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Decision-Making in Additive Manufacturing Supply Chains: A Systematic Literature Review

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Abstract: Additive Manufacturing (AM) is reshaping supply chain (SC) structures by enabling decentralised production, digital inventories, and on-demand manufacturing. These transformations demand new decision-making approaches to manage disruptions in SC configuration, inventory management, supplier selection, and manufacturing design. This study systematically reviews 27 peer-reviewed studies to assess decision-support tools—such as optimisation models, simulation techniques, and multi-criteria decision-making (MCDM) frameworks—used to facilitate AM integration. A structured mapping is proposed to map AM-induced SC changes to appropriate decision tools. The findings provide structured insights to enhance SC performance, adaptability, and resilience in AM-enabled environments.

Keywords: Additive Manufacturing, Supply Chain Management, Decision-Making, Multi-Criteria Decision Making, Decision Support Systems.

1. INTRODUCTION

Additive Manufacturing (AM), commonly known as 3D printing, has evolved from a prototyping technology into a transformative production method across industries such as aerospace, healthcare, automotive, and consumer goods. Unlike conventional manufacturing (CM), AM enables layer-by-layer fabrication directly from digital models, eliminating the need for molds or tooling (ISO, 2020). This shift enhances flexibility, customisation, and material efficiency while simultaneously disrupting traditional supply chains (SCs) (Gibson et al., 2015; Verboeket & Krikke, 2019).

Global SCs, traditionally reliant on centralised production, extensive inventories, and complex logistics networks, have proven vulnerable to disruptions, as seen during the COVID-19 pandemic. AM challenges these norms by promoting more dispersed (or even localised) production, reducing reliance on physical stock, and shortening transportation distances (Kunovjanek et al., 2022). Additionally, AM's design flexibility allows for function-driven product optimisation, reducing part count and assembly complexity (Durach et al., 2017).

Beyond localisation, AM alters supplier relationships, procurement strategies, and logistics models. High initial investment costs, shifts in supplier dependencies, and the need for agile distribution networks create cascading SC impacts (Jimo et al., 2022; Chen et al., 2023). A survey of 327 manufacturers across Germany, Japan, and the USA found that while 59% had adopted AM, 98% encountered adoption challenges, highlighting the need for structured decision-making approaches (Supply Chain Movement, 2023).

While existing research highlights AM's technical capabilities, a gap remains in understanding how SCs adapt to its integration, particularly in managing inventory uncertainties, supplier realignment, and reconfigured logistics. Decision-making tools play a critical role in addressing these challenges. This study addresses two research questions (RQs):

1. (**RQ1**): What is the impact of AM adoption on SCs?
2. (**RQ2**) How are decision-making tools applied to address these changes?

To address these questions, this study systematically reviews 27 peer-reviewed studies, identifying key SC disruptions in configuration, inventory management, supplier selection, and manufacturing design. It evaluates decision-support methodologies—including optimisation models, simulation techniques, and multi-criteria decision-making (MCDM) frameworks—to determine their effectiveness in AM integration.

There are two main contributions from this research. First, it proposes a structured mapping linking AM-induced SC changes to decision-making tools, offering structured guidance for researchers and practitioners. Second, it identifies research gaps and provides insights into optimising SC resilience and adaptability in AM-driven environments.

The paper is structured as follows: Section 2 details the methodology, Section 3 presents a descriptive analysis of the reviewed literature, Section 4 discusses SC processes affected by AM, Section 5 examines decision-making tools, Section 6 presents the structured mapping of AM-driven SC disruptions to decision-making tools, and Section 7 concludes with key findings and future research directions.

2. REVIEW METHODOLOGY

This study employs a systematic, multistage literature review to examine decision-making tools supporting AM integration into SCs. The methodology follows the approach outlined by

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Tranfield et al. (2003) and Snyder (2019) to ensure rigour, transparency, and reproducibility.

2.1 Literature Search Strategy

The literature search was conducted using Scopus and Web of Science (WoS) due to their extensive peer-reviewed coverage in operations management, SC logistics, and manufacturing technologies. The search terms were structured into three categories:

- **AM Technologies**: "additive manufacturing", "3D printing", "direct digital manufacturing", "three-dimensional printing".
- **SC Systems**: "supply chain", "value chain", "demand chain", "supply network".
- **Decision-Making Tools**: "decision making", "decision support system", "multi-criteria decision making", "MCDM".

