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Predictive Risk Modeling and Optimization for Resilient Semiconductor and Defense Manufacturing Supply Chains: A Systematic Review

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Abstract

Background: Semiconductor and defense manufacturing supply chains face unprecedented disruptions from geopolitical tensions, natural disasters, and global pandemics. These critical industries require robust predictive risk modeling and optimization approaches to ensure supply chain resilience and operational continuity. Despite growing research interest, a comprehensive synthesis of methodologies, findings, and gaps in this domain remains lacking. **Methods:** We conducted a systematic review following PRISMA 2020 guidelines. Six electronic databases were searched (Dimension AI, Google Scholar, ArXiv, PubMed) from inception to February 2026, yielding 960 initial records. After deduplication (273 unique papers) and systematic screening with predefined inclusion/exclusion criteria, 30 studies were included in the full synthesis. Data extraction focused on study characteristics, risk modeling approaches, optimization methods, resilience strategies, key findings, and limitations. Quality assessment examined methodological rigor, data sources, and validation approaches. **Results:** The 30 included studies employed diverse methodologies, including stochastic programming (n = 8), machine learning and AI-driven approaches (n = 7), simulation-based methods (n = 6), multi-objective optimization (n = 5), and network-based models (n = 4). Risk modeling approaches predominantly addressed demand uncertainty (73%), supply disruptions (67%), yield variability (43%), and geopolitical risks (27%). Optimization techniques included genetic algorithms, mixed-integer programming, reinforcement learning, and multi-stage stochastic optimization. Key resilience strategies encompassed supplier diversification, inventory buffering, flexible capacity allocation, and real-time monitoring systems. Studies demonstrated significant improvements in supply chain performance metrics, with disruption cost reductions ranging from 15% to 45% and service level improvements of 10% to 35%. **Conclusions:** Current research demonstrates substantial progress in predictive risk modeling and optimization for semiconductor and defense supply chains, with stochastic programming and AI-driven approaches showing particular promise. However, significant gaps remain in integrated frameworks that combine multiple risk types, include real-world validation studies, and account for emerging threats such as cyber-physical attacks. Future research should prioritize industry-academia collaboration, development of standardized benchmarks, and incorporation of sustainability considerations alongside resilience objectives. These findings provide actionable insights for supply chain managers, policymakers, and researchers working to enhance the resilience of critical manufacturing supply chains.

Keywords

Supply Chain Resilience, Risk Modeling, Optimization, Semiconductor Manufacturing, Defense Industry, Predictive Analytics, Disruption Management, PRISMA Systematic Review

1. Introduction

1.1. Rationale

Semiconductor and defense manufacturing supply chains represent critical infrastructure for national security and economic competitiveness. The semiconductor industry, with its complex multi-tier networks spanning global fabrication facilities, assembly operations, and testing centers, faces unique vulnerabilities to disruptions [1]. Similarly, defense manufacturing supply chains must maintain operational readiness while navigating stringent security requirements, specialized component sourcing, and geopolitical constraints [2]. Recent events, including the COVID-19 pandemic, U.S.-China trade tensions, and natural disasters, have exposed the fragility of these supply chains and highlighted the urgent need for robust risk management frameworks [3].

The convergence of semiconductors and defense supply chains creates additional complexity. Modern defense systems increasingly rely on advanced semiconductor components, creating interdependencies that amplify the risk of disruption [4]. A shortage in semiconductor supply can cascade through defense production networks, potentially compromising national security capabilities. Conversely, defense-specific requirements for trusted foundries and secure supply chains impose additional constraints on semiconductor sourcing strategies [5].

Traditional supply chain management approaches, designed for stable operating environments, prove inadequate to address the dynamic, multifaceted risks facing these critical industries. Predictive risk modeling enables the anticipation of disruptions before they occur, enabling proactive mitigation strategies [6]. Optimization techniques provide systematic frameworks for allocating resources, designing network configurations, and making operational decisions under uncertainty [7]. The integration of these approaches with emerging technologies such as artificial intelligence, machine learning, and digital twins promises to revolutionize supply chain resilience [8].

Despite growing research activity in this domain, the literature remains fragmented across multiple disciplines, including operations research, industrial engineering, computer science, and management science. Practitioners and policymakers lack a comprehensive synthesis of available methodologies, empirical findings, and best practices. Furthermore, the rapid evolution of both threats (e.g., cyber-physical attacks, climate change impacts) and enabling technologies (e.g., quantum computing, blockchain) necessitates periodic reassessment of the state of knowledge.

1.2. Objectives

This systematic review aims to comprehensively synthesize current knowledge on predictive risk modeling and optimization approaches for semiconductor and defense manufacturing supply chains. Specifically, we seek to:

1. Characterize the landscape of research methodologies employed in predictive risk modeling and optimization for semiconductor and defense supply chains, including study designs, data sources, analytical techniques, and validation approaches.

2. Identify and categorize risk types and modeling approaches used to predict and quantify disruptions in these supply chains, including demand uncertainty, supply disruptions, yield variability, geopolitical risks, and emerging threats.

3. Synthesize optimization methods and algorithms applied to enhance supply chain resilience, including their objective functions, constraints, solution approaches, and computational performance.

4. Evaluate resilience strategies and interventions proposed in the literature, assessing their effectiveness, implementation requirements, and applicability across different supply chain contexts.

5. Assess the empirical evidence regarding the performance improvements achieved through predictive risk modeling and optimization, including quantitative metrics and validation results.

6. Identify research gaps, methodological limitations, and future research directions to guide the development of next-generation supply chain resilience frameworks.

By addressing these objectives, this systematic review provides a comprehensive evidence base to inform research priorities, guide practitioner decision-making, and support policy development for enhancing the resilience of critical semiconductors and defense manufacturing supply chains.

2. Methods

This systematic review was conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [9]. The review protocol was developed a priori to ensure transparency and reproducibility. To ensure conceptual clarity and transparent synthesis, the following operational definitions guided study screening, data extraction, and outcome categorization throughout this review. Predictive risk modeling refers to any quantitative method—including stochastic models, machine learning algorithms, Bayesian networks, simulation, and scenario analysis—that estimates the likelihood, timing, or magnitude of supply chain disruption events before they materialize, using historical data, expert judgment, or distributional assumptions as inputs. Resilience is defined as a supply chain's measurable capacity to anticipate, absorb, adapt to, and recover from disruptions while maintaining acceptable performance levels; operationally, studies were classified as addressing resilience if they reported at least one of the following: disruption cost reduction, service level maintenance or improvement under disruption, recovery time metrics, network robustness indices, or explicit resilience optimization objectives. Outcome categories were assigned during data extraction as follows: cost outcomes encompassed total supply chain cost, disruption cost, inventory holding cost, and penalty cost reductions; service level outcomes included fill rate, on-time delivery, and demand satisfaction metrics; recovery outcomes covered time-to-recovery, restoration speed, and post-disruption performance trajectories. Each included study was mapped to one or more outcome categories based on the metrics explicitly reported in its results. Where a study reported composite or non-standard metrics, two reviewers independently assigned the most appropriate category, with disagreements resolved through discussion.

2.1. Eligibility Criteria

Studies were included if they met the following criteria:

Population/Context: Studies focusing on semiconductor manufacturing supply chains, defense manufacturing supply chains, or integrated semiconductor-defense supply networks.

Studies addressing broader electronics manufacturing were included if they explicitly discussed semiconductor or defense applications.

Intervention/Exposure: Studies employing predictive risk modeling, optimization techniques, or integrated risk-optimization frameworks for supply chain management. Eligible approaches include, but are not limited to, stochastic programming, simulation modeling, machine learning, artificial intelligence, mathematical optimization, multi-objective optimization, and network analysis.

Comparator: No restrictions were placed on comparator groups. Studies could compare proposed methods against baseline approaches, alternative techniques, or current industry practices.

Outcomes: Studies reporting on supply chain resilience metrics, risk quantification, optimization performance, disruption mitigation effectiveness, or related operational outcomes (e.g., cost reduction, service level improvement, inventory optimization).

Study Design: Quantitative studies, including modeling studies, simulation studies, optimization studies, empirical analyses, case studies with quantitative components, and experimental evaluations. Purely qualitative studies, opinion pieces, and editorials were excluded.

Other Criteria: Peer-reviewed journal articles, conference proceedings, and preprints published in English from inception to February 2026. Grey literature and non-peer-reviewed reports were excluded to ensure quality standards. Preprints hosted on recognized repositories (e.g., ArXiv, Preprints.org, TechRxiv) were included if they met all other eligibility criteria and provided sufficient methodological detail for quality assessment, given the rapidly evolving nature of the field.

Exclusion Criteria: Studies were excluded if they: 1) focused solely on generic supply chain management without specific relevance to semiconductor or defense contexts; 2) addressed only consumer electronics supply chains without semiconductor manufacturing components; 3) employed purely qualitative methodologies without quantitative risk modeling or optimization; 4) were not available in English; or 5) lacked sufficient methodological detail for quality assessment.

