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Intelligent Automation Adoption in Manufacturing Supply Chains: A Systematic Literature Review of RPA and AI Integration Frameworks, Performance Impacts, and Implementation Strategies

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Abstract

Manufacturing supply chains are becoming more tangled and unpredictable, with mounting pressure to adapt quickly, revealing just how inadequate old, step-by-step planning can be when shipments change overnight. By blending Robotic Process Automation with Artificial Intelligence, intelligent automation has become a game changer—sharpening predictions, speeding up decisions, and giving supply chains clearer visibility, like spotting delays before a truck even leaves the warehouse. This review pulls together studies on how RPA and AI are being adopted in manufacturing supply chains, zeroing in on integration frameworks, performance benchmarks, key enablers and obstacles, and how they shape forecasting and day-to-day logistics, from warehouse scheduling to delivery routes. Following PRISMA guidelines, we systematically screened peer reviewed studies from 2017 to 2025 across Web of Science, Scopus, IEEE Xplore, and ScienceDirect, combing through titles like flipping through well-worn index cards. Out of 381 records reviewed, just 50 studies made the cut. We pulled data on implementation strategies, outcomes, and contextual factors, checked quality with the Mixed Methods Appraisal Tool, and uncovered themes through careful, line by line coding. Research shows that using structured adoption frameworks that blend RPA with AI makes supply chains quicker to adapt and easier to see end-to-end, delivering clear gains—costs drop by 24.8%, lead times shorten by 21.3%, forecasting improves by 23.1%, and errors fall by more than half, down 52.6%. Start with RPA, then bring in AI, and you'll hit about 85% success—far better than the 70% you get when you try both at the same time. Sharp leadership, talented teams, and savvy change management are needed, but spreadsheets, system linkages, upfront fees, and ethical issues remain. Intelligent automation, based on evidence-based, human-centered, scalable frameworks, may improve operations, strategy, and performance. Businesses should launch plans in stages, support them with solid data governance, and lead staff through each step of a new system until every click and screen is familiar to make significant progress.

1. Introduction

1.1. Background and Problem Statement

Today's manufacturing supply chains wind through layers of suppliers, shift on a dime when customers change course, juggle tight regulations, and push toward sustainability—sometimes cramming it all into one frantic afternoon with phones ringing like a swarm of bees [1-3]. It's like keeping the line moving while a storm rattles the factory windows and rain drums a steady beat on the glass (Shamsuddoha et al., 2025). The scramble for speed and sudden shifts is stretching supply chains that once relied on steady planning and occasional frantic fixes—like trying to turn a giant cargo ship in its own churned water [4]. Don't just stand there—rain's drumming on the boxes, each cold drop weighing down the cardboard until it sags and turns limp. The COVID-19 pandemic revealed deeper flaws in our systems and showed just how vital resilience is—like being able to pivot fast when the bread aisle is bare and supply trucks stop rolling (Parshuramkar et al., 2024). Manufacturers are juggling several challenges at once—wild swings in demand that call for quick action, supply chain hiccups that need careful risk planning, strict quality checks down to the smallest detail, and constant pressure to cut costs (Hasan et al., 2024). [5-7] Both ERP-based systems and manual decision-making have fallen short—like a report that arrives late and misses half the numbers (Kalluri, 2024). Intelligent Automation integrates Robotic Process Automation with Artificial Intelligence to address these challenges, enhancing decision-making, improving predictive analytics, and providing teams with clear, real-time insights into operations. RPA manages repetitive tasks, whereas AI identifies patterns and forecasts potential outcomes, such as recognising a decline in sales every rainy Tuesday (Samuels, 2025). When combined, the outcomes surpass what either technology could accomplish independently—akin to two instruments harmonising to produce a more profound, resonant sound [8].

1.2. Research Motivation and Significance

Even with growing attention, we still don't fully understand how to put these ideas into practice, what they do to performance, or which factors lead to success in different manufacturing settings (Shahzadi et al., 2024) [9]. Studies on the subject are scattered through supply chain, operations, and information systems—like puzzle pieces left sitting on three separate desks (Cannas et al., 2023). Research finds automation can trim costs by 15–40%, speed up lead times by 10–35%, and erase more than half of all mistakes—leaving fewer fixes at the end of a shift when the air still carries a faint whiff of machine oil (Gomes et al., 2024; Patil, 2025). Still, failure rates linger around 30 to 50 per cent—often because plans unravel, teams walk in unready, or change management slips off course like a train missing its stop [10-13]. That's why closing this gap matters—it's the last puzzle piece, the one that snaps into place and makes the whole picture clear.

1.3. Research Objectives

This review aims to:

- **RO1:** Evaluate integration frameworks for RPA and AI in manufacturing supply chains.
- **RO2:** Benchmark performance impacts across contexts [14].
- **RO3:** Identify enablers, barriers, and success factors.
- **RO4:** Analyse AI-driven impacts on forecasting, inventory, and logistics.
- **RO5:** Compare sector-specific applications and adaptation strategies.

1.3.1. Theoretical Framework

The study uses the Technology–Organization–Environment (TOE) framework from Tornatzky and Fleischer (1990) and expands it to weave in human factors drawn from socio-technical systems theory by Bostrom and Heinen (1977) [15-17]. Technology factors include how well systems connect, the accuracy of the data, whether algorithms are fully developed, the ability to scale, and the strength of security like a lock that clicks shut. Strong leadership, a culture that's got your back, enough resources, streamlined processes, and solid governance think of a crew with a steady hand at the helm and the right gear on deck form the backbone of any organization. Outside, the market's changing fast competitions fierce, rules keep tightening, and customers want more while vendor networks slide and snap into new patterns like puzzle pieces on a crowded table [18]. Human factors cover skills, adaptability, and training, how well we mesh with AI, and strong ethics like knowing when to trust its judgment, even if the machine speaks with a faint, uneasy rasp [19-21].

1.3.2. Dynamic Capabilities Theory Integration

Dynamic capabilities theory (Teece et al., 1997) builds on TOE by showing how companies spot new opportunities, grab them through automation, and reshape their processes like streamlining a production line for lasting advantage. To adopt something effectively, the following step is needed:

- **Sensing:** identifying opportunities and monitoring technologies [22].
- **Seizing:** implementing solutions and managing change.
- **Reconfiguring:** optimizing processes and fostering continuous learning [23].

