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RESEARCH ARTICLE

From Smart Automation to Resilient Production: A Narrative Review and Integrated Architecture for Intelligent Manufacturing Systems

Syed Jalal Ahmed

Master of Science (M.Sc.) in Engineering Management, Wichita State University, Wichita, Kansas, USA.

Corresponding Author: Syed Jalal Ahmed, **E-mail:** syedjalalahmed96@gmail.com

ABSTRACT

Manufacturing systems are increasingly expected to operate as intelligent, connected, and adaptive production environments while maintaining performance under equipment failures, demand shifts, cyber-physical disturbances, and operational uncertainty. Yet the literature on smart manufacturing, cyber-physical production, digital twins, industrial artificial intelligence, reconfigurable manufacturing, smart maintenance, and resilience has largely developed as partially separated streams. This narrative review synthesizes 25 peer-reviewed studies published between 2015 and 2024 to examine how these streams can be integrated into a coherent architecture for intelligent and resilient automated production. The review uses a structured narrative synthesis in which the selected studies are coded by technology, manufacturing level, resilience relevance, resilience dimension, methodological approach, limitation, and architectural role. Three major gaps emerge: fragmentation between intelligence and resilience mechanisms; insufficient closed-loop integration from sensing and prediction to recovery and reconfiguration; and limited operationalization of resilience through comparable metrics, human-centered governance, cybersecurity, and cross-sector validation. In response, the review develops an integrated architecture comprising physical production and reconfiguration, cyber-physical connectivity, digital twin and data infrastructure, AI-enabled prediction and decision support, resilience orchestration, and human governance layers. The synthesis shows that resilience is not produced by any single Industry 4.0 technology. Rather, it depends on coordinated capabilities for visibility, anticipation, diagnosis, adaptation, reconfiguration, maintenance, recovery, and organizational learning. The proposed architecture, therefore, reframes intelligent manufacturing from technology adoption toward a closed-loop resilience capability that links operational data to adaptive action. The paper concludes with a research agenda for measurable, interoperable, secure, and human-centered resilient manufacturing systems.

KEYWORDS

intelligent manufacturing; resilient manufacturing; smart manufacturing; cyber-physical systems; digital twin; artificial intelligence; reconfigurable manufacturing systems; Industry 4.0; Industry 5.0; automated production

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1. Introduction

Automated production has moved beyond isolated programmable machines toward connected manufacturing ecosystems in which physical equipment, sensors, software, data platforms, analytical models, and human decision makers interact continuously. This transformation is commonly described through smart manufacturing, Industry 4.0, cyber-physical production systems, industrial artificial intelligence (AI), and digital-twin-enabled operations. Foundational studies positioned cyber-physical systems (CPS) as the connective architecture between physical production and computational intelligence, while later work expanded the concept toward data-rich smart factories, digital twins, distributed decision making, and AI-enabled monitoring and control (Lee et al., 2015; Monostori et al., 2016; Zhong et al., 2017; Tao & Zhang, 2017).

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The technological progress is substantial, but intelligence alone does not ensure that a production system can continue, adapt, and recover when conditions deviate from plan. Automated environments remain exposed to machine degradation, process variability, product and volume changes, network failures, cyber threats, model errors, and unexpected disturbances. This makes resilience a system-level requirement rather than a secondary performance characteristic. Reconfigurable manufacturing research has long emphasized responsiveness, scalability, convertibility, and diagnosability, while smart maintenance has focused on reliability and failure prevention. More recent resilience research explicitly adds robustness, survivability, adaptation, and recovery to the manufacturing agenda (Koren et al., 2018; Bortolini et al., 2018; Bokrantz et al., 2020; Lee et al., 2022; El-Breshy et al., 2024).

A central challenge is that these research traditions do not yet form a single operational logic. CPS literature explains connectivity and distributed intelligence; digital-twin studies emphasize synchronization, virtual representation, simulation, and verification; industrial AI research develops prediction, diagnosis, prognostics, optimization, and control; reconfigurable manufacturing provides mechanisms for physical adaptation; and resilience research defines the desired ability to absorb, adapt to, and recover from disturbances. The value of these streams becomes greater when they are treated as interdependent components of one closed-loop production architecture rather than as independent technology categories.

This narrative review addresses that integration problem. It synthesizes 25 influential and closely aligned studies published between 2015 and 2024. The aim is not to estimate a pooled effect or claim exhaustive bibliometric coverage. Instead, the review critically connects conceptual architectures, review studies, applied frameworks, prototypes, and empirical agenda-setting work to explain how intelligent manufacturing capabilities can be organized around resilience outcomes. The review makes three contributions. First, it identifies three persistent research gaps across the selected literature. Second, it organizes the evidence into a capability-based narrative spanning sensing, digital representation, prediction, decision, reconfiguration, maintenance, recovery, and governance. Third, it proposes an integrated architectural framework that connects Industry 4.0 intelligence with Industry 5.0 resilience and human-centricity.

2. Research Gaps and Research Questions

2.1 Gap 1: Fragmented integration of intelligence and resilience capabilities

The first gap is the separation between technology-centered smart-manufacturing architectures and resilience-centered manufacturing research. Early CPS and smart-manufacturing studies establish connectivity, data acquisition, cloud services, analytics, distributed control, and intelligent scheduling, but resilience is frequently treated as an implicit benefit rather than an explicitly designed and measured system capability (Lee et al., 2015; Kang et al., 2016; Monostori et al., 2016; Zhong et al., 2017; Kusiak, 2018). Conversely, reconfigurable manufacturing and later resilience studies specify adaptability, robustness, recovery, and survivability but do not always integrate the full contemporary stack of digital twins, AI, smart maintenance, cybersecurity, and human-centered governance (Koren et al., 2018; Lee et al., 2022; El-Breshy et al., 2024). The resulting literature offers strong components but limited architectural unification.

RQ1. How have cyber-physical systems, digital twins, industrial AI, reconfigurable manufacturing, and smart maintenance been connected to resilience capabilities in automated production environments?

2.2 Gap 2: Incomplete closed-loop transition from monitoring and prediction to adaptive recovery

The second gap concerns the operational loop through which intelligence becomes resilience. Digital-twin and AI studies provide visibility, synchronization, diagnosis, prediction, simulation, and optimization, while reconfiguration studies demonstrate mechanisms for changing physical or control configurations (Qi & Tao, 2018; Wang et al., 2018; Lu et al., 2020; Leng et al., 2020). However, the evidence base is still uneven in its linking of disturbance detection to diagnosis, consequence assessment, response selection, virtual verification, physical reconfiguration, maintenance action, recovery confirmation, and learning. Demonstrations are often technology-specific or bounded to a particular use case. Thus, an integrated disturbance-to-recovery control logic remains underdeveloped.

RQ2. What closed-loop functions are required to transform manufacturing data and intelligent prediction into timely adaptation, reconfiguration, maintenance, and recovery?

2.3 Gap 3: Limited resilience measurement, validation, cybersecurity integration, and human-centered governance

The third gap is the limited operationalization and validation of resilience. Across the selected literature, resilience-related constructs include flexibility, robustness, adaptability, reconfigurability, diagnosability, survivability, fault tolerance, continuity, and recovery. Yet these dimensions are not consistently translated into comparable performance measures. Cross-sector

validation, longitudinal testing, causal evidence, and multi-disturbance experiments remain limited. Cybersecurity appears as an important CPS concern, and adversarial resilience has begun to enter manufacturing AI, but cyber risk and model robustness are not routinely embedded in manufacturing resilience architectures (Babiceanu & Seker, 2016; Mukherjee et al., 2022). Industry 5.0 additionally raises the importance of human adaptability, governance, sustainability, and collaborative intelligence, indicating that resilient automation must be socio-technical rather than purely technical (Zhang et al., 2023; van Erp et al., 2024).

