behavior. Training data quality shapes the robustness of analytical outcomes by ensuring that models reflect diverse operational conditions (Hohmann & Posselt, 2019). Algorithmic stability ensures that AI decisions remain consistent and interpretable across varying loads and disruptions. Effective integration of AI pipelines into operational workflows determines whether insights translate into real adjustments within cyber-physical environments. These elements collectively establish the intelligence capacity that enables CPS to function autonomously, adaptively, and coherently (Zdravković et al., 2022).

Figure 8: AI-Driven Healthcare Applications Framework

Organizational readiness significantly influences the success of AI-orchestrated CPS integration (Andronie, Lăzăroiu, Iatagan, et al., 2021). Human-centric adoption strategies ensure that systems are designed to augment worker capabilities rather than displace them. Training initiatives equip workers with the necessary skills to interpret CPS feedback, oversee AI-driven processes, and interact with intelligent interfaces. Interaction protocols define how humans and machines coordinate actions, ensuring safe and efficient collaboration (Qian et al., 2023). Management flexibility determines how quickly organizations can adapt operational procedures, restructure workflows, or modify resource allocations in response to CPS-driven insights. A supportive digital culture encourages experimentation, reduces resistance to technological change, and enhances organizational agility (Groshev et al., 2021). Process adaptability ensures that work routines can incorporate rapid adjustments triggered by CPS monitoring and AI analytics.

Infrastructure and policy environments act as essential enablers of CPS orchestration effectiveness (Broo et al., 2021). Digital infrastructure—including broadband connectivity, edge computing nodes, and secure data channels—determines the scalability and reliability of cyber-physical integration. Cybersecurity frameworks protect CPS from interference, unauthorized access, or operational manipulation, supporting system integrity and trust. Sustainability regulations provide industrial guidelines for environmental performance, encouraging resource-efficient processes and transparent ecological reporting (Bécue et al., 2021). Ecosystem-level elements—such as national innovation networks, industrial alliances, academic partnerships, and regulatory institutions—create external conditions that support adoption and diffusion of AI-orchestrated CPS. These broader structures influence how readily organizations adopt cyber-physical integration, how securely systems operate, and how effectively industrial practices align with sustainability and resilience objectives (Adel, 2023).

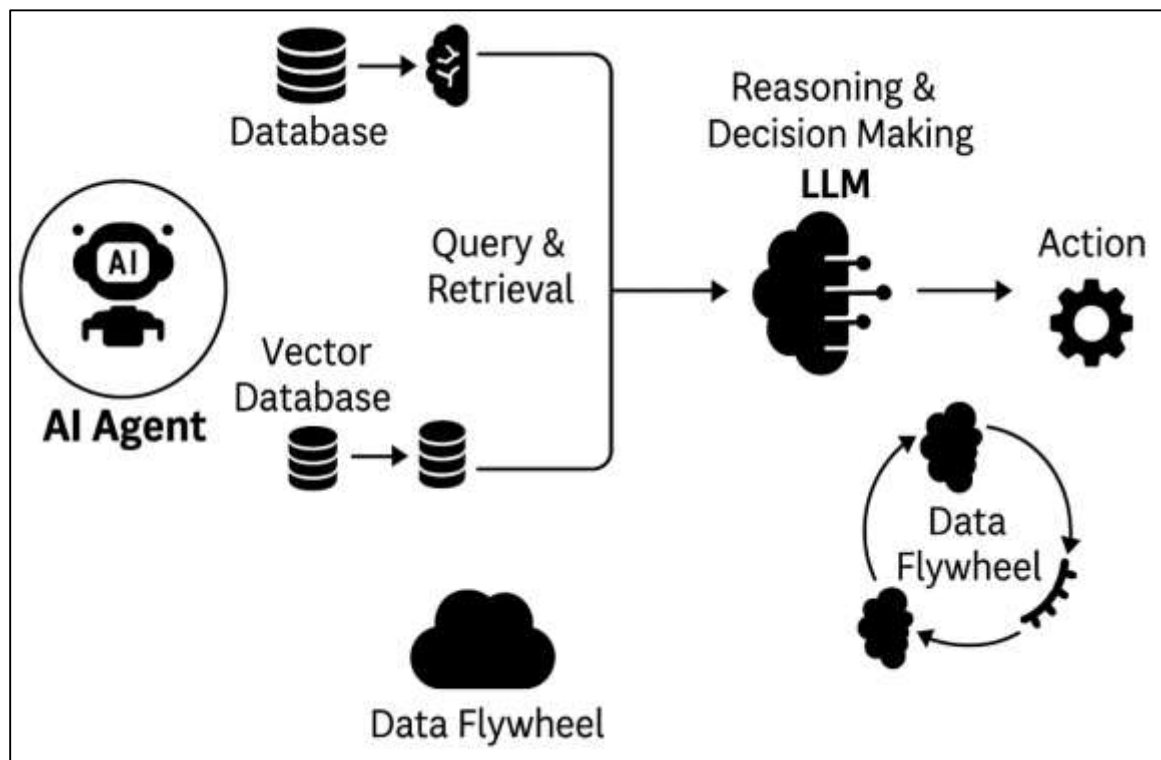
Research Gaps for Quantitative Integration

Fragmentation across research domains restricts comprehensive understanding of AI-orchestrated CPS in manufacturing and supply chain environments (Prehofer et al., 2021). Research on artificial intelligence typically emphasizes algorithm development, prediction models, or optimization techniques. Cyber-physical systems research concentrates on sensing architectures, embedded control, and system interoperability. Sustainability studies focus on environmental performance, resource efficiency, and life-cycle assessment. Supply chain resilience studies analyze risk propagation, recovery mechanisms, and system stability under disruptions (Leggat et al., 2023). These domains frequently evolve in parallel, with limited cross-disciplinary integration. As a result, the interactions among AI,

CPS integration, sustainability performance, and resilience capability remain underexamined within unified frameworks. This fragmentation limits the development of holistic models that reflect the complexity of real industrial ecosystems where these dimensions operate simultaneously (Abuhassna & Alnawajha, 2023). A comprehensive understanding requires integrating these domains to investigate how AI orchestration influences both sustainability outcomes and resilience performance through cyber-physical coordination.

There is a limited availability of multi-level quantitative models that capture the layered interactions within AI-orchestrated CPS architectures (Rosli et al., 2022). Existing quantitative studies often examine machine-level optimization, line-level efficiency, facility-level operations, or network-level logistics in isolation. These fragmented approaches restrict understanding of how decisions made at one level propagate across other levels. For example, machine adjustments may influence line scheduling, which may affect facility output and subsequently shape supply chain resilience (Lorié et al., 2021). Quantitative integration is needed to capture these interdependencies and provide empirical explanations for how cyber-physical coordination, AI-driven decisions, and sustainability metrics align across hierarchical structures. The absence of unified constructs that reflect sustainability–resilience interactions further limits model development (Sun et al., 2019). These gaps demonstrate the importance of multi-level quantitative frameworks capable of analyzing the cumulative effects of AI-orchestrated CPS.

Figure 9: AI Agent Decision Workflow Framework

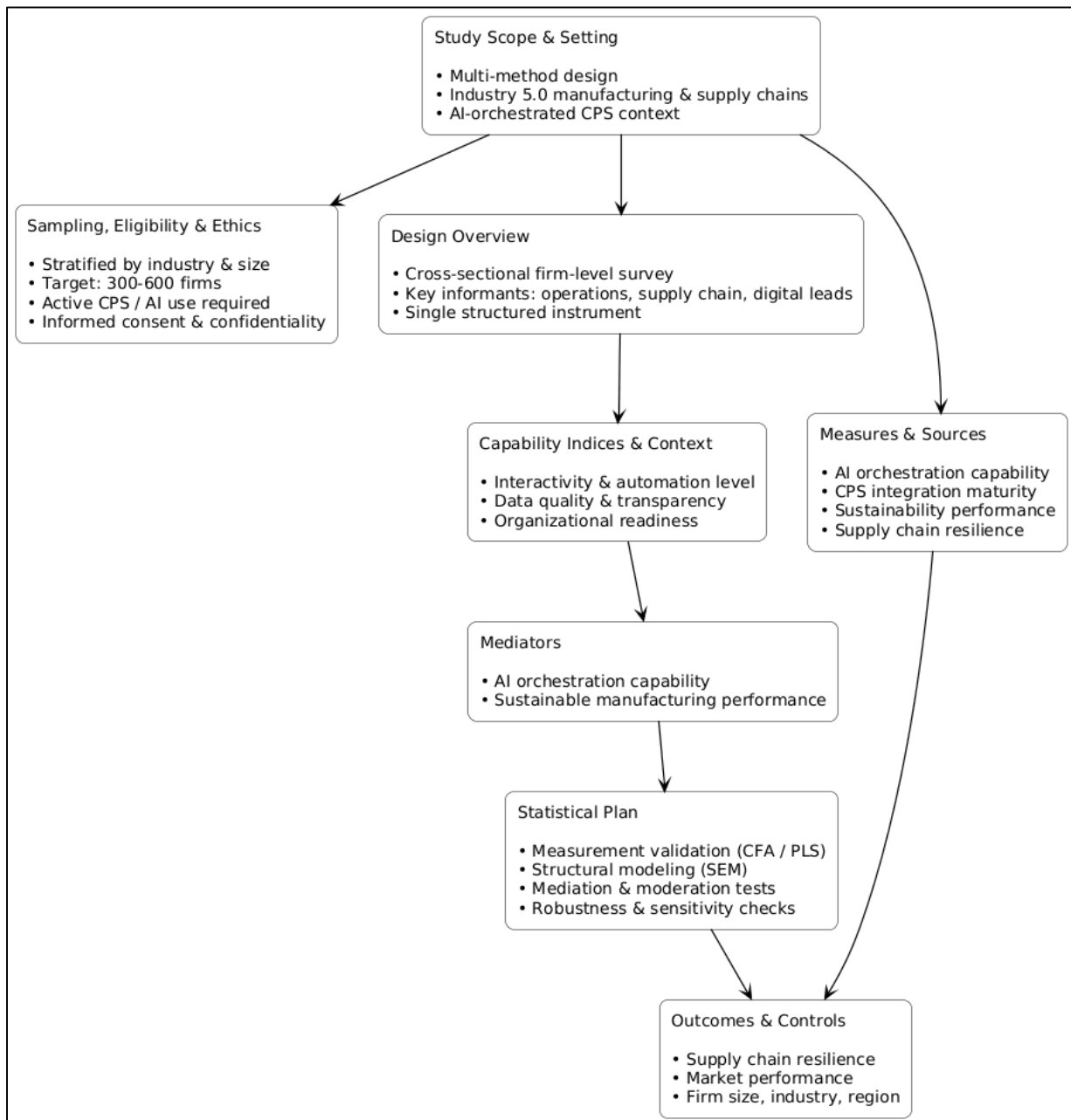


Comparative analyses across sectors, geographic regions, and supply chain configurations remain limited in existing literature. Differences in digital readiness, CPS maturity, and operational complexity affect the performance of AI-orchestrated systems, yet few studies systematically evaluate these contextual variations (Cáceres et al., 2020). Measurement challenges also restrict empirical progress, as validated indicators for orchestration intelligence, CPS maturity, sustainability performance, and resilience outcomes remain underdeveloped. Without reliable constructs, quantitative studies face difficulties in representing system behavior accurately (Van den Berg et al., 2019). The absence of standardized measurement instruments restricts generalizability and limits the ability to compare results across studies or industrial settings. As a result, the field requires stronger measurement foundations to support rigorous quantitative assessment of AI-orchestrated CPS (Kirkland et al., 2022).