Boolean operators (AND/OR) combined these terms to create comprehensive search strings (see Table 1).

2.2 Study Selection and Screening

The initial search yielded 114 publications. The following filtering process was applied:

1. **Inclusion criteria**: Peer-reviewed studies in English discussing AM integration into SCs and applying decision-making tools.
2. **Exclusion criteria**: Papers lacking SC impact, insufficient methodological rigor, or focusing solely on AM without decision-making relevance.

After the below refinement process:

- Language and peer-review screening → 98 studies retained.
- Duplicate removal → 88 studies retained.
- Abstract screening for relevance → 69 studies retained.
- Full-text review for methodological depth → 45 studies retained.
- Backward snowballing identified additional sources, but after applying the same criteria, the final dataset comprised 27 publications.

The systematic filtering process ensured the final dataset reflected both breadth and depth in AM-SC decision-making research.

2.3 Addressing Potential Bias

Despite a structured selection process, biases may arise from keyword choices, database coverage, and subjective inclusion/exclusion criteria. Also, human error during screening and data extraction could impact comprehensiveness. These limitations were mitigated through multiple-reviewer validation and adherence to transparent selection criteria. This methodology ensures a rigorous foundation for analysing AM-induced SC disruptions and the decision-making tools addressing them.

Table 1. Formulation of search strings

Search string 1		Search string 2		Search string 3
(“additive manufactur*" OR “3D print*” OR “three?dimensional print*” OR “direct digital manufactur*”)	AND	(“supply chain*” OR “value chain*” OR “demand chain*” OR “supply network*”)	AND	(“decision mak*” OR “decision support system*” OR “multi?criteria decision mak*” OR “MCDM”)

3. DESCRIPTIVE ANALYSIS

This section provides an overview of the selected 27 studies, examining publication trends, sectoral applications, and geographical distribution.

3.1 Publication Trends

The distribution of reviewed studies spans from 2016 to 2024, reflecting increasing academic interest in AM-driven SC transformation. While early research (2016–2018) was sparse, a significant rise in publications occurred after 2019, peaking in 2023 with six studies. This growth coincides with advancements in AM technologies and their adoption to address SC challenges. To improve clarity, Figure 2 displays these trends using a bar chart.

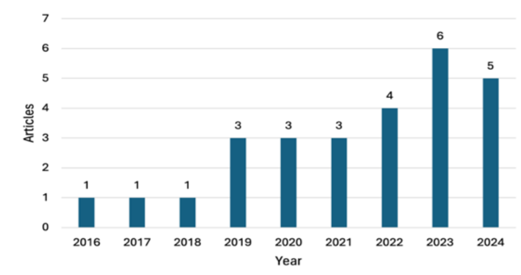

Figure 2. Documents by years.

3.2 Sectoral Applications

As shown in Figure 3, AM adoption varies across industries, with general manufacturing (47%) being the most represented, followed by automotive (20%), aerospace (13%), healthcare (7%), and defense (7%). Smaller contributions exist in oil & gas (3%) and retail (3%). Figure 3 shows to avoid overlap, ensuring that “manufacturing” refers to general production processes rather than a specific industry sector.

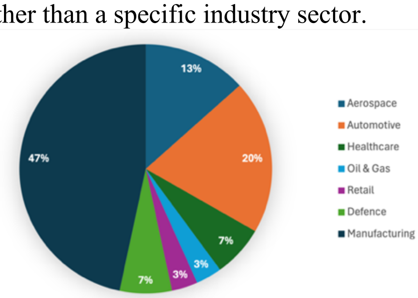

Figure 3. SC sectors considered in the reviewed studies.

3.3 Geographical Distribution

As shown in Figure 4, the research landscape is dominated by Europe (45%) and Asia (43.8%), with notable contributions from Italy, the UK, Germany, India, Japan, and Turkey. The Americas (11.1%), primarily the USA and Brazil, show limited representation, while Africa and Oceania remain absent.

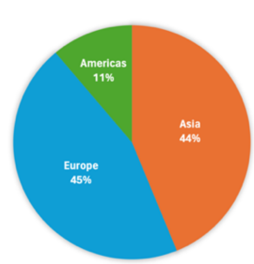

Figure 4. Geographic distribution of reviewed studies.