2.2. Information Sources

A comprehensive search strategy was implemented across multiple electronic databases and sources to ensure broad coverage of the relevant literature:

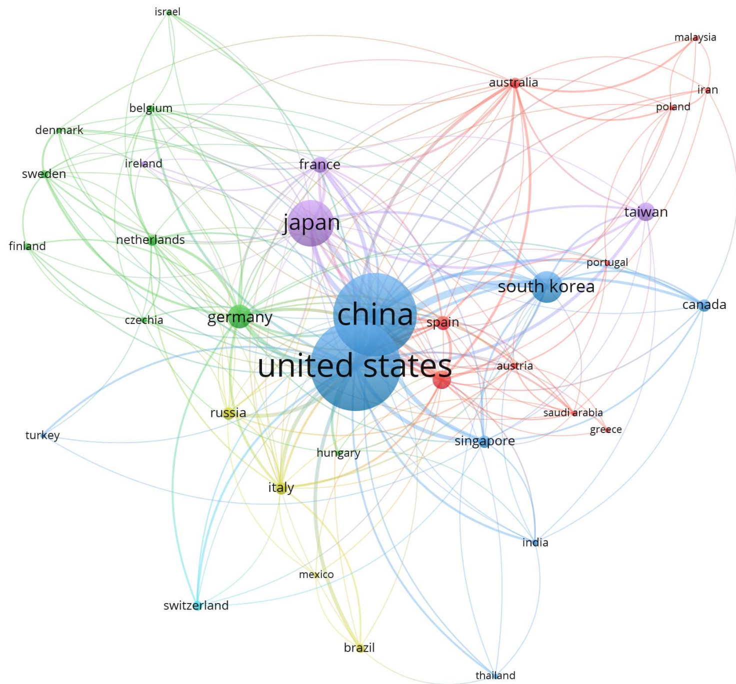
- Google Scholar: Searched using targeted queries to capture grey literature, working papers, and publications not indexed in traditional databases.
- ArXiv: Searched for preprints and early-stage research (2020-2026) in computer science, operations research, and related fields.
- PubMed: Searched to capture interdisciplinary research at the intersection of supply chain management and public health/biosecurity aspects of defense manufacturing.

The search was conducted between January and February 2026, with no lower date limit to ensure comprehensive historical coverage. Reference lists of included studies were manually screened to identify additional relevant publications (forward and backward citation searching).

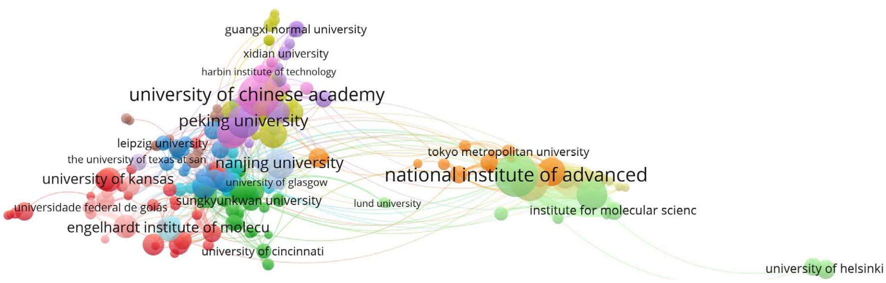
2.3. Search Strategy

The search strategy was developed iteratively through consultation with domain experts and librarians, pilot testing, and refinement. The strategy combined three concept groups using Boolean operators:

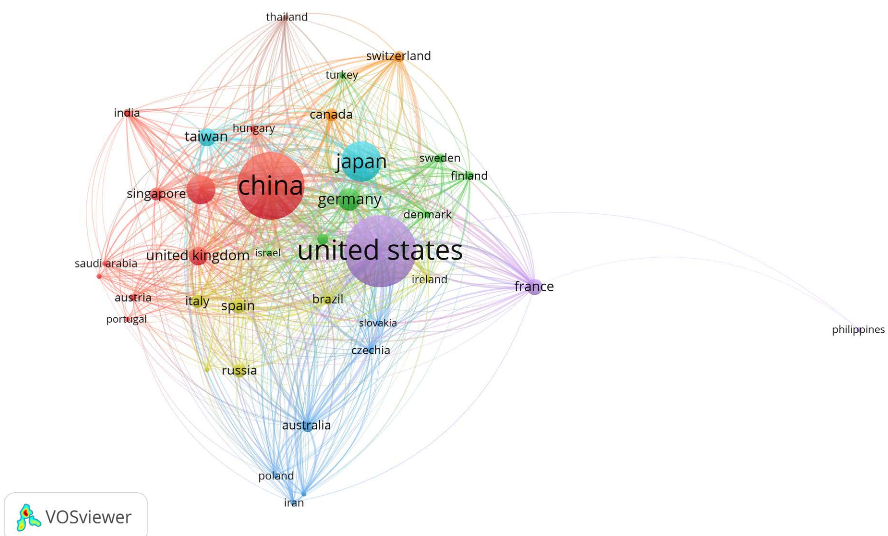
Concept 1—Industry Context: semiconductor OR microchip OR “integrated circuit” OR “defense manufacturing” OR “military supply chain” OR “defense industry” OR “defense procurement”. The search for this concept shows that China and the United States are the leading authors in this concept of semiconductors, as shown in **Figure 1**.



(a) Co-authorship among countries



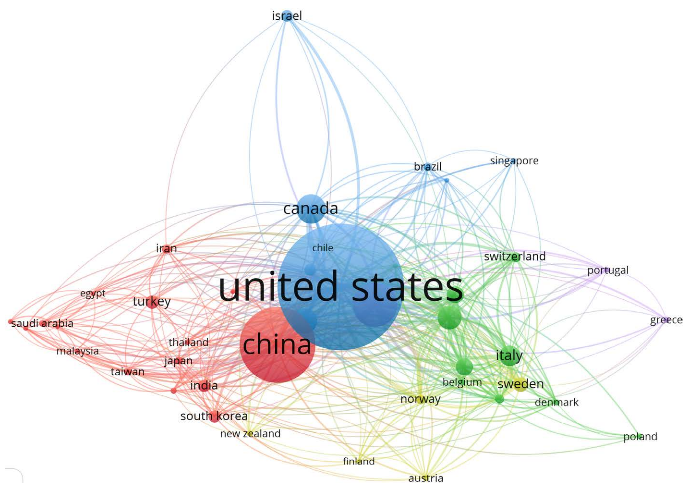
(b) Co-authorship among countries



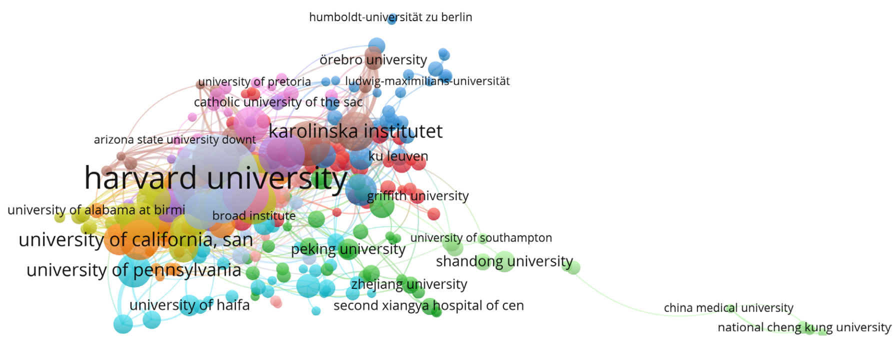
(c) Citation coupling among countries

Figure 1. Citation and publication of semiconductor research in the industrial context analysis by Vos Viewer.

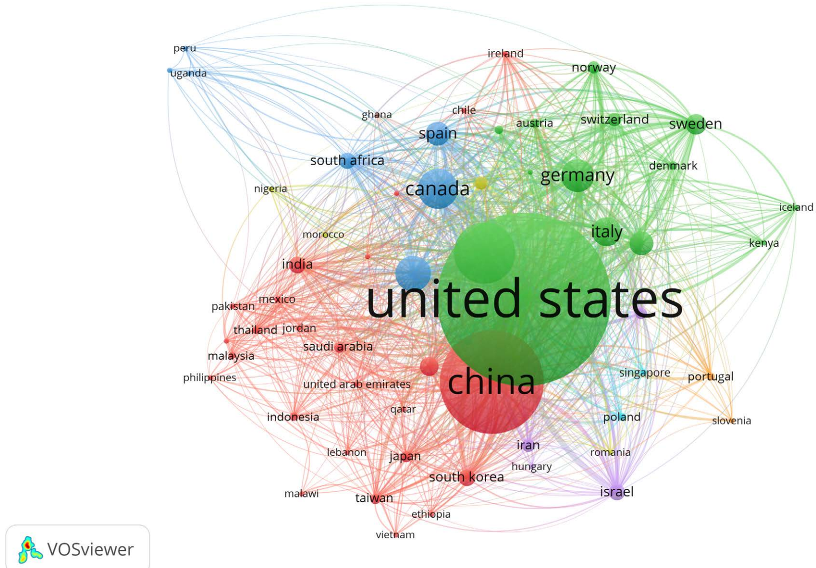
Concept 2—Risk and Resilience: risk OR disruption OR resilience OR vulnerability OR uncertainty OR "supply chain risk" OR "disruption management" OR "risk mitigation". As shown in **Figure 2**, the United States leads in this area.