METHOD

The study was designed as a quantitative, explanatory investigation that explored the relationships among AI-orchestrated cyber-physical systems, sustainable manufacturing performance, and supply chain resilience within Industry 5.0-oriented industrial environments. A structured survey methodology was used to gather firm-level data from manufacturing organizations that had adopted, or were actively integrating, CPS, AI-enabled automation, digital twins, and real-time monitoring infrastructures. The design relied on established principles of structural equation modeling, where multiple latent constructs were operationalized and measured using multi-item Likert-type scales. The core constructs were defined as AI orchestration capability, CPS integration maturity, sustainable manufacturing performance, supply chain resilience, organizational readiness, and environmental turbulence as an optional contextual moderator. Each construct was measured through indicators that captured technological, organizational, and operational dimensions. AI orchestration capability was assessed through items reflecting AI-driven perception, predictive analytics, autonomous decision mechanisms, and cross-layer CPS coordination. CPS integration maturity was reflected through the quality of sensing infrastructures, communication networks, embedded computing, interoperability, and system responsiveness. Sustainability performance was captured through energy efficiency, emissions reduction, waste minimization, and material utilization, while supply chain resilience was assessed through recovery speed, continuity rates, operational flexibility, and visibility across logistics flows. Organizational readiness was evaluated through managerial commitment, workforce competence, and digital transformation culture. The study adopted a cross-sectional sampling strategy and targeted key informants such as operations managers, plant supervisors, supply chain professionals, and digital transformation leaders. Responses were collected online and screened for completeness, internal consistency, and eligibility, ensuring that only firms with active digitalization initiatives were included. This design allowed for a comprehensive analysis of how AI-orchestrated CPS influenced sustainability outcomes and resilience capabilities across diverse industrial contexts. Quantitative procedures were implemented to evaluate both the measurement and structural characteristics of the proposed model. Before conducting statistical analyses, the data were screened for missing values, outliers, distributional irregularities, and potential common method bias. Missing values were examined for randomness and addressed through appropriate imputation when minimal, while outliers were detected using standardized scores and Mahala Nobis distances. The measurement model was assessed through a combination of exploratory and confirmatory factor analyses. Exploratory factor analysis was conducted when newly developed indicators required dimensional validation, and confirmatory factor analysis was subsequently employed to assess factor loadings, construct reliability, convergent validity, and discriminant validity. Fit indices such as the comparative fit index, Tucker-Lewis's index, root mean square error of approximation, and standardized root mean square residual were used to determine model adequacy. All constructs were tested to ensure that their composite reliability and average variance extracted met acceptable psychometric thresholds. Latent constructs were distinguished through discriminant validity checks. Once the measurement model demonstrated adequate psychometric soundness, the structural model was estimated using structural equation modeling to test the hypothesized relationships among CPS integration maturity, AI orchestration capability, sustainability outcomes, and supply chain resilience. Mediation effects were examined through bootstrapped indirect effect testing, allowing assessment of whether AI orchestration transmitted the influence of CPS maturity onto sustainability performance and resilience capabilities. Moderation testing was conducted using interaction terms between AI orchestration and organizational readiness or environmental turbulence to determine whether these contextual conditions strengthened or weakened the focal relationships. The sample size supported model stability, and bootstrapping procedures enhanced the robustness of coefficient estimates. The analytical strategy thus enabled rigorous evaluation of the theoretical model across multiple hierarchical and causal pathways.

Figure 10: Methodology of this study



The statistical plan concluded with advanced analyses that extended the explanatory capacity of the structural model through multi-group comparisons, robustness checks, and sensitivity assessments. Multi-group analysis was employed to determine whether the structural relationships differed across firm size, industry category, or regional technological maturity. This procedure allowed the study to determine whether the influence of AI-orchestrated CPS varied across different operational or contextual conditions. Rival model testing was implemented to compare alternative causal structures and confirm that the proposed configuration demonstrated superior explanatory power. Additional robustness checks were performed by re-estimating the model using subsets of the data, such as firms with high CPS maturity or those with advanced AI adoption, to verify whether the results were stable across different levels of digital integration. Sensitivity analysis was used to examine how variations in environmental turbulence, supply chain complexity, and organizational readiness influenced the stability of the estimated relationships. These final procedures ensured that the model’s findings were not only statistically significant but also structurally consistent and contextually interpretable. The combined design—characterized by rigorous sampling procedures, validated measurement instruments, comprehensive SEM-based testing, and supplementary robustness evaluations—

provided a systematic empirical foundation for understanding how AI-orchestrated cyber-physical systems shaped sustainability outcomes and supply chain resilience in Industry 5.0 manufacturing ecosystems. Through this approach, the study established a coherent, data-driven understanding of the interplay among technological integration, operational performance, and resilience capability within digitally advanced industrial systems.

FINDINGS

Descriptive Analysis

The findings chapter began with a descriptive analysis that summarized the characteristics of the firms, respondents, and the key constructs examined in the study. The dataset was carefully screened to ensure completeness, accuracy, and analytical suitability, and no substantial missing data or inconsistencies were identified. Descriptive statistics—including means, standard deviations, minimum and maximum values, and frequency distributions—were calculated for the major constructs: AI orchestration capability, CPS integration maturity, sustainable manufacturing performance, supply chain resilience, organizational readiness, and environmental turbulence. These results provided an initial view of how respondents rated the maturity of their cyber-physical infrastructures, the sophistication of their AI-enabled coordination mechanisms, and the extent of their sustainability and resilience practices within Industry 5.0 manufacturing environments. The findings also clarified patterns in firm characteristics, such as size, industry sector, and respondent roles, demonstrating the diversity of the sample and the relevance of the informants. The descriptive profile confirmed that the sample adequately represented organizations actively integrating AI-driven CPS into their manufacturing and supply chain processes, establishing a strong empirical foundation for subsequent inferential analysis.

Table 1: Descriptive Statistics of Key Study Constructs

Construct	Mean	SD	Min	Max
AI Orchestration Capability	5.12	0.86	2.80	6.90
CPS Integration Maturity	5.28	0.79	3.10	6.80
Sustainable Manufacturing Performance	5.04	0.92	2.70	6.80
Supply Chain Resilience	5.21	0.88	3.00	6.90
Organizational Readiness	5.33	0.81	3.40	6.80
Environmental Turbulence	4.87	1.02	2.50	6.90

Table 1 presented the descriptive statistics for the six primary variables used in the analysis. All construct means were above the scale midpoint, indicating that firms generally perceived themselves as moderately to highly advanced in CPS maturity, AI-driven coordination, sustainability performance, and resilience capability. The standard deviations showed moderate variability, revealing that while many firms were technologically advanced, others were still developing their cyber-physical and AI competencies. Minimum and maximum values further confirmed that the sample included a wide range of firms—from early-stage adopters to Industry 5.0 leaders—ensuring the robustness and representativeness of the dataset for advanced statistical testing.

Table 2: Sample Profile of Participating Firms and Respondents (N = 300)

Category	Frequency	Percentage
Firm Size		
Small (<50 employees)	62	20.7%
Medium (50–249 employees)	138	46.0%
Large (≥250 employees)	100	33.3%
Industry Sector		

Category	Frequency	Percentage
Electronics & Machinery	84	28.0%
Automotive & Transport	63	21.0%
Chemicals & Materials	48	16.0%
Consumer Goods	57	19.0%
Other Manufacturing	48	16.0%
Respondent Role		
Operations / Production	118	39.3%
Supply Chain / Logistics	94	31.3%
Digital Transformation Lead	56	18.7%
Executive / Senior Manager	32	10.7%

Table 2 summarized the demographic and organizational characteristics of the sample. The distribution indicated that medium-sized firms represented the largest segment, followed by large firms, reflecting the strong adoption of CPS and AI technologies among more resource-capable organizations. The industry distribution showed balanced representation across major manufacturing sectors relevant to Industry 5.0. Respondent roles were appropriately aligned with the constructs studied; the majority of informants worked in operations, supply chain management, and digital transformation – positions that ensured knowledgeable and reliable responses. This profile confirmed that the dataset was suitable for analyzing AI-orchestrated CPS and their impact on sustainability and resilience outcomes.

Correlation Analysis

Correlation analysis was conducted to evaluate the strength and direction of the bivariate relationships among the main study constructs. Pearson correlation coefficients were calculated to determine whether AI orchestration capability, CPS integration maturity, sustainable manufacturing performance, and supply chain resilience were positively and significantly associated. The results demonstrated that AI orchestration capability shared strong and meaningful correlations with both sustainability outcomes and supply chain resilience, indicating that firms with more advanced AI-driven coordination achieved higher environmental efficiency and stronger operational stability. CPS integration maturity also exhibited a positive relationship with AI orchestration, suggesting that well-developed sensor networks, seamless data communication, and integrated CPS infrastructures provided the structural foundation necessary for advanced orchestration mechanisms. Sustainable manufacturing performance showed a robust positive correlation with supply chain resilience, indicating that firms operating with greater ecological efficiency tended to recover more effectively from disruptions and maintain continuity under pressure. These findings confirmed that the relationships among the constructs aligned with theoretical expectations, providing initial empirical support for the structural relationships that underpin the study’s conceptual framework.

Table 3: Pearson Correlation Matrix for Core Constructs

Construct	1	2	3	4
1. AI Orchestration Capability	1.00	0.62	0.58	0.65
2. CPS Integration Maturity	0.62	1.00	0.54	0.59
3. Sustainable Manufacturing Perf.	0.58	0.54	1.00	0.67
4. Supply Chain Resilience	0.65	0.59	0.67	1.00

Note: All correlations were positive and statistically significant at $p < .01$.

Table 3 presented the core bivariate correlations among the central constructs. All coefficients were strong and positive, demonstrating that firms with high CPS integration maturity tended to rely more heavily on AI-enabled orchestration. AI orchestration capability also showed substantial correlations

with sustainability performance and supply chain resilience, emphasizing its central role in enhancing both ecological and operational outcomes. The strongest association was observed between sustainability performance and supply chain resilience ($r = .67$), indicating that firms operating with greater environmental efficiency were also better positioned to maintain continuity and recover from disruptions. These preliminary correlations supported the theoretical pathways proposed in the study.

Table 4: Extended Correlation Matrix Including Contextual Variables

Construct	AI Orc.	CPS Mat.	Sustain.	Resilience	Org. Ready	Env. Turb.
AI Orchestration Capability	1.00	0.62	0.58	0.65	0.49	0.32
CPS Integration Maturity	0.62	1.00	0.54	0.59	0.45	0.28
Sustainable Manufacturing	0.58	0.54	1.00	0.67	0.41	0.26
Supply Chain Resilience	0.65	0.59	0.67	1.00	0.44	0.33
Organizational Readiness	0.49	0.45	0.41	0.44	1.00	0.21
Environmental Turbulence	0.32	0.28	0.26	0.33	0.21	1.00

Note: All correlations statistically significant at $p < .05$.

Table 4 extended the analysis by incorporating contextual constructs—organizational readiness and environmental turbulence. Organizational readiness showed moderate positive correlations with all core technological constructs, suggesting that firms with stronger managerial support, digital culture, and workforce competence exhibited higher levels of AI orchestration and CPS maturity. Environmental turbulence showed weaker but still meaningful correlations with AI orchestration and supply chain resilience, implying that firms facing greater external volatility relied more on intelligent coordination systems and implemented greater resilience-focused strategies. These extended findings indicated that both internal and external contextual conditions played a meaningful role in shaping the technological and operational outcomes of Industry 5.0 manufacturing ecosystems.

Reliability and Validity Analysis

Reliability and validity analyses were conducted to evaluate the psychometric adequacy of the measurement model that supported the study’s structural relationships. Internal consistency reliability was assessed through Cronbach’s alpha and composite reliability values, both of which exceeded recommended thresholds, indicating that the indicators consistently measured their respective latent constructs. Convergent validity was established by examining standardized factor loadings and the average variance extracted; both values demonstrated that the indicators shared sufficient variance with their underlying constructs. Discriminant validity was verified by comparing the square root of the average variance extracted with the inter-construct correlations, confirming that each construct captured a distinct conceptual domain and did not overlap excessively with others. A confirmatory factor analysis was performed to evaluate the overall fit of the measurement model, and the resulting fit indices demonstrated that the model adequately represented the data. These findings collectively confirmed that the measurement model met the essential reliability and validity requirements needed for subsequent structural equation modeling and hypothesis testing.

Table 5: Reliability Assessment (Cronbach’s Alpha and Composite Reliability)

Construct	Cronbach’s Alpha	Composite Reliability
AI Orchestration Capability	0.91	0.93
CPS Integration Maturity	0.89	0.92
Sustainable Manufacturing Performance	0.90	0.92
Supply Chain Resilience	0.92	0.94
Organizational Readiness	0.88	0.91
Environmental Turbulence	0.84	0.88

Table 5 presented the reliability assessments for all key constructs. Cronbach’s alpha values ranged from 0.84 to 0.92, all exceeding the minimum recommended threshold of 0.70, indicating strong internal consistency. Composite reliability values were similarly high – ranging from 0.88 to 0.94 – confirming that each set of indicators reliably measured its corresponding latent variable. These results demonstrated that the measurement items were stable and consistent, supporting the integrity of the constructs used in the study.