4. IMPACT OF AM ON SC STRUCTURES AND PROCESSES

To address RQ1, this section examines how AM adoption disrupts traditional SCs by shifting production from centralised models to decentralised, demand-driven networks. This transformation affects key SC dimensions, including inventory management, SC configuration, supplier selection, and manufacturing design. These areas were selected based on their frequent discussion in the literature as the most significantly impacted by AM adoption (Kunovjanek et al., 2022; Singh et al., 2024)

4.1 Inventory Management

AM enables on-demand production, reducing the need for large inventories and minimising obsolescence risks (Kunovjanek & Reiner, 2020). Digital warehousing allows firms to store product designs electronically rather than maintaining physical stock. Studies show AM adoption reduces raw material inventories by 4% (Peron et al., 2024) and improves availability of high-value, low-volume components, such as aerospace spare parts (Ghadge et al., 2018). In e-commerce, AM enhances reactive replenishment (real-time production) and proactive replenishment (predictive analytics-based production) (Ekren et al., 2023), improving demand responsiveness.

4.2 Supply Chain Configuration

AM challenges centralised production by enabling localised, distributed manufacturing, reducing transportation costs, emissions, and lead times (Ohmori, 2021). However, hybrid SC models, where AM complements CM, offer the best balance between cost efficiency and flexibility (Ronchini et al., 2023). Strategic AM hub placement is crucial for minimising delays and optimising component availability (Tuzkaya & Şahin, 2021). Moreover, AM supports sustainable SC models, reducing carbon footprints and material waste (Singh et al., 2024; Rinaldi et al., 2021).

4.3 Supplier Selection

AM reconfigures supplier relationships, enabling dynamic sourcing and reducing dependency on fixed suppliers (Akmal et al., 2022). Firms increasingly adopt a "make-and-buy" strategy, leveraging AM for low-volume, high-value parts while outsourcing mass production (Ronchini et al., 2023). AM also consolidates production steps, streamlining procurement and logistics (Jimo et al., 2022), while fostering closer collaboration with AM specialists for material expertise and process optimisation (Delic et al., 2019).

4.4 Manufacturing Design

Unlike CM, which imposes tooling constraints, AM enhances design flexibility, enabling customisation, waste reduction, and improved resource efficiency (Chiu & Lin, 2016). Layer-by-layer fabrication optimises small-batch, high-precision manufacturing, minimising downtime (Yılmaz, 2020). Furthermore, AM integrates production planning with logistics, synchronising manufacturing and distribution to reduce lead times and operational costs (Ransikarbum et al., 2020).

As AM transforms SC structures—reshaping inventory management, production configurations, supplier relationships, and manufacturing design—firms must adopt advanced decision-making tools to navigate these changes effectively. The next section categorises and evaluates key methodologies, including optimisation models, heuristic techniques, MCDM frameworks, simulation tools, statistical modeling, and theoretical frameworks, to support AM-driven SC decision-making.

5. DECISION-MAKING TOOLS

Effective decision-making is crucial for optimising AM-integrated SCs, enhancing resilience, and improving operational efficiency. This section categorises decision-making tools into six key groups: optimisation, heuristics, MCDM, simulation, statistical modeling, and theoretical frameworks. These methodologies provide structured approaches for addressing AM-related SC challenges.

5.1 Optimisation Tools

Optimisation models provide data-driven solutions for SC configuration, production scheduling, and inventory management.

- Mixed-integer linear programming (MILP) balances cost, demand fluctuations, and production constraints in AM adoption (Mecheter et al., 2023).
- Mixed-integer nonlinear programming (MINLP) optimises capacity allocation and AM hub placement (Cokyasar & Jin, 2023).
- Stochastic optimisation enhances SC resilience by incorporating uncertainty in production and logistics planning (Ahmed et al., 2023).
- Multi-objective optimisation helps balance cost, efficiency, and sustainability in AM scheduling (Ransikarbum et al., 2020).
- Multi-echelon inventory optimisation determines optimal stock levels in AM-enabled SCs, reducing waste and improving service levels (Ohmori, 2021).

5.2 Heuristic Tools

Heuristic tools provide computationally efficient alternatives to complex optimisation models.