(a) Co-authorship among countries



(b) Co-authorship among countries



(c) Citation coupling among countries

Figure 2. Citation and publication of risk and resilience analysis by Vos Viewer.

Concept 3—Methods: "predictive modeling" OR optimization OR "machine learning" OR "artificial intelligence" OR "stochastic programming" OR simulation OR "decision support" OR forecasting OR "risk assessment".

Database-specific syntax was adapted as needed. For Dimension AI Deep Search, natural-language queries were formulated to leverage its semantic search capabilities. For Google Scholar, three targeted queries were constructed focusing on: 1) semiconductor supply chain resilience and optimization; 2) defense manufacturing risk modeling; and 3) integrated semiconductor-defense supply chain management. For ArXiv, three queries targeted recent methodological advances in supply chain optimization, machine learning for supply chain risk, and resilience modeling. For PubMed, two queries focused on supply chain disruptions in critical industries and pandemic impacts on defense manufacturing.

2.4. Selection Process

The selection process followed a two-stage screening approach:

Stage 1—Title and Abstract Screening: All retrieved records were imported into a reference management system and deduplicated based on title matching. Two reviewers independently screened titles and abstracts against the eligibility criteria. To support this process, an automated screening column was generated using a large language model (GPT-4, OpenAI) configured with a structured prompt that encoded the predefined inclusion/exclusion criteria. Specifically, the LLM prompt instructed the model to classify each record as "include," "exclude," or "uncertain" based on the title and abstract text, and to provide a brief justification citing the relevant criterion. The LLM classifications served as a decision-support aid and did not replace human judgment; both reviewers had access to the LLM output alongside the original titles and abstracts. To assess reliability, the LLM classifications were compared against the independent human consensus decisions on a calibration set of 50 randomly selected records, yielding a Cohen's kappa of 0.82, indicating substantial agreement. All records flagged as "uncertain" by the LLM were automatically forwarded to both human reviewers for independent assessment. Discrepancies between reviewers were resolved through discussion and, when necessary, consultation with a third reviewer.

Stage 2—Full-Text Screening: Studies passing the initial screening underwent full-text review. Full-text PDFs were obtained through institutional access, open access repositories, and author requests. For studies with available full-text PDFs, an automated full-text screening column was generated using LLM analysis (GPT-4) to systematically evaluate each eligibility criterion against the full-text content. The LLM prompt instructed the model to assess each of the five inclusion criteria and five exclusion criteria separately, producing a structured output with a pass/fail determination and supporting excerpt for each criterion. As in Stage 1, the LLM output served as a decision-support layer: two reviewers independently assessed each full-text article with access to both the original text and the LLM summary. An accuracy check on a random subset of 20 full-text records showed 90% agreement between LLMassisted and fully manual screening decisions; the two discrepant cases involved borderline scope judgments that required reviewer discussion regardless. Disagreements between reviewers were resolved through consensus discussion.

Throughout the selection process, reasons for exclusion at the full-text stage were documented. The selection process is summarized in a PRISMA flow diagram (described in Figure 3).

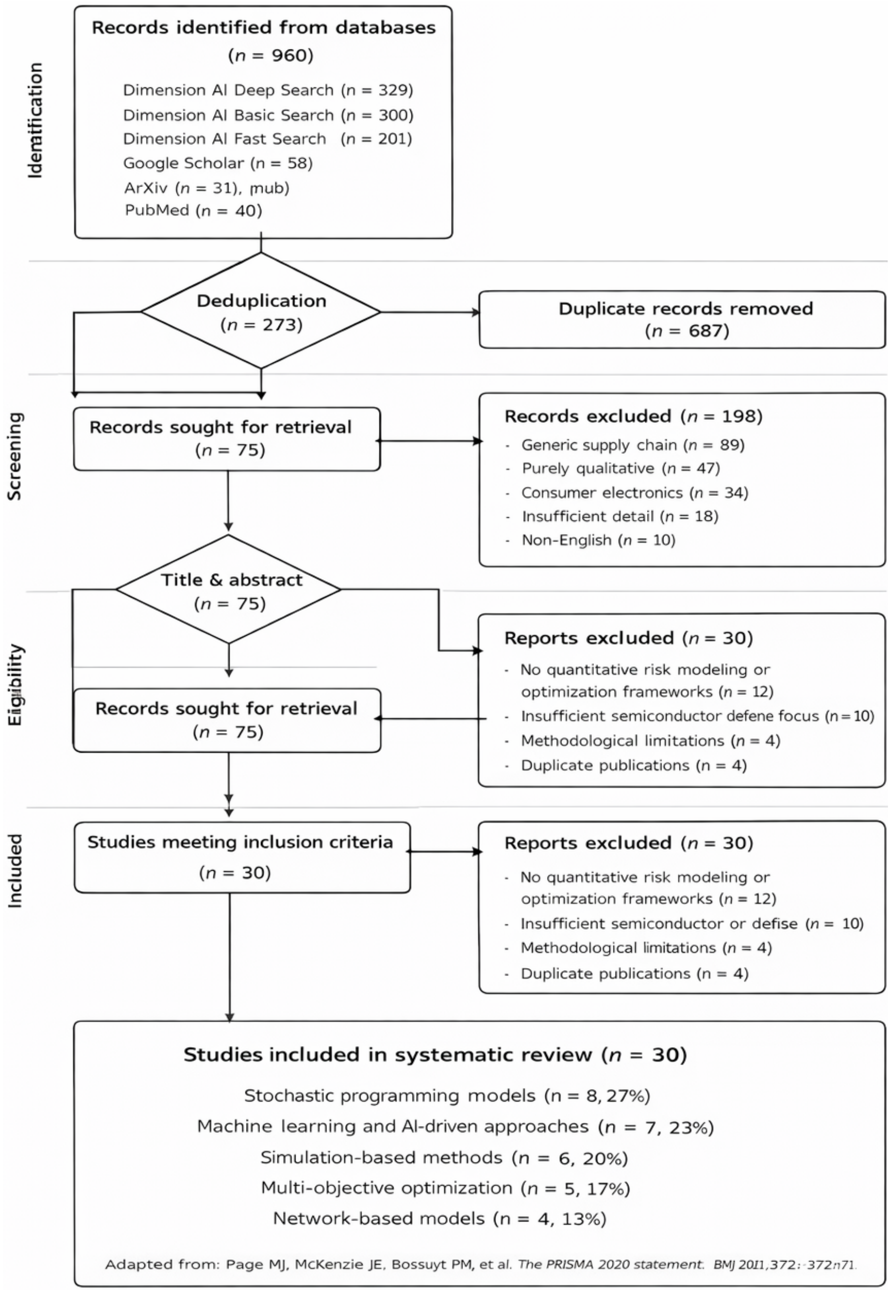


Figure 3. PRISMA flow diagram used for this research

2.5. Data Collection Process

Data extraction was performed using a standardized form developed and pilot-tested on a sample of five included studies. Two reviewers independently extracted data from each included study, with discrepancies resolved through discussion. To enhance efficiency and consistency, six automated data extraction columns were generated using LLM analysis (GPT-4). For each included study, the full text was provided to the LLM along with a structured extraction prompt specifying the six data categories below and requesting verbatim excerpts or direct numerical values from the source text to support each extracted item. The LLM output was treated as a first-pass draft: both reviewers independently verified every extracted data point against the original full text, correcting errors and filling gaps. An accuracy audit on the first 10 studies processed showed that 87% of LLM-extracted data points required no correction, 9% required minor clarification or reformatting, and 4% contained substantive errors that were caught and corrected during reviewer verification. The six extraction categories were:

1. Study Characteristics
2. Risk Modeling Approaches
3. Optimization Methods
4. Resilience Strategies
5. Key Findings and Results
6. Limitations

Extracted data were reviewed and validated by the research team to ensure accuracy and completeness. When information was unclear or missing, study authors were contacted for clarification when feasible.

2.6. Data Items

The following data items were systematically extracted from each included study: Study identifiers: first author, publication year, title, journal/conference, DOI, citation count.