RQ3. How can manufacturing resilience be operationalized and governed through measurable, secure, human-centered, and cross-sector architectural mechanisms?

3. Methodology

3.1 Review design

A narrative review design was adopted to integrate heterogeneous evidence on intelligent and resilient manufacturing systems. Narrative review was appropriate because the selected literature spans conceptual architectures, state-of-the-art reviews, systematic and structured reviews, technology surveys, design-science studies, prototypes, case applications, simulation-oriented methods, and qualitative industry evidence. These studies do not share a common intervention, outcome measure, experimental design, or effect-size structure that would support meta-analysis. The analytical objective was therefore interpretive and integrative: to connect complementary research streams and develop an architectural synthesis for automated production environments.

3.2 Scope and evidence base

The review covers peer-reviewed literature published from 2015 through 2024. The final evidence base contains 25 articles from established publishers and professional societies, including Elsevier, Springer Nature, IEEE, Taylor & Francis, ASME, Emerald, and CIRP-associated outlets. The corpus was deliberately bounded to studies with direct relevance to at least one of the following areas: smart or intelligent manufacturing; cyber-physical manufacturing; digital twins; industrial AI and machine learning; reconfigurable manufacturing systems; smart maintenance; manufacturing resilience; or Industry 5.0 manufacturing strategy. All 25 records in the working literature matrix include a DOI recorded as verified and a DOI resolver link.

3.3 Selection logic

Studies were retained if they made a substantive contribution to understanding the architecture, enabling technologies, operational mechanisms, or resilience capabilities of automated manufacturing systems. Priority was given to work that could support cross-study synthesis rather than narrow application description. The evidence base, therefore, includes foundational architecture papers, broad technology reviews, resilience-focused reviews, and applied studies that demonstrate how digital twins, reconfiguration, maintenance, AI, or remote commissioning can support adaptation and continuity. Studies centered primarily on non-manufacturing domains or on supply-chain resilience without a clear production-system connection were outside the intended analytical boundary.

3.4 Data extraction and coding

A structured literature matrix was used to maintain consistency across the 25 studies. For each article, the following information was coded: authors and year; title and outlet; publisher and DOI; study type; primary theme; enabling technologies; manufacturing level; degree of resilience relevance; resilience dimensions; key contribution; method or evidence base; limitation or gap relevant to the present review; and potential role in an integrated architecture. Manufacturing levels were interpreted broadly across machine, cell, shop-floor, factory, enterprise, production-line, lifecycle, and system-of-systems contexts. Resilience-related codes captured concepts such as monitoring, robustness, flexibility, adaptability, diagnosability, prediction, reconfiguration, continuity, recovery, survivability, and human adaptability.

3.5 Narrative synthesis procedure

The synthesis proceeded in four analytical stages. First, the studies were read comparatively by primary theme to identify the technological foundations of intelligent manufacturing. Second, resilience-related terms and functions were compared across studies to distinguish enabling technologies from resilience capabilities. Third, the coded framework roles were consolidated into architectural layers representing physical production, cyber-physical connectivity, digital representation and data, AI-enabled intelligence, resilience orchestration, and human-governance functions. Fourth, the limitations recorded across the studies were compared to identify recurring gaps and derive the three research questions. This approach emphasizes conceptual convergence and contradiction rather than frequency counting alone.

3.6 Descriptive Quantitative Synthesis

To complement the narrative synthesis, a descriptive quantitative analysis was conducted using the structured data extracted from the 25 included studies. This analysis was intended to characterize patterns within the selected literature rather than to provide inferential or bibliometric estimates of the wider research field. Each study was coded using binary indicators (1 = present; 0 = not identified) for major technological enablers, resilience capabilities, and components of the proposed integrated manufacturing architecture. Technology categories included cyber-physical systems (CPS), Internet of Things/Industrial Internet of Things (IoT/IIoT), artificial intelligence and machine learning (AI/ML), digital twins, Big Data and analytics, cloud/virtualization technologies, reconfigurable manufacturing, maintenance and diagnostics, simulation and commissioning, human/robotic interaction, and cybersecurity/standards. Resilience capabilities were coded according to seven functional stages: anticipate, detect/observe, diagnose, decide/optimize, adapt/reconfigure, recover/continue, and learn/improve.

Frequencies and percentages were calculated relative to the 25-study corpus. Because individual studies could address multiple technologies, resilience capabilities, or architectural layers, these categories were treated as non-mutually exclusive and their percentages were not expected to sum to 100%. The coded evidence was additionally mapped against the six layers of the proposed integrated architecture: physical production and reconfiguration; connectivity and observability; digital twin and data management; intelligence and decision support; resilience orchestration and closed-loop control; and human, organizational, and governance functions. The resulting frequency distributions were used to support, rather than replace, the qualitative narrative synthesis and to identify areas of concentrated research attention and comparatively underrepresented capabilities. No inferential statistical tests were performed because the purposively selected corpus of literature was not treated as a statistically representative sample of the broader research population.

3.7 Quality and credibility considerations

Credibility was supported by using peer-reviewed sources with traceable DOI records and by maintaining a transparent coding matrix. The corpus includes multiple study types and publishers, reducing dependence on a single methodological tradition or outlet. Nevertheless, the review is narrative rather than exhaustive. The 25-paper corpus was purposively selected for conceptual relevance and architectural coverage; consequently, it should not be interpreted as a complete census of all manufacturing-resilience research published during 2015–2024. The conclusions identify patterns within this curated evidence base and are intended to support theory integration and framework development rather than prevalence estimates.

4. Main Findings of the 25-Study Evidence Base and Quantitative Analysis

Tables 1 & 2 and Figures 1-3 summarizes the principal contribution, evidence approach, resilience relevance, and review-specific implications of each of the 25 studies. The table is intentionally interpretive: the final column identifies how each paper contributes to the integrated architecture rather than merely restating its abstract.

Table 1. Synthesis of the 25 studies included in the narrative review

Study	Research focus / method	Main finding / contribution	Resilience relevance and architectural implication
Jay Lee et al. (2015)	Cyber-physical manufacturing architecture Conceptual synthesis and architecture development	Proposes the widely used 5C CPS architecture (connection, conversion, cyber, cognition, configuration) as an implementation pathway for Industry 4.0 manufacturing.	High: Monitoring; adaptability; collaboration; fault awareness Core architectural foundation for sensing-to-decision-to-reconfiguration layers.
Shiyong Wang et al. (2016)	Smart factory and multi-agent control Framework design with system-level implementation logic	Develops a smart-factory framework using self-organized agents plus big-data feedback to coordinate physical manufacturing resources.	High: Self-organization; coordination; adaptability; reconfiguration Supports decentralized decision and adaptive coordination layers.
László	Cyber-physical	Synthesizes CPS concepts,	High: Adaptability; robustness;