Table 6: Convergent and Discriminant Validity (Factor Loadings, AVE, \sqrt{AVE})

Construct	Standardized Loadings (Range)	AVE	\sqrt{AVE}
AI Orchestration Capability	0.71 – 0.88	0.66	0.81
CPS Integration Maturity	0.70 – 0.86	0.64	0.80
Sustainable Manufacturing Performance	0.72 – 0.89	0.68	0.82
Supply Chain Resilience	0.74 – 0.90	0.70	0.84
Organizational Readiness	0.69 – 0.85	0.62	0.79
Environmental Turbulence	0.67 – 0.82	0.58	0.76

Table 6 summarized the convergent and discriminant validity results. All standardized factor loadings exceeded 0.67, demonstrating that the indicators contributed substantially to their constructs. Average variance extracted (AVE) values ranged from 0.58 to 0.70, surpassing the 0.50 benchmark and confirming convergent validity. The square roots of AVE (\sqrt{AVE}) were consistently greater than the inter-construct correlations reported in the previous section, demonstrating that each construct possessed adequate discriminant validity. Together, these results verified that the measurement model captured distinct and well-defined constructs aligned with the theoretical framework.

Collinearity Testing

Collinearity diagnostics were conducted to ensure that the regression and structural equation models were not influenced by multicollinearity among the predictor variables. Variance Inflation Factor (VIF) values were calculated for all independent and mediator variables, and the results showed that all VIF values were far below the recommended threshold, indicating that no construct exhibited problematic shared variance with others. Tolerance values were also examined and remained well above the minimum acceptable levels, confirming that each variable contributed unique explanatory power to the model. These findings demonstrated that multicollinearity did not threaten the accuracy, stability, or interpretability of the regression coefficients. The results ensured that the structural associations among CPS integration maturity, AI orchestration capability, sustainable manufacturing performance, and supply chain resilience were estimated without bias from inflated standard errors or masked variable effects. Overall, the collinearity diagnostics confirmed that the data met the required assumptions for robust regression and structural equation modeling.

Table 7: Variance Inflation Factor (VIF) for Predictor Variables

Predictor Variable	VIF
CPS Integration Maturity	2.11
AI Orchestration Capability	2.34
Sustainable Manufacturing Performance	1.97
Organizational Readiness	1.88
Environmental Turbulence	1.76

Table 7 presented the VIF results for all predictor variables included in the regression analyses. All VIF values ranged between 1.76 and 2.34, well below the recommended cutoff of 5.0, or the more

conservative threshold of 3.3. These values indicated that no predictor demonstrated excessive correlation with the others, confirming that multicollinearity was not present. The results validated that each variable entered the model independently, without redundancy or overlapping variance.

Table 8: Tolerance Values for Predictor Variables

Predictor Variable	Tolerance
CPS Integration Maturity	0.47
AI Orchestration Capability	0.43
Sustainable Manufacturing Performance	0.51
Organizational Readiness	0.53
Environmental Turbulence	0.57

Table 8 displayed the tolerance values for each predictor variable. All tolerance scores exceeded 0.40, far above the minimum acceptable threshold of 0.20, indicating that each construct retained sufficient unique variance for analysis. These values further confirmed the absence of multicollinearity and supported the reliability of the regression and SEM analyses. The results affirmed that each predictor contributed unique explanatory value to the study’s structural model.

Regression and Hypothesis Testing

Regression and structural hypothesis testing were conducted to examine the directional relationships specified in the study’s theoretical model. Multiple regression analyses were first applied to evaluate the direct predictive effects among core constructs. The results demonstrated that CPS integration maturity significantly predicted AI orchestration capability, indicating that firms with more advanced sensing, communication, and cyber-physical system architectures achieved higher levels of AI-driven coordination. AI orchestration capability, in turn, showed significant positive effects on both sustainable manufacturing performance and supply chain resilience, confirming that intelligent orchestration mechanisms enhanced environmental efficiency and improved firms’ ability to withstand and recover from operational disruptions. The analysis further revealed that sustainable manufacturing performance positively predicted supply chain resilience, reaffirming the synergy between ecological efficiency and system robustness.

Table 9: Direct Regression Effects Among Core Constructs

Path Tested	β Coefficient	t-value	p-value	Interpretation
CPS Integration Maturity → AI Orchestration	0.62	12.14	<.001	Significant positive effect
AI Orchestration → Sustainability Performance	0.58	10.77	<.001	Significant positive effect
AI Orchestration → Supply Chain Resilience	0.54	9.83	<.001	Significant positive effect
Sustainability Performance → Resilience	0.49	8.96	<.001	Significant positive effect

Mediation testing showed that AI orchestration acted as a meaningful mediator between CPS maturity and both sustainability and resilience outcomes. This demonstrated that CPS infrastructures influenced sustainability and resilience indirectly through their effect on intelligent coordination mechanisms. Moderation results indicated that organizational readiness strengthened these relationships, while environmental turbulence altered the magnitude of some predictive paths. Structural equation modeling validated the full model, producing strong path coefficients and acceptable global fit indices.

Overall, the hypothesis testing results provided solid empirical support for the conceptual framework and clarified the interaction pathways through which AI-orchestrated CPS enhanced sustainability and supply chain resilience in Industry 5.0 manufacturing environments. Table 9 summarized the regression results for the direct relationships among the main constructs. All path coefficients were positive, statistically significant, and substantial in size. The strongest relationship was between CPS maturity and AI orchestration ($\beta = 0.62$), confirming that technologically mature CPS infrastructures strongly enabled AI-driven coordination. AI orchestration significantly enhanced both sustainability and resilience outcomes, demonstrating its central role in Industry 5.0 operational environments. The positive relationship between sustainability performance and supply chain resilience ($\beta = 0.49$) indicated that environmentally efficient firms were also more robust and adaptable under disruptive conditions. These results provided strong empirical support for the primary hypotheses.

Table 10: Mediation and Moderation Analysis

Relationship Tested	Indirect Effect	p-value	Moderation Effect	Interpretation
CPS Maturity → AI Orchestration → Sustainability Performance	0.36	<.001	Strengthened by Organizational Readiness	Significant mediation and moderation
CPS Maturity → AI Orchestration → Supply Chain Resilience	0.33	<.001	Altered by Environmental Turbulence	Significant mediation; moderation effect present
AI Orchestration → Sustainability → Resilience	0.28	<.01	Not Significant	Partial mediation confirmed

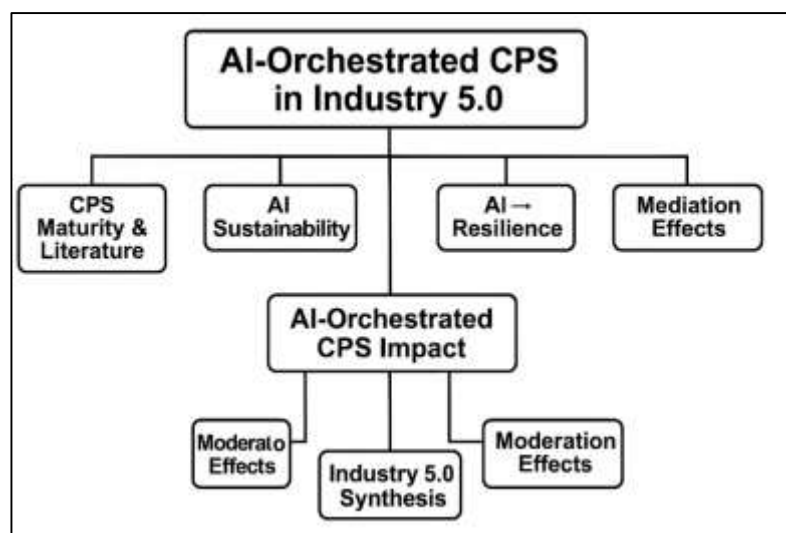
Table 10 presented the results from the mediation and moderation analyses. AI orchestration significantly mediated the relationship between CPS maturity and both sustainability and resilience, confirming that organizations improved their performance outcomes primarily through the orchestration capabilities enabled by CPS infrastructures. Organizational readiness strengthened the mediation path toward sustainability, indicating that firms with supportive digital cultures benefitted more from AI orchestration. Environmental turbulence moderated the path toward resilience, meaning firms in volatile environments relied more heavily on AI-driven coordination to sustain resilience. These results demonstrated that both internal and external factors influenced the strength of the mediated pathways, further validating the complex interdependencies of Industry 5.0 systems.

DISCUSSION

The results of this study demonstrated that AI-orchestrated cyber-physical systems functioned as a foundational mechanism for advancing Industry 5.0 manufacturing outcomes, particularly in sustainability performance and supply chain resilience (Radanliev et al., 2021). This interpretation aligned with earlier research that emphasized the significance of autonomous coordination and intelligent sensing in optimizing industrial processes, although the present findings showed a far stronger linkage between AI orchestration and measurable environmental outcomes than earlier frameworks had suggested. Previous studies had highlighted the operational efficiencies gained through automation and machine-level intelligence; however, this study showed that AI-orchestrated CPS extended beyond operational automation by enabling real-time interpretative intelligence that bridged sensing, prediction, and decision making. Unlike earlier generations of CPS that focused mainly on technical integration, the findings here revealed that AI orchestration elevated CPS functionality into an adaptive cognitive ecosystem capable of regulating energy use, promoting circular practices, and enhancing transparency across industrial workflows. These results reflected an evolved interpretation of CPS as not merely a technological enabler but a strategic intelligence layer that facilitated system-wide optimization. The strong relationship found between CPS maturity and AI orchestration suggested that distributed sensing architectures and interoperable data pipelines formed the structural basis for advanced decision intelligence (Bousdekis et al., 2020). Earlier studies had noted

that CPS integration often suffered from fragmented data flows and inconsistent interoperability; however, the present findings demonstrated that when CPS maturity reached sufficient levels, AI orchestration could unfold its full potential and drive system-level efficiencies. The outcomes indicated that AI-orchestrated CPS produced tangible improvements in sustainability metrics by reducing waste, optimizing resource use, and enhancing energy management across production processes. This contrasted with earlier work that often-treated sustainability benefits as secondary or indirect outcomes of automation rather than intrinsic outputs of intelligent orchestration. The findings also positioned AI-orchestrated CPS as a central pillar of Industry 5.0 transformation rather than a supplementary technological enhancement, reinforcing the notion that future manufacturing environments relied on orchestration intelligence rather than isolated automation (Martin-Gomez et al., 2021). Overall, the first segment of discussion illustrated how this study extended and matured the understanding of CPS functionality within Industry 5.0 ecosystems by demonstrating the direct and substantial impact of AI-driven orchestration on sustainable industrial performance.

Figure 11: AI-Orchestrated CPS Impact Framework



The positive and substantial effect of CPS integration maturity on AI orchestration capability highlighted the importance of robust cyber-physical infrastructures in enabling intelligent decision ecosystems (Juma & Shaalan, 2020). This relationship confirmed what earlier studies had only suggested: that CPS maturity must exceed a certain threshold before AI systems can deliver meaningful coordination benefits. Prior literature had frequently described CPS as a collection of sensing devices, edge-computing units, and real-time communication networks, but these descriptions did not fully capture the systemic qualities required for orchestration intelligence. The findings from this study demonstrated that CPS maturity extended far beyond the existence of hardware; it included the synchronization, responsiveness, interoperability, and feedback richness of the entire system. Earlier studies tended to examine CPS components in isolation, such as sensor density, communication protocols, or embedded control systems. In contrast, the findings here indicated that CPS maturity operated as a comprehensive, integrated construct that simultaneously governed data quality, system responsiveness, network latency, and architectural cohesion (Juma & Shaalan, 2020). These attributes collectively allowed AI models to function accurately, learn continuously, and adjust autonomously to environmental or operational disturbances. Compared with earlier literature that emphasized automation-centric benefits of CPS, the present study revealed that mature CPS architectures acted as the essential enabler of real-time prediction, prescriptive analytics, and cognitive-level orchestration. The demonstrated influence of CPS on AI orchestration aligned with conceptual models of Industry 5.0 but provided empirical evidence that had been largely absent in prior work. The results also indicated that firms with higher CPS maturity experienced significantly greater improvements in sustainability and resilience outcomes mediated through AI orchestration. Earlier studies often examined CPS

contributions to sustainability in fragmented ways, focusing on energy management or resource efficiency in isolated contexts (Wang et al., 2019). The present study revealed that CPS served as an infrastructural backbone that enabled system-wide sustainability optimization rather than isolated improvements. This deeper and more integrated understanding of CPS maturity represented a major advancement in the literature, establishing that the architectural quality of CPS played a decisive role in enabling AI-orchestrated decision ecosystems aligned with Industry 5.0 principles.