- Genetic algorithms optimise AM facility selection, minimising costs and lead times (Tuzkaya et al., 2021).
- Decision trees support AM adoption decisions by comparing cost, material savings, and logistics efficiency (Cantini et al., 2024; Peron et al., 2024).
- Best-fit heuristic algorithms improve AM production scheduling, ensuring efficient resource allocation (Yılmaz, 2020).

5.3 Multi-Criteria Decision-Making (MCDM) Tools

MCDM methods help evaluate trade-offs between SC factors such as cost, lead time, and sustainability.

- Analytic hierarchy process (AHP) supports structured decision-making in AM scheduling and supplier evaluation (Ransikarbum et al., 2020).
- Other MCDM methods, combined with big data analytics, optimise AM facility selection and operational efficiency (Chen et al., 2023).

5.4 Simulation Tools

Simulation tools predict SC performance and allow firms to assess AM integration risks before implementation.

- Monte Carlo simulation models cost fluctuations, demand variability, and logistics efficiency (Roozkhosh et al., 2024).
- Discrete event simulation (DES) optimises on-demand spare parts supply, reducing dependency on physical inventories (Zhang et al., 2019).
- System dynamics simulation facilitates long-term AM adoption planning, particularly in aerospace and automotive SCs (Li et al., 2024; Ghadge et al., 2018).

5.5 Statistical Modeling

Statistical models provide empirical insights into AM's impact on SC performance, supplier integration, and resilience.

- Structural equation modeling (SEM) evaluates AM's role in SC flexibility and efficiency (Delic et al., 2019; Singh et al., 2024).
- Principal component analysis (PCA) simplifies AM facility selection by reducing complex data into key decision factors (Chen et al., 2023).

5.6 Theoretical Frameworks

Theoretical models help conceptualise strategic AM adoption decisions and SC transformation.

- Transaction cost economics (TCE) evaluates make-or-buy decisions, balancing in-house AM production and outsourcing (Ronchini et al., 2023).
- Scenario analysis explores centralised vs. decentralised AM networks to optimise SC configurations (Durão et al., 2017).
- Resource dependence theory (RDT) provides insights into AM adoption trends and long-term SC strategies (Jimo et al., 2022).

This classification of decision-making tools offers a structured approach to managing AM-driven SC changes. The next section integrates these insights into a structured mapping that systematically links SC disruptions to decision methodologies.

6. STRUCTURED MAPPING: LINKING CHANGES TO DECISION-MAKING TOOLS

The integration of AM is fundamentally reshaping SC structures, requiring firms to adopt structured decision-making approaches to manage emerging disruptions. Traditional SCs—characterised by centralised mass production, extensive inventories, and rigid supplier networks—are shifting toward decentralised, demand-driven, and digitally integrated systems (Durão et al., 2017; Ohmori, 2021). While these changes enhance flexibility, efficiency, and resilience, they introduce new decision-making challenges that necessitate systematic methodologies.

To address these complexities, this study proposes a structured mapping (Figure 5) that systematically maps four major AM-driven SC disruptions to corresponding decision-making tools:

1. **SC Configuration** – Transitioning between centralised, decentralised, and hybrid models, optimising AM hub placement.
2. **Inventory Management** – Shifting from physical stockpiling to on-demand digital warehousing, minimising waste and cost.
3. **Supplier Selection** – Enabling dynamic sourcing strategies, reducing reliance on traditional supplier contracts.
4. **Manufacturing Design** – Enhancing customisation and process efficiency through AM-enabled design flexibility.

6.1 Decision-Making Tools for SC Disruptions

Each SC disruption requires tailored decision-making tools:

- **Optimisation models** (e.g., MILP, MINLP) support SC configuration by determining the optimal mix of AM and CM, facility placement, and production allocation (Ahmed et al., 2023; Cokyasar & Jin, 2023).
- **Heuristic techniques** (e.g., genetic algorithms, decision trees) provide efficient solutions for facility selection and production scheduling in complex SC networks (Tuzkaya et al., 2021).
- **MCDM frameworks** (e.g., AHP, TOPSIS) evaluate supplier selection and facility trade-offs, balancing cost, lead time, and sustainability (Cardeal et al., 2023; Valtonen et al., 2022).
- **Simulation tools** (e.g., Monte Carlo analysis, system dynamics) allow firms to test SC scenarios, forecasting inventory needs and mitigating risks before full-scale AM adoption (Li et al., 2019; Roozkhosh et al., 2024).
- **Statistical modeling** (e.g., SEM, PCA) provides data-driven insights into supplier performance, AM integration efficiency, and SC resilience (Singh et al., 2024; Chen et al., 2023).
- **Theoretical frameworks** (e.g., TCE, RDT) guide long-term strategic decisions on outsourcing, AM adoption trends, and resilience planning (Jimo et al., 2022; Ronchini et al., 2023).