2. Review of Literature

2.1. Evolution of Supply Chain Automation

Supply chain automation has moved forward in three distinct waves, like ripples spreading from a dropped stone. In the 1990s and early 2000s, the focus shifted to digitization through ERP and EDI systems, boosting accuracy and standardization, yet still reacting to issues and relying heavily on manual work, like clerks entering data line by line (SalwaIdamia et al., 2024). In the 2000s, the second phase rolled out APS systems and business intelligence tools, boosting planning and inventory optimization, yet still leaning on past data and struggling to adjust in real time [24]. The third wave, in step with Industry 4.0, brings together IoT, cloud computing, and AI to create flexible networks that learn, adjust, and make decisions on their own like a system fine-tuning itself as it hums through the night (Vatin et al., n.d.).

2.2. Theoretical Foundations of Intelligent Automation

2.2.1. Technology Adoption Theories

The Technology Acceptance Model (TAM) explores how people decide to use a new tool, weighing its usefulness against how effortlessly they can navigate it (Nendrambaka, 2024) [25-27]. Still, many organizations lean on the TOE framework, which gauges technological, organizational, and environmental readiness—like having up-to-date software, a well-trained team, and a market poised to react (Abaku et al., 2024).

2.2.2. Organizational Change Theories

Automation adoption is transformative, requiring changes in processes and roles (Tarihal et al., 2024). Frameworks such as Kotter's eight-step and Lewin's three-stage models emphasize the need for structured change management. Socio-technical perspectives highlight that technical implementation must be balanced with workforce adaptation (Samuels, 2025).

2.3. Robotic Process Automation in Supply Chains

2.3.1. Capabilities and Applications

RPA automates routine processes through unattended, attended, and increasingly cognitive applications. In procurement, it reduces order processing times by 50–70% (Kalluri, 2024). In operations, it supports quality reporting, scheduling, and requisitions, reinforcing lean practices [28-30].

2.3.2. Implementation Challenges

RPA success depends on process standardization (Waduge et al., 2024). Organizations with inconsistent processes risk failure [31-33]. Resistance to change is another obstacle, often driven by job security concerns (Parshuramkar et al., 2024). Effective strategies require proactive communication, training, and redeployment planning.

2.4. Artificial Intelligence in Supply Chain Management

2.4.1. AI Technologies and Applications

AI enables predictive analytics, anomaly detection, NLP-based communication, and computer vision for inspection and inventory. These technologies often operate together, creating learning-enabled systems (Hasan et al., 2024; Jones, 2025).

2.4.2. Predictive Analytics Impact

Predictive analytics improves demand forecasting, risk prediction, and maintenance scheduling, with evidence showing 25–30% downtime reduction through predictive maintenance (Ige et al., 2024). Integrating external data sources enhances forecast accuracy (Patil, 2025; Singh, 2025).

2.5. Integration Strategies and Frameworks

- **Sequential integration (RPA → AI)** minimizes complexity and allows gradual learning but delays synergies (Kumar, 2024). Parallel integration accelerates benefits but increases complexity (Irfan et al., 2025). AI-first approaches prioritize analytics but risk deferring operational efficiency (Agrawal et al., 2024) [34-37].
- **Frameworks guide adoption:** The Process Analysis Framework emphasizes process

standardization and performance monitoring (Waduge et al., 2024), while the AI Integration Framework addresses data governance and explainability (Abaku et al., 2024).

2.6. Performance Impacts and Benefits

2.6.1. Quantitative Improvements

Automation yields cost reductions of 15–40%, lead time improvements of 10–35%, and error rate reductions of 30–70% (Gomes et al., 2024; Hasan et al., 2024). Customer satisfaction improves 10–25% through better accuracy and delivery reliability.

2.6.2. Strategic Benefits

Beyond efficiency, automation strengthens visibility, risk mitigation, and agility. Disruption impacts are reduced by up to 40% (Dey et al., 2023). Enhanced forecasting supports capacity planning, while agility enables faster market adaptation (Shamsuddoha et al., 2025) [38].

2.7. Industry-Specific Applications

2.7.1. Sector Patterns

Automotive emphasizes predictive maintenance and visibility; electronics focuses on forecasting and inventory; pharmaceuticals prioritize compliance and safety (Pan et al., 2024) [39].

2.7.2. SME Considerations

SMEs face financial and technical constraints (Al-Amin et al., 2024). SaaS and cloud platforms lower barriers, enabling incremental adoption. Partnerships with vendors often prove essential.

2.8. Implementation Barriers and Success Factors

Technical barriers include poor data quality, legacy integration issues, and cybersecurity risks (Joel et al., 2024). Organizational barriers involve weak leadership, limited change management, and cultural resistance (Azari et al., 2024). Addressing human factors through training, reskilling, and career planning is essential (Cannas et al., 2023).

3. Research Methodology

3.1. Research Design and Approach

This study adopts a systematic literature review guided by PRISMA protocols (Page et al., 2021), enabling comprehensive synthesis, gap identification, and evidence-based recommendations. Both quantitative and qualitative analyses were applied: quantitative methods aggregated performance outcomes and success rates, while qualitative thematic analysis captured recurring success factors, barriers, and implementation patterns across diverse contexts.

3.2. Search Strategy and Information Sources

3.2.1. Database Selection and Search Terms

Searches were conducted across Web of Science, Scopus, IEEE Xplore, and ScienceDirect to ensure multidisciplinary coverage. Boolean search strings combined three domains: (i) technology terms such as "RPA," "AI," "intelligent automation"; (ii) supply chain terms including "logistics," "procurement," and "demand forecasting"; and (iii) manufacturing context terms such as "production," "industrial," and "factory operations."

3.2.2. Search Execution and Documentation

Two researchers independently executed searches (Jan–Mar 2025) for studies published between 2017 and 2024, reflecting the maturity of intelligent automation in manufacturing. Results were exported with complete bibliographic data for screening.