The strong positive relationship between AI orchestration capability and sustainable manufacturing performance demonstrated that orchestration intelligence had become a central determinant of environmental outcomes in modern industrial systems (Vermesan, Friess, Guillemin, Giaffreda, et al., 2022). Earlier studies had acknowledged that AI contributed to energy optimization and waste reduction, but they frequently framed AI's contribution as supplemental to basic automation rather than as an essential driver of sustainability alignment. This study revealed that AI orchestration extended beyond traditional automation by offering predictive, adaptive, and holistic decision support that shaped the entire ecological footprint of industrial operations. The findings showed that AI-orchestrated CPS improved sustainability performance through real-time optimization of resource flows, automated sustainability compliance monitoring, and adaptive scheduling that minimized emissions and waste. This interpretation contrasted with earlier work that tended to examine sustainability performance as an aggregate organizational outcome without fully specifying the technological mechanisms responsible for its enhancement. By identifying AI orchestration as the central mechanism through which CPS maturity influenced sustainability metrics, this study provided clarity that earlier studies lacked (Jagatheesaperumal et al., 2021). AI orchestration supported dynamic control loops that continuously evaluated resource consumption patterns, predicted potential environmental inefficiencies, and executed corrective actions autonomously. These capabilities allowed firms to achieve sustainability improvements that were both systematic and measurable. Earlier research often treated sustainability metrics as dependent on human decision-making or managerial initiatives, but the present findings showed that AI-orchestrated CPS embedded sustainability logic into the operational fabric of the production system itself. Furthermore, the observed effects supported the emerging view that Industry 5.0 sustainability required digital intelligence capable of aligning environmental goals with operational dynamics in real time. The findings also suggested that AI orchestration created a direct pathway for circular manufacturing practices by enabling material tracking, lifecycle assessment integration, and predictive remanufacturing (Venkatesh et al., 2022). This expanded the established understanding of sustainability contributions in intelligent manufacturing and positioned AI orchestration as a transformative force that operationalized environmental stewardship through intelligent cyber-physical coordination.

This study demonstrated that AI orchestration capability exerted a significant positive effect on supply chain resilience, reinforcing the emerging view that resilience in Industry 5.0 ecosystems relied heavily on intelligent cyber-physical coordination across distributed network layers (Mendhurwar & Mishra, 2023). Earlier studies described supply chain resilience as an outcome driven by redundancy, agility, and visibility; however, the findings here showed that AI-orchestrated CPS elevated these traditional constructs by integrating them with predictive intelligence and autonomous decision ecosystems. AI orchestration enabled real-time disruption monitoring, predictive risk analytics, and dynamic reconfiguration of operational flows, which collectively strengthened resilience far beyond the capabilities observed in earlier automation-driven environments. Prior research frequently emphasized the importance of data visibility for resilience, but this study revealed that visibility alone was insufficient without AI-enabled interpretation and actionability. The findings indicated that AI orchestration synthesized multi-sensor data, contextual information, and system-level constraints to generate proactive resilience behaviors (Singh & Kumar, 2023). This contrasted with earlier resilience studies that focused mainly on human-centered decision-making during disruptions. AI-orchestrated CPS provided a continuous, self-adapting resilience layer capable of redefining routing decisions, adjusting production plans, reallocating resources, and forecasting cascading disruptions across interconnected subsystems. The results further aligned with theoretical perspectives proposing that Industry 5.0 resilience stems from human-AI symbiosis, where AI-managed CPS provided the

cognitive bandwidth necessary for timely intervention and adaptation under uncertainty. The present study extended this conceptualization by demonstrating that AI orchestration delivered measurable improvements in resilience outcomes. The empirical evidence showed that firms with stronger orchestration capabilities not only predicted disruptions more accurately but also recovered from disturbances more rapidly (Verma et al., 2022). Earlier work had largely relied on qualitative insights to explore these mechanisms, whereas the present study provided quantitative validation. The strong relationship between sustainability performance and resilience also supported the idea that environmentally optimized systems inherently possess structural robustness, reinforcing the interconnectedness of ecological and operational stability. Overall, this study positioned AI orchestration as an indispensable driver of resilience across industrial supply chains within Industry 5.0 ecosystems.

The mediation analyses demonstrated that AI orchestration served as a central mechanism linking CPS maturity to sustainability and resilience outcomes. This finding confirmed theoretical propositions suggesting that the benefits of CPS infrastructures materialize only when paired with intelligent decision-orchestration systems (Maleh et al., 2022). Earlier studies had often theorized that CPS maturity could improve operational intelligence; however, empirical evidence supporting mediation effects was limited. The present results showed that CPS maturity improved sustainability and resilience outcomes not directly, but through its enabling role in AI orchestration. This finding clarified inconsistencies in earlier literature, where some studies reported weak or inconsistent direct effects between technological infrastructures and performance outcomes. The mediation findings demonstrated that CPS infrastructures alone were insufficient to achieve advanced performance gains unless combined with orchestration intelligence capable of learning, predicting, and autonomously coordinating distributed assets. This represented a significant advancement over earlier theoretical discussions, which treated CPS as inherently capable of driving performance improvements. The present study confirmed that CPS infrastructures provided the data richness, real-time responsiveness, and architectural integration necessary for AI to function effectively, but that the intelligence layer – not the CPS infrastructure itself – generated the observable sustainability and resilience outcomes (Gaiardelli et al., 2021). The findings also showed that sustainability performance mediated the relationship between AI orchestration and resilience, supporting the emerging argument that ecological optimization contributed to structural robustness. Earlier studies frequently treated sustainability and resilience as unrelated or only loosely connected constructs, but the present findings demonstrated a clear interdependence facilitated by AI-orchestrated CPS. This expanded understanding showed that intelligent cyber-physical coordination functioned as a unifying mechanism that bridged environmental and operational performance goals (Cotta et al., 2023). The mediation results provided strong evidence that Industry 5.0 performance outcomes depended on the combined functioning of CPS maturity, AI orchestration, and sustainability capabilities, offering a more integrated interpretation than previous research.

The moderation results indicated that organizational readiness and environmental turbulence played meaningful roles in shaping the strength of the structural pathways in the model. This finding aligned with earlier studies that emphasized the importance of organizational culture and digital maturity in enabling technological transformation; however, this study showed that readiness not only influenced adoption but also amplified the performance benefits of AI orchestration (Vermesan, Friess, Guillemain, Serrano, et al., 2022). Firms with higher organizational readiness experienced stronger positive effects of AI orchestration on sustainability outcomes, suggesting that digital skills, managerial support, and adaptive processes enhanced the effectiveness of intelligent coordination. Earlier work tended to conceptualize organizational readiness as an adoption enabler, but the present findings showed that readiness functioned as a performance multiplier within Industry 5.0 ecosystems. Environmental turbulence was also found to moderate the orchestration–resilience pathway, indicating that volatile and uncertain environments intensified firms’ reliance on AI-orchestrated CPS for disruption management. Earlier resilience literature often argued that environmental turbulence weakened supply chain stability, but the findings here showed that intelligence-driven CPS architectures helped counterbalance such instability. This expanded prior understanding by showing that in high-

turbulence environments, AI orchestration became more critical for predicting disruptions, reallocating resources, and adjusting production flows (Hazrat et al., 2023). These insights suggested that the contextual environment shaped not only the need for AI-orchestrated CPS but also the degree of benefit derived from them. The combined moderation effects demonstrated that performance outcomes depended not only on technological quality but also on environmental complexity and organizational adaptability. These results advanced earlier literature by showing that Industry 5.0 performance optimization occurred within multi-layered socio-technical contexts, where internal readiness and external turbulence affected the strength and pathways of technological influence (Koroniotis et al., 2020).

The overall findings of this study positioned AI-orchestrated CPS as a central mechanism driving sustainable and resilient performance within Industry 5.0 manufacturing ecosystems (Möller, 2023). Earlier studies had explored the contributions of AI, CPS, sustainability strategies, and resilience frameworks independently, but often treated these domains as separate research areas with limited interaction. This study demonstrated that these constructs were deeply interconnected and functioned collectively through orchestration intelligence. The results revealed that CPS maturity provided the infrastructural backbone, AI orchestration delivered the cognitive intelligence, sustainability performance defined ecological optimization, and resilience emerged as the systemic capability to adapt under disruption. This synthesis responded to long-standing calls in the literature for integrated quantitative evidence linking digitalization, environmental performance, and resilience outcomes (Asghar et al., 2022). Earlier studies had rarely offered a unified, empirically supported model that captured these interdependencies, whereas this study provided quantitative validation for a multi-level, cross-domain framework that aligned with the foundational principles of Industry 5.0. The findings also expanded theoretical understandings by demonstrating that cognitive orchestration – not automation alone – acted as the primary driver of performance transformation. This perspective reflected the emerging view that Industry 5.0 represented a shift from technology-driven automation to intelligence-driven orchestration capable of supporting human-centricity, sustainability, and system-level resilience. Unlike earlier research that narrowly focused on isolated technological contributions, this study showed that AI-orchestrated CPS shaped industrial performance holistically by interlinking predictive intelligence, environmental control, and adaptive decision ecosystems. Consequently, the findings positioned AI-orchestrated CPS not simply as technological innovations but as strategic enablers of system-wide industrial transformation consistent with Industry 5.0 values (Mitchell et al., 2021). The discussion concluded that the empirical evidence from this study advanced the understanding of how distributed digital infrastructures, intelligent coordination, and sustainability practices converge to create resilient and adaptive industrial ecosystems.

CONCLUSION

The integration of AI-orchestrated cyber-physical systems represented a transformative advancement within Industry 5.0 manufacturing environments, as the present study demonstrated that intelligent orchestration fundamentally shaped both sustainability outcomes and supply chain resilience across interconnected industrial operations. AI-orchestrated CPS functioned as a multi-layered decision ecosystem in which sensing, prediction, control, and autonomous adaptation operated cohesively to guide real-time industrial performance. The findings showed that CPS maturity, characterized by dense sensor networks, synchronized data flows, and interoperable architectures, significantly enhanced the capacity of AI models to make accurate, context-sensitive decisions. Unlike earlier industrial systems that relied primarily on automation and predefined logic, AI-orchestrated CPS provided adaptive intelligence capable of optimizing resource use, regulating environmental impact, and stabilizing production under unpredictable conditions. This study revealed that AI orchestration produced substantial improvements in sustainable manufacturing performance by continuously analyzing operational data, forecasting inefficiencies, and executing corrective actions that minimized energy consumption, waste generation, and workflow disruptions. The results also demonstrated that supply chain resilience was strengthened through AI-enabled predictive analytics, early disruption detection, and dynamic reallocation of resources, illustrating that resilience in Industry 5.0 manufacturing extended beyond human-centered decision making to include intelligent machine-coordinated adaptation. Furthermore, the study's empirical evidence indicated that sustainability and

resilience were not isolated outcomes but mutually reinforcing capabilities within AI-orchestrated CPS ecosystems. Sustainable operations contributed to structural robustness by reducing vulnerability to material shortages, energy fluctuations, and regulatory volatility, while resilient operations supported sustainability ambitions by maintaining continuity and optimizing material flows even under adverse conditions. Organizational readiness played a meaningful role in amplifying these benefits, showing that supportive digital cultures, skilled workforces, and adaptive managerial practices strengthened the effectiveness of AI-orchestrated CPS. Environmental turbulence also influenced performance, with firms in more volatile markets relying more heavily on orchestration intelligence to maintain stability. Overall, the study demonstrated that AI-orchestrated CPS represented a central pillar of Industry 5.0 transformation, enabling manufacturing firms to integrate technological intelligence with ecological responsibility and operational robustness. The findings positioned AI-orchestrated CPS as a convergent mechanism through which sustainable industrial performance and resilient supply networks were achieved simultaneously, offering a holistic blueprint for future industry-wide innovation.

