Artificial Intelligence Applications for Resilience in Manufacturing — A Systematic Literature Review

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***Abstract*— This review provides a structured literature analysis of Artificial Intelligence (AI) applications in enhancing manufacturing resilience. The research is guided by three primary questions addressing the use cases, technologies, and benefits of AI across the five resilience phases: Prepare, Prevent, Protect, Respond, and Recover. Findings from 78 papers reveal that AI significantly contributes to predictive maintenance, risk mitigation, and quality control, with machine learning and deep learning being the predominant technologies. The study highlights the pivotal role of AI in advancing manufacturing towards proactive, resilient, and adaptable operations. The insights gleaned offer a roadmap for future research and practical AI integration in manufacturing, underscoring the value of AI in driving industrial innovation and efficiency.**

Keywords—* *Artificial Intelligence, Manufacturing Resilience, Predictive Maintenance, Smart Manufacturing, Machine Learning, Deep Learning, Fault Detection, Zero-Defect Manufacturing, Systematic Literature Review

I. Introduction

In the evolving landscape of manufacturing, resilience has become a pivotal aspect for businesses striving to maintain continuity and competitiveness amidst various challenges. Drawing inspiration from Fischer's model [79] and Thoma's 'Resilience-by-Design' [80], the concept of resilience in manufacturing can be structured into five distinct phases. These phases serve as a framework for manufacturers to not only withstand disruptions, but also to adapt and thrive in the face of adversity. Below, we explore how each of these phases – Prepare, Prevent, Protect, Respond, and Recover – plays a crucial role in building a robust manufacturing sector that can effectively navigate the complexities of modern industrial challenges.

Phase 1 Prepare: This phase involves the initial steps where a manufacturing entity anticipates potential disruptions and prepares accordingly. Preparation might include assessing risks, gathering resources, training personnel, and establishing protocols for dealing with potential crises or disruptions.

Phase 2 Prevent: In this phase, the focus is on taking proactive measures to prevent disruptions before they occur. This could involve implementing advanced technologies for early detection of problems, improving quality control measures, or refining supply chain processes to mitigate risks.

Phase 3 Protect: The protection phase is about safeguarding the critical assets and functions of the manufacturing process. This involves deploying systems and strategies to protect against identified risks, whether they are physical (like machinery and infrastructure) or digital (such as cybersecurity measures).

Phase 4 Respond: When a disruption occurs, the response phase kicks in. This is about effectively managing and mitigating the impact of the disruption on the manufacturing process. Response actions might include activating contingency plans, reallocating resources, or using alternative processes to maintain production.

Phase 5 Recover: Post-disruption, the recovery phase focuses on returning to normal operations as quickly and efficiently as possible. This involves repairing any damages, addressing supply chain disruptions, learning from the incident, and improving processes and systems to better handle future disruptions.

These phases represent a comprehensive approach to building resilience in the manufacturing sector, encompassing proactive and reactive strategies to handle potential disruptions effectively. Transitioning into the realm of Artificial Intelligence (AI), it's intriguing to consider how AI technologies can significantly bolster each of the five resilience phases in manufacturing. AI's capabilities in data analysis, predictive modeling, automation, and real-time decision-making can be harnessed to enhance the effectiveness of each phase, offering a more dynamic and intelligent approach to resilience. In the following sections, we delve into the specific roles AI can play in Prepare, Prevent, Protect, Respond, and Recover phases, illustrating how AI not only complements but also elevates the resilience of the manufacturing sector. This exploration underscores the transformative potential of AI in redefining the resilience strategies within the industry.

II. Research Methodology

A. *Systematic Literature Review*

A Systematic Literature Review (SLR) is a methodical approach to collate, evaluate, and synthesize all relevant findings on a research topic, aimed at addressing specific research queries. Recognized as a standard methodology for deriving insights from literature based on prior studies [81]. This study encompasses a wide array of esteemed publications, including IEEE Xplore, Science Direct, Springer, and ResearchGate and MDPI. The SLR process involves several key steps: defining the scope of the research, formulating research questions, gathering research data, and conducting thorough analyses and summaries of the findings.