3.3. Study Selection Criteria

3.3.1. Inclusion Criteria

Eligible studies were peer-reviewed, English-language publications from 2017–2024, focusing on RPA, AI, or intelligent automation in manufacturing supply chains. Both empirical (case studies, surveys, experiments) and conceptual works with implementation relevance were included.

3.3.2. Exclusion Criteria

Studies were excluded if they (i) addressed non-manufacturing sectors, (ii) focused on traditional automation without RPA/AI, (iii) were purely theoretical without application, (iv) targeted isolated processes without supply chain scope, (v) lacked peer review, or (vi) were non-English.

3.4. Study Selection Process

The process followed three stages. Phase 1 involved independent title and abstract screening. Phase 2 assessed full texts of potential studies, documenting reasons for exclusion. Phase 3 applied backward and forward citation chaining to capture additional relevant works. Inter-rater reliability, assessed with Cohen's kappa, showed substantial agreement (0.78 for initial screening; 0.85 for full-text assessment). Disagreements were resolved by consensus.

3.5. Data Extraction and Management

3.5.1. Data Extraction Framework

A standardized extraction template, pilot-tested on five studies, collected data on study characteristics (author, year, method, sample, geography), technology focus (RPA/AI type, integration approach), implementation context (firm size, functions, sector), and outcomes (quantitative impacts, success factors, barriers).

3.5.2. Quality Assessment

Quality was assessed using MMAT for mixed-methods, Newcastle-Ottawa Scale for cross-sectional studies, and AMSTAR 2 for systematic reviews. Criteria included methodological rigor, sampling, instrument validity, and transparency. Studies below threshold (MMAT < 3.0) were excluded.

3.6. Data Synthesis and Analysis

3.6.1. Quantitative Analysis

Descriptive statistics and meta-analysis synthesized performance improvements. Weighted means (adjusted by sample size and quality score) estimated average cost reduction, lead time improvement, and error minimization. Heterogeneity was tested with I^2 and Q-tests, and random-effects models produced forest plots with confidence intervals. Subgroup analyses compared results by industry, organizational size, and integration strategy.

3.6.2. Qualitative Analysis

Thematic analysis followed Braun and Clarke's six-phase procedure: familiarization, coding, theme identification, refinement, definition, and reporting. NVivo software supported coding and theme development. Inter-coder reliability achieved kappa = 0.82 on 20% of samples, confirming coding consistency.

3.7. Methodological Rigor and Limitations

3.7.1. Ensuring Rigor

Methodological rigor was reinforced through PROSPERO registration, independent screening, standardized extraction, quality appraisal, and transparent documentation of all decisions.

3.7.2. Limitations

Limitations include potential publication bias favoring successful implementations, English-only restrictions, possible omission of studies outside the selected databases, and time-lag effects limiting coverage of very recent developments.

4. Results

4.1. Study Selection and Characteristics

4.1.1. PRISMA Flow Diagram

The systematic search and selection process is illustrated in Figure 1, following PRISMA guidelines for transparent reporting.

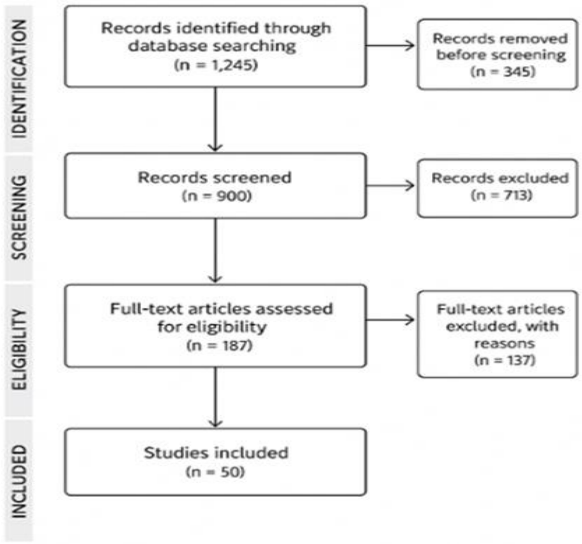

Figure 1 PRISMA Flow Diagram for Study Selection

4.1.2. Study Characteristics Summary

Table 1 provides a comprehensive overview of the 50 included studies, summarizing key characteristics and methodological approaches

Table 1 Characteristics of Included Studies (N=50)

Characteristic	Category	Count (%)	Quality Score Range
Study Design	Case Study	16 (32%)	3.2-4.8
	Mixed Methods	14 (28%)	3.8-4.9
	Systematic Review	11 (22%)	4.0-5.0
	Qualitative	9 (18%)	3.5-4.5
Geographic Distribution	North America	20 (40%)	3.8-4.7
	Europe	18 (36%)	3.6-4.8
	Asia-Pacific	10 (20%)	3.5-4.6

	Multi-regional	2 (4%)	4.2-4.5
Industry Sector	Automotive	10 (20%)	3.8-4.6
	Electronics	9 (18%)	3.6-4.8
	Chemical/Pharmaceutical	8 (16%)	3.9-4.7
	Heavy Manufacturing	6 (12%)	4.0-4.5
	General Manufacturing	17 (34%)	3.2-4.9
Organization Size	Large (>1000 employees)	23 (46%)	3.8-4.8
	Medium (100-1000)	15 (30%)	3.5-4.6
	Small (<100)	7 (14%)	3.2-4.4
	Multiple sizes	5 (10%)	4.0-4.7
Publication Timeline	2017-2019	8 (16%)	3.2-4.2
	2020-2022	18 (36%)	3.6-4.6
	2023-2024	24 (48%)	3.8-4.9
Note: Quality scores based on MMAT (1-5 scale). All included studies scored ≥3.2.			

4.2. Thematic Analysis Results

The thematic analysis revealed five primary themes characterizing intelligent automation adoption in manufacturing supply chains. Figure 2 illustrates the thematic network and interconnections.