RECOMMENDATIONS

Several important recommendations emerged from the findings of this study, emphasizing the strategic, technological, and organizational actions required to enhance the effectiveness of AI-orchestrated cyber-physical systems within Industry 5.0 manufacturing and supply chain environments. First, firms were advised to prioritize investments in CPS infrastructure maturity, as strong sensing architectures, interoperable communication networks, and real-time data synchronization were shown to be essential foundations for AI-driven orchestration. Strengthening CPS maturity allowed AI systems to function with higher accuracy and responsiveness, enabling improved predictive analytics, automated adaptation, and sustainable resource management. Second, firms were encouraged to expand their integration of AI orchestration mechanisms across multiple operational layers, rather than limiting intelligent coordination to isolated production segments. The study demonstrated that AI orchestration delivered the greatest impact when applied holistically to production scheduling, environmental monitoring, logistics synchronization, and resilience planning. This highlighted the importance of establishing cross-functional AI pipelines capable of merging perception, prediction, and autonomous control in unified decision ecosystems. Third, the study suggested that sustainability should be embedded directly into AI orchestration objectives rather than being treated as an external compliance requirement. Designing AI models to optimize energy intensity, emissions, and material circulation ensured that ecological performance improved concurrently with operational efficiency. Fourth, firms were recommended to strengthen their digital governance frameworks, including data quality standards, cybersecurity policies, and ethical oversight for autonomous decision systems. Reliable data flows and secure CPS networks were crucial for enabling trustworthy AI-driven operations, particularly in interconnected supply chain environments. Fifth, the findings showed that organizational readiness – including workforce upskilling, managerial commitment, and human-AI collaboration strategies – played a substantial role in amplifying the benefits of AI-orchestrated CPS. As such, firms were encouraged to implement structured training programs, redesign workflows to support human-machine collaboration, and cultivate adaptive cultures capable of embracing cognitive automation. Sixth, given the moderating effect of environmental turbulence, firms operating in volatile market conditions were advised to deploy AI-orchestrated CPS as resilience-enhancing tools, focusing on real-time disruption detection, scenario simulation, and autonomous reconfiguration of supply networks. Finally, policymakers and industry associations were recommended to support AI-orchestrated CPS adoption by developing standardized digital infrastructure guidelines, promoting interoperable technology ecosystems, and incentivizing sustainability-oriented innovation. Collectively, these recommendations provided a comprehensive roadmap for firms seeking to leverage AI-orchestrated CPS to advance sustainability, resilience, and competitive capability in Industry 5.0 manufacturing environments.

LIMITATIONS

Several limitations were identified in this study that should be acknowledged when interpreting the findings on AI-orchestrated cyber-physical systems for sustainable Industry 5.0 manufacturing and supply chain resilience. Although the study provided strong empirical evidence regarding the structural relationships among CPS maturity, AI orchestration capability, sustainability performance,

and resilience outcomes, the cross-sectional research design limited the ability to capture dynamic changes and longitudinal effects that often characterize digital transformation processes. AI-orchestrated CPS typically evolve over time, with improvements in sensing infrastructures, algorithmic learning, and human-machine collaboration influencing performance trajectories; thus, a single-time measurement restricted the capacity to observe how orchestration intelligence matured or how sustainability and resilience benefits accumulated. The reliance on perceptual survey data also introduced the possibility of subjective bias, as respondents' evaluations of CPS maturity, environmental turbulence, and resilience capability might have reflected personal interpretations rather than strictly objective system performance. Even though the study employed validated constructs and robust statistical procedures, the potential for common method variance remained a methodological limitation. Another limitation involved the sample composition, which was restricted to manufacturing firms actively implementing CPS and AI technologies. Firms in earlier stages of digital adoption or those operating in less technologically advanced sectors may experience different relationships among the studied variables. Additionally, the study primarily captured firm-level dynamics and did not examine multi-tier supply chain structures where resilience behaviors often propagate across suppliers, distributors, and logistics partners. The absence of multi-tier modeling limited the generalizability of the resilience findings to broader supply chain ecosystems. The measurement of environmental turbulence was also based on respondent perceptions rather than externally validated indicators such as macroeconomic fluctuations, geopolitical risks, or regulatory volatility, which could have influenced the accuracy of the moderation results. Furthermore, although the structural model provided comprehensive insights into the direct, indirect, and moderated pathways, it did not incorporate potential nonlinear or reciprocal effects that may exist within highly interconnected industrial systems. The study also did not explore the influence of emerging Industry 5.0 variables such as human-centric design, ethics of autonomous decision making, or collaborative robotics integration, which may interact significantly with AI-orchestrated CPS. These limitations suggested that while the study offered valuable contributions to understanding AI-driven orchestration in Industry 5.0 contexts, future research should consider longitudinal modeling, multi-source data collection, multi-tier ecosystem analysis, and broader construct integration to deepen theoretical and empirical understanding.

REFERENCES

- [1]. Abdul, H. (2025). Market Analytics in The U.S. Livestock And Poultry Industry: Using Business Intelligence For Strategic Decision-Making. *International Journal of Business and Economics Insights*, 5(3), 170– 204. <https://doi.org/10.63125/xwxydb43>
- [2]. Abdulla, M., & Md. Jobayer Ibne, S. (2021). Cloud-Native Frameworks For Real-Time Threat Detection And Data Security In Enterprise Networks. *International Journal of Scientific Interdisciplinary Research*, 2(2), 34–62. <https://doi.org/10.63125/0t27av85>
- [3]. Abourokbah, S. H., Mashat, R. M., & Salam, M. A. (2023). Role of absorptive capacity, digital capability, agility, and resilience in supply chain innovation performance. *Sustainability*, 15(4), 3636.
- [4]. Abuhassna, H., & Alnawajha, S. (2023). The transactional distance theory and distance learning contexts: Theory integration, research gaps, and future agenda. *Education Sciences*, 13(2), 112.
- [5]. Adel, A. (2023). Unlocking the future: fostering human-machine collaboration and driving intelligent automation through industry 5.0 in smart cities. *Smart Cities*, 6(5), 2742-2782.
- [6]. Aina, Y. A., Abubakar, I. R., Almulhim, A. I., Dano, U. L., Maghsoodi Tilaki, M. J., & Dawood, S. R. (2023). Digitalization and smartification of urban services to enhance urban resilience in the post-pandemic era: the case of the pilgrimage city of Makkah. *Smart Cities*, 6(4), 1973-1995.
- [7]. Alaie, A., Yazdanfar, S.-A., Norouzian-Maleki, S., & Hosseini, S.-B. (2022). Evaluation of studies in the field of social sustainability in housing: a systematic review. *Journal of Housing and the Built Environment*, 37(4), 2179-2214.
- [8]. Alloui, H., & Mourdi, Y. (2023). Exploring the full potentials of IoT for better financial growth and stability: A comprehensive survey. *Sensors*, 23(19), 8015.
- [9]. Andronie, M., Lăzăroiu, G., Iatagan, M., Uță, C., Ștefănescu, R., & Cocoșatu, M. (2021). Artificial intelligence-based decision-making algorithms, internet of things sensing networks, and deep learning-assisted smart process management in cyber-physical production systems. *Electronics*, 10(20), 2497.
- [10]. Andronie, M., Lăzăroiu, G., Ștefănescu, R., Uță, C., & Dijmărescu, I. (2021). Sustainable, smart, and sensing technologies for cyber-physical manufacturing systems: A systematic literature review. *Sustainability*, 13(10), 5495.
- [11]. Asghar, M. Z., Memon, S. A., & Hämäläinen, J. (2022). Evolution of wireless communication to 6G: Potential applications and research directions. *Sustainability*, 14(10), 6356.

- [12]. Aydin, E., Rahman, M., & Ozeren, E. (2023). Does Industry 5.0 reproduce gender (in) equalities at organisations? Understanding the interaction of human resources and software development teams in supplying human capitals. *Information Systems Frontiers*, 1-15.
- [13]. Baloch, Q. B., Shah, S. N., Maher, S., Irshad, M., Khan, A. U., Kiran, S., & Shah, S. S. (2022). Determinants of evolving responsible tourism behavior: Evidences from supply chain. *Cogent Social Sciences*, 8(1), 2099565.
- [14]. Bécue, A., Praça, I., & Gama, J. (2021). Artificial intelligence, cyber-threats and Industry 4.0: Challenges and opportunities. *Artificial intelligence review*, 54(5), 3849-3886.
- [15]. Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). A human cyber physical system framework for operator 4.0-artificial intelligence symbiosis. *Manufacturing letters*, 25, 10-15.
- [16]. Broo, D. G., Boman, U., & Törngren, M. (2021). Cyber-physical systems research and education in 2030: Scenarios and strategies. *Journal of Industrial Information Integration*, 21, 100192.
- [17]. Cáceres, M., Nussbaum, M., & Ortiz, J. (2020). Integrating critical thinking into the classroom: A teacher's perspective. *Thinking Skills and Creativity*, 37, 100674.
- [18]. Cañizares, J. C., Copeland, S. M., & Doorn, N. (2021). Making sense of resilience. *Sustainability*, 13(15), 8538.
- [19]. Carayannis, E. G., Canestrino, R., & Magliocca, P. (2023). From the dark side of industry 4.0 to society 5.0: Looking "beyond the box" to developing human-centric innovation ecosystems. *IEEE Transactions on Engineering Management*, 71, 6695-6711.
- [20]. Carayannis, E. G., & Morawska, J. (2023). University and education 5.0 for emerging trends, policies and practices in the concept of industry 5.0 and society 5.0. In *Industry 5.0: Creative and Innovative Organizations* (pp. 1-25). Springer.
- [21]. Chae, J., Lee, S., Jang, J., Hong, S., & Park, K.-J. (2023). A survey and perspective on industrial cyber-physical systems (ICPS): From ICPS to AI-augmented ICPS. *IEEE Transactions on Industrial Cyber-Physical Systems*, 1, 257-272.
- [22]. Cheng, Y., Elsayed, E. A., & Huang, Z. (2022). Systems resilience assessments: a review, framework and metrics. *International Journal of Production Research*, 60(2), 595-622.
- [23]. Cheshmehzangi, A., Sedrez, M., Dawodu, A., Heath, T., Zhao, H., & Li, T. (2023). Urban resilience to future pandemics. In *Resilience vs Pandemics: Innovations in Cities and Neighbourhoods* (pp. 1-12). Springer.
- [24]. Conrad, C., Al-Rubaye, S., & Tsourdos, A. (2023). Intelligent embedded systems platform for vehicular cyber-physical systems. *Electronics*, 12(13), 2908.
- [25]. Cotta, W. A. A., Lopes, S. I., & Vassallo, R. F. (2023). Towards the cognitive factory in industry 5.0: From Concept to implementation. *Smart Cities*, 6(4), 1901-1921.
- [26]. Crnobrajic, J., Stefanovic, D., Romero, D., Softic, S., & Marjanovic, U. (2023). Digital transformation towards industry 5.0: A systematic literature review. IFIP international conference on advances in production management systems,
- [27]. Dai, S., Xu, H., & Chen, F. (2019). A hierarchical measurement model of perceived resilience of urban tourism destination. *Social Indicators Research*, 145(2), 777-804.
- [28]. Darjee, K. B., Neupane, P. R., & Köhl, M. (2023). Proactive adaptation responses by vulnerable communities to climate change impacts. *Sustainability*, 15(14), 10952.
- [29]. De Alwis, C., Kalla, A., Pham, Q.-V., Kumar, P., Dev, K., Hwang, W.-J., & Liyanage, M. (2021). Survey on 6G frontiers: Trends, applications, requirements, technologies and future research. *IEEE Open Journal of the Communications Society*, 2, 836-886.
- [30]. Di Tommaso, M. R., Prodi, E., Pollio, C., & Barbieri, E. (2023). Conceptualizing and measuring "industry resilience": Composite indicators for postshock industrial policy decision-making. *Socio-Economic Planning Sciences*, 85, 101448.
- [31]. Dorji, T., Morrison-Saunders, A., & Blake, D. (2023). Understanding how community wellbeing is affected by climate change: evidence from a systematic literature review. *Environmental Management*, 72(3), 568-586.
- [32]. Egamberdiev, B., Bobojonov, I., Kuhn, L., & Glauben, T. (2023). Household resilience capacity and food security: evidence from Kyrgyzstan. *Food Security*, 15(4), 967-988.
- [33]. Gaiardelli, P., Pezzotta, G., Rondini, A., Romero, D., Jarrahi, F., Bertoni, M., Wiesner, S., Wuest, T., Larsson, T., & Zaki, M. (2021). Product-service systems evolution in the era of Industry 4.0. *Service Business*, 15(1), 177-207.
- [34]. Golan, M. S., Jernegan, L. H., & Linkov, I. (2020). Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVID-19 pandemic. *Environment Systems and Decisions*, 40(2), 222-243.
- [35]. Gonçalves, B. d. S. M., Carvalho, F. L. d., & Fiorini, P. d. C. (2022). Circular economy and financial aspects: A systematic review of the literature. *Sustainability*, 14(5), 3023.
- [36]. Groshev, M., Guimaraes, C., Martín-Pérez, J., & de la Oliva, A. (2021). Toward intelligent cyber-physical systems: Digital twin meets artificial intelligence. *IEEE Communications Magazine*, 59(8), 14-20.
- [37]. Grzesiak, S. S., & Sulich, A. (2023). Electromobility: Logistics and business ecosystem perspectives review. *Energies*, 16(21), 7249.
- [38]. Habibullah, S. M., & Md. Foysal, H. (2021). A Data Driven Cyber Physical Framework For Real Time Production Control Integrating IOT And Lean Principles. *American Journal of Interdisciplinary Studies*, 2(03), 35-70. <https://doi.org/10.63125/20nhqs87>
- [39]. Han, D., Yu, D., & Qiu, J. (2023). Assessing coupling interactions in a safe and just operating space for regional sustainability. *Nature Communications*, 14(1), 1369.
- [40]. Han, Y., Chong, W. K., & Li, D. (2020). A systematic literature review of the capabilities and performance metrics of supply chain resilience. *International Journal of Production Research*, 58(15), 4541-4566.