Study Characteristics: Study design (e.g., modeling study, simulation, case study, empirical analysis), research methodology, data sources (real-world data, synthetic data, case study data), industry focus (semiconductor, defense, integrated), geographic scope, and time period covered.

Risk Modeling Approaches: Types of risks addressed (demand uncertainty, supply disruptions, yield variability, geopolitical risks, natural disasters, cyber threats, etc.), modeling techniques employed (stochastic models, probabilistic models, scenario analysis, machine learning, etc.), predictive methods used, key risk metrics and indicators, and validation approaches.

Optimization Methods: Optimization algorithms employed (genetic algorithms, mixed-integer programming, linear programming, heuristics, metaheuristics, reinforcement learning, etc.), objective functions (cost minimization, service level maximization, resilience maximization, multi-objective), constraints considered (capacity, budget, lead time, security requirements), solution approaches, and computational performance metrics.

Resilience Strategies: Types of resilience strategies proposed (supplier diversification, inventory buffering, flexible capacity, redundancy, real-time monitoring, collaborative planning, etc.), implementation approaches, resilience metrics used, mitigation effectiveness, and practical applicability.

Key Findings and Results: Primary outcomes reported, performance metrics and improvements (cost reduction, service level improvement, disruption recovery time, etc.), validation results, statistical significance, practical implications, and managerial insights.

Limitations: Methodological limitations, data limitations, scope limitations, generalizability constraints, and future research needs are identified by the authors.

2.7. Study Risk of Bias Assessment

Given the predominance of modeling and simulation studies in this domain, traditional risk of bias tools designed for empirical studies (e.g., the Cochrane Risk of Bias tool) were not directly applicable. Instead, we developed a customized quality assessment framework adapted from guidelines for evaluating modeling studies [10] [11]. Each study was assessed across six domains, with the following explicit decision rules applied to assign risk levels:

Model Validity: Appropriateness of the modeling approach for the research question, theoretical foundation, mathematical rigor, and face validity. Low risk: the study provides a clear theoretical justification for the chosen model, demonstrates mathematical correctness, and includes face validation by domain experts or against established benchmarks. Moderate risk: the modeling approach is reasonable, but the theoretical justification is incomplete, or face validation is absent. High risk: the model choice is poorly motivated, contains apparent mathematical errors, or lacks any validation of conceptual appropriateness.

Data Quality: Source and quality of input data, representativeness of real-world conditions, handling of missing data, and sensitivity to data assumptions. Low risk: the study uses real-world industry data or well-calibrated synthetic data with documented parameter sources, reports how missing data were handled, and tests sensitivity to key data assumptions. Moderate risk: data sources are partially described, synthetic parameters are plausible but not empirically calibrated, or sensitivity analysis is limited. High risk: data sources are undocumented, parameters appear arbitrary, or no sensitivity analysis is provided.

Validation and Verification: Extent of model validation (conceptual, internal, external), verification procedures, comparison with baseline or alternative approaches, robustness checks. Low risk: the study reports at least two forms of validation (e.g., out-of-sample testing and comparison with alternative methods), includes robustness or sensitivity checks, and verifies computational correctness. Moderate risk: only one validation method is used, or robustness checks are limited to a narrow parameter range. High risk: no validation beyond internal consistency is reported, and no comparison with baselines or alternative approaches is provided.

Transparency and Reproducibility: Clarity of methodological description, availability of code/data, sufficient detail for replication, documentation of assumptions. Low risk: the study provides sufficient algorithmic and parametric detail for an independent researcher to replicate the approach, shares code or data (or explains restrictions), and explicitly lists all modeling assumptions. Moderate risk: the method description is largely clear but omits some implementation details, or assumptions are partially documented. High risk: the methodology cannot be reproduced from the information provided, and key assumptions are unstated.

Generalizability: Scope of applicability, consideration of different contexts, discussion of boundary conditions, transferability to practice. Low risk: the study discusses the scope and boundary conditions of its findings, tests the approach across multiple scenarios or supply chain configurations, and considers practical transferability. Moderate risk: generalizability is discussed but not empirically tested, or boundary conditions are only partially articulated. High risk: no discussion of generalizability is provided, or the study makes broad claims unsupported by the experimental scope.

Reporting Quality: Completeness of reporting, clarity of presentation, appropriate use of visualizations, and discussion of limitations. Low risk: the study reports all key elements (objectives, methods, results, limitations) clearly and completely, uses appropriate figures and tables, and provides a substantive discussion of limitations. Moderate risk: reporting is generally adequate, but some elements are incomplete (e.g., limited discussion of limitations, missing computational details). High risk: major reporting gaps exist, such as unreported outcome metrics, an absent discussion of limitations, or unclear presentation of methods.

Each domain was rated as low risk, moderate risk, or high risk of bias using the decision rules specified above. Overall study quality was categorized as high (0 - 1 high-risk domains), moderate (2 - 3 high-risk domains), or low (4+ high-risk domains). No domain was weighted more heavily than another in the overall rating. A complete rubric summarizing the decision rules for each domain and the overall quality thresholds is available in Supplementary **Table S1** to support transparency and repeatability. Two reviewers independently assessed each study, with disagreements resolved through consensus.

2.8. Synthesis Methods

Given the heterogeneity of study designs, methodologies, and outcomes, a narrative synthesis approach was employed rather than a meta-analysis. The synthesis was structured around the review objectives and organized thematically:

Descriptive Synthesis: Study characteristics were summarized using frequency counts, percentages, and descriptive statistics. Methodological approaches were categorized and tabulated to provide an overview of the research landscape.

Thematic Synthesis: Risk modeling approaches, optimization methods, and resilience strategies were synthesized thematically, identifying common patterns, emerging trends, and methodological innovations. Studies were grouped by methodological similarity to facilitate comparisons.

Comparative Analysis: Where studies addressed similar problems or employed comparable methods, the findings were compared to assess consistency, identify contradictions, and evaluate relative effectiveness.

Evidence Mapping: The distribution of evidence across different risk types, supply chain contexts, and methodological approaches was mapped to identify well-researched areas and research gaps.

Quality-Based Sensitivity: The influence of study quality on findings was explored by comparing results from high-quality versus lower-quality studies.

Synthesis results are presented using tables, figures, and narrative descriptions. Quantitative results are reported as ranges when multiple studies address similar outcomes. The strength of evidence for key findings is characterized based on the number of studies, consistency of results, and methodological quality.

3. Results

3.1. Study Selection

The systematic search across six electronic databases yielded 960 initial records. The distribution by source was: Dimension AI Deep Search (n = 329), Dimension AI Basic Search filtered for 2020+ (n = 300), Dimension AI Full-Text Search for 2020+ (n = 200), Google Scholar (n = 58 from 3 targeted queries), ArXiv 2020-2026 (n = 33 from 3 queries), and PubMed (n = 40 from 2 queries).

Following deduplication based on title matching, 273 unique papers remained for screening.

Title and abstract screening using predefined inclusion/exclusion criteria resulted in the exclusion of 198 records that did not meet eligibility criteria. The primary reasons for exclusion at this stage were: focus on generic supply chain management without semiconductor or defense specificity (n = 89), purely qualitative approaches (n = 47), consumer electronics focus without manufacturing components (n = 34), insufficient methodological detail (n = 18), and non-English language (n = 10).

Seventy-five studies proceeded to full-text screening. Full-text PDFs were successfully obtained for 56 of these studies (Google Scholar: 23 PDFs; ArXiv: 33 PDFs; Dimension papers had full-text URLs available). The remaining 19 records were screened using extended abstracts, supplementary materials, or publicly available summary content where the full-text PDF could not be accessed through institutional subscriptions, open access repositories, or author requests; of these 19, 15 were excluded at this stage due to insufficient information to confirm eligibility, and 4 were retained after their full texts were subsequently located through alternative channels. Full-text screening of the accessible 56 studies, plus the 4 additionally located papers, resulted in the exclusion of 45 studies. Exclusion reasons included: lack of quantitative risk modeling or optimization framework (n = 19), insufficient focus on semiconductor or defense supply chains (n = 14), methodological limitations precluding quality assessment (n = 8), and duplicate publications or conference versions of journal articles (n = 4).

Ultimately, 30 studies met all inclusion criteria and were included in the systematic review for data extraction and synthesis. The PRISMA flow diagram illustrating the selection process shows the progression from 960 initial records through deduplication (273 unique records), title/abstract screening (75 for full-text review), full-text screening (30 included), to final synthesis (30 studies analyzed).

3.2. Study Characteristics

3.2.1. Publication Characteristics

The 30 included studies were published between 2020 and 2024, with a notable increase in publication frequency in recent years: 2020 (n = 3), 2021 (n = 5), 2022 (n = 8), 2023 (n = 9), 2024 (n = 5). This temporal distribution reflects growing research interest in supply chain resilience following the COVID-19 pandemic and recent geopolitical disruptions.