Study	Research focus / method	Main finding / contribution	Resilience relevance and architectural implication
Monostori et al. (2016)	production systems CIRP state-of-the-art review	applications, research challenges and their role in next-generation manufacturing systems.	decentralization; real-time response Provides principles for cyber–physical integration and distributed control.
Radu F. Babiceanu et al. (2016)	Big data and virtualization in manufacturing CPS Literature survey	Explains how big data, virtualization and connected sensing can enable predictive manufacturing and identifies cybersecurity as a central CPS issue.	Moderate-High: Predictive capability; security; observability; fault anticipation Data/virtualization layer and cyber-risk dimension.
Hyoung Seok Kang et al. (2016)	Smart manufacturing evolution Broad literature review	Maps the evolution, enabling technologies and research trajectory of smart manufacturing and identifies future research directions.	Moderate: Flexibility; responsiveness; connectivity Background taxonomy for intelligent manufacturing capabilities.
Ray Y. Zhong et al. (2017)	Intelligent manufacturing / Industry 4.0 Review of 165 papers plus strategic initiatives	Reviews intelligent, IoT-enabled and cloud manufacturing and organizes core Industry 4.0 enabling technologies and application functions.	Moderate-High: Flexibility; real-time monitoring; smart control; smart scheduling Technology-enabler layer and smart monitoring/control/scheduling functions.
Fei Tao et al. (2017)	Digital-twin shop floor Conceptual architecture and implementation discussion	Introduces the Digital Twin Shop-Floor concept linking physical shop floor, virtual shop floor, services and twin data for smart operations.	High: Visibility; synchronization; adaptive control; reconfiguration Digital-twin layer connecting physical assets, virtual models, services and data.
Andrew Kusiak (2018)	Smart manufacturing foundations Conceptual synthesis of research and trends	Defines smart manufacturing through six pillars and integrates data, predictive engineering, sustainability and networked resources.	Moderate-High: Prediction; flexibility; resource sharing; networked response High-level design principles and capability pillars.
Pai Zheng et al. (2018)	Smart manufacturing system framework Review and scenario-based conceptual analysis	Presents an Industry 4.0 smart-manufacturing conceptual framework and application scenarios across design, machining, control, monitoring and scheduling.	High: Monitoring; adaptive control; scheduling; flexibility Functional architecture spanning core manufacturing operations.
Yoram Koren et al. (2018)	Reconfigurable manufacturing systems Review of RMS principles and design trends	Synthesizes RMS principles and design features for rapid adaptation to demand and product changes.	Very High: Responsiveness; reconfigurability; scalability; diagnosability Physical-system reconfiguration and capacity adaptation layer.
Marco Bortolini et al. (2018)	Reconfigurable manufacturing systems Structured review of RMS literature	Reviews RMS research from 1999–2017, identifies five research streams and links reconfigurability to Industry 4.0.	Very High: Reconfigurability; flexibility; capacity adaptation; recovery Evidence base for reconfiguration mechanisms and design choices.

Study	Research focus / method	Main finding / contribution	Resilience relevance and architectural implication
Qinglin Qi et al. (2018)	Digital twin and big data Comparative literature synthesis	Compares digital-twin and big-data concepts, relationships and complementary roles for smart manufacturing.	High: Prediction; visibility; synchronization; decision support Data-intelligence and virtual-representation integration.
Jinjiang Wang et al. (2018)	Deep learning in smart manufacturing Methods-and-applications review	Reviews deep-learning methods and applications for handling high-volume manufacturing data and improving system performance and decision-making.	High: Anomaly detection; diagnosis; prognosis; predictive response AI analytics layer for condition awareness and predictive decisions.
Chiara Cimino et al. (2019)	Digital twin applications Deep literature review plus illustrative application	Reviews manufacturing digital-twin applications and assesses services offered by twins to physical systems, highlighting limited bidirectional feedback in many implementations.	High: Monitoring; maintenance; optimization; safety Evidence for digital-twin maturity and closed-loop control requirements.
Yuqian Lu et al. (2020)	Digital-twin-driven smart manufacturing Review of technologies and representative applications	Proposes a digital-twin reference model covering information modeling, data processing and industrial communications, and identifies key research issues.	Very High: Simulation; prediction; monitoring; optimization; adaptive control Reference architecture for twin-based monitoring, prediction and control.
Jiewu Leng et al. (2020)	Digital-twin-driven reconfiguration Architecture development, optimization model, demonstrative prototype and physical case study	Develops and physically demonstrates a digital-twin approach for rapid reconfiguration of automated manufacturing systems using open-architecture machine tools and IIoT.	Very High: Rapid reconfiguration; adaptability; recovery; optimization Key mechanism linking disturbance detection, optimization, verification and physical reconfiguration.
Jon Bokrantz et al. (2020)	Smart maintenance Industry focus groups and interviews; contingency-model development	Builds a Smart Maintenance research agenda from focus groups/interviews with more than 110 experts across more than 20 firms.	Very High: Reliability; failure prevention; maintainability; recovery Maintenance/reliability layer and organizational implementation factors.
Jorge F. Arinez et al. (2020)	Industrial AI / advanced manufacturing State-of-the-art review organized by manufacturing hierarchy	Reviews AI across manufacturing-system optimization, human–robot collaboration, process monitoring/diagnostics/prognostics, and process control.	Very High: Prediction; diagnosis; control; optimization; human–robot collaboration Intelligence/decision layer across hierarchy levels.
Jeff Morgan et al. (2021)	Smart reconfigurable machines Fundamental research review and	Reviews RMS, modern machine control and machine intelligence and proposes a vision for next-generation smart reconfigurable machines.	Very High: Reconfigurability; decentralization; adaptability; continuity Physical/cyber reconfiguration and decentralized machine-intelligence layer.

Study	Research focus / method	Main finding / contribution	Resilience relevance and architectural implication
	comparative analysis		
Jiewu Leng et al. (2021)	Digital-twin commissioning System development and industrially oriented case study	Proposes and validates a digital-twin-based remote semi-physical commissioning approach using a smartphone assembly-line case.	High: Remote operability; continuity; verification; adaptation Virtual commissioning/validation layer for resilient deployment and change management.
Jay Lee et al. (2022)	Resilient manufacturing systems Conceptual synthesis	Re-conceptualizes manufacturing resilience and presents a unified framework explaining how automation, digital transformation and AI can support resilient systems.	Direct / Very High: Agility; robustness; survivability Direct theoretical foundation for defining resilience objectives and dimensions.
Avik Mukherjee et al. (2022)	ML resilience for manufacturing Cross-domain conceptual method with simulation orientation	Transfers adversarial-ML resilience concepts into manufacturing and proposes deliberately attacking ML models to identify properties that improve manufacturing-system resilience.	Direct / Very High: Robustness; attack tolerance; learning-system resilience AI-robustness and adversarial-resilience component.
Chao Zhang et al. (2023)	Human-centric smart manufacturing / Industry 5.0 Systematic literature review	Systematically reviews human-centric smart manufacturing, introduces its architecture and enabling technologies, and frames resilience as a core Industry 5.0 value.	Very High: Resilience; human adaptability; sustainability; collaborative intelligence Human/organizational layer and Industry 5.0 extension of the architecture.
Sara El-Breshy et al. (2024)	Manufacturing-system resilience + Industry 4.0 Four-phase systematic literature review	Systematically analyzes intersections among Industry 4.0 technologies, manufacturing systems and resilience and identifies research opportunities and metric gaps.	Direct / Very High: Absorption; adaptation; recovery; robustness; fault tolerance Recent evidence base for selecting resilience functions and metrics.
Tim van Erp et al. (2024)	Industry 5.0 manufacturing strategy Framework design with qualitative verification	Proposes an Industry 5.0 strategy framework combining a process model with a fluid cyber-physical system model for resilient, sustainable and human-centric value creation.	Direct / Very High: Resilience; adaptability; sustainability; human-centricity Top-level Industry 5.0 governance and system-of-systems architecture.

