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Synopsis Of

A Multi-Phase Decision-Making Framework for Quantifying the Impact of Additive Manufacturing in Automotive Industry: Enabling Resilient and Sustainable Automotive Supply Chains

A Thesis

To be submitted by

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For the award of the degree

Of

DOCTOR OF PHILOSOPHY

1 Abstract

The automotive supply chain is increasingly strained by global disruptions, sustainability pressures, and volatile demand. While Additive Manufacturing (AM) offers capabilities such as on-demand production, design consolidation, and decentralized operations, its adoption remains limited by the absence of integrated, system-level decision frameworks.

This thesis proposes a multi-phase, data-driven framework to strategically integrate AM into automotive supply chains with a focus on resilience, sustainability, and agility. First, a Generative AI–enhanced multi-criteria decision-making (MCDM) model prioritizes high-impact parts by balancing conflicting cross-functional criteria such as demand volatility, logistics risk, design changes, and sourcing complexity, followed by exploring Design for Additive Manufacturing (DfAM) feasibilities to consolidate multi-component assemblies, demonstrated through a fuel pump sub-assembly case study that reduces part count, supplier dependence, and logistics overhead.

Third, an agent-based simulation model evaluates end-to-end supply chain performance under normal and disruption scenarios, comparing traditional and AM-enabled supply chains using Total Cost of Ownership (TCO), Total Carbon Footprint (TCF), and Order Fulfillment Rate (OFR). Finally, a spatial postponement strategy is implemented through a multi-objective AM hub location model that balances capital investment, postponement benefits, and last-mile efficiency.

2 Objectives of the research

(i) To develop a Generative AI–enhanced multi-criteria decision-making (MCDM) framework for prioritizing automotive parts suitable for additive manufacturing based on demand volatility, logistics risk, part churn, and sourcing complexity.

(ii) To apply Design for Additive Manufacturing (DfAM) principles to consolidate multi-component automotive assemblies and quantify their impact on part count reduction, supplier dependency, and logistical complexity.

(iii) To model and compare traditional and AM-enabled automotive supply chains using an agent-based simulation framework under normal and disruption scenarios.

(iv) To evaluate supply chain sustainability and resilience performance by analyzing Total Cost of Ownership (TCO), Total Carbon Footprint (TCF), and Order Fulfillment Rate (OFR) across different supply chain configurations.

(v) To optimize the spatial deployment of additive manufacturing hubs using a multi-objective location model that balances capital investment, postponement benefits, and last-mile delivery efficiency.

3 Existing Gaps which were Bridged

(i) Prior AM adoption approaches rely on static or single-criterion part selection methods, failing to balance cross-functional priorities such as procurement risk, logistics variability, and engineering complexity.

(ii) While Design for Additive Manufacturing is well studied at the component level, limited research demonstrates its impact on supplier dependency, logistics structure, and supply chain resilience.

(iii) Most supply chain resilience studies assess disruptions qualitatively or in isolation, without simulation-based comparison between traditional and AM-enabled supply chains under realistic disruption scenarios.

(iv) Existing AM location and decentralization models rarely operationalize spatial postponement by jointly considering capital investment, resilience benefits, sustainability impacts, and last-mile delivery efficiency.

4 Methodology

The proposed framework (Figure 1) presents a four-phase, end-to-end decision-making approach for integrating Additive Manufacturing (AM) into automotive supply chains. Phase 1 focuses on part prioritization, where supply chain data are collected, transformed, and analyzed using quantitative techniques to rank and select components exposed to high supply chain risk. Phase 2 emphasizes design unification and rationalization by evaluating whether AM can be leveraged at a higher structural level; this involves gathering component attributes, assessing Design for Additive Manufacturing (DfAM) compliance, consolidating multiple components, and identifying AM-feasible parts that enable functional integration. Phase 3 performs a quantitative evaluation by mapping the value stream, collecting AM and traditional manufacturing (TM) cost data, defining model parameters, and comparing AM and TM alternatives across key performance dimensions to quantify benefits and trade-offs. Finally, Phase 4 treats AM as a postponement enabler by integrating optimization modeling to determine suitable AM hub locations and deployment strategies, enabling a system-level comparison of outcomes. Together, the framework provides a structured pathway from part selection to supply chain reconfiguration, enabling data-driven assessment of AM's impact on cost, sustainability, and resilience across the automotive value chain.