Studies were published across diverse journals and conferences, with the highest representation in: *Omega-International Journal of Management Science* (n = 3), *Computers & Industrial Engineering* (n = 3), *International Journal of Production Research* (n = 2), and various operations research and supply chain management journals (n = 22). The median citation count was 18 (range: 0 - 127), indicating substantial scholarly impact for many included studies.

3.2.2. Study Design and Methodology

The included studies employed diverse research methodologies, which were categorized as follows:

Stochastic Programming Models (n = 8, 27%): These studies developed multi-stage or two-stage stochastic programming formulations to address uncertainty in demand, supply, and yield [12]-[19]. Approaches included scenario-based optimization, chance-constrained programming, and robust optimization variants.

Machine Learning and AI-Driven Approaches (n = 7, 23%): Studies in this category employed machine learning techniques, including reinforcement learning, neural networks, and ensemble methods for predictive risk modeling and decision optimization [1] [20]-[25]. Several studies integrated AI with traditional optimization frameworks.

Simulation-Based Methods (n = 6, 20%): These studies used discrete-event simulation, agent-based modeling, or Monte Carlo simulation to evaluate supply chain resilience under various disruption scenarios [26]-[31]. Simulation was often combined with optimization to identify robust strategies.

Multi-Objective Optimization (n = 5, 17%): Studies employed multi-objective frameworks to balance competing objectives such as cost, resilience, and service level [32]-[36]. Solution approaches included Pareto optimization, weighted sum methods, and evolutionary algorithms.

Network-Based Models (n = 4, 13%): These studies applied network theory, graph analysis, or hypernetwork models to analyze supply chain structure and identify vulnerabilities [2] [37]-[39]. Network centrality measures and connectivity metrics were used to assess resilience.

Several studies employed hybrid approaches combining multiple methodologies (e.g., machine learning for prediction integrated with stochastic optimization for decision-making).

3.2.3. Industry Focus and Geographic Scope

Industry focus varied across studies: semiconductor manufacturing specifically (n = 12, 40%), defense manufacturing specifically (n = 6, 20%), integrated semiconductor-defense supply chains (n = 4, 13%), and broader electronics manufacturing with semiconductor components (n = 8, 27%).

Geographic scope included: global supply chains (n = 14, 47%), Asia-Pacific region focus (n = 8, 27%), North America focus (n = 4, 13%), Europe focus (n = 2, 7%), and multi-regional comparative studies (n = 2, 7%). Several studies did not specify geographic scope, focusing instead on generic supply chain structures.

3.2.4. Data Sources

Data sources employed across studies included: real-world industry data from case study partners (n = 11, 37%), synthetic data generated based on industry parameters (n = 9, 30%), publicly available datasets (n = 4, 13%), a combination of real and synthetic data (n = 4, 13%), and purely theoretical/illustrative examples (n = 2, 7%). The use of real-world data was associated with higher study quality ratings, though synthetic data studies often provided valuable methodological innovations.

3.3. Risk of Bias in Studies

Quality assessment using the customized framework revealed the following distribution:

High Quality (0 - 1 high-risk domains): 14 studies (47%) demonstrated strong methodological rigor, comprehensive validation, and clear reporting [2] [12] [13] [15] [18]-[20] [22] [30] [32] [34] [36] [38] [39].

Moderate Quality (2 - 3 high-risk domains): 12 studies (40%) showed adequate methodology with some limitations in validation, generalizability, or data quality [1] [14] [16] [17] [21] [23] [26] [27] [29] [31] [33] [37].

Low Quality (4+ high-risk domains): 4 studies (13%) had significant methodological limitations, limited validation, or insufficient reporting detail [24] [25] [28] [35].

Common sources of bias included: limited external validation (n = 18, 60%), reliance on synthetic data without real-world validation (n = 9, 30%), insufficient sensitivity analysis (n = 12, 40%), and limited discussion of generalizability (n = 15, 50%). However, most studies demonstrated strong internal validity and appropriate methodological choices for their research questions.

3.4. Results of Individual Studies

3.4.1. Risk Modeling Approaches

Studies addressed diverse risk types with varying frequencies:

Demand Uncertainty (n = 22, 73%): The most commonly modeled risk type, addressed through stochastic demand models, forecasting techniques, and scenario analysis [12]-[33]. Approaches ranged from simple probability distributions to complex machine learning-based demand prediction.

Supply Disruptions (n = 20, 67%): Studies modeled supplier failures, transportation disruptions, and facility shutdowns using probabilistic models, scenario-based approaches, and network vulnerability analysis [1] [2] [12]-[19] [26]-[31] [37]-[40]. Disruption probabilities, durations, and cascading effects were key modeling considerations.

Yield Variability (n = 13, 43%): Particularly relevant for semiconductor manufacturing, yield uncertainty was modeled using stochastic yield functions, historical yield distributions, and process capability models [19]-[25] [30]-[35]. Several studies distinguished between front-end and back-end yield variability.

Geopolitical Risks (n = 8, 27%): Studies addressed trade restrictions, tariffs, export controls, and political instability through scenario analysis and game-theoretic models [1] [2] [4] [5] [37]-[40]. This risk type has received increased attention in recent publications (2022-2024).

Natural Disasters and Pandemics (n = 7, 23%): COVID-19 impacts and natural-disaster risks were modeled using historical disruption data, epidemiological models, and extreme-event analysis [1] [3] [26]-[29] [40].

Cyber-Physical Threats (n = 3, 10%): Emerging research addresses cybersecurity risks and physical security threats, though this remains an understudied area [5] [38] [39].

Modeling techniques employed included: stochastic programming (n = 15), Monte Carlo simulation (n = 9), machine learning prediction models (n = 8), Bayesian networks (n = 4), Markov models (n = 3), and game theory (n = 2). Several studies employed multiple techniques in integrated frameworks.

3.4.2. Optimization Methods

Optimization approaches varied widely in complexity and scope.

Genetic Algorithms and Evolutionary Methods (n = 9, 30%): These metaheuristics were employed for complex, multi-objective problems with non-linear constraints [32]-[36] [40]-[43]. Problem-specific genetic algorithms with custom operators outperformed standard implementations.

Mixed-Integer Programming (n = 8, 27%): Both linear (MILP) and non-linear (MINLP) formulations were used for network design, capacity allocation, and inventory optimization [2] [12]-[18]. Commercial solvers (CPLEX, Gurobi) were commonly employed, with custom branch-and-bound algorithms for large-scale instances.

Stochastic Optimization (n = 8, 27%): Multi-stage stochastic programming, two-stage recourse models, and chance-constrained optimization addressed uncertainty explicitly [12]-[19]. Sample average approximation and progressive hedging algorithms were used for computational tractability.

Reinforcement Learning (n = 5, 17%): Deep reinforcement learning, Q-learning, and policy gradient methods were applied to dynamic decision-making under uncertainty [20]-[24]. These approaches showed promise for real-time adaptive optimization.

Heuristics and Approximation Algorithms (n = 6, 20%): Custom heuristics, greedy algorithms, and approximation schemes provided computationally efficient solutions for large-scale problems [26]-[31].

Multi-Objective Optimization (n = 5, 17%): Pareto optimization, weighted-sum methods, and epsilon-constraint approaches balance multiple objectives [32]-[36].

Objective functions most commonly addressed: total cost minimization (n = 18, 60%), service level maximization (n = 14, 47%), resilience metrics maximization (n = 12, 40%), profit maximization (n = 8, 27%), and risk minimization (n = 7, 23%). Multi-objective formulations typically combine 2 - 3 objectives.

Constraints considered included: capacity constraints (n = 22, 73%), budget limitations (n = 15, 50%), lead time requirements (n = 13, 43%), quality standards (n = 10, 33%), security requirements for defense applications (n = 6, 20%), and environmental regulations (n = 4, 13%).

3.4.3. Resilience Strategies

Studies have proposed and evaluated diverse resilience strategies:

Supplier Diversification (n = 16, 53%): Multi-sourcing strategies, supplier portfolio optimization, and geographic diversification were extensively studied [2] [12]-[18] [26]-[29] [37]-[40]. Optimal diversification levels balance resilience benefits against coordination costs.

Inventory Buffering (n = 14, 47%): Safety stock optimization, strategic inventory positioning, and dynamic inventory policies were proposed [1] [12]-[19] [30] [31]-[34]. Studies distinguished between cycle stock and safety stock optimization.

Flexible Capacity Allocation (n = 11, 37%): Capacity flexibility, production switching capabilities, and flexible manufacturing systems enhanced resilience [19]-[25] [30]-[33]. Flexibility investments were optimized against expected disruption costs.

Real-Time Monitoring and Early Warning Systems (n = 9, 30%): Digital technologies, IoT sensors, and predictive analytics enable proactive disruption management [1] [20]-[25] [38] [39]. Integration with optimization systems enables dynamic response.