Table 2: Descriptive Quantitative Characteristics of the 25 Studies Included in the Narrative Review

Analysis	Result from the 25 studies	Interpretation
High/Very High resilience relevance	24/25 (96%)	The corpus is strongly concentrated on resilience-relevant manufacturing research
Explicitly direct/very-high resilience relevance	4/25 (16%)	Relatively few papers make resilience itself the primary construct
CPS-related technologies	10/25 (40%)	CPS is the most recurrent technological foundation
IoT	7/25 (28%)	Connectivity and real-time data acquisition are prominent
Digital twin	5/25 (20%)	Digital twins form an important but comparatively newer architectural

Analysis	Result from the 25 studies	Interpretation
		component
AI	5/25 (20%)	AI is increasingly important for prediction, decision support, and adaptation
Cloud technologies	5/25 (20%)	Cloud infrastructure supports data integration and distributed intelligence
Big data	4/25 (16%)	Data-intensive manufacturing is a recurring enabling capability
Studies published by Elsevier/CIRP	17/25 (68%)	The selected literature is strongly represented by manufacturing journals from this publisher group
Springer Nature	3/25 (12%)	Second-largest publisher representation
IEEE	2/25 (8%)	Mainly contributes digital-twin/CPS-oriented work

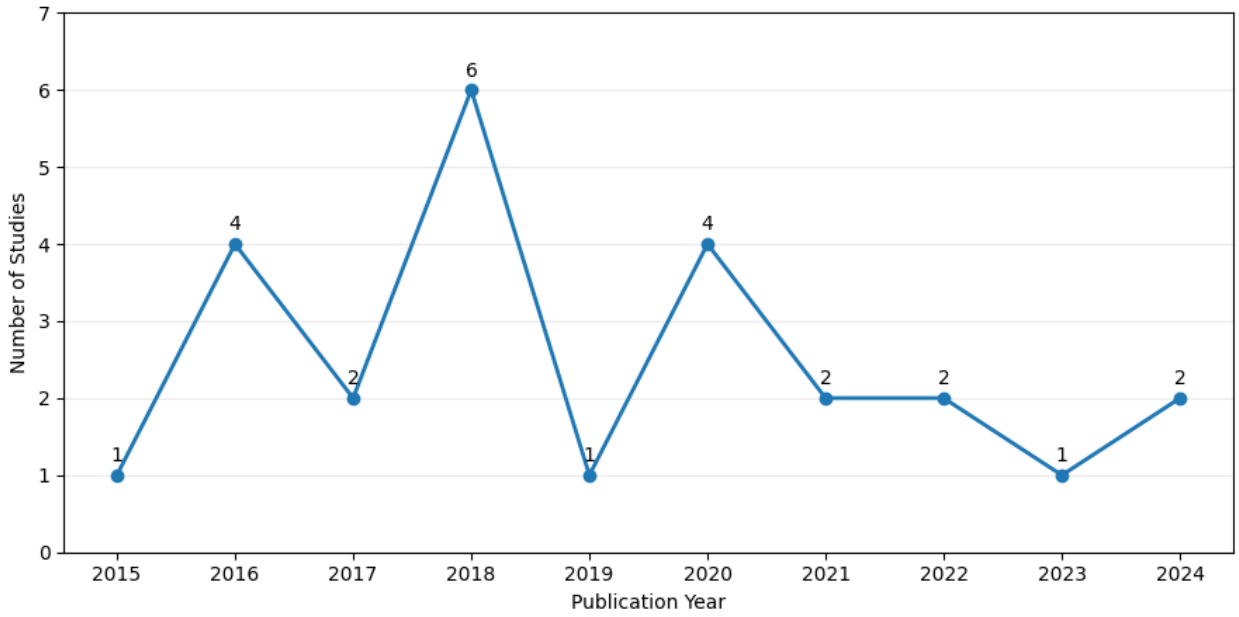


Figure 1: *Publication trends over the 25 selected studies*

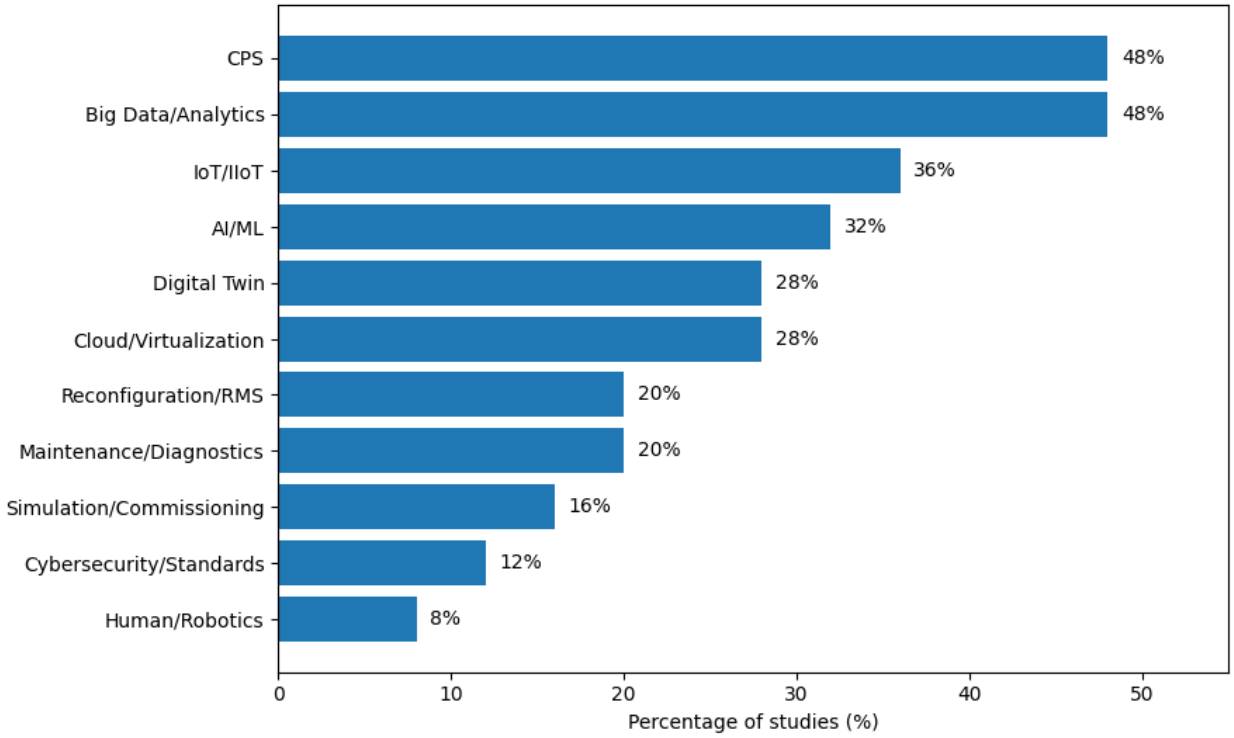


Figure 2: Dominant Technological Enablers. This demonstrates that CPS and Big Data/Analytics are the strongest technological foundations (48% each), followed by IoT/IIoT (36%) and AI/ML (32%).