5 Most Important Contributions

The subsections list out the key contributions of the study:

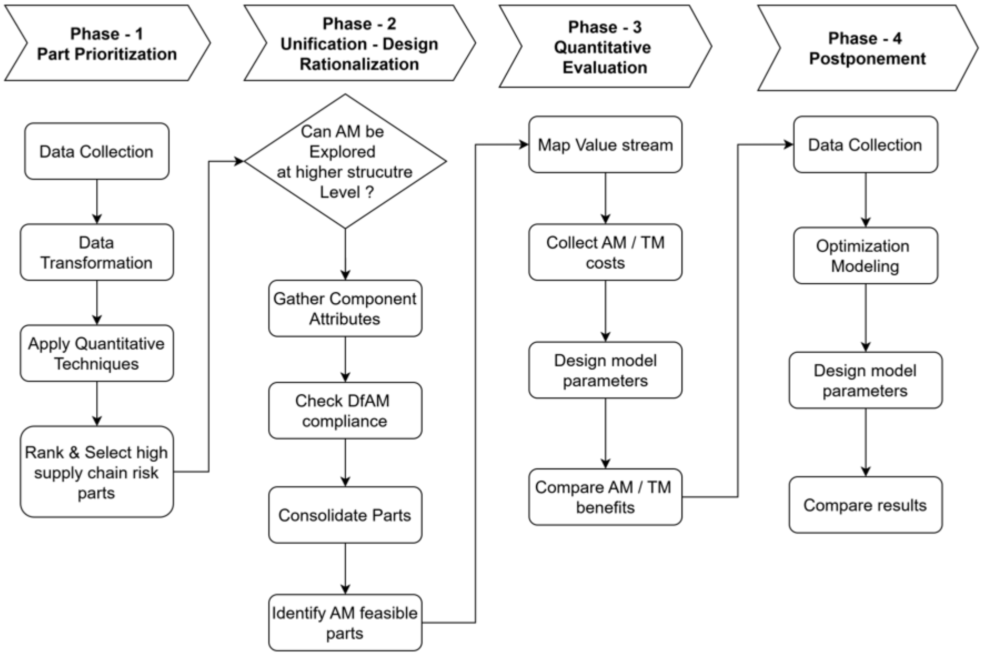


Figure 1: Multi-Phase decision making framework for adopting AM in Automotive Industry

5.1 Generative AI enabled external logistics intelligence

The study leverages Generative AI as a logistics risk intelligence (Kmiecik and Skórnóg (2025)) layer that classifies transportation routes by risk severity based on foundational knowledge (Alavi *et al.* (2024)) and generates explainable risk labels, which could be used further to influence decision making while prioritizing parts for Additive manufacturing (Table 1).

5.2 Multi-Criteria Decision Making for Part Prioritization

This framework (Figure 2) integrates purchasing, logistics, manufacturing, and marketing signals to identify critical supply chain characteristics such as demand volatility, lead-time risk, design churn, and disruptions.

Table 1: Risk assessment for origin–destination pairs along the shipping route using LLM

Origin Destination Pair	**Final Risk Level**	**Key Factors generated from LLM/Gen AI**
Origin Country: United States	Low	Stable political environment, well-developed infrastructure, skilled workforce
Port of Departure: Chicago, Illinois, USA	Low	Major transportation hub with efficient port operations
Atlantic Ocean	Moderate	Potential for storms and piracy in certain areas
Mediterranean Sea	Moderate	Geopolitical tensions and potential for piracy
Suez Canal	High	Critical chokepoint with potential for political instability and security threats
Red Sea	Moderate	Potential for piracy and geopolitical tensions
Indian Ocean	Moderate	Potential for piracy and geopolitical tensions
Chennai Port	Low	Stable political environment, well-developed infrastructure, skilled workforce
Logistics Risk	Moderate	Implement comprehensive mitigation strategies