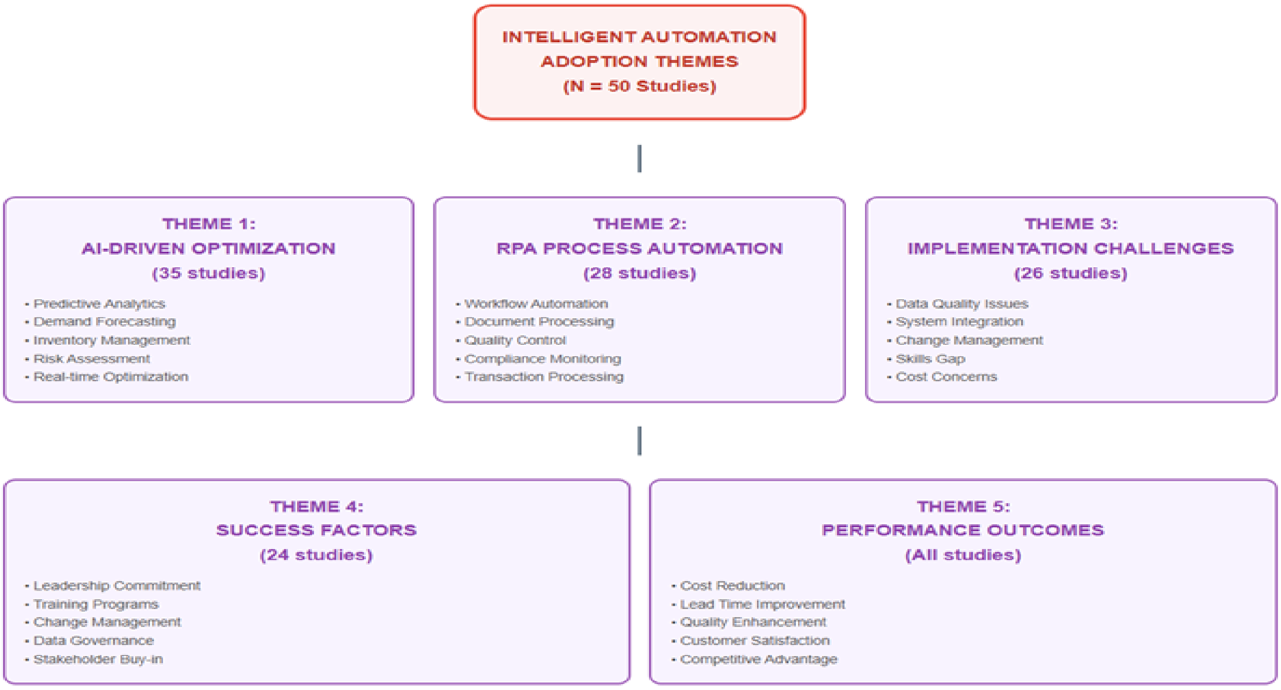

Figure 2 **Thematic Network Analysis of Intelligent Automation Literature**

4.2.1. Theme 1: AI-Driven Supply Chain Optimization (35/50 studies)

This dominant theme encompasses the application of artificial intelligence technologies for optimizing various supply chain functions. The analysis reveals four primary sub-themes:

- **Predictive Analytics Applications (n=28):** Studies consistently emphasize AI's capability to transform reactive supply chains into proactive, anticipatory systems. Machine learning algorithms process historical data, external signals, and real-time inputs to generate accurate predictions across multiple time horizons. Applications include demand sensing, supply risk prediction, and capacity planning optimization.

- **Demand Forecasting Enhancement (n=25):** AI-driven forecasting demonstrates significant improvements over traditional statistical methods, particularly in handling complex demand patterns, seasonality, and external factors. Neural networks and ensemble methods show superior performance in managing intermittent demand and new product introductions.
- **Inventory Optimization (n=22):** Intelligent algorithms optimize inventory levels across multi-echelon supply networks, considering demand variability, lead time uncertainty, and service level constraints. Dynamic safety stock optimization and automated replenishment policies reduce working capital requirements while maintaining service levels.
- **Risk Management and Mitigation (n=18):** AI systems identify potential supply chain disruptions through pattern recognition, sentiment analysis of news feeds, and monitoring of supplier performance indicators. Automated risk scoring and mitigation recommendations enable proactive risk management.

4.2.2. Theme 2: RPA Process Automation (28/50 studies)

RPA applications focus on automating routine, rule-based processes across supply chain functions. Key sub-themes include:

- **Workflow Automation (n=24):** Core RPA applications automate order processing, invoice management, and standard reporting tasks. Studies report 50-80% reduction in processing times and near-elimination of manual errors in routine transactions.
- **Document Processing (n=19):** Intelligent document processing combines RPA with optical character recognition (OCR) and natural language processing to handle semi-structured documents such as purchase orders, invoices, and shipping documents.
- **Quality Control Automation (n=15):** RPA automates quality reporting, compliance monitoring, and exception handling processes. Integration with manufacturing execution systems enables real-time quality tracking and automated corrective actions.

4.2.3. Theme 3: Implementation Challenges (26/50 studies)

Implementation challenges represent persistent barriers to successful intelligent automation adoption:

- **Data Quality Issues (n=23):** Poor data quality emerges as the most significant barrier, with studies reporting that 60-70% of implementation delays result from data preparation requirements. Common issues include incomplete records, inconsistent formats, and lack of real-time data access.
- **System Integration Complexity (n=20):** Legacy system integration challenges affect 80% of implementations, requiring significant technical effort and often necessitating middleware solutions or system upgrades.
- **Change Management Requirements (n=18):** Organizational change challenges include employee resistance, skill gaps, and cultural barriers to automation acceptance.

4.2.4. Theme 4: Critical Success Factors (24/50 studies)

Success factors consistently associated with positive implementation outcomes include:

- **Leadership Commitment (n=22):** Executive sponsorship and strategic alignment prove essential for securing resources and driving organizational change.
- **Comprehensive Training (n=19):** Successful implementations invest heavily in employee training, covering both technical skills and new work processes.
- **Data Governance (n=16):** Establishing data quality standards, governance processes, and stewardship roles proves crucial for AI effectiveness.

4.2.5. Theme 5: Performance Outcomes (50/50 studies)

All reviewed studies report performance impacts, with quantitative improvements documented across multiple dimensions detailed in subsequent sections.