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B. *Research Questions and Motivation*

To develop a comprehensive understanding of the role of Artificial Intelligence (AI) in enhancing manufacturing resilience, it's crucial to explore each research question in depth. Here are the three research questions.

TABLE I. RESEARCH QUESTIONS

ID	Research Question
RQ1	What are the specific use cases within each of the five phases of the resilience cycle where AI is applied in manufacturing?
RQ2	Which AI technologies have been employed to implement the use cases for enhancing resilience in manufacturing?
RQ3	What are the anticipated benefits and positive impacts of integrating AI technologies for enhancing resilience in manufacturing?

Each research question is designed to uncover layers of AI application in manufacturing resilience, providing a nuanced understanding that can guide future research, development, and practical implementation in the field.

1) RQ1: What are the specific use cases within each of the five phases of the resilience cycle where AI is applied in manufacturing?

This question seeks to identify AI's practical applications in enhancing manufacturing resilience. Understanding these use cases helps manufacturers tailor AI solutions to their specific needs throughout different resilience phases.

2) RQ2: Which AI technologies have been employed to implement the use cases for enhancing resilience in manufacturing?

This question aims to map out the AI technologies used in manufacturing resilience. Identifying these technologies provides insights into the current technical landscape and aids in the dissemination of effective AI applications in the industry.

3) RQ3: What are the anticipated benefits and positive impacts of integrating AI technologies for enhancing resilience in manufacturing?

This inquiry focuses on the expected advantages of AI integration in manufacturing. Understanding these benefits is crucial for justifying AI investments and informs strategic decisions related to efficiency, downtime reduction, and adaptability.

C. *Result Finding*

To answer the Research Question above, the researcher conducted a search on research papers published in several popular literatures with specific search terms. The search term is “AI for Resilience in manufacturing plant”.

Utilizing multiple criteria, we implement a sequential filtering process. Initially, we apply the E1 criterion as the primary filter. Subsequently, we integrate and employ the I1, I2, and I3 criteria for the second stage of filtration. Finally, the third stage involves the simultaneous application of the E2 and E3 criteria, resulting in the selection of 78 pertinent papers

TABLE II. SEARCH RESULTS OF EACH DATABASE JOURNAL

Database journal	***Search term***	***Number of articles found***	***Relevant***
Science Direct	AI for Resilience in manufacturing plant	928	39
IEEE Xplore		33	14
Springer		401	6
ResearchGate		2341	16
MDPI		14	3
	Total	3717	78

TABLE III. INCLUSION AND EXCLUSION CRITERIA

Criteria		
Inclusion	I1	Research papers related to utilization of Artificial intelligence in manufacturing, focusing on how it enhances resilience in manufacturing plant.
	I2	Papers published from 2010 to 2023.
	I3	Only research papers will be taken into consideration; books will not be included.
Exclusion	E1	Papers which are not in English.
	E2	Papers that are from different database.
	E3	Research papers addressing supply chain issues in manufacturing.

III. RESEARCH RESULT

This section presents a synthesis of the selected studies, providing a coherent narrative of how AI is driving advancements in manufacturing resilience and setting the stage for an era of smart manufacturing.

A. *Use Case Utilization Across Resilience Phases*

TABLE IV. USE CASE UTILIZATION ACROSS RESILIENCE PHASES

AI Technology	***Prepare***	***Prevent***	***Protect***	***Respond***	***Recover***
Fault detection	[8], [43], [72]	[13], [14], [21], [43], [64], [69], [72]	[11], [13], [16], [30], [31], [32], [34], [35], [36], [37], [38], [39], [40], [51], [53], [64], [69], [72]	[16], [21], [31], [32], [43]	[16], [31], [32], [43], [72]
Fault diagnosis	[43]	[13], [14], [21], [33], [43]	[11], [13], [16], [34], [35], [36], [37], [38], [39], [40], [51], [53]	[16], [21], [43]	[16], [43]
Fault tolerant	[43]	[43]	[27], [31], [32]	[31], [32], [43]	[31], [32], [43]
Predictive mainten-ance	[2], [5], [8], [22], [28], [42], [43], [44], [60], [72], [76]	[42], [43], [57], [60], [72], [76]	[11], [15], [16], [17], [72]	[16], [17], [43]	[16], [17], [43], [72]
Product inspection for faults	[8], [43], [77]	[23], [24], [25],	[52], [77]	[43]	[43]