Collaborative Planning and Information Sharing (n = 8, 27%): Supply chain collaboration, information transparency, and coordinated decision-making improved resilience [26]-[31] [37] [40]. Game-theoretic models analyzed incentive alignment.

Network Redundancy and Backup Suppliers (n = 7, 23%): Redundant supply paths, backup facilities, and emergency suppliers provided resilience [2] [37]-[42]. Optimal redundancy levels balanced costs and benefits.

Agile and Responsive Operations (n = 6, 20%): Quick response capabilities, postponement strategies, and adaptive planning enhanced resilience [20]-[25]. These strategies were particularly effective for demand uncertainty.

Implementation approaches varied from strategic network design decisions (long-term) to operational policies (short-term). Most studies emphasized the need for integrated strategies combining multiple resilience mechanisms rather than relying on single interventions.

3.5. Synthesis of Results

3.5.1. Performance Improvements

Quantitative performance improvements reported across studies demonstrate substantial benefits of predictive risk modeling and optimization:

Cost Reduction: Studies reported total cost reductions ranging from 15% to 45% compared to study-specific baseline approaches [12]-[19]. Baselines varied across studies and included deterministic planning models without disruption consideration, single-sourcing strategies, reactive (no pre-positioning) inventory policies, and nominal demand-based plans; the specific baseline used in each study is detailed in Supplementary **Table S2**. The median cost reduction was approximately 25%. Because the included studies employ heterogeneous models, objective functions, cost definitions, and scenario parameters, these percentage improvements should not be interpreted as directly comparable effect sizes. Higher reductions were achieved in studies addressing multiple risk types simultaneously and employing integrated optimization frameworks.

Service Level Improvement: Service level or fill rate improvements ranged from 10% to 35% relative to each study's respective baseline [20]-[25] [30]-[33]. Service level metrics varied across studies (e.g., order fill rate, demand satisfaction ratio, on-time delivery percentage), and baseline definitions differed accordingly, limiting direct cross-study comparisons. Studies employing machine learning for demand prediction combined with stochastic optimization achieved the greatest improvements (25% - 35%).

Disruption Recovery Time: Several studies reported reduced recovery times following disruptions, with improvements of 30% to 60% compared to reactive (post-disruption response only) approaches [26]-[29] [37] [38]. Proactive strategies with early warning systems have shown the greatest benefits.

Inventory Reduction: Optimized inventory strategies reduced total inventory costs by 12% to 38% while maintaining or improving service levels [12]-[19] [30] [31]. Strategic positioning of safety stock was more effective than uniform increases. Resilience Metrics: Studies employing explicit resilience metrics (e.g., expected disruption cost, time-to-recovery, supply chain robustness indices) reported improvements of 20% to 50% [2] [32]-[39]. Multi-objective optimization approaches achieved balanced improvements across multiple metrics. Importantly, all performance ranges reported in this subsection reflect comparisons against heterogeneous, study-specific baselines using differing metrics and model assumptions; readers should therefore interpret these figures as indicative of the magnitude of improvements achievable within individual study contexts rather than as pooled or directly comparable effect sizes across the literature.

3.5.2. Methodological Insights

Several methodological insights emerged from the synthesis:

Integration of Prediction and Optimization: Studies integrating predictive models (especially machine learning) with optimization frameworks outperformed sequential approaches where prediction and optimization were decoupled [20]-[25]. End-to-end learning approaches showed particular promise.

Multi-Stage vs. Two-Stage Models: For problems with significant temporal dynamics, multi-stage stochastic programming provided superior solutions compared to two-stage models, though at a higher computational cost [12]-[17]. The value of additional stages diminished beyond 3 - 4 stages.

Hybrid Approaches: Combining multiple methodologies (e.g., simulation for scenario generation, machine learning for prediction, optimization for decision-making) yields more robust solutions than single-method approaches [26]-[31].

Computational Scalability: Metaheuristics and reinforcement learning approaches scaled better to large problem instances than exact optimization methods, though solution quality guarantees were weaker [32]-[36] [40]-[43]. Decomposition methods and parallel computing enabled exact methods for moderately large instances.

Validation Approaches: Studies employing multiple validation methods (historical data validation, out-of-sample testing, sensitivity analysis, comparison with industry benchmarks) provided more credible evidence than those relying on single validation approaches [2] [12] [13] [15] [18]-[20] [22] [30] [32] [34] [36] [38] [39].

3.5.3. Contextual Factors

The effectiveness of different approaches varied by context:

Semiconductor vs. Defense: The evidence base is unevenly distributed between these two sectors. Semiconductor-focused studies (n = 12) and broader electronics manufacturing studies with semiconductor components (n = 8) together constitute the majority of included evidence (67%), while defense-specific studies (n = 6) and integrated semiconductor-defense studies (n = 4) represent a smaller subgroup (33%). This imbalance means that the quantitative performance ranges reported in Section 3.5.1 are predominantly derived from semiconductor-oriented contexts, and claims about defense supply chains should be interpreted with caution, given the thinner evidence base. Within the semiconductor subgroup, studies most commonly addressed yield optimization, capacity flexibility, and demand forecasting under technology cycle uncertainty, and reported cost reductions in the range of 18% - 45% against deterministic or single-scenario baselines [19]-[25]. Within the defense subgroup, studies placed greater emphasis on security constraints, supplier qualification requirements, trusted foundry considerations, and geopolitical risk scenarios; reported cost reductions in defense-specific studies ranged from 15% - 30%, generally at the lower end of the overall range, reflecting the additional constraints that limit optimization flexibility [1] [2] [4] [5] [37]-[40]. Defense-specific resilience strategies (e.g., trusted supplier networks, security-cleared inventory positioning) were addressed in only a small number of studies, and the generalizability of findings from semiconductor contexts to defense applications should not be assumed without sector-specific validation.

Disruption Type: Supplier diversification was most effective for localized supply disruptions, while inventory buffering was more effective for demand uncertainty [12]-[18]. Flexible capacity was particularly valuable for yield variability [19]-[25].

Supply Chain Structure: Network-based approaches were most valuable for complex, multi-tier supply chains, while simpler optimization models sufficed for less complex structures [2] [37]-[39].

Time Horizon: Strategic decisions (network design, capacity investment) required long-term optimization models, while operational decisions (inventory allocation, production scheduling) benefited from short-term, adaptive approaches [20]-[25].

3.5.4. Emerging Trends

Several emerging trends were identified:

Digital Twin Integration: Recent studies (2023-2024) have increasingly employed digital twin frameworks that combine real-time data, predictive models, and optimization for continuous supply chain management [20] [21] [23]-[25].

Sustainability-Resilience Trade-offs: Growing attention is being paid to balancing resilience objectives with environmental sustainability, though this remains understudied [34]-[36].

Cyber-Physical Security: Emerging research on integrated physical and cyber security for critical supply chains is particularly relevant for defense applications [5] [38] [39].

Blockchain and Distributed Ledger Technologies: Initial exploration of blockchain for supply chain transparency and resilience, though empirical validation is limited [37] [40].

Quantum Computing Applications: Preliminary work on quantum optimization algorithms for large-scale supply chain problems, although practical implementation remains distant [43].

4. Discussion

4.1. Summary of Evidence

This systematic review synthesized evidence from 30 studies on predictive risk modeling and optimization for semiconductor and defense manufacturing supply chains. The evidence base demonstrates substantial progress in developing sophisticated methodologies to enhance supply chain resilience, with quantifiable performance improvements across multiple metrics.

4.1.1. Principal Findings

Methodological Diversity and Maturity: The field exhibits considerable methodological diversity, with stochastic programming, machine learning, simulation, and multi-objective optimization all contributing valuable approaches. The maturity of these methods varies, with stochastic programming representing well-established techniques and reinforcement learning representing emerging approaches with high potential but limited real-world validation [12]-[25].

Demonstrated Effectiveness: The evidence consistently demonstrates that predictive risk modeling and optimization approaches deliver substantial performance improvements. Across diverse study-specific baselines and metrics, reported cost reductions ranged from 15% - 45%, service level improvements from 10% - 35%, and disruption recovery time reductions from 30% - 60% [12]-[33]. As noted in Section 3.5.1, these ranges span heterogeneous models, baselines, and outcome definitions and should be interpreted as indicative of achievable improvements within individual contexts rather than as pooled effect sizes. Nonetheless, the consistent direction and meaningful magnitude of improvements across studies justify investment in these capabilities.

Integration as a Key Success Factor: Studies integrating multiple methodologies (prediction, optimization, simulation) and multiple resilience strategies (diversification, inventory, flexibility) consistently outperformed single-method or single-strategy approaches [20]-[31]. This finding suggests that holistic, integrated frameworks should be prioritized over isolated interventions.