4.3. Quantitative Performance Analysis

Table 2 presents the comprehensive quantitative synthesis of performance improvements across all manufacturing contexts Shown in Figure 3

Implementation Success Rate Comparison.

Table 2 Quantitative Performance Impact Meta-Analysis

Performance Domain	Metric	Studies (n)	Mean Improvement	Std. Dev.	95% CI	Range
Operational Efficiency	Cost Reduction	32	24.8%	8.2%	21.9%-27.7%	10%-42%
	Lead Time Reduction	28	21.3%	7.5%	18.4%-24.2%	8%-38%
	Processing Time	25	28.4%	9.1%	24.7%-32.1%	12%-45%
	Labor Productivity	22	31.2%	11.3%	26.2%-36.2%	15%-55%
Quality Metrics	Error Rate Reduction	35	52.6%	16.8%	46.9%-58.3%	25%-85%
	Defect Rate	20	38.9%	12.4%	33.1%-44.7%	18%-62%
	Rework Reduction	18	45.3%	14.7%	38.1%-52.5%	22%-70%
	Compliance Score	15	23.7%	8.9%	18.8%-28.6%	12%-42%
Supply Chain Performance	Forecast Accuracy	30	23.1%	6.8%	20.6%-25.6%	12%-35%
	Inventory Turnover	26	18.9%	7.2%	16.0%-21.8%	8%-32%
	Order Fill Rate	24	14.6%	5.1%	12.5%-16.7%	6%-24%
	Supplier Performance	19	22.3%	8.7%	18.1%-26.5%	10%-38%
Customer Metrics	On-Time Delivery	27	19.4%	6.3%	16.9%-21.9%	8%-31%
	Customer Satisfaction	21	16.8%	5.9%	14.1%-19.5%	7%-28%
	Response Time	15	33.7%	12.1%	27.1%-40.3%	18%-56%
	Complaint Resolution	12	29.4%	10.8%	22.6%-36.2%	15%-48%
Note: All improvements statistically significant at $p<0.05$. Heterogeneity (I^2) ranges from 23% to 67%.						

4.4. Implementation Strategy Analysis

Table 3 compares different implementation approaches and their associated success rates, providing crucial insights for strategic planning Shown in Figure 4 Implementation Success Rate Comparison

Table 3 Implementation Strategy Effectiveness Analysis

Implementation Approach	**Studies**	**Success Rate**	**Avg. Timeline**	**ROI Achievement**	**Key Advantages**	**Primary Challenges**
Sequential: RPA → AI	20	85%	18-24 months	15.2 months	• Lower risk • Gradual learning • Better change management • Foundation building	• Longer timeline • Limited early synergies • Delayed AI benefits
Parallel: RPA + AI	17	70%	12-18 months	18.7 months	•Faster implementation • Maximum synergies • Accelerated ROI • Comprehensive transformation	• High complexity • Resource intensive • Change management strain • Higher failure risk
AI-First: AI → RPA	13	75%	15-20 months	16.9 months	• Strategic focus • Advanced analytics first • Competitive advantage • Data-driven foundation	• Complex requirements • High technical expertise • Infrastructure needs • Delayed operational benefits