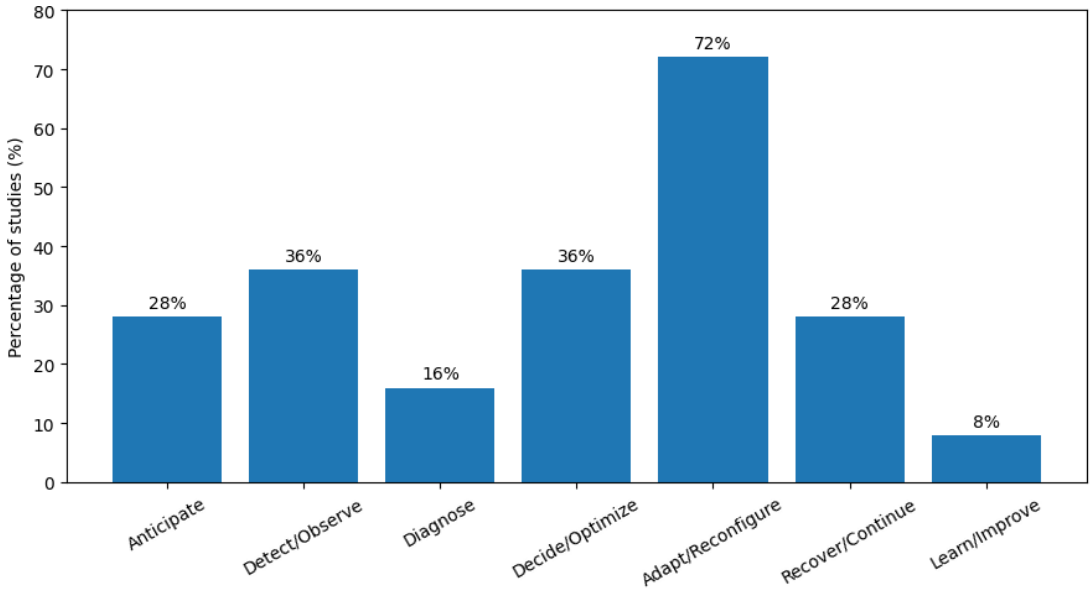


Figure 3: Coverage of Resilience Capabilities. This is particularly important for the research-gap argument. Adaptation/reconfiguration dominates (72%), whereas diagnosis (16%) and especially learning/improvement (8%) remain substantially underrepresented.

5. Evolution from Smart Manufacturing to Resilient Manufacturing

5.1 Cyber-physical foundations and smart-factory coordination

The first stage of the literature establishes the cyber-physical foundation of intelligent production. Lee et al. (2015) proposed the 5C architecture—connection, conversion, cyber, cognition, and configuration—as a progression from machine data

acquisition to self-configuring cyber-physical manufacturing. This model is important for resilience because it implicitly links visibility and cognition to configuration. Wang et al. (2016) extended the decentralization logic through a self-organized multi-agent smart-factory architecture in which big-data feedback supports coordination among manufacturing resources. Monostori et al. (2016) situated CPS more broadly as an enabling paradigm for distributed intelligence, real-time interaction, and adaptive manufacturing.

These studies collectively show that resilience begins with observability and connectivity. A production system cannot respond effectively to disturbance if relevant physical states are invisible, delayed, or isolated. However, connectivity is not equivalent to resilience. Early CPS architectures are strongest in explaining how data and computational functions are connected to production assets, while disturbance taxonomies, recovery objectives, and resilience metrics are less developed. This distinction becomes important for later architectural integration: the CPS layer should be treated as the nervous system of resilience, not resilience itself.

5.2 Data, virtualization, and digital-twin intelligence

The second stream moves from connectivity toward digital representation. Babiceanu and Seker (2016) highlighted big data, virtualization, and cybersecurity as central concerns in manufacturing CPS. Tao and Zhang (2017) then formalized the Digital Twin Shop-Floor paradigm, connecting physical shop-floor entities, virtual models, services, and twin data. Qi and Tao (2018) clarified the complementary roles of digital twins and big data, while Cimino et al. (2019) reviewed manufacturing applications and emphasized the diversity of digital-twin purposes. Lu et al. (2020) further consolidated digital-twin-driven smart manufacturing by developing a reference model and analysing research issues.

For resilience, digital twins contribute more than visualization. Their strategic value lies in synchronized state estimation, scenario testing, virtual commissioning, predictive assessment, and decision verification before changes are imposed on physical production. Leng et al. (2020) provide a particularly important bridge by demonstrating rapid, digital-twin-driven reconfiguration through an open-architecture model. Leng et al. (2021) extend this logic to remote semi-physical commissioning, showing how virtual and physical integration can support continuity when direct on-site intervention is constrained. Together, these studies suggest that the digital twin can function as a resilience sandbox: a controlled virtual environment in which alternative responses are assessed before execution.

5.3 Industrial AI as the prediction and decision layer

A third stream concerns AI and machine learning. Wang et al. (2018) review deep learning methods for smart manufacturing and demonstrate their relevance to data-driven recognition, monitoring, diagnosis, and prediction. Arinez et al. (2020) position AI across manufacturing-system optimization, human–robot collaboration, process monitoring, diagnostics, prognostics, and process control. These functions are directly relevant to resilience because they can shorten the interval between weak-signal detection and corrective action. Predictive intelligence also supports maintenance prioritization, anomaly recognition, quality control, and adaptive scheduling.

Yet AI introduces a new dependency: resilience increasingly depends on the reliability of models and machines. Mukherjee et al. (2022) make this issue explicit by transferring adversarial machine-learning resilience concepts into manufacturing-system design. Their contribution expands the resilience boundary from physical failure toward model vulnerability and attack tolerance. This implies that an intelligent production architecture should not simply contain AI; it should monitor AI performance, uncertainty, drift, and susceptibility to manipulation. An AI model that fails silently during disruption can amplify rather than reduce system fragility.

5.4 Reconfigurability as the physical mechanism of adaptation

Reconfigurable manufacturing provides the physical counterpart to digital intelligence. Koren et al. (2018) synthesize principles of reconfigurable manufacturing systems (RMS), emphasizing responsiveness, scalable capacity, reconfigurability, and diagnosability. Bortolini et al. (2018) review the RMS literature, identify major research streams, and connect reconfiguration to Industry 4.0. Morgan et al. (2021) later combined RMS with distributed control and decentralized machine intelligence to envision smart reconfigurable manufacturing machines.

The importance of this stream is architectural: sensing, analytics, and prediction cannot create resilience unless the production system possesses feasible response options. Reconfigurability supplies those options through modular equipment, adjustable capacity, changeable routing, adaptable control, and machine-level intelligence. The digital-twin reconfiguration work of Leng et al. (2020) illustrates how the cyber and physical sides can be connected. A resilient architecture therefore requires both

decision intelligence and actuation flexibility. Without the former, reconfiguration may be slow or poorly targeted; without the latter, intelligent diagnosis may produce recommendations that cannot be executed.

5.5 Smart maintenance and reliability-centered resilience

Maintenance represents another critical pathway from intelligence to resilience. Bokrantz et al. (2020) develop a Smart Maintenance research agenda grounded in extensive engagement with industrial experts. Their work frames maintenance as a digitally enabled management capability rather than an isolated technical function. In resilient production, maintenance has at least three roles: preventing avoidable disturbances, limiting degradation before functional loss, and accelerating restoration after failure. Connected condition data and predictive models can, therefore, transform maintenance from reactive repair into a resilience mechanism.

This maintenance perspective also clarifies why resilience should be evaluated over time. A system may appear robust during a short disturbance but accumulate hidden degradation that increases future vulnerability. Smart maintenance links immediate operational response with longer-term asset health and organizational learning. Consequently, maintenance data should feed the same digital representation and decision architecture used for scheduling, quality, and reconfiguration.