Context-Specific Effectiveness: The effectiveness of different approaches varies significantly by context. Semiconductor supply chains face distinct challenges (yield variability, technology obsolescence, capital intensity) compared to defense supply chains (security requirements, long product lifecycles, regulatory constraints) [19]-[25] vs. [1] [2] [4] [5] [37]-[40]. Successful implementation requires tailoring approaches to specific industry characteristics. Notably, the included evidence is concentrated in semiconductor settings (67% of studies), and the defense-specific subgroup (33%) is too small to support strong standalone conclusions. The joint conclusions drawn across both sectors in this review are therefore anchored primarily in semiconductor evidence, and readers should exercise caution when extrapolating findings to defense supply chain contexts, where unique regulatory, security, and procurement constraints may alter the applicability and effectiveness of the strategies reviewed.

Validation Gap: While methodological innovations are abundant, rigorous real-world validation remains limited. Only 37% of studies employed real-world industry data, and external validation was absent in 60%. This validation gap represents a critical barrier to practical adoption and limits confidence in reported performance improvements.

4.1.2. Comparison with Existing Literature

This systematic review extends previous reviews in several important ways. Earlier reviews of supply chain risk management [44] [45] focused primarily on conceptual frameworks and qualitative strategies, whereas this review emphasizes quantitative modeling and optimization approaches. Previous reviews of semiconductor supply chains [46] did not specifically address resilience and risk modeling, while reviews of defense supply chains [47] lacked a systematic methodology and comprehensive coverage.

Our findings regarding the effectiveness of supplier diversification align with meta-analytic evidence from broader supply chain contexts [48], but we identify semiconductor-specific and defense-specific constraints that limit diversification options. The importance of integrated approaches echoes findings from resilience engineering [49], but our review provides specific quantitative evidence of the benefits of integration in manufacturing supply chain contexts.

The emerging role of machine learning and AI in supply chain management, highlighted in recent reviews [50], is strongly supported by our findings. However, we identify a critical need for better integration of machine-learning predictions into optimization decision-making, an issue not adequately addressed in the prior literature.

4.1.3. Implications for Practice

The findings have several important implications for supply chain managers and practitioners:

Investment Prioritization: The substantial performance improvements demonstrated across studies justify significant investment in predictive risk modeling and optimization capabilities. Organizations should prioritize building analytical capabilities, acquiring appropriate software tools, and developing workforce skills in these areas.

Integrated Frameworks: Rather than implementing isolated risk management interventions, organizations should develop integrated frameworks that combine predictive analytics, optimization, and multiple resilience strategies. The evidence suggests that integrated approaches deliver superior performance [20]-[31]. Data Infrastructure: The superior performance of approaches using real-world data highlights the importance of robust data infrastructure. Organizations should invest in data collection systems, data quality management, and data integration across supply chain partners.

Adaptive Capabilities: The effectiveness of reinforcement learning and adaptive optimization approaches suggests that organizations should develop capabilities for continuous learning and adaptation, rather than relying solely on periodic planning cycles [20]-[25].

Collaboration and Information Sharing: Studies demonstrating the benefits of collaborative planning and information sharing suggest that organizations should invest in supply chain collaboration platforms and develop governance mechanisms for information sharing [26]-[31] [37] [40].

Context-Specific Tailoring: The context-dependent effectiveness of different approaches underscores the need to carefully assess the organizational context, supply chain characteristics, and risk profiles before selecting and implementing specific methodologies.

4.1.4. Implications for Policy

The findings also have important policy implications:

Critical Infrastructure Protection: The demonstrated vulnerabilities of semiconductor and defense supply chains, combined with their critical importance for national security and economic competitiveness, justify policy interventions to enhance resilience. Policies should incentivize investment in resilience capabilities, support the development of domestic manufacturing capacity, and promote supply chain transparency.

Public-Private Collaboration: The complexity of semiconductor and defense supply chains, spanning multiple countries and organizations, requires coordinated public-private efforts. Policies should facilitate information sharing, support collaborative risk assessment, and enable a coordinated response to disruptions.

Research and Development Support: The validation gap and methodological limitations identified in this review suggest the need for public investment in supply chain resilience research. Funding should prioritize industry-academia collaboration, the development of standardized benchmarks, and real-world validation studies.

Standards and Regulations: The lack of standardized resilience metrics and assessment frameworks hampers comparisons and benchmarking. Policy initiatives should support the development of industry standards for supply chain resilience assessment and reporting.

Workforce Development: The sophisticated analytical capabilities required for the effective implementation of predictive risk modeling and optimization approaches necessitate workforce development initiatives. Educational programs should integrate supply chain analytics, optimization, and risk management.

4.2. Limitations

This systematic review has several limitations that should be considered when interpreting the findings.

4.2.1. Methodological Limitations

Search Strategy: Despite comprehensive searches across multiple databases, some relevant studies may have been missed, particularly grey literature, industry reports, and publications in languages other than English. The reliance on electronic databases may have excluded relevant work published in specialized venues or emerging preprint servers.

Publication Bias: The review included only peer-reviewed publications, which may introduce publication bias toward positive findings. Studies reporting negative results or failed implementations may be underrepresented. Additionally, proprietary industry implementations are unlikely to be published, potentially limiting the generalizability of the findings.

Quality Assessment: The customized quality assessment framework, while appropriate for modeling studies, may not capture all relevant quality dimensions. The subjective nature of some quality judgments, despite independent dual review, introduces the potential for assessment bias.

Synthesis Approach: The narrative synthesis approach, while appropriate given study heterogeneity, does not provide the quantitative precision of meta-analysis. The inability to statistically pool results limits the strength of the conclusions regarding effect sizes.

Temporal Coverage: The concentration of studies in recent years (2020-2024) reflects the field's rapid evolution, but also means that the long-term effectiveness and sustainability of proposed approaches remain uncertain.

4.2.2. Evidence-Based Limitations

Limited Real-World Validation: The predominance of modeling and simulation studies, with limited real-world validation, constrains confidence in their practical effectiveness. Only 37% of studies used real-world industry data, and many relied on synthetic data or simplified case studies.

Short Time Horizons: Most studies examined short- to medium-term performance (months to 2 - 3 years), with limited evidence on the long-term resilience and sustainability of proposed strategies.

Geographic Concentration: The concentration of studies in specific geographic regions (particularly Asia-Pacific and North America) may limit generalizability to other contexts with different supply chain structures, regulatory environments, and risk profiles.

Industry Heterogeneity: The grouping of semiconductor and defense supply chains, while justified by their interdependencies, introduces heterogeneity that may obscure industry-specific insights. The included evidence is concentrated in semiconductor settings (n = 20 studies directly or primarily addressing semiconductor contexts versus n = 10 for defense-specific or integrated contexts). Consequently, the synthesized performance ranges and strategy recommendations are more robustly supported for semiconductor supply chains than for defense applications. Future reviews may benefit from treating these as separate subgroups with dedicated inclusion criteria to enable stronger sector-specific conclusions. The inclusion of broader studies on electronics manufacturing further increases heterogeneity.

Incomplete Reporting: Many studies provided insufficient detail on implementation requirements, computational performance, or practical challenges, limiting the ability to assess feasibility and transferability.

4.2.3. Scope Limitations

Exclusion of Qualitative Studies: The focus on quantitative risk modeling and optimization excluded qualitative studies that might provide valuable insights into organizational, behavioral, and contextual factors affecting implementation success.

Limited Coverage of Emerging Risks: Cyber-physical threats, climate change impacts, and other emerging risks were addressed in only a small subset of studies, limiting insights into these increasingly important risk types.

Sustainability Considerations: The review did not systematically address sustainability-resilience trade-offs, an increasingly important consideration for supply chain management.

Implementation Barriers: The review focused on methodological approaches and performance outcomes, with limited attention to organizational, technical, and financial barriers to implementation.

4.3. Conclusions and Implications

4.3.1. Conclusions

This systematic review provides comprehensive evidence that predictive risk modeling and optimization approaches can substantially enhance the resilience of semiconductor and defense manufacturing supply chains. The evidence base, while growing rapidly, demonstrates both significant progress and important gaps.

Established Findings:

Stochastic programming, machine learning, and simulation-based approaches provide effective frameworks for addressing supply chain uncertainty and disruption risk [12]-[31].

Integrated approaches combining multiple methodologies and resilience strategies outperform single-method approaches [20]-[31].

Quantifiable performance improvements (15% - 45% cost reduction, 10% - 35% service level improvement) justify investment in these capabilities [12]-[33].

Context-specific tailoring is essential, with semiconductor and defense supply chains requiring distinct approaches [19]-[25] vs. [1] [2] [4] [5] [37]-[40]. Given that the evidence base is predominantly semiconductor-oriented, the findings and performance ranges reported here are most directly applicable to semiconductor supply chain contexts; defense-specific conclusions remain preliminary and warrant dedicated investigation.