6.2 Structure of the Mapping Approach

The proposed structured mapping (Figure 5) systematically links AM-driven SC disruptions to the most suitable decision-making tools, ensuring a structured approach to AM integration.

- **Core Layer – SC Disruptions**: Four key AM-induced SC challenges—SC configuration, inventory management, supplier selection, and manufacturing design—require structured decision-making.
- **Decision-Making Layer – Tool Application**: Each SC challenge is addressed by specific tools:
    - **SC configuration** relies on optimisation models (MILP, MINLP) and simulation tools for facility placement and network design.
    - **Inventory management** benefits from multi-echelon inventory optimisation and Monte Carlo simulations to support digital warehousing.
    - **Supplier selection** is aided by MCDM frameworks (AHP, TOPSIS) to evaluate sourcing trade-offs.
    - **Manufacturing design** leverages statistical modeling (PCA, SEM) and theoretical frameworks (TCE, RDT) for strategic decision-making.
- **Methodological Layer – Decision Tool Categories**: Decision tools are classified into six key categories:

optimisation, heuristics, MCDM, simulation, statistical modeling, and theoretical frameworks, ensuring a structured response to AM-induced SC transformations.

This mapping offers a systematic approach to aligning decision-making tools with AM-induced SC disruptions, supporting firms in making informed strategic choices.

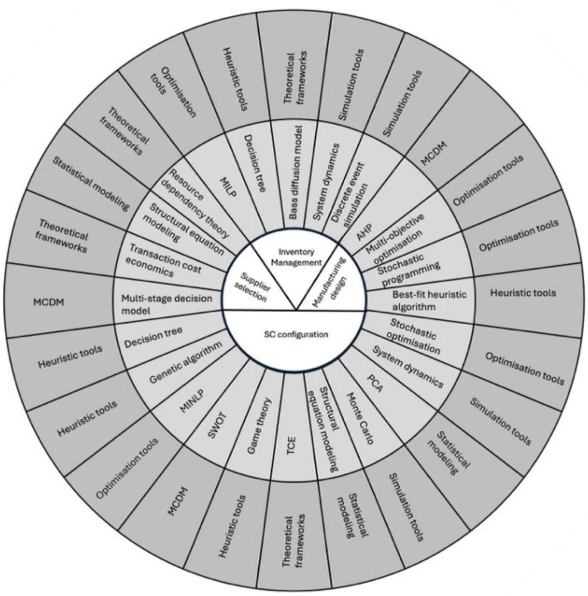

Figure 5. Structured mapping linking AM-SC challenges to decision-making tools.

7. CONCLUSIONS AND FUTURE DIRECTIONS

This study systematically reviews decision-making tools for managing AM-induced disruptions in SCs. By analysing 27 studies, it identifies four key challenges—SC configuration, inventory management, supplier selection, and manufacturing design—and maps them to six decision-making approaches, providing a structured framework for AM integration.

A key novelty of this study is the introduction of a structured mapping that links AM-driven SC disruptions to decision-making tools, offering a new perspective on how firms can navigate these challenges. Unlike previous reviews that focus solely on AM adoption or SC changes, this study bridges the gap by explicitly connecting disruptions with decision-support methodologies. Also, this review identifies underexplored gaps in AM decision methodologies, particularly the lack of integrated multi-tool approaches and the need to account for uncertainties in real-world applications.

Findings highlight that AM adoption requires both technological readiness and robust decision methodologies. While tools like optimisation models, simulation techniques, and MCDM frameworks enhance adaptability and resilience, their effectiveness depends on industry-specific applications.

Despite a rigorous selection process, potential biases exist in keyword selection, database coverage, and inclusion criteria. Future research should focus on empirical validation through case studies, scalable decision models for evolving AM roles, and sustainability integration to align AM with environmental and social objectives.

By addressing these areas, future studies can strengthen the link between AM and SC resilience, ensuring data-driven, sustainable decision-making for AM-enabled supply chains.

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Abu-Abdoun, Dana I.

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