5.6 Industry 5.0: resilience as a socio-technical objective

The most recent literature expands the concept of resilience beyond technical continuity. Lee et al. (2022) explicitly conceptualize resilient manufacturing systems around automation, digitalization, industrial AI, agility, robustness, and survivability. Zhang et al. (2023) place resilience alongside human-centricity and sustainability within Industry 5.0, emphasizing human–machine collaboration and collaborative intelligence. El-Breshy et al. (2024) systematically review manufacturing-system resilience in the Industry 4.0 era and identify the need for multi-technology studies and stronger metrics. Van Erp et al. (2024) further position Industry 5.0 as a strategic framework linking resilience, sustainability, adaptability, and human-centered value creation.

This shift changes the unit of analysis. Resilience is no longer only the capacity of equipment to avoid downtime; it is the capacity of a socio-technical production system to anticipate, absorb, adapt, recover, and learn while preserving acceptable operational objectives. Human operators, engineers, maintenance personnel, and managers remain part of the control structure because they provide contextual judgment, exception handling, ethical oversight, and strategic prioritization. The implication is that fully autonomous resilience should not be assumed to be the universal endpoint. Instead, automation levels should be matched to risk, explainability, response time, and human oversight requirements.

6. Integrated Architectural Framework for Intelligent and Resilient Automated Production

The synthesis supports a six-layer integrated architecture (Figures 4 and 5). The layers are analytically distinct but operationally connected through continuous feedback. The framework is designed around a disturbance-to-learning cycle rather than a simple technology stack. Its central proposition is that resilience emerges when information can move reliably from physical state sensing to digital interpretation, intelligent decision, validated response, physical adaptation, recovery assessment, and organizational learning.

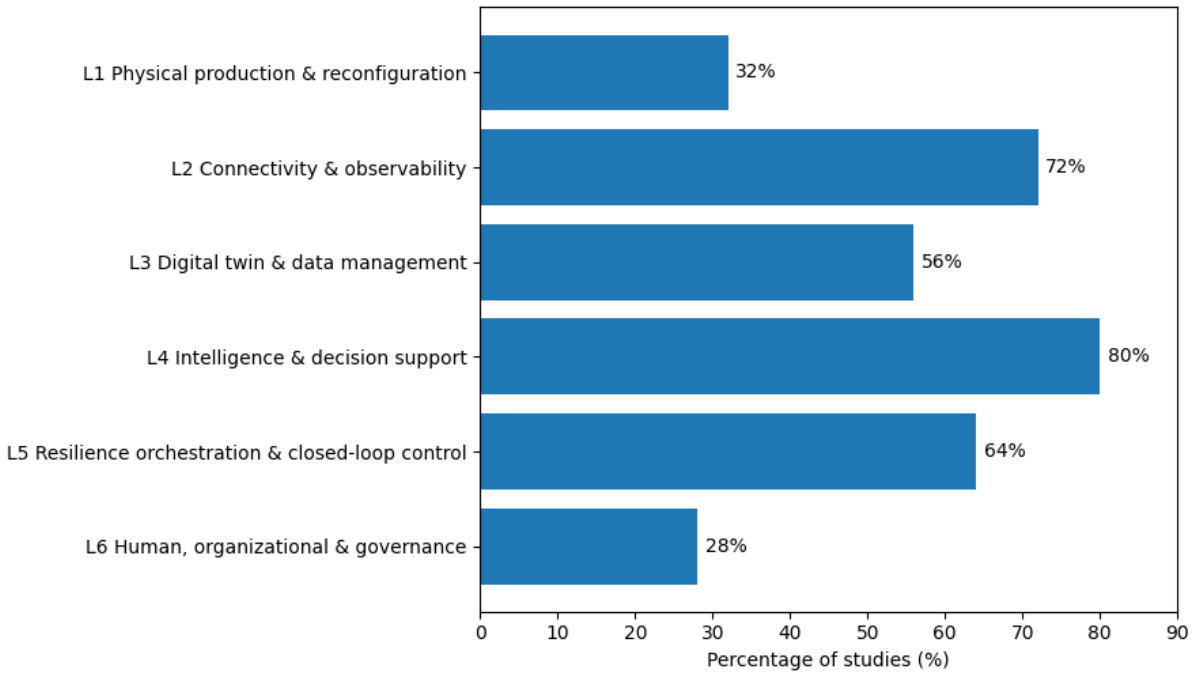


Figure 4: *Coverage of the Six-Layer Integrated Architecture. Intelligence and decision support have the highest coverage (80%), followed by connectivity/observability (72%) and resilience orchestration (64%). Human, organizational and governance considerations receive only 28% coverage.*

6.1 Layer 1: Physical production and reconfiguration

The foundation contains machines, robots, tooling, material-handling systems, production cells, lines, and associated physical resources. Resilience at this layer depends on modularity, diagnosability, scalable capacity, routing alternatives, and the ability to reconfigure hardware or control logic. RMS research provides the strongest theoretical foundation for this layer (Koren et al., 2018; Bortolini et al., 2018; Morgan et al., 2021). The layer converts decisions into physical action, thereby determining the system's feasible response envelope.

6.2 Layer 2: Cyber-physical connectivity and observability

The second layer links physical resources to computational functions through sensors, industrial networks, IoT/IIoT connectivity, controllers, and distributed agents. Its resilience functions are state visibility, event detection, communication continuity, decentralized coordination, and secure data transfer. The 5C CPS model, multi-agent smart-factory architecture, and broader CPS literature provide the conceptual basis for this layer (Lee et al., 2015; Wang et al., 2016; Monostori et al., 2016). Cybersecurity should be treated as an architectural property because compromised connectivity can undermine every higher-level resilience function (Babiceanu & Seker, 2016).

6.3 Layer 3: Digital twin, data, and virtual validation

The third layer maintains digital representations of assets, processes, configurations, and system states. It integrates operational histories, contextual data, simulation models, and service functions. The layer supports synchronization, traceability, what-if analysis, remote commissioning, and pre-execution validation (Tao & Zhang, 2017; Qi & Tao, 2018; Cimino et al., 2019; Lu et al., 2020; Leng et al., 2021). During disruption, this layer should provide a current virtual state against which alternative response scenarios can be evaluated.

6.4 Layer 4: AI-enabled prediction, diagnosis, and decision support

The fourth layer transforms data into operational intelligence. Functions include anomaly detection, quality prediction, remaining-useful-life estimation, diagnostics, prognostics, scheduling, optimization, and adaptive process control. Deep learning and broader industrial AI research establish these capabilities (Wang et al., 2018; Arinez et al., 2020). To support resilience, models should also expose indicators of confidence, uncertainty, drift, and robustness. Adversarial and model-level

resilience should be monitored where AI recommendations directly influence safety- or continuity-critical decisions (Mukherjee et al., 2022).

6.5 Layer 5: Resilience orchestration and closed-loop recovery

The fifth layer is the integrating element missing from many technology-specific architectures. It converts intelligence into coordinated resilience action. Its logic can be expressed as: detect a disturbance; diagnose the cause and affected functions; estimate the operational consequences; generate response alternatives; simulate or validate the alternatives; select a response subject to safety and production constraints; execute reconfiguration, maintenance, rescheduling, or controlled degradation; verify recovery; and update models and policies. Digital-twin-driven rapid reconfiguration provides a concrete precedent for this closed-loop logic, while resilience-focused studies supply the objectives of robustness, agility, adaptation, recovery, and survivability (Leng et al., 2020; Lee et al., 2022; El-Breshy et al., 2024).