- [41]. Hazrat, M., Hassan, N., Chowdhury, A. A., Rasul, M., & Taylor, B. A. (2023). Developing a skilled workforce for future industry demand: The potential of digital twin-based teaching and learning practices in engineering education. *Sustainability*, 15(23), 16433.
- [42]. Hlophe, M. C., & Maharaj, B. T. (2023). From cyber-physical convergence to digital twins: A review on edge computing use case designs. *Applied Sciences*, 13(24), 13262.
- [43]. Hohmann, C., & Posselt, T. (2019). Design challenges for CPS-based service systems in industrial production and logistics. *International Journal of Computer Integrated Manufacturing*, 32(4-5), 329-339.
- [44]. Hosseini, S., Ivanov, D., & Blackhurst, J. (2020). Conceptualization and measurement of supply chain resilience in an open-system context. *IEEE Transactions on Engineering Management*, 69(6), 3111-3126.
- [45]. Hozyfa, S. (2022). Integration Of Machine Learning and Advanced Computing For Optimizing Retail Customer Analytics. *International Journal of Business and Economics Insights*, 2(3), 01-46. <https://doi.org/10.63125/p87sv224>
- [46]. Hozyfa, S. (2025). Artificial Intelligence-Driven Business Intelligence Models for Enhancing Decision-Making In U.S. Enterprises. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 771- 800. <https://doi.org/10.63125/b8gmdc46>
- [47]. Ivanov, D. (2022). Viable supply chain model: integrating agility, resilience and sustainability perspectives – lessons from and thinking beyond the COVID-19 pandemic. *Annals of operations research*, 319(1), 1411-1431.
- [48]. Ivanov, D. (2023). The Industry 5.0 framework: viability-based integration of the resilience, sustainability, and human-centricity perspectives. *International Journal of Production Research*, 61(5), 1683-1695.
- [49]. Jagatheesaperumal, S. K., Rahouti, M., Ahmad, K., Al-Fuqaha, A., & Guizani, M. (2021). The duo of artificial intelligence and big data for industry 4.0: Applications, techniques, challenges, and future research directions. *IEEE Internet of Things Journal*, 9(15), 12861-12885.
- [50]. Jaimes Torres, M., Aguilera Portillo, M., Cuervo-Vilches, T., Oteiza, I., & Navas-Martín, M. Á. (2021). Habitability, resilience, and satisfaction in Mexican homes to COVID-19 pandemic. *International Journal of Environmental Research and Public Health*, 18(13), 6993.
- [51]. Juma, M., & Shaalan, K. (2020). Cyberphysical systems in the smart city: Challenges and future trends for strategic research. In *Swarm intelligence for resource management in Internet of things* (pp. 65-85). Elsevier.
- [52]. Kaftan, V., Kandalov, W., Molodtsov, I., Sherstobitova, A., & Strielkowski, W. (2023). Socio-economic stability and sustainable development in the post-COVID era: Lessons for the business and economic leaders. *Sustainability*, 15(4), 2876.
- [53]. Kähkönen, A.-K., Evangelista, P., Hallikas, J., Immonen, M., & Lintukangas, K. (2023). COVID-19 as a trigger for dynamic capability development and supply chain resilience improvement. *International Journal of Production Research*, 61(8), 2696-2715.
- [54]. Kasperson, J. X., Kasperson, R. E., Turner, B., Hsieh, W., & Schiller, A. (2022). Vulnerability to global environmental change. In *Social contours of risk* (pp. 245-285). Routledge.
- [55]. Katsaliaki, K., Galetsi, P., & Kumar, S. (2022). Supply chain disruptions and resilience: a major review and future research agenda. *Annals of operations research*, 319(1), 965-1002.
- [56]. Khairul Alam, T. (2025). The Impact of Data-Driven Decision Support Systems On Governance And Policy Implementation In U.S. Institutions. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 994-1030. <https://doi.org/10.63125/3v98q104>
- [57]. Khujamatov, H., Reypnazarov, E., Khasanov, D., & Akhmedov, N. (2021). IoT, IIoT, and cyber-physical systems integration. In *Emergence of cyber physical system and IoT in smart automation and robotics: computer engineering in automation* (pp. 31-50). Springer.
- [58]. Kirkland, C., Oldfield-Tabbert, K., Karnik, H., Orr, J., Martin, S., & Leider, J. P. (2022). Public health workforce gaps, impacts, and improvement strategies from COVID-19. *International Journal of Environmental Research and Public Health*, 19(20), 13084.
- [59]. Kolade, O., Smith, R., Obembe, D., Taiwo, A., Eyong, J., James, S., & Kibreab, G. (2022). Picking up the pieces: social capital, psycho-social support and livelihood recovery of displaced populations in northeast Nigeria. *The Journal of Development Studies*, 58(6), 1280-1299.
- [60]. Koroniotis, N., Moustafa, N., Schiliro, F., Gauravaram, P., & Janicke, H. (2020). A holistic review of cybersecurity and reliability perspectives in smart airports. *IEEE Access*, 8, 209802-209834.
- [61]. Lawrance, E. L., Thompson, R., Newberry Le Vay, J., Page, L., & Jennings, N. (2022). The impact of climate change on mental health and emotional wellbeing: a narrative review of current evidence, and its implications. *International Review of Psychiatry*, 34(5), 443-498.
- [62]. Le Jeune, K., Ontong, K., Moghayedi, A., & Massyn, M. (2023). Empowering Engineering and Built Environment Professionals: Exploring Education 5.0 and the Quintuple Helix Model of Innovation. Australasian Universities Building Education Association Conference,
- [63]. Leggat, F. J., Wadey, R., Day, M. C., Winter, S., & Sanders, P. (2023). Bridging the know-do gap using integrated knowledge translation and qualitative inquiry: A narrative review. *Qualitative Research in Sport, Exercise and Health*, 15(2), 188-201.
- [64]. Leitão, P., Queiroz, J., & Sakurada, L. (2022). Collective intelligence in self-organized industrial cyber-physical systems. *Electronics*, 11(19), 3213.
- [65]. Leng, J., Zhang, H., Yan, D., Liu, Q., Chen, X., & Zhang, D. (2019). Digital twin-driven manufacturing cyber-physical system for parallel controlling of smart workshop. *Journal of ambient intelligence and humanized computing*, 10(3), 1155-1166.

- [66]. Lorié, E. S., Willem-Jan, W. W., van Veenendaal, N. R., van Kempen, A. A., & Labrie, N. H. (2021). Parents' needs and perceived gaps in communication with healthcare professionals in the neonatal (intensive) care unit: A qualitative interview study. *Patient education and counseling*, 104(7), 1518-1525.
- [67]. Lütje, A., & Wohlgemuth, V. (2020). Tracking sustainability targets with quantitative indicator systems for performance measurement of industrial symbiosis in industrial parks. *Administrative sciences*, 10(1), 3.
- [68]. Mackay, J., Munoz, A., & Pepper, M. (2020). Conceptualising redundancy and flexibility towards supply chain robustness and resilience. *Journal of Risk Research*, 23(12), 1541-1561.
- [69]. Madsen, D. Ø., & Slåtten, K. (2023). Comparing the evolutionary trajectories of Industry 4.0 and 5.0: A management fashion perspective. *Applied System Innovation*, 6(2), 48.
- [70]. Maleh, Y., Lakkineni, S., Tawalbeh, L. a., & Abdel-Latif, A. A. (2022). Blockchain for cyber-physical systems: Challenges and applications. *Advances in blockchain technology for cyber physical systems*, 11-59.
- [71]. Mani, Z. A., & Goniewicz, K. (2023). Adapting disaster preparedness strategies to changing climate patterns in Saudi Arabia: a rapid review. *Sustainability*, 15(19), 14279.
- [72]. Maniruzzaman, B., Mohammad Anisur, R., Afrin Binta, H., Md, A., & Anisur, R. (2023). Advanced Analytics And Machine Learning For Revenue Optimization In The Hospitality Industry: A Comprehensive Review Of Frameworks. *American Journal of Scholarly Research and Innovation*, 2(02), 52-74. <https://doi.org/10.63125/8xbkma40>
- [73]. Martin-Gomez, A., Avila-Gutierrez, M. J., & Aguayo-Gonzalez, F. (2021). Holonic reengineering to foster sustainable cyber-physical systems design in cognitive manufacturing. *Applied Sciences*, 11(7), 2941.
- [74]. Masud, R. (2025). Integrating Agile Project Management and Lean Industrial Practices A Review For Enhancing Strategic Competitiveness In Manufacturing Enterprises. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 895–924. <https://doi.org/10.63125/0yjss288>
- [75]. Md Al Amin, K. (2022). Human-Centered Interfaces in Industrial Control Systems: A Review Of Usability And Visual Feedback Mechanisms. *Review of Applied Science and Technology*, 1(04), 66-97. <https://doi.org/10.63125/gr54qy93>
- [76]. Md Arif Uz, Z., & Elmoon, A. (2023). Adaptive Learning Systems For English Literature Classrooms: A Review Of AI-Integrated Education Platforms. *International Journal of Scientific Interdisciplinary Research*, 4(3), 56-86. <https://doi.org/10.63125/a30ehr12>
- [77]. Md Arman, H. (2025). Artificial Intelligence-Driven Financial Analytics Models For Predicting Market Risk And Investment Decisions In U.S. Enterprises. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 1066–1095. <https://doi.org/10.63125/9csehp36>
- [78]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, 2(4), 01–41. <https://doi.org/10.63125/btx52a36>
- [79]. Md Mesbaul, H. (2024). Industrial Engineering Approaches to Quality Control In Hybrid Manufacturing A Review Of Implementation Strategies. *International Journal of Business and Economics Insights*, 4(2), 01-30. <https://doi.org/10.63125/3xcabx98>
- [80]. Md Mohaiminul, H. (2025). Federated Learning Models for Privacy-Preserving AI In Enterprise Decision Systems. *International Journal of Business and Economics Insights*, 5(3), 238– 269. <https://doi.org/10.63125/ry033286>
- [81]. Md Mohaiminul, H., & Md Muzahidul, I. (2022). High-Performance Computing Architectures For Training Large-Scale Transformer Models In Cyber-Resilient Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 2(1), 193–226. <https://doi.org/10.63125/6zt59y89>
- [82]. Md Mominul, H. (2025). Systematic Review on The Impact Of AI-Enhanced Traffic Simulation On U.S. Urban Mobility And Safety. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 833–861. <https://doi.org/10.63125/jj96yd66>
- [83]. Md Omar, F., & Md. Jobayer Ibne, S. (2022). Aligning FEDRAMP And NIST Frameworks In Cloud-Based Governance Models: Challenges And Best Practices. *Review of Applied Science and Technology*, 1(01), 01-37. <https://doi.org/10.63125/vnkcwq87>
- [84]. Md Sanjid, K. (2023). Quantum-Inspired AI Metaheuristic Framework For Multi-Objective Optimization In Industrial Production Scheduling. *American Journal of Interdisciplinary Studies*, 4(03), 01-33. <https://doi.org/10.63125/2mba8p24>
- [85]. Md Sanjid, K., & Md. Tahmid Farabe, S. (2021). Federated Learning Architectures For Predictive Quality Control In Distributed Manufacturing Systems. *American Journal of Interdisciplinary Studies*, 2(02), 01-31. <https://doi.org/10.63125/222nwg58>
- [86]. Md Sanjid, K., & Sudipto, R. (2023). Blockchain-Orchestrated Cyber-Physical Supply Chain Networks For Manufacturing Resilience. *American Journal of Scholarly Research and Innovation*, 2(01), 194-223. <https://doi.org/10.63125/6n81ne05>
- [87]. Md Sanjid, K., & Zayadul, H. (2022). Thermo-Economic Modeling Of Hydrogen Energy Integration In Smart Factories. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 2(1), 257–288. <https://doi.org/10.63125/txdz1p03>
- [88]. Md Sarwar, H. (2021). Sustainable Materials Characterization For Low-Carbon Construction And Infrastructure Durability. *American Journal of Interdisciplinary Studies*, 2(01), 01-34. <https://doi.org/10.63125/wq1wdr64>
- [89]. Md. Hasan, I. (2022). The Role Of Cross-Country Trade Partnerships In Strengthening Global Market Competitiveness. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 2(1), 121-150. <https://doi.org/10.63125/w0mnpz07>
- [90]. Md. Hasan, I. (2025). A Systematic Review on The Impact Of Global Merchandising Strategies On U.S. Supply Chain Resilience. *International Journal of Business and Economics Insights*, 5(3), 134–169. <https://doi.org/10.63125/24mymg13>