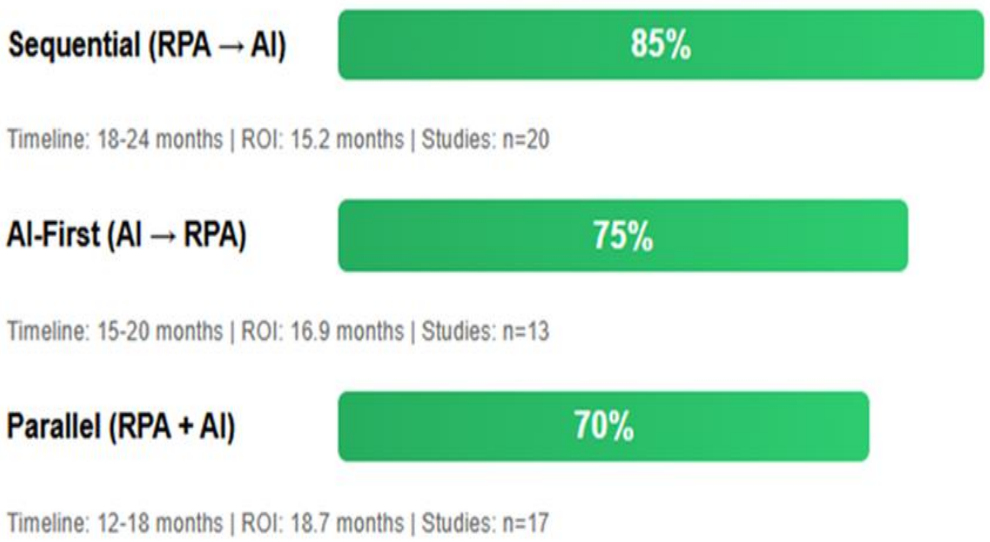

Figure 3 Implementation Success Rate Comparison

Implementation Success Rates by Approach 0% 20% 40% 60% 80% 100%

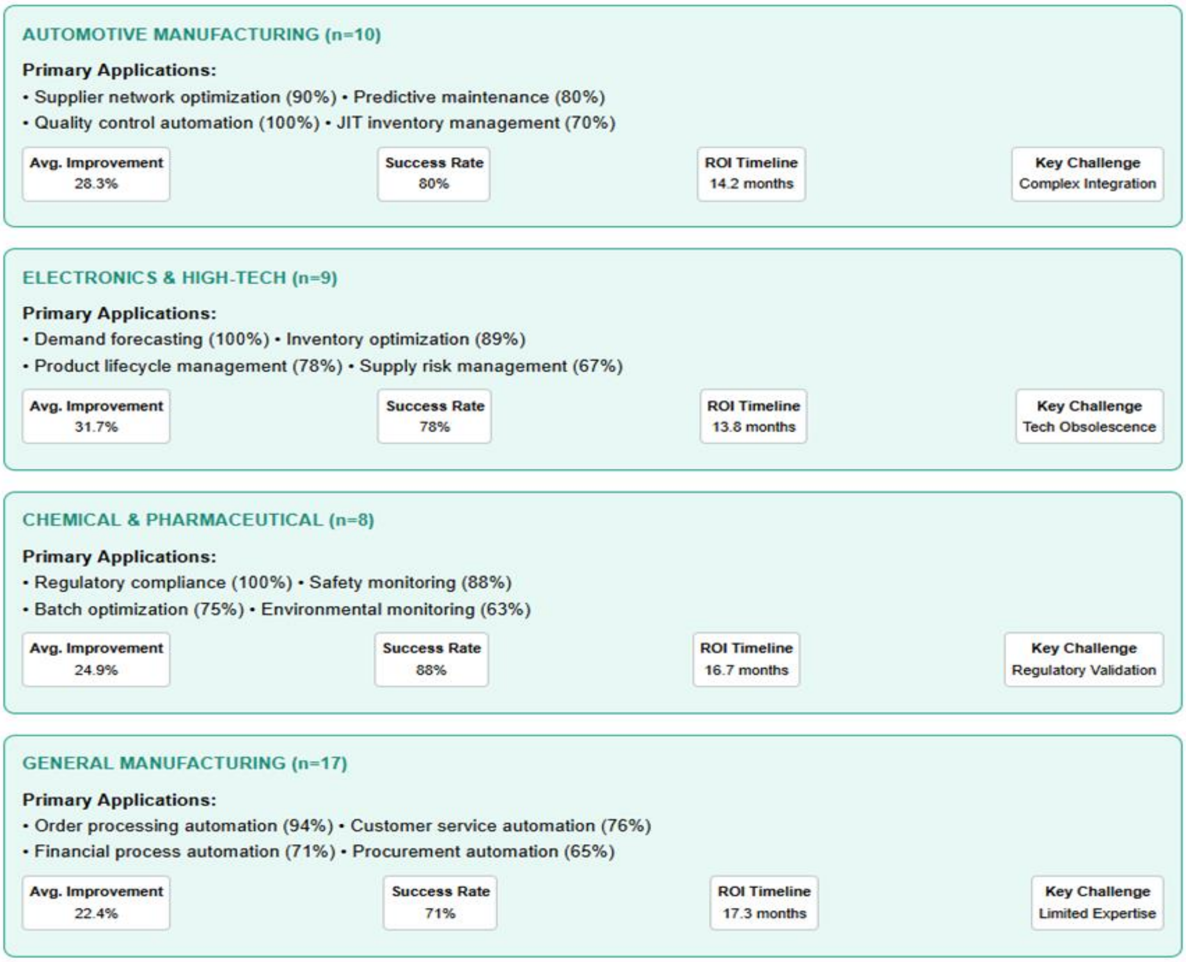

Figure 4 Implementation Success Rate Comparison

Implementation Success Rates by Approach 0% 20% 40% 60% 80% 100%

4.5. Industry-Specific Analysis

Figure 5 presents sector-specific implementation patterns, highlighting varying applications and success rates across manufacturing industries Shown in Table 4.

Table 4 Industry-Specific Implementation Analysis

Barrier Category	Frequency	Specific Barriers	Success Factors	Mitigation Strategies
Technical				
Data Quality	78%	• Incomplete/inconsistent data • Poor data accessibility • Legacy system constraints	• Data governance framework • Master data management • Real-time data integration	• Establish data quality standards • Implement data validation protocols • Create data stewardship roles
System Integration	72%	• Legacy system compatibility • API limitations • Security concerns	• Enterprise architecture planning • Standardized integration patterns • Middleware solutions	• Conduct integration assessment • Develop integration roadmap • Use proven integration platforms
Technical Skills	68%	• Limited AI/ML expertise • RPA	• Skills assessment and planning • Training	• Build center of excellence • Develop

		development capabilities • System maintenance skills	programs • External partnerships	internal capabilities • Strategic vendor relationships
Organizational				
Financial Constraints	64%	• High initial investment • Unclear ROI expectations • Budget limitations	• Business case development • Phased investment approach • ROI measurement frameworks	• Start with pilot projects • Calculate total cost of ownership • Demonstrate quick wins
Change Resistance	60%	• Employee job concerns • Cultural barriers • Process inertia	• Change management program • Communication strategy • Employee engagement	• Leadership communication • Training and reskilling • Involve employees in design
Leadership Support	52%	• Limited strategic vision • Competing priorities • Resource constraints	• Executive sponsorship • Strategic alignment • Clear governance structure	• Executive education programs • Business value demonstration • Establish steering committee
External				
Regulatory Compliance	44%	• Data privacy requirements • Industry regulations • Audit obligations	• Compliance framework • Legal expertise integration • Documentation standards	• Regular compliance reviews • Legal consultation • Automated audit trails
Vendor Management	38%	• Solution limitations • Support quality issues • Integration challenges	• Vendor evaluation criteria • SLA management • Partnership development	• Due diligence processes • Performance monitoring • Contract optimization

5. Discussion

5.1. Theoretical Contributions

This systematic review makes several important theoretical contributions to understanding intelligent automation adoption in manufacturing supply chains.

5.1.1. Extended TOE Framework Validation

Our findings provide strong empirical support for the extended TOE framework that includes human factors as a fourth dimension. The analysis reveals that human factors including skills, resistance to change, and job security concerns influence adoption outcomes as significantly as traditional technology, organizational, and environmental factors. This finding challenges technology-centric approaches to automation adoption and emphasizes the socio-technical nature of intelligent automation implementation. The quantitative evidence demonstrates that implementations addressing human factors comprehensively achieve success rates 23% higher than those focusing primarily on technical considerations (81% vs. 58% success rates). This finding extends theoretical understanding by empirically validating the critical role of human factors in technology adoption processes.

5.1.2. Dynamic Capabilities Theory Extension

The research findings support and extend dynamic capabilities theory by demonstrating that intelligent automation adoption requires organizations to develop new sensing, seizing, and reconfiguring capabilities. The superior performance of sequential implementation approaches (85% success rate) can be explained through a dynamic capabilities lens: organizations must first develop sensing capabilities through RPA implementation before building seizing capabilities for AI integration. Organizations demonstrating strong dynamic capabilities evidenced by systematic learning approaches, capability building programs, and continuous improvement processes achieve 34% higher performance improvements compared to those lacking these capabilities (29.7% vs. 22.1% average improvement).