6.6 Layer 6: Human, organizational, and governance layer

The sixth layer spans the entire architecture. It defines decision rights, escalation rules, maintenance responsibilities, human override, model governance, cybersecurity accountability, performance targets, and learning processes. Industry 5.0 research makes clear that resilience should remain human-centered and sustainable rather than being reduced to autonomous optimization (Zhang et al., 2023; van Erp et al., 2024). This layer also determines when automated responses are acceptable and when human authorization is required, particularly for high-impact reconfiguration or uncertain AI recommendations.

6.7 Cross-layer resilience cycle

Across the six layers, the architecture operates as a continuous cycle of anticipate–detect–diagnose–decide–validate–adapt–recover–learn. Anticipation uses asset condition, process trends, and predictive models. Detection identifies deviations or disturbances. Diagnosis links events to likely causes and affected production functions. Decision combines AI recommendations with operational constraints. Validation uses digital twins or simulation, where time and criticality permit. Adaptation executes control changes, reconfiguration, maintenance, rescheduling, or controlled degradation. Recovery confirms restoration of required performance. Learning updates thresholds, models, maintenance plans, and response policies. This cycle converts separate Industry 4.0 technologies into a resilience capability.

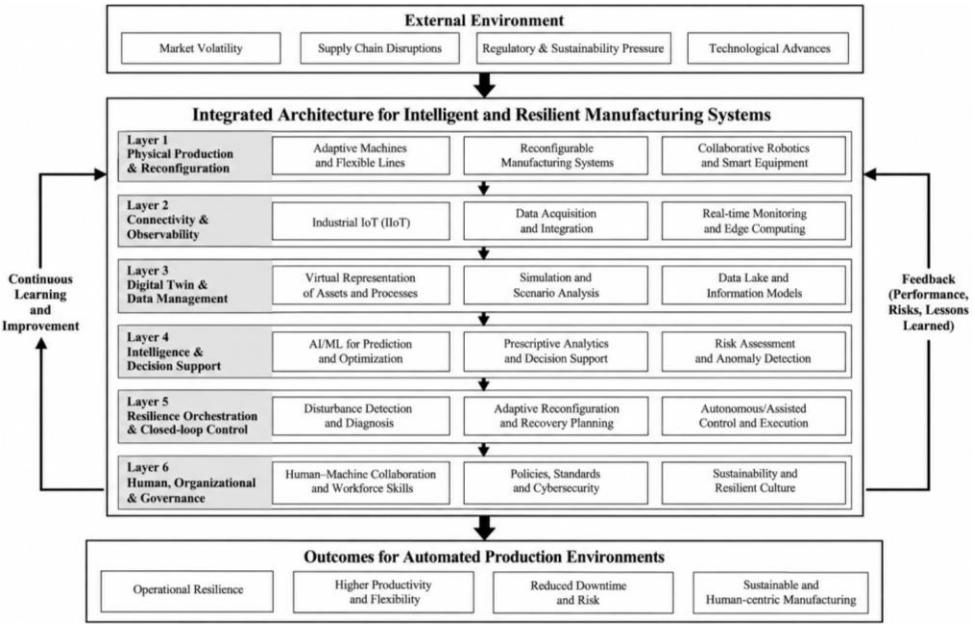


Figure 5: Integrated architectural framework for intelligent and resilient manufacturing systems in automated production environments

7. Answering the Research Questions

7.1 RQ1: Connecting intelligent technologies to resilience capabilities

The literature indicates a complementary rather than a substitutive relationship among the major technology families. CPS provides connectivity and distributed awareness; digital twins provide synchronized representation and virtual

experimentation; AI provides prediction, diagnosis, and optimization; RMS provides physical and control flexibility; and smart maintenance provides reliability and restoration capability. Resilience emerges when these technologies are coordinated around explicit system objectives such as robustness, adaptability, continuity, and recovery. No single technology is sufficient. The strongest conceptual pathway is therefore a capability chain from visibility to cognition to response flexibility and verified recovery.

7.2 RQ2: Functions required for a closed-loop resilient production system

The synthesis identifies eight essential closed-loop functions: disturbance anticipation, event detection, diagnosis, consequence assessment, response generation, virtual or analytical validation, adaptive execution, and recovery verification with learning. Existing literature contains most of these functions, but they are distributed across separate research streams. Digital-twin reconfiguration and remote commissioning come closest to integrating virtual validation with physical action, while smart maintenance connects prediction with reliability action. The research opportunity is to integrate these functions under a common orchestration layer with explicit timing, safety, and performance constraints.

7.3 RQ3: Operationalization and governance of resilience

Manufacturing resilience should be operationalized as a multidimensional performance construct rather than a binary state. Relevant measures include time to detect, time to diagnose, time to recover, performance loss during disturbance, recovery completeness, reconfiguration time, availability, fault-tolerance level, maintenance responsiveness, prediction reliability, and the stability of AI models under drift or attack. The exact metric set should depend on the manufacturing context. Governance should additionally capture human override, explainability for high-impact decisions, cybersecurity controls, and post-event learning. Cross-sector and longitudinal validation are needed before universal thresholds can be proposed.