AI Technology	*Prepare*	*Prevent*	*Protect*	*Respond*	*Recover*
		[26], [43], [52], [77]			
Prognostics and health management	[8]	[21], [33]	[37]	[21]	
Scheduling	[45], [46], [47], [55], [56], [58], [59]	[9], [55], [56], [75]	[46], [47], [75]		
Smart manufacturing	[1], [2], [3], [4], [6], [7], [20], [42], [65], [66], [68], [70], [71], [72], [73], [74], [78]	[10], [42], [72]	[17], [72]	[17], [20]	[17], [72]
Zero defect manufacturing			[15]		

1) Resilience Phase Contribution

Each phase of resilience in manufacturing is enhanced by the strategic application of AI technologies, improving the sector's ability to withstand and quickly bounce back from various challenges. These advancements indicate a shift towards a more proactive, intelligent, and resilient manufacturing industry.

1. Prepare: In the preparation phase, AI technologies, particularly machine learning, are utilized for predictive analytics and self-organizing systems, helping plants anticipate changes and prepare for potential disruptions.

2. Prevent: Prevention efforts are bolstered by AI through predictive maintenance and risk assessments, using machine learning algorithms to proactively address potential issues before they manifest.

3. Protect: AI aids in the protection of manufacturing operations from identified risks, deploying systems like Digital Twins and neural networks to safeguard against both physical and digital threats.

4. Respond: During the response phase, AI is critical for managing and mitigating the impact of disruptions through rapid fault detection and health monitoring, employing machine learning and deep learning to adapt and make real-time decisions.

5. Recover: AI's role in the recovery phase is characterized by self-healing mechanisms and predictive maintenance, using deep learning to predict equipment failure and facilitate efficient recovery.

2) Use Case Contribution

Each of the following nine use cases demonstrates the diverse and impactful ways in which AI is being used to enhance manufacturing resilience, with the potential to significantly improve efficiency, quality, and sustainability within the sector.

1. Predictive Maintenance: AI, particularly machine learning, is central to predictive maintenance, enabling the early detection of potential failures and scheduling timely maintenance activities, thus minimizing downtime and extending machinery life.

2. Zero Defect Manufacturing: Techniques such as deep learning and data mining are applied to achieve zero defect manufacturing, focusing on defect detection, prevention, and compensation to maintain high-quality standards in production.

3. Scheduling: AI technologies, including various forms of evolutionary algorithms and reinforcement learning, are used to enhance scheduling efficiency, particularly under conditions of uncertainty and machine breakdowns, ensuring continuous production flow.

4. Fault Detection: Through the application of image processing and neural networks, AI is employed to detect faults in real-time, providing crucial data for maintaining the integrity and reliability of the manufacturing process.

5. Fault Diagnosis: AI's diagnostic capabilities are showcased through the use of deep learning and machine learning algorithms that interpret sensor data and identify the root causes of equipment malfunctions, leading to informed decision-making.

6. Fault Tolerant: AI contributes to the creation of fault-tolerant systems by employing machine learning algorithms that anticipate and compensate for potential system errors, thereby ensuring uninterrupted manufacturing operations.

7. Smart Manufacturing: AI is a key driver of smart manufacturing, with its applications ranging from real-time monitoring and control to intelligent adaptation based on predictive analytics, enhancing overall manufacturing intelligence.

8. Product Inspection for Faults: Advanced image processing and deep learning techniques are implemented for the inspection of final products, ensuring that any defects are identified and addressed before the products are shipped.

9. Prognostics and Health Management: In prognostics and health management, AI leverages predictive analytics and machine learning to forecast the remaining useful life of machinery, enabling proactive maintenance and resource planning.