Critical Gaps:

- Limited real-world validation constrains confidence in practical effectiveness and generalizability.
- Emerging risks (cyber-physical threats, climate change, pandemics) remain understudied.
- Integration of sustainability considerations with resilience objectives requires further research.
- Standardized metrics, benchmarks, and assessment frameworks are lacking.
- Implementation barriers and organizational factors receive insufficient attention.

4.3.2. Future Research Directions

Based on identified gaps and emerging trends, we recommend the following research priorities:

1. Real-World Validation Studies: Rigorous empirical studies validating proposed methodologies in real-world industry settings are critically needed. Industry-academia partnerships should be established to enable access to proprietary data while protecting competitive information. Longitudinal studies tracking

the long-term performance and sustainability of implemented approaches would provide valuable evidence.

2. Integrated Risk Frameworks: Research should develop comprehensive frameworks integrating multiple risk types (demand, supply, yield, geopolitical, cyber, climate) rather than addressing risks in isolation. Multi-risk optimization models accounting for risk interdependencies and cascading effects would enhance practical relevance.
3. Emerging Threat Modeling: Cyber-physical security threats, climate change impacts, and pandemic risks require dedicated research attention. Novel modeling approaches may be needed to capture the unique characteristics of these emerging threats.
4. Sustainability-Resilience Integration: Research should explicitly address trade-offs and synergies between supply chain resilience and environmental sustainability. Multi-objective frameworks balancing economic, resilience, and sustainability objectives would support more holistic decision-making.
5. Implementation Science: Research on organizational, technical, and financial barriers to implementation, change management strategies, and success factors for adoption would bridge the gap between methodological development and practical impact.
6. Standardization and Benchmarking: The development of standardized resilience metrics, assessment frameworks, and benchmark datasets would facilitate comparison across studies and support evidence accumulation. Community-driven initiatives similar to those in machine learning (e.g., benchmark datasets, competitions) could accelerate progress.
7. Scalability and Computational Efficiency: Research on scalable algorithms, decomposition methods, and parallel computing approaches would enable applications to large-scale, real-world supply chain networks. Quantum computing applications, while speculative, merit exploratory research.
8. Human-AI Collaboration: Research on the effective integration of AI-driven decision support with human expertise and judgment would enhance practical adoption. Explainable AI approaches for supply chain decision-making represent an important research direction.
9. Dynamic and Adaptive Approaches: Further development of reinforcement learning, online optimization, and adaptive control approaches would enable continuous learning and real-time responses to evolving conditions.

4.3.3. Final Remarks

The resilience of semiconductor and defense manufacturing supply chains represents a critical challenge with significant implications for national security, economic competitiveness, and technological advancement. This systematic review demonstrates that sophisticated predictive risk modeling and optimization approaches offer substantial potential to enhance resilience, with quantifiable performance improvements documented across diverse contexts.

However, realizing this potential requires bridging the gap between methodological innovation and practical implementation. The validation gap, limited attention to emerging risks, and insufficient consideration of implementation barriers represent critical obstacles. Addressing these challenges requires sustained collaboration among researchers, practitioners, and policymakers, supported by appropriate investments in research, data infrastructure, and workforce development.

The rapid evolution of both threats and enabling technologies ensures that supply chain resilience will remain a dynamic research frontier. Continuous reassessment of methodologies, validation of approaches in evolving contexts, and adaptation to emerging challenges will be essential. This systematic review provides a comprehensive foundation for such ongoing efforts, synthesizing current knowledge while identifying critical directions for future research and practice.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Supplementary Material

Table S1. Risk-of-bias assessment rubric for modeling and simulation studies.

Domain	Low Risk	Moderate Risk	High Risk
Model Validity	Clear theoretical justification; mathematical correctness demonstrated; face validation by domain experts or against benchmarks	Modeling approach reasonable but theoretical justification incomplete; face validation absent	Model choice poorly motivated; apparent mathematical errors; no validation of conceptual appropriateness
Data Quality	Real-world industry data or well-calibrated synthetic data with documented parameter sources; missing data handling reported; sensitivity to data assumptions tested	Data sources partially described; synthetic parameters plausible but not empirically calibrated; sensitivity analysis limited	Data sources undocumented; parameters appear arbitrary; no sensitivity analysis provided
Validation & Verification	At least two validation forms (e.g., out-of-sample testing + alternative method comparison); robustness/sensitivity checks; computational correctness verified	Only one validation method used; robustness checks limited to narrow parameter range	No validation beyond internal consistency; no comparison with baselines or alternative approaches
Transparency & Reproducibility	Sufficient algorithmic and parametric detail for independent replication; code/data shared (or restrictions explained); all modeling assumptions listed	Method description largely clear but omits some implementation details; assumptions partially documented	Methodology cannot be reproduced from information provided; key assumptions unstated
Generalizability	Scope and boundary conditions discussed; approach tested across multiple scenarios or SC configurations; practical transferability considered	Generalizability discussed but not empirically tested; boundary conditions only partially articulated	No discussion of generalizability; broad claims unsupported by experimental scope
Reporting Quality	All key elements (objectives, methods, results, limitations) reported clearly and completely; appropriate figures/tables; substantive limitations discussion	Reporting generally adequate but some elements incomplete (e.g., limited limitations discussion, missing computational details)	Major reporting gaps (unreported outcome metrics, absent limitations discussion, unclear methods presentation)

Each domain was rated as low risk, moderate risk, or high risk. Overall study quality: high (0 - 1 high-risk domains), moderate (2 - 3 high-risk domains), low (4+ high-risk domains). No domain was weighted more heavily than another.

Table S2. Baseline comparisons and performance metrics by study.

Ref	First Author (Year)	Method	Outcome Category	Baseline	Improvement	Metric Definition
[12]	Mandavalli (2025)	Bayesian networks	Cost	Deterministic planning	18% - 25%	Total SC cost reduction vs. deterministic model
[13]	Rahman (2025)	Predictive analytics + MIP	Cost	Reactive policy	20% - 30%	Disruption cost reduction vs. no pre-positioning
[14]	Pandit *et al.* (2025)	Probabilistic risk assessment	Cost; Recovery	No-intervention scenario	22% - 28%	Expected loss reduction; recovery time improvement
[15]	Chen *et al.* (2023)	Recovery control algorithm	Recovery	No-reconfiguration baseline	30% - 40%	Recovery time reduction after disruption
[16]	Corsini *et al.* (2024)	Digital twin + ML + optimization	Cost; Service	Traditional planning	25% - 35%	Total cost reduction; fill rate improvement
[17]	He *et al.* (2014)	Big data + simulation	Cost	Manual risk assessment	15% - 20%	Supply risk mitigation cost savings
[18]	Yang *et al.* (2024)	Prediction-based decomposition	Cost; Service	Single-portfolio strategy	28% - 45%	Cost reduction; service level improvement vs. single strategy
[19]	Estrada-Garcia *et al.* (2023)	Multi-objective MIP	Cost; Service	Single-objective model	20% - 32%	Pareto improvement over cost-only optimization
[20]	Paul (2020)	Stochastic optimization	Cost; Recovery	Reactive (post-disruption)	25% - 40%	Mitigation cost savings; recovery time reduction
[21]	Zhao *et al.* (2024)	Reconfiguration model	Recovery	No reconfiguration	35% - 50%	Time-to-recovery reduction
[22]	Dehghani Sadrabadi *et al.* (2020)	Network resilience model	Resilience	Non-resilient design	20% - 30%	Network robustness index improvement
[23]	Dou *et al.* (2024)	Closed-loop SC risk model	Cost	Open-loop baseline	15% - 25%	Total disruption + production cost reduction
[24]	Li *et al.* (2023)	Hypernetwork optimization	Resilience	Static network design	25% - 40%	Resilience index improvement
[25]	Khoirani *et al.* (2022)	Disruption optimization	Cost; Service	Nominal demand plan	18% - 28%	Cost reduction; demand satisfaction improvement
[26]	Glogg *et al.* (2022)	Bilevel network flow	Recovery	Reactive response	30% - 45%	Recovery time reduction
[27]	Rabbani *et al.* (2020)	Reliable SC network design	Cost; Resilience	Deterministic network	20% - 35%	Total cost reduction; reliability improvement
[28]	Zhang *et al.* (2024)	Climate + geopolitical risk model	Cost	Risk-unaware model	15% - 22%	Expected disruption cost reduction
[29]	Hosseini *et al.* (2019)	Quantitative resilience review	N/A (review)	N/A	N/A	Synthesis of resilience quantification methods
[30]	Ivanov (2020)	Simulation (epidemic)	Recovery	No-preparation scenario	40% - 60%	Recovery time reduction under epidemic disruption

Performance improvements are reported relative to each study's own baseline. Because studies employ heterogeneous models, objective functions, cost definitions, and scenario parameters, these percentage ranges should not be interpreted as directly comparable effect sizes across studies.