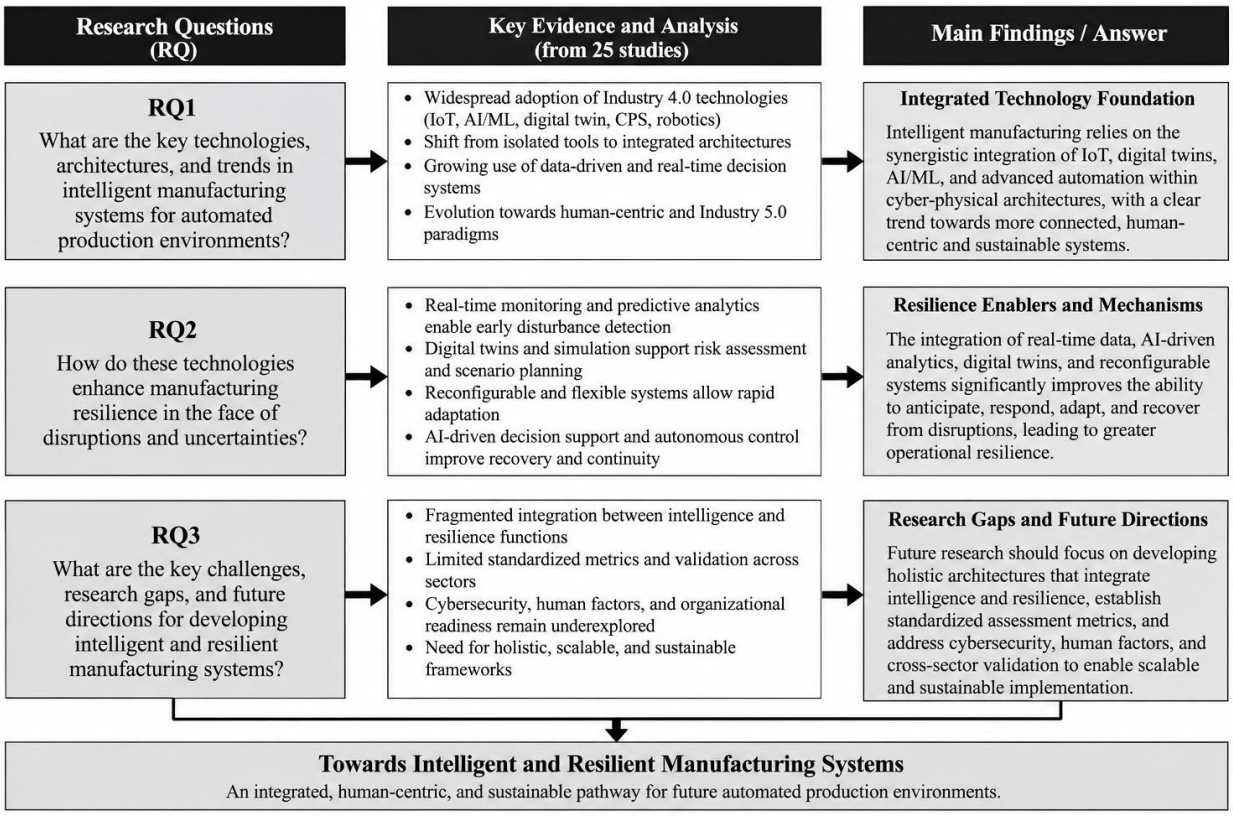


Fig. 2. Research questions, evidence, and key findings from the narrative review.

Figure 6: Research questions, evidence, and key findings from the narrative review

8. Discussion

The central finding of this review is that intelligent manufacturing and resilient manufacturing should not be treated as separate maturity paths. Intelligence becomes strategically meaningful when it improves the production system's ability to preserve function under uncertainty. Likewise, resilience becomes increasingly difficult to achieve without digital visibility,

predictive intelligence, and flexible automation. The relationship is therefore reciprocal: intelligence accelerates the speed and quality of resilience decisions, while resilience provides the performance objective that guides intelligent technologies.

This synthesis also distinguishes enabling infrastructure from resilience mechanisms. Sensors, networks, cloud platforms, digital twins, and AI are enabling infrastructure and analytical capabilities. Resilience mechanisms are the actions and properties through which the system withstands or responds to disturbance: redundancy, graceful degradation, maintenance, rescheduling, reconfiguration, decentralized coordination, safe shutdown, restoration, and learning. This distinction helps avoid a common conceptual shortcut that assumes the adoption of Industry 4.0 technology automatically makes a factory resilient.

The proposed architecture further highlights the importance of latency and decision criticality. Some disturbances require millisecond or second-level local control, while others permit higher-level optimization or human approval. A resilient architecture should therefore distribute decisions across edge, machine, cell, shop-floor, and enterprise levels rather than routing every event through a centralized intelligence layer. Multi-agent and decentralized-control research provides useful foundations for this principle, while digital twins and enterprise analytics can support slower, more deliberative response planning.

Another implication concerns interoperability. The reviewed digital-twin and smart-manufacturing literature repeatedly depends on data moving across heterogeneous assets, models, services, and control systems. Resilience magnifies this requirement because a disturbance may cross functional boundaries. A machine fault can affect quality, maintenance, scheduling, material flow, and delivery commitments simultaneously. Future architectures therefore require semantic and operational interoperability sufficient to support cross-layer reasoning, not merely device connectivity.

Finally, the review supports a socio-technical interpretation of resilient automation. Human operators should not be conceptualized only as sources of variability to be removed. In uncertain or novel disruptions, human expertise can provide causal reasoning and contextual judgment unavailable to trained models. At the same time, poorly designed interfaces, unclear decision rights, or excessive alarm loads can weaken resilience. Industry 5.0, therefore, raises an important governance question: how should authority be allocated among autonomous control, AI recommendations, and human decision-makers under different levels of risk and uncertainty?

9. Research Agenda

Future research should prioritize integrated demonstrations that span the complete disturbance-to-recovery loop. Rather than evaluating a predictive model, digital twin, or reconfiguration algorithm in isolation, studies should test whether combined architectures reduce performance loss and recovery time under defined disturbances. Experimental designs should report disturbance type, severity, affected functions, baseline configuration, response policy, recovery criterion, and post-recovery performance.

A second priority is resilience measurement. Manufacturing research would benefit from a common core of metrics that can be adapted to sector-specific contexts. Candidate measures include detection latency, diagnostic accuracy, maximum performance loss, cumulative performance loss, time to functional recovery, time to full recovery, reconfiguration duration, service-level preservation, maintenance restoration time, and recurrence after recovery. For AI-enabled systems, model confidence, model drift, adversarial robustness, and decision error under disturbances should be included.

A third priority is research on multi-disturbance and cascading failure. Much of the technology literature demonstrates performance under bounded scenarios. Real production disruptions can interact: equipment degradation may coincide with network instability, quality drift, labor constraints, or demand changes. Digital twins and simulation provide a promising environment for testing compound scenarios without exposing production assets to unacceptable risk.

A fourth priority is human-centered resilience engineering. Research should investigate how operators interpret AI recommendations, how decision authority shifts during disruption, how interfaces communicate uncertainty, and how organizations learn after recovery. These questions are essential to Industry 5.0 because technical recovery that creates unsafe workload, opaque decisions, or unsustainable operating conditions cannot be considered fully resilient.

A fifth priority is cross-sector validation. Architectures developed in discrete manufacturing, assembly, process industries, or high-automation environments may not transfer directly. Comparative studies should examine which architectural functions are universal and which depend on production volume, product variety, automation level, regulatory environment, and safety criticality. Such evidence would allow the proposed architecture to evolve from a conceptual synthesis toward configurable reference architectures.

10. Limitations

This review has several limitations. First, the evidence base is a purposive set of 25 peer-reviewed articles rather than an exhaustive systematic search of all publications from 2015 to 2024. The synthesis, therefore, emphasizes conceptual coverage and architectural relevance rather than publication-frequency estimates. Second, the selected studies are methodologically heterogeneous, ranging from conceptual papers and reviews to prototypes, case studies, simulation-oriented work, and qualitative industry research. Direct comparison of performance outcomes is consequently inappropriate. Third, the architectural framework is derived from literature synthesis and has not been experimentally validated as a complete implementation. Its value is presently conceptual: it identifies functions, interfaces, and research propositions that can guide future empirical work. Finally, the rapid development of industrial AI, digital twins, cybersecurity, and Industry 5.0 means that new evidence may extend or modify the proposed layers and metrics.

11. Conclusion

The literature from 2015 to 2024 shows a clear progression from connected and smart manufacturing toward production systems expected to remain effective under disruption. CPS established the infrastructure for connected intelligence; digital twins added synchronized virtual representation and validation; AI expanded prediction, diagnosis, and optimization; reconfigurable manufacturing supplied physical adaptability; and smart maintenance strengthened reliability and recovery. Recent resilience and Industry 5.0 research brings these capabilities together around robustness, adaptability, survivability, human-centeredness, and sustainability.

The main unresolved challenge is integration. The field contains many of the necessary technological components, but fewer studies connect them through an explicit closed-loop resilience logic. The architecture proposed in this review addresses this gap through six interacting layers: physical production and reconfiguration; cyber-physical connectivity; digital twin and data infrastructure; AI-enabled intelligence; resilience orchestration; and human-organizational governance. Across these layers, the core operational cycle is anticipate, detect, diagnose, decide, validate, adapt, recover, and learn. This framing shifts the discussion from whether a factory possesses smart technologies to whether those technologies collectively preserve and restore manufacturing function when conditions change. Future empirical research should test this architecture across sectors, quantify resilience using comparable metrics, and examine how secure AI, digital twins, reconfigurable assets, maintenance, and human decision-making can be coordinated under real-world disturbances.

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