B. *AI Technology Utilization Across Resilience Phases*

This section provides an overview of how different Artificial Intelligence (AI) technologies are applied across the five resilience phases in manufacturing: Prepare, Prevent, Protect, Respond, and Recover. It identifies which specific AI technologies, such as Machine Learning, Deep Learning, Image Processing, Reinforcement Learning, and Miscellaneous AI Technologies, are being utilized in each phase. The table lists references to papers that exemplify the use of these technologies in corresponding phases, providing a comprehensive view of the technological landscape in manufacturing resilience.

TABLE V. AI TECHNOLOGY UTILIZATION ACROSS RESILIENCE PHASES

AI Technology	*Prepare*	*Prevent*	*Protect*	*Respond*	*Recover*
Machine Learning	[1], [4], [28], [76]	[2], [5], [45], [46]	[21], [27], [48]	[11], [15], [30], [53]	[19], [42], [43], [69], [72]
Deep Learning		[2], [21]		[8], [30], [53]	[29], [31], [72]
Image Processing				[23], [24], [25], [26]	
Reinforce-ment Learning				[8], [45], [52], [67]	
Miscellaneous AI Technologies	[1], [19], [28], [76]	[2], [3], [5], [10], [21], [46]	[3], [20], [21], [27], [48], [68]	[8], [15], [39], [40]	[19], [42], [43], [69], [72]

1. Machine Learning: Machine Learning (ML) is extensively used across various applications such as predictive maintenance, risk assessment, and process optimization, showcasing its foundational role in enhancing manufacturing resilience.

2. Deep Learning: Deep Learning (DL) is particularly prominent in complex tasks like image recognition for product inspection, fault detection, and diagnostics, due to its ability to interpret high-dimensional data and learn from it effectively.

3. Image Processing: Image processing is critical for quality inspection and fault detection, with applications ranging from assessing final product defects to monitoring manufacturing processes in real-time.

4. Reinforcement Learning: Employed for dynamic and complex decision-making tasks such as scheduling and motion planning, Reinforcement Learning allowing for adaptable and optimized operations in manufacturing plants.

5. Miscellaneous AI Technologies: Other AI technologies, including various evolutionary algorithms like Genetic algorithms and computer vision algortihms in combination with neural networks, are applied to niche areas like device authentication, system optimization, and resilience modeling, contributing to the robustness and adaptability of manufacturing systems. Also Digital Twins are used for risk prediction, taking design decisions and management, creating virtual models that can simulate and analyze real-world manufacturing scenarios for improved decision-making and operator. However, Digital Twins are considered for this paper as composed systems and not as single technology.

C. *AI Technology Utilization Across Use Cases*

Table VI, Part 1, illustrates the application of various AI technologies in the first four of nine identified use cases in manufacturing: Predictive Maintenance, Zero Defect Manufacturing, Scheduling, and Fault Detection. The table maps each AI technology — Machine Learning, Deep Learning, Image Processing, Reinforcement Learning, and Miscellaneous AI Technologies — to the relevant use cases, accompanied by references to specific studies. This table highlights the diverse roles that AI technologies play in enhancing different aspects of manufacturing operations.

TABLE VI. AI TECHNOLOGY UTILIZATION ACROSS USE CASES (PART 1)

AI Technology	*Predictive Mainte-nance*	*Zero Defect Manufactu-ring*	*Schedu-ling*	*Fault Detection*
Machine Learning	[1], [4], [28], [76]	[13], [16], [51]	[9], [45], [46]	[14], [30], [35]
Deep Learning	[28], [76]	[51], [63]		[23], [30], [34]
Image Processing				[23], [24], [25], [26]
Reinforcement Learning			[45], [75]	
Miscellaneous AI Technologies	[1], [28], [76]	[13], [16], [51], [63]	[9], [46], [47]	[14], [36], [37]

TABLE VII. AI TECHNOLOGY UTILIZATION ACROSS USE CASES (PART 2)