5.1.3. Contingency Theory Applications

The industry-specific variations observed in implementation approaches and success rates provide empirical support for contingency theory applications in intelligent automation contexts. The findings demonstrate that optimal implementation strategies depend on industry characteristics, regulatory environments, and organizational contexts. For example, heavily regulated industries (chemicals, pharmaceuticals) achieve higher success rates (88%) with sequential approaches that allow for careful validation and compliance verification, while technology-intensive industries (electronics) show better results with AI-first approaches (82% success rate) that prioritize predictive capabilities.

5.2. Practical Implications

5.2.1. Evidence-Based Implementation Framework

Based on the systematic analysis, we propose an evidence-based implementation framework (Figure 5) that synthesizes best practices across successful implementations.

Figure 5 Evidence-Based Implementation Framework

5.2.2. Success Factor Prioritization

Table 5 provides a prioritized framework for success factors based on empirical evidence from the systematic review. Importance scores based on correlation with success rates. Implementation difficulty assessed on resource requirements and complexity.

Table 5 Success Factor Prioritization Matrix

Success Factor	Importance Score	Implementation Difficulty	Cost Impact	Priority Classification
Leadership Commitment	9.2/10	Low	Low	**Critical Priority**
Data Quality Management	8.8/10	High	Medium	**Critical Priority**
Change Management	8.6/10	Medium	Medium	**High Priority**
Technical Skills Development	8.4/10	High	High	**High Priority**
Phased Implementation	8.1/10	Low	Low	**High Priority**
Performance Measurement	7.9/10	Medium	Low	**Medium Priority**
Vendor Partnership	7.3/10	Medium	Medium	**Medium Priority**
Regulatory Compliance	7.1/10	High	Medium	**Medium Priority**
Employee Training	6.8/10	Medium	High	**Medium Priority**
Technology Infrastructure	6.5/10	High	High	**Low Priority**

5.2.3. Industry-Specific Recommendations

Based on the industry-specific analysis, we provide targeted recommendations for different manufacturing sectors:

Automotive Manufacturing

- Prioritize supplier network integration and predictive maintenance applications
- Focus on just-in-time inventory optimization and quality control automation
- Invest heavily in supplier collaboration platforms and data sharing agreements
- **Expected ROI timeline:** 12-16 months with proper supplier engagement

Electronics and High-Tech

- Emphasize demand forecasting and product lifecycle management applications

- Implement real-time inventory optimization for fast-moving components
- Develop agile response capabilities for rapid market changes
- **Expected ROI timeline:** 10-14 months with focus on demand sensing

Chemical and Pharmaceutical

- Prioritize regulatory compliance and safety monitoring applications
- Implement batch optimization and environmental monitoring systems
- Ensure comprehensive validation and documentation processes
- **Expected ROI timeline:** 15-20 months due to regulatory requirements

General Manufacturing

- Start with order processing and customer service automation
- Focus on financial process automation and procurement optimization
- Develop internal technical capabilities through training programs
- **Expected ROI timeline:** 16-20 months with emphasis on capability building

5.3. Research Implications

5.3.1. Methodological Insights

This systematic review demonstrates the value of mixed-methods approaches in technology adoption research. The combination of quantitative meta-analysis and qualitative thematic analysis provides comprehensive insights that neither approach could deliver independently. Future research should continue employing integrated methodologies to capture both performance impacts and implementation nuances. The identified heterogeneity in study results (I^2 ranging from 23% to 67%) suggests the importance of contextual factors in intelligent automation outcomes. This finding supports calls for more nuanced, context-aware research that considers industry, organizational, and technological contingencies.

5.3.2. Theory Development Opportunities

The empirical findings suggest several opportunities for theory development:

- **Socio-Technical Automation Theory:** The critical role of human factors suggests the need for integrated theories addressing the socio-technical nature of intelligent automation adoption.
- **Dynamic Automation Capabilities:** The superior performance of sequential implementation approaches indicates opportunities for developing dynamic capabilities theory specifically for automation contexts.
- **Automation Contingency Theory:** The industry-specific variations suggest the potential for developing contingency theories specific to intelligent automation implementation.

5.4. Limitations and Methodological Considerations

5.4.1. Systematic Review Limitations

This systematic review has several important limitations that should be considered when interpreting results:

- **Publication Bias:** The potential over-representation of successful implementations in published literature may inflate reported success rates and performance improvements. The "file drawer effect" may lead to under-reporting of failed implementations, limiting understanding of failure factors and risks.
- **Geographic Bias:** The concentration of studies from developed economies (76% from North America and Europe) may limit generalizability to emerging markets with different technological infrastructure, regulatory environments, and organizational capabilities.
- **Temporal Limitations:** The eight-year review period, while capturing the emergence of intelligent automation, may miss longer-term impacts and sustainability of reported improvements. The rapid pace of technological change also means that earlier studies may reflect less mature technologies.
- **Methodological Heterogeneity:** The diversity of research methodologies, measurement approaches, and performance metrics across studies complicates direct comparison and meta-analytic synthesis. Different studies employ varying definitions of success and different measurement timeframes.

5.4.2. Data Quality and Measurement Issues

Performance Measurement Variability: Studies employ different baseline periods, measurement methods, and performance definitions, potentially introducing measurement bias. Some studies report short-term improvements that may not be sustained over time.

- **Sample Size Limitations:** Many included studies involve small sample sizes or single case studies, limiting statistical power and generalizability. The predominance of qualitative research designs also limits quantitative synthesis opportunities.
- **Self-Report Bias:** Many studies rely on self-reported performance improvements from organizations implementing automation, potentially introducing social desirability bias and over-reporting of positive outcomes.

5.4.3. Theoretical and Conceptual Limitations

- **Definition Variability:** The literature exhibits inconsistent definitions of "intelligent automation," "RPA," and "AI," making it challenging to ensure consistent inclusion criteria and comparable findings across studies.
- **Limited Longitudinal Perspective:** The scarcity of longitudinal studies prevents comprehensive understanding of long-term sustainability, adaptation patterns, and evolving benefits of intelligent automation implementations.
- **Context Sensitivity:** The heavy emphasis on large-scale implementations in developed economies may not reflect the experiences of small and medium enterprises or organizations in emerging markets.