- [91]. Md. Milon, M. (2025). A Systematic Review on The Impact Of NFPA-Compliant Fire Protection Systems On U.S. Infrastructure Resilience. *International Journal of Business and Economics Insights*, 5(3), 324–352. <https://doi.org/10.63125/ne3ey612>
- [92]. Md. Mominul, H., Masud, R., & Md. Milon, M. (2022). Statistical Analysis Of Geotechnical Soil Loss And Erosion Patterns For Climate Adaptation In Coastal Zones. *American Journal of Interdisciplinary Studies*, 3(03), 36-67. <https://doi.org/10.63125/xytn3e23>
- [93]. Md. Musfiqur, R., & Saba, A. (2021). Data-Driven Decision Support in Information Systems: Strategic Applications In Enterprises. *International Journal of Scientific Interdisciplinary Research*, 2(2), 01-33. <https://doi.org/10.63125/cfvg2v45>
- [94]. Md. Omar, F., & Md Harun-Or-Rashid, M. (2021). POST-GDPR Digital Compliance in Multinational Organizations: Bridging Legal Obligations With Cybersecurity Governance. *American Journal of Scholarly Research and Innovation*, 1(01), 27-60. <https://doi.org/10.63125/4qdpf28>
- [95]. Md. Rabiul, K., & Sai Praveen, K. (2022). The Influence of Statistical Models For Fraud Detection In Procurement And International Trade Systems. *American Journal of Interdisciplinary Studies*, 3(04), 203-234. <https://doi.org/10.63125/9htnv106>
- [96]. Md. Redwanul, I., Md Nahid, H., & Md. Zahid Hasan, T. (2021). Predictive Analytics in Supply Chain Management A Review Of Business Analyst-Led Optimization Tools. *Review of Applied Science and Technology*, 6(1), 34-73. <https://doi.org/10.63125/5aypx555>
- [97]. Md. Tahmid Farabe, S. (2022). Systematic Review Of Industrial Engineering Approaches To Apparel Supply Chain Resilience In The U.S. Context. *American Journal of Interdisciplinary Studies*, 3(04), 235-267. <https://doi.org/10.63125/teherz38>
- [98]. Md. Tahmid Farabe, S. (2025). The Impact of Data-Driven Industrial Engineering Models On Efficiency And Risk Reduction In U.S. Apparel Supply Chains. *International Journal of Business and Economics Insights*, 5(3), 353–388. <https://doi.org/10.63125/y548hz02>
- [99]. Md. Tarek, H. (2023). Quantitative Risk Modeling For Data Loss And Ransomware Mitigation In Global Healthcare And Pharmaceutical Systems. *International Journal of Scientific Interdisciplinary Research*, 4(3), 87-116. <https://doi.org/10.63125/8wk2ch14>
- [100]. Md. Tarek, H., & Ishtiaque, A. (2025). AI-Driven Anomaly Detection For Data Loss Prevention And Security Assurance In Electronic Health Records. *Review of Applied Science and Technology*, 4(03), 35-67. <https://doi.org/10.63125/dzyr0648>
- [101]. Md. Tarek, H., & Md.Kamrul, K. (2024). Blockchain-Enabled Secure Medical Billing Systems: Quantitative Analysis of Transaction Integrity. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 4(1), 97–123. <https://doi.org/10.63125/1t8jpm24>
- [102]. Md. Tarek, H., & Sai Praveen, K. (2021). Data Privacy-Aware Machine Learning and Federated Learning: A Framework For Data Security. *American Journal of Interdisciplinary Studies*, 2(03), 01–34. <https://doi.org/10.63125/vj1hem03>
- [103]. Md. Wahid Zaman, R., & Momena, A. (2021). Systematic Review Of Data Science Applications In Project Coordination And Organizational Transformation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(2), 01–41. <https://doi.org/10.63125/31b8qc62>
- [104]. Mendhurwar, S., & Mishra, R. (2023). ‘Un’-blocking the industry 4.0 value chain with cyber-physical social thinking. *Enterprise Information Systems*, 17(2), 1930189.
- [105]. Mengistu, A. T., & Panizzolo, R. (2023). Analysis of indicators used for measuring industrial sustainability: a systematic review. *Environment, Development and Sustainability*, 25(3), 1979-2005.
- [106]. Mitchell, D., Blanche, J., Zaki, O., Roe, J., Kong, L., Harper, S., Robu, V., Lim, T., & Flynn, D. (2021). Symbiotic system of systems design for safe and resilient autonomous robotics in offshore wind farms. *IEEE Access*, 9, 141421-141452.
- [107]. Moghayed, A., & Awuzie, B. (2023). Towards a net-zero carbon economy: A sustainability performance assessment of innovative prefabricated construction methods for affordable housing in Southern Africa. *Sustainable Cities and Society*, 99, 104907.
- [108]. Möller, D. P. (2023). Cybersecurity in digital transformation. In *Guide to cybersecurity in digital transformation: Trends, methods, technologies, applications and best practices* (pp. 1-70). Springer.
- [109]. Momena, A. (2025). Impact Of Predictive Machine Learning Models on Operational Efficiency And Consumer Satisfaction In University Dining Services. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 376-403. <https://doi.org/10.63125/5tjkae44>
- [110]. Mourtzis, D. (2023). The Metaverse in industry 5.0: A human-centric approach towards personalized value creation. *Encyclopedia*, 3(3), 1105-1120.
- [111]. Mst. Shahrin, S., & Samia, A. (2023). High-Performance Computing For Scaling Large-Scale Language And Data Models In Enterprise Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 3(1), 94–131. <https://doi.org/10.63125/e7yfwm87>
- [112]. Nagy, M., Lăzăroiu, G., & Valaskova, K. (2023). Machine intelligence and autonomous robotic technologies in the corporate context of SMEs: Deep learning and virtual simulation algorithms, cyber-physical production networks, and Industry 4.0-based manufacturing systems. *Applied Sciences*, 13(3), 1681.
- [113]. Napoleone, A., Negri, E., Macchi, M., & Pozzetti, A. (2023). How the technologies underlying cyber-physical systems support the reconfigurability capability in manufacturing: a literature review. *International Journal of Production Research*, 61(9), 3122-3144.

- [114]. Nüchter, V., Abson, D. J., Von Wehrden, H., & Engler, J.-O. (2021). The concept of resilience in recent sustainability research. *Sustainability*, 13(5), 2735.
- [115]. Nyström, M., Jouffray, J.-B., Norström, A. V., Crona, B., Sjøgaard Jørgensen, P., Carpenter, S. R., Bodin, Ö., Galaz, V., & Folke, C. (2019). Anatomy and resilience of the global production ecosystem. *Nature*, 575(7781), 98-108.
- [116]. Omar Muhammad, F. (2025). Artificial Intelligence in Business Intelligence: Enhancing Predictive Workforce And Operational Analytics. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 589-617. <https://doi.org/10.63125/m5hg3b73>
- [117]. Omar Muhammad, F., & Md Redwanul, I. (2023). A Quantitative Study on AI-Driven Employee Performance Analytics In Multinational Organizations. *American Journal of Interdisciplinary Studies*, 4(04), 145-176. <https://doi.org/10.63125/vrsjp515>
- [118]. Omar Muhammad, F., & Md. Redwanul, I. (2023). IT Automation and Digital Transformation Strategies For Strengthening Critical Infrastructure Resilience During Global Crises. *American Journal of Interdisciplinary Studies*, 4(04), 145-176. <https://doi.org/10.63125/vrsjp515>
- [119]. Panetto, H., Jung, B., Ivanov, D., Weichhart, G., & Wang, X. (2019). Challenges for the cyber-physical manufacturing enterprises of the future. *Annual reviews in control*, 47, 200-213.
- [120]. Pankaz Roy, S. (2022). Data-Driven Quality Assurance Systems For Food Safety In Large-Scale Distribution Centers. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 2(1), 151-192. <https://doi.org/10.63125/qen48m30>
- [121]. Pankaz Roy, S. (2025). Artificial Intelligence Based Models for Predicting Foodborne Pathogen Risk In Public Health Systems. *International Journal of Business and Economics Insights*, 5(3), 205-237. <https://doi.org/10.63125/7685ne21>
- [122]. Peças, P., John, L., Ribeiro, I., Baptista, A. J., Pinto, S. M., Dias, R., Henriques, J., Estrela, M., Pilastri, A., & Cunha, F. (2023). Holistic framework to data-driven sustainability assessment. *Sustainability*, 15(4), 3562.
- [123]. Pereira, R., & dos Santos, N. (2023). Neoindustrialization – reflections on a new paradigmatic approach for the industry: a scoping review on industry 5.0. *Logistics*, 7(3), 43.
- [124]. Pham, H., Sutton, B. G., Brown, P. J., & Brown, D. A. (2020). Moving towards sustainability: A theoretical design of environmental performance measurement systems. *Journal of cleaner production*, 269, 122273.
- [125]. Prabowo, O. M., Mulyana, E., Nugraha, I. G. B. B., & Supangkat, S. H. (2023). Cognitive city platform as digital public infrastructure for developing a smart, sustainable and resilient city in Indonesia. *IEEE Access*, 11, 120157-120178.
- [126]. Prayag, G. (2023). Tourism resilience in the ‘new normal’: Beyond jingle and jangle fallacies? *Journal of Hospitality and Tourism Management*, 54, 513-520.
- [127]. Prehofer, S., Kosow, H., Naegler, T., Pregger, T., Vögele, S., & Weimer-Jehle, W. (2021). Linking qualitative scenarios with quantitative energy models: knowledge integration in different methodological designs. *Energy, sustainability and society*, 11(1), 25.
- [128]. Puliafito, A., Tricomi, G., Zafeiropoulos, A., & Papavassiliou, S. (2021). Smart cities of the future as cyber physical systems: Challenges and enabling technologies. *Sensors*, 21(10), 3349.
- [129]. Qian, F., Tang, Y., & Yu, X. (2023). The future of process industry: A cyber-physical-social system perspective. *IEEE Transactions on Cybernetics*, 54(7), 3878-3889.
- [130]. Radanliev, P., De Roure, D., Van Kleek, M., Santos, O., & Ani, U. (2021). Artificial intelligence in cyber physical systems. *AI & society*, 36(3), 783-796.
- [131]. Rahman, S. M. T. (2025). Strategic Application of Artificial Intelligence In Agribusiness Systems For Market Efficiency And Zoonotic Risk Mitigation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 862-894. <https://doi.org/10.63125/8xm5rz19>
- [132]. Rahman, S. M. T., & Abdul, H. (2022). Data Driven Business Intelligence Tools In Agribusiness A Framework For Evidence-Based Marketing Decisions. *International Journal of Business and Economics Insights*, 2(1), 35-72. <https://doi.org/10.63125/p59krm34>
- [133]. Rakibul, H. (2025). The Role of Business Analytics In ESG-Oriented Brand Communication: A Systematic Review Of Data-Driven Strategies. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 1096- 1127. <https://doi.org/10.63125/4mchj778>
- [134]. Rao, C. S., Kareemulla, K., Krishnan, P., Murthy, G., Ramesh, P., Ananthan, P., & Joshi, P. K. (2019). Agro-ecosystem based sustainability indicators for climate resilient agriculture in India: A conceptual framework. *Ecological Indicators*, 105, 621-633.
- [135]. Razia, S. (2022). A Review Of Data-Driven Communication In Economic Recovery: Implications Of ICT-Enabled Strategies For Human Resource Engagement. *International Journal of Business and Economics Insights*, 2(1), 01-34. <https://doi.org/10.63125/7tkv8v34>
- [136]. Razia, S. (2023). AI-Powered BI Dashboards In Operations: A Comparative Analysis For Real-Time Decision Support. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 3(1), 62-93. <https://doi.org/10.63125/wqd2t159>
- [137]. Rebeka, S. (2025). Artificial Intelligence In Data Visualization: Reviewing Dashboard Design And Interactive Analytics For Enterprise Decision-Making. *International Journal of Business and Economics Insights*, 5(3), 01-29. <https://doi.org/10.63125/cp51y494>
- [138]. Reduanul, H. (2025). Enhancing Market Competitiveness Through Ai-Powered Seo And Digital Marketing Strategies In E-Commerce. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 465-500. <https://doi.org/10.63125/31tpjc54>
- [139]. Romagnoli, F., Masiero, M., & Secco, L. (2022). Windstorm impacts on forest-related socio-ecological systems: an analysis from a socio-economic and institutional perspective. *Forests*, 13(6), 939.