AI Technology	*Fault Diagnosis*	*Fault Tolerant*	*Smart Manu-facturing*	*Product Inspection*	*Prognostics & Health Mgmt.*
Machine Learning	[15], [31], [32]	[10], [27], [39], [40]	[7], [22], [65], [73]	[23], [24], [25]	[11], [42], [60], [69]
Deep Learning	[31], [32], [33]		[29], [65]	[23], [77]	
Image Processing				[23], [24], [25], [26], [77]	
Reinforcement Learning			[67]		
Miscellaneous AI Technologies	[15], [38], [53]	[10], [27], [39], [40]	[7], [20], [22], [73]	[24], [25], [26]	[11], [42], [43], [60], [69]

Table VII, Part 2, continues the exploration of AI technology applications in manufacturing, covering the remaining five use cases: Fault Diagnosis, Fault Tolerant, Smart Manufacturing, Product Inspection, and Prognostics & Health Management. Similar to Part 1, it maps various AI technologies to these use cases and includes references to pertinent research papers. This table completes the comprehensive view of how AI technologies contribute to different functional areas within the manufacturing sector.

IV. DISCUSSION

In summary, AI's integration into manufacturing resilience is transformative, driving the sector towards more intelligent, efficient, and adaptable operations. The insights from this review not only highlight the current state of AI applications in manufacturing but also pave the way for future innovations and practical implementations in this field. Detailed, the reaseach questions can be answered as folloed:

A. *RQ1: What are the specific use cases within each of the five phases of the resilience cycle where AI is applied in manufacturing?*

AI applications in manufacturing resilience are diverse and impactful. In the 'Prepare' phase, AI assists in predictive analytics and anticipatory measures. The 'Prevent' phase sees AI in predictive maintenance and risk assessments. In 'Protect', AI technologies safeguard operations through Digital Twins and neural networks. During 'Respond', AI aids in managing disruptions through rapid fault detection and health monitoring. Finally, in the 'Recover' phase, AI facilitates efficient recovery through predictive maintenance and assisted self-healing mechanisms. See also table IV. Use case utilization Across resilience phases.

B. *RQ2: Which AI technologies have been employed to implement the use cases for enhancing resilience in manufacturing?*

The predominant AI technologies in manufacturing resilience are Machine Learning and Deep Learning. Machine Learning is crucial for predictive maintenance, risk assessment, and process optimization. Deep Learning excels in complex tasks like image recognition for product inspection and fault diagnostics. Image Processing, Reinforcement Learning, and other AI technologies play vital roles in specific areas, contributing to the industry's robustness and adaptability.

C. *RQ3: What are the anticipated benefits and positive impacts of integrating AI technologies for enhancing resilience in manufacturing?*

The integration of AI technologies in manufacturing resilience is expected to bring multiple benefits:

1. Increased Efficiency: AI enables more efficient manufacturing processes through automation, predictive analytics and scheduling.
2. Reduced Downtime: Predictive maintenance capabilities of AI minimize downtime by foreseeing and addressing potential failures in advance.
3. Enhanced Adaptability: AI's data-driven insights facilitate adaptable responses to disruptions, improving the overall resilience of manufacturing operations.
4. Quality Improvement: AI aids in maintaining high-quality standards in production through advanced product inspection and fault detection techniques.
5. Cost-Effectiveness: AI can lead to cost savings by optimizing resource utilization and reducing waste.
6. Informed Decision-Making: AI's ability to analyze vast amounts of data supports better strategic and operational decisions.

V. Conclusion

This systematic literature review has rigorously analyzed the role of Artificial Intelligence (AI) in bolstering the resilience of the manufacturing sector across the five critical phases: Prepare, Prevent, Protect, Respond, and Recover. The convergence of AI with manufacturing processes emerges as a key enabler for transforming traditional practices into dynamic, intelligent systems capable of anticipating, withstanding, and rapidly adapting to disruptions. AI's predictive maintenance capabilities stand out as a cornerstone for preparation and prevention strategies, significantly reducing unplanned downtime and fostering a zero-defect manufacturing approach. The implementation of AI across various functions, from fault detection to recovery planning, illustrates a paradigm shift toward self-aware, self-optimizing manufacturing ecosystems. As we step into an era of smart manufacturing, the integration of AI is not just enhancing the resilience of operations but is also redefining the competitiveness and sustainability of the manufacturing industry.

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