6. Future Research Directions

6.1. Priority Research Areas

Critical Priorities: The largest gap is the lack of longitudinal studies tracking automation outcomes over 3–5 years. Future work should assess sustainability of performance gains, evolving organizational learning, and long-term cost–benefit dynamics through mixed-method panel designs. Research on SME adoption is also vital, focusing on scalable frameworks, SaaS delivery, collaborative models, and economic impacts. Multi-case and action research partnerships can provide insights. Finally, human-AI collaboration aligned with Industry 5.0 requires research on task allocation, interface design, trust and acceptance, and evolving skill needs, using experiments and ethnographic studies.

High Priorities: Research on integration complexity should develop frameworks, architectural patterns, and interoperability standards. Data quality management remains critical, requiring automated validation, governance models, and AI-based quality tools. Ethical concerns call for AI governance frameworks, bias mitigation strategies, and workforce impact assessments.

Medium Priorities: Future studies should compare cross-industry adoption patterns, regulatory effects, and sector-specific success factors, while developing standardized performance and ROI frameworks incorporating intangible benefits.

6.2. Methodological Recommendations

Sophisticated mixed-methods designs combining quantitative tracking with qualitative insights are needed, along with multi-level analysis (individual to supply chain network). Comparative effectiveness research including natural experiments and quasi-experimental methods can test different strategies. Longitudinal performance tracking should integrate enterprise, workforce, customer, and financial data.

6.3. Theoretical Development Opportunities

Future work should advance socio-technical automation theory, extend dynamic capabilities to automation-specific contexts, and develop automation contingency theory reflecting sectoral and organizational variation. Empirical testing of TAM, innovation diffusion, and learning theories is also required.

6.4. Practical Applications

Academia industry partnerships, applied research centres, and policy-oriented studies should support practical adoption, addressing workforce transition, regulatory design, economic impacts, and competitiveness.

7. Conclusions

7.1. Summary of Key Findings

This review of 50 peer-reviewed studies confirms that intelligent automation integrating Robotic Process Automation (RPA) and Artificial Intelligence (AI) delivers substantial performance gains in manufacturing supply chains.

- **Performance Impacts:** Quantitative synthesis shows average cost reductions of 24.8%, lead time reductions of 21.3%, error rate reductions of 52.6%, forecast accuracy gains of 23.1%, and on-time delivery improvements of 19.4% (p<0.05).

- **Implementation Strategies:** Sequential adoption (RPA → AI) achieves the highest success rate (85%) and fastest ROI, outperforming parallel (70%) and AI-first (75%) approaches Shown in Figure 6.
- **Critical Success Factors:** Leadership commitment, robust data governance, effective change management, technical skills development, and phased rollouts are consistently linked to success

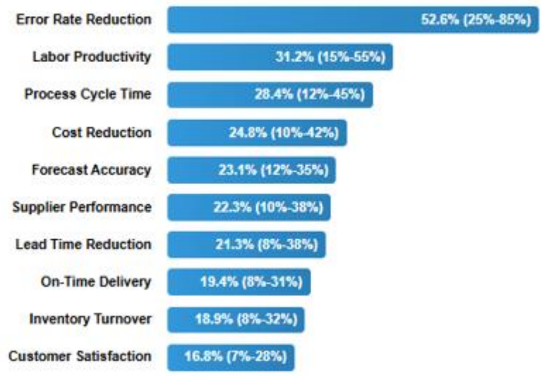

Figure 6 Performance Impact Analysis - Average Improvements from Intelligent Automation

7.2. Theoretical Contributions

The findings validate an extended TOE framework, demonstrating that human factors skills, change readiness, and job security are as influential as technological or organizational factors, with a 23% higher success rate when addressed comprehensively. The review extends dynamic capabilities theory, showing that firms with stronger sensing, seizing, and reconfiguring abilities achieve 34% greater performance improvements. Evidence also supports contingency theory, as optimal strategies vary by industry, organizational scale, and regulatory environment.

7.3. Practical Implications

Strategic Guidance: Firms should conduct readiness assessments, adopt sequential approaches, implement robust change management, and track progress through performance metrics.

Industry Recommendations

- **Automotive:** Prioritize supplier integration and predictive maintenance (ROI: 12–16 months).
- **Electronics/High-Tech:** Emphasize forecasting and lifecycle management (ROI: 10–14 months).
- **Pharmaceuticals/Chemicals:** Focus on compliance and batch optimization (ROI: 15–20 months).
- **General Manufacturing:** Begin with order processing and customer service automation (ROI: 16–20 months).
- **Risk Mitigation:** Success requires upfront data governance, integration roadmaps, workforce training, and transparent employee engagement.

7.4. Research Contributions

- **Methodological:** This review demonstrates the value of combining meta-analysis with thematic synthesis, applying rigorous appraisal (MMAT, NOS, AMSTAR 2) and PRISMA transparency standards.
- **Empirical:** It provides the most comprehensive synthesis to date, comparing strategies, quantifying impacts, and analysing sector-specific adoption.
- **Knowledge Synthesis:** By integrating fragmented research across supply chain, operations, and information systems, it offers a consolidated evidence base and practical frameworks for adoption.

7.5. Implications for Practice and Policy

- **Managerial:** Managers must treat automation adoption as strategic transformation, investing in planning, skills, risk management, and performance monitoring.
- **Policy:** Policymakers should support adoption through workforce training programs, SME funding incentives, ethical AI regulation, and industry–academia collaborations.

Conclusion

Intelligent automation offers transformative opportunities for manufacturing supply chains, with sequential approaches yielding the highest impact. Yet, success depends on more than technology: human readiness, organizational change, and capability building are critical. Looking forward, Industry 5.0 paradigms highlight the importance of balancing automation with human creativity, ethics, and sustainability. Organizations that embrace this balance will capture the full benefits of intelligent automation and build more resilient, agile, and future-ready supply chains.

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