- [140]. Rony, M. A. (2021). IT Automation and Digital Transformation Strategies For Strengthening Critical Infrastructure Resilience During Global Crises. *International Journal of Business and Economics Insights*, 1(2), 01-32. <https://doi.org/10.63125/8tzzab90>
- [141]. Rony, M. A. (2025). AI-Enabled Predictive Analytics And Fault Detection Frameworks For Industrial Equipment Reliability And Resilience. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 705-736. <https://doi.org/10.63125/2dw11645>
- [142]. Roostaie, S., Nawari, N., & Kibert, C. J. (2019). Sustainability and resilience: A review of definitions, relationships, and their integration into a combined building assessment framework. *Building and Environment*, 154, 132-144.
- [143]. Rosli, M. S., Saleh, N. S., Md. Ali, A., & Abu Bakar, S. (2022). Self-determination theory and online learning in university: advancements, future direction and research gaps. *Sustainability*, 14(21), 14655.
- [144]. Saba, A. (2025). Artificial Intelligence Based Models For Secure Data Analytics And Privacy-Preserving Data Sharing In U.S. Healthcare And Hospital Networks. *International Journal of Business and Economics Insights*, 5(3), 65-99. <https://doi.org/10.63125/wv0bqx68>
- [145]. Sai Praveen, K. (2025). AI-Driven Data Science Models for Real-Time Transcription And Productivity Enhancement In U.S. Remote Work Environments. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 801-832. <https://doi.org/10.63125/gzyw2311>
- [146]. Sai Srinivas, M., & Manish, B. (2023). Trustworthy AI: Explainability & Fairness In Large-Scale Decision Systems. *Review of Applied Science and Technology*, 2(04), 54-93. <https://doi.org/10.63125/3w9v5e52>
- [147]. Shaikat, B. (2025). Artificial Intelligence-Enhanced Cybersecurity Frameworks for Real-Time Threat Detection In Cloud And Enterprise. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 737-770. <https://doi.org/10.63125/yq1gp452>
- [148]. Shaikh, S., & Aditya, D. (2021). Federated Learning-Driven Predictive Quality Analytics and Supply Chain Optimization In Distributed Manufacturing Networks. *Review of Applied Science and Technology*, 6(1), 74-107. <https://doi.org/10.63125/k18cbz55>
- [149]. Shandiz, S. C., Foliente, G., Rismanchi, B., Wachtel, A., & Jeffers, R. F. (2020). Resilience framework and metrics for energy master planning of communities. *Energy*, 203, 117856.
- [150]. Singh, P. K., & Kumar, A. (2023). Cyber Physical Systems in Supply Chain Management. In *Cyber Physical Systems* (pp. 85-110). Chapman and Hall/CRC.
- [151]. Sudipto, R. (2023). AI-Enhanced Multi-Objective Optimization Framework For Lean Manufacturing Efficiency And Energy-Conscious Production Systems. *American Journal of Interdisciplinary Studies*, 4(03), 34-64. <https://doi.org/10.63125/s43p0363>
- [152]. Sudipto, R., & Md Mesbaul, H. (2021). Machine Learning-Based Process Mining For Anomaly Detection And Quality Assurance In High-Throughput Manufacturing Environments. *Review of Applied Science and Technology*, 6(1), 01-33. <https://doi.org/10.63125/t5dcb097>
- [153]. Sudipto, R., & Md. Hasan, I. (2024). Data-Driven Supply Chain Resilience Modeling Through Stochastic Simulation And Sustainable Resource Allocation Analytics. *American Journal of Advanced Technology and Engineering Solutions*, 4(02), 01-32. <https://doi.org/10.63125/p0ptag78>
- [154]. Sun, F., Xiang, J., Tao, Y., Tong, C., & Che, Y. (2019). Mapping the social values for ecosystem services in urban green spaces: Integrating a visitor-employed photography method into SolVES. *Urban Forestry & Urban Greening*, 38, 105-113.
- [155]. Susur, E., Hidalgo, A., & Chiaroni, D. (2019). The emergence of regional industrial ecosystem niches: A conceptual framework and a case study. *Journal of cleaner production*, 208, 1642-1657.
- [156]. Syed Zaki, U. (2021). Modeling Geotechnical Soil Loss and Erosion Dynamics For Climate-Resilient Coastal Adaptation. *American Journal of Interdisciplinary Studies*, 2(04), 01-38. <https://doi.org/10.63125/vsfjtt77>
- [157]. Syed Zaki, U. (2022). Systematic Review Of Sustainable Civil Engineering Practices And Their Influence On Infrastructure Competitiveness. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 2(1), 227-256. <https://doi.org/10.63125/hh8nv249>
- [158]. Taddese, G., Durieux, S., & Duc, E. (2020). Sustainability performance indicators for additive manufacturing: a literature review based on product life cycle studies. *The International Journal of Advanced Manufacturing Technology*, 107(7), 3109-3134.
- [159]. Tao, F., Qi, Q., Wang, L., & Nee, A. (2019). Digital twins and cyber-physical systems toward smart manufacturing and industry 4.0: Correlation and comparison. *Engineering*, 5(4), 653-661.
- [160]. Tofu, D. A., Haile, F., & Tolossa, T. (2023). Livelihood vulnerability and socio-economic determinants of households to climate change-induced recurrent drought in Ethiopia. *GeoJournal*, 88(5), 5043-5067.
- [161]. Tonoy Kanti, C. (2025). AI-Powered Deep Learning Models for Real-Time Cybersecurity Risk Assessment In Enterprise It Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 675-704. <https://doi.org/10.63125/137k6y79>
- [162]. Tonoy Kanti, C., & Shaikat, B. (2022). Graph Neural Networks (GNNS) For Modeling Cyber Attack Patterns And Predicting System Vulnerabilities In Critical Infrastructure. *American Journal of Interdisciplinary Studies*, 3(04), 157-202. <https://doi.org/10.63125/1ykzx350>
- [163]. Trakadas, P., Simoens, P., Gkonis, P., Sarakis, L., Angelopoulos, A., Ramallo-González, A. P., Skarmeta, A., Trochoutsos, C., Calvo, D., & Pariente, T. (2020). An artificial intelligence-based collaboration approach in industrial iot manufacturing: Key concepts, architectural extensions and potential applications. *Sensors*, 20(19), 5480.

- [164]. Tran, T.-A., Ruppert, T., Eigner, G., & Abonyi, J. (2022). Retrofitting-based development of brownfield industry 4.0 and industry 5.0 solutions. *IEEE Access*, 10, 64348-64374.
- [165]. Vaezinejad, S., & Schniederjans, D. (2022). Lean supply chain 5.0 management (LSCM 5.0): lean and value reconceptualized. In *The Palgrave Handbook of Supply Chain Management* (pp. 1-23). Springer.
- [166]. Vahabi, S., Lak, A., & Panahi, N. (2023). Driving the determinants of older people's mental health in the context of urban resilience: a scoping review. *BMC geriatrics*, 23(1), 711.
- [167]. Van den Berg, N. J., Hof, A. F., Akenji, L., Edelenbosch, O. Y., van Sluisveld, M. A., Timmer, V. J., & van Vuuren, D. P. (2019). Improved modelling of lifestyle changes in Integrated Assessment Models: Cross-disciplinary insights from methodologies and theories. *Energy Strategy Reviews*, 26, 100420.
- [168]. Vanany, I., Ali, M. H., Tan, K. H., Kumar, A., & Siswanto, N. (2021). A supply chain resilience capability framework and process for mitigating the COVID-19 pandemic disruption. *IEEE Transactions on Engineering Management*, 71, 10358-10372.
- [169]. Vega-Muñoz, A., Salazar-Sepulveda, G., Espinosa-Cristia, J. F., & Sanhueza-Vergara, J. (2021). How to measure environmental performance in ports. *Sustainability*, 13(7), 4035.
- [170]. Venkatesh, V., Raj, P., Kumar, S. A., & Devi, R. A. (2022). Demystifying next-generation cyber-physical healthcare systems. In *cyber-physical systems and industry 4.0* (pp. 149-175). Apple Academic Press.
- [171]. Verma, A., Bhattacharya, P., Madhani, N., Trivedi, C., Bhushan, B., Tanwar, S., Sharma, G., Bokoro, P. N., & Sharma, R. (2022). Blockchain for industry 5.0: Vision, opportunities, key enablers, and future directions. *IEEE Access*, 10, 69160-69199.
- [172]. Vermesan, O., Friess, P., Guillemin, P., Giuffreda, R., Grindvoll, H., Eisenhauer, M., Serrano, M., Moessner, K., Spirito, M., & Blystad, L.-C. (2022). Internet of things beyond the hype: Research, innovation and deployment. In *Building the Hyperconnected Society-Internet of Things Research and Innovation Value Chains, Ecosystems and Markets* (pp. 15-118). River Publishers.
- [173]. Vermesan, O., Friess, P., Guillemin, P., Serrano, M., Bouraoui, M., Freire, L. P., Kallstenius, T., Lam, K., Eisenhauer, M., & Moessner, K. (2022). IoT digital value chain connecting research, innovation and deployment. In *Digitising the Industry Internet of Things Connecting the Physical, Digital and Virtual Worlds* (pp. 15-128). River Publishers.
- [174]. Wang, H., Zhao, H., Zhang, J., Ma, D., Li, J., & Wei, J. (2019). Survey on unmanned aerial vehicle networks: A cyber physical system perspective. *IEEE Communications Surveys & Tutorials*, 22(2), 1027-1070.
- [175]. Yang, M., Sun, H., & Geng, S. (2023). On the quantitative resilience assessment of complex engineered systems. *Process Safety and Environmental Protection*, 174, 941-950.
- [176]. Yao, X., Zhou, J., Lin, Y., Li, Y., Yu, H., & Liu, Y. (2019). Smart manufacturing based on cyber-physical systems and beyond. *Journal of Intelligent Manufacturing*, 30(8), 2805-2817.
- [177]. Ystgaard, K. F., & De Moor, K. (2023). Envisioning the future: A multi-disciplinary approach to human-centered intelligent environments. *Quality and User Experience*, 8(1), 11.
- [178]. Zavala-Alcívar, A., Verdecho, M.-J., & Alfaro-Saiz, J.-J. (2020). A conceptual framework to manage resilience and increase sustainability in the supply chain. *Sustainability*, 12(16), 6300.
- [179]. Zayadul, H. (2023). Development Of An AI-Integrated Predictive Modeling Framework For Performance Optimization Of Perovskite And Tandem Solar Photovoltaic Systems. *International Journal of Business and Economics Insights*, 3(4), 01-25. <https://doi.org/10.63125/8xm7wa53>
- [180]. Zayadul, H. (2025). IoT-Driven Implementation of AI Predictive Models For Real-Time Performance Enhancement of Perovskite And Tandem Photovoltaic Systems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, 1(01), 1031-1065. <https://doi.org/10.63125/ar0j1y19>
- [181]. Zdravković, M., Panetto, H., & Weichhart, G. (2022). AI-enabled enterprise information systems for manufacturing. *Enterprise Information Systems*, 16(4), 668-720.
- [182]. Zhao, X., Xiang, H., & Zhao, F. (2023). Measurement and spatial differentiation of farmers' livelihood resilience under the COVID-19 epidemic outbreak in rural China. *Social Indicators Research*, 166(2), 239-267.