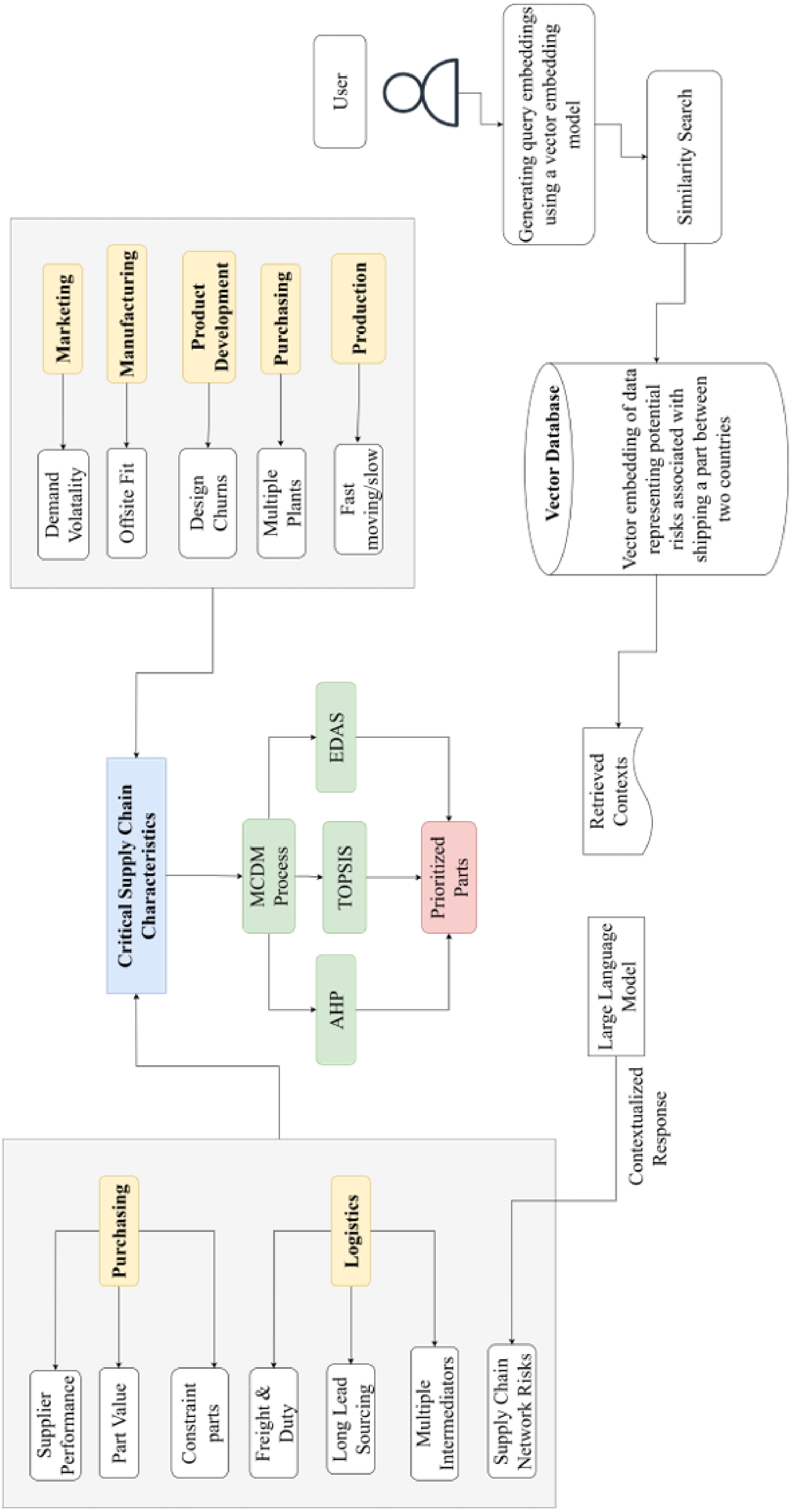


Figure 2: Gen AI enabled MCDM in Automotive Supply Chain

This study integrates Generative AI–derived external logistics risk intelligence with a multi-criteria decision-making (MCDM) framework for robust part prioritization. Internal supply chain criteria are combined with GenAI-classified logistics risk indicators (Deiva Ganesh and Kalpana (2022)) to construct a unified criteria matrix, which is refined through expert judgment and consistency-validated weight computation. The resulting decision matrix (Saaty (1977)) for candidate parts is normalized and evaluated using multiple complementary MCDM techniques, including the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), Multi-Objective Optimization by Ratio Analysis (MOORA), and Evaluation based on Distance from Average Solution (EDAS), to mitigate method-specific bias. Rankings from these methods are consolidated to identify a consensus set of high-priority parts, which are then selected for subsequent AM-focused design and supply chain analysis.

5.3 Agent Based Simulation Modeling to compare Traditional and AM Enabled Automotive Supply Chain

This study develops and simulates a multi-echelon automotive supply chain value stream for traditional and additive manufacturing (Figure 3) under geographically diverse sourcing and disruption scenarios, using an agent-based model (Table 2) that incorporates real-time Sales and Operational Planning (S&OP) processes, supplier expedites and port-level detention and demurrage costs to evaluate resilience and sustainability impacts (Carvalho *et al.* (2012)).

In the sustainability part, it takes the total cost of ownership (Figure 4a), total carbon footprint (Figure 4b) and total opportunity loss (Figure 4c). In the resilience part, it takes the ability of the supply chain entity's (tier one supplier) order fulfillment rate (Figure 5a, Figure 5b, Figure 5c). Results indicate that compared to TM , AM is less susceptible to logistical and manufacturing disruptions and demonstrates resilience across all scenarios, despite raw material suppliers being imported and procured in smaller quantities.

Table 2: Parameters of Supply Chain Agents

Parameters	**Values for TM (VS–1,2,3,4)**	**Values for AM (VS–5)**	**Unit**
Number of variants of part	8	8	units
Unit cost per part variant	2	2	USD
Replenishment policy	Fixed Time Variable Quantity	Variable Time Fixed Quantity	–
Minimum actual weekly car demand quantity	2900	2900	units
Maximum actual weekly car demand quantity	3200	3200	units
Demand percentage of fast-moving parts (DF)	75% of actual weekly car demand (3 parts equally distributed – 25% each)	75% of actual weekly car demand (3 parts equally distributed – 25% each)	units
Demand percentage of slow-moving parts (DS)	25% of actual weekly car demand (randomly distributed)	25% of actual weekly car demand (randomly distributed)	units
Minimum safety stock of finished goods (fast and slow moving)	1	2	weeks
Minimum safety stock of raw material (fast and slow moving)	Not applicable	4	weeks
Raw material cost per unit	2	16	USD
Profit per unit	5.4	Not applicable (in-house)	USD
Total manufacturing cost per unit	30	44.5	USD
Obsolescence quantity	2% of total end parts produced	Not applicable (Just-in-Time)	%

Note : All the above parameters taken in the table are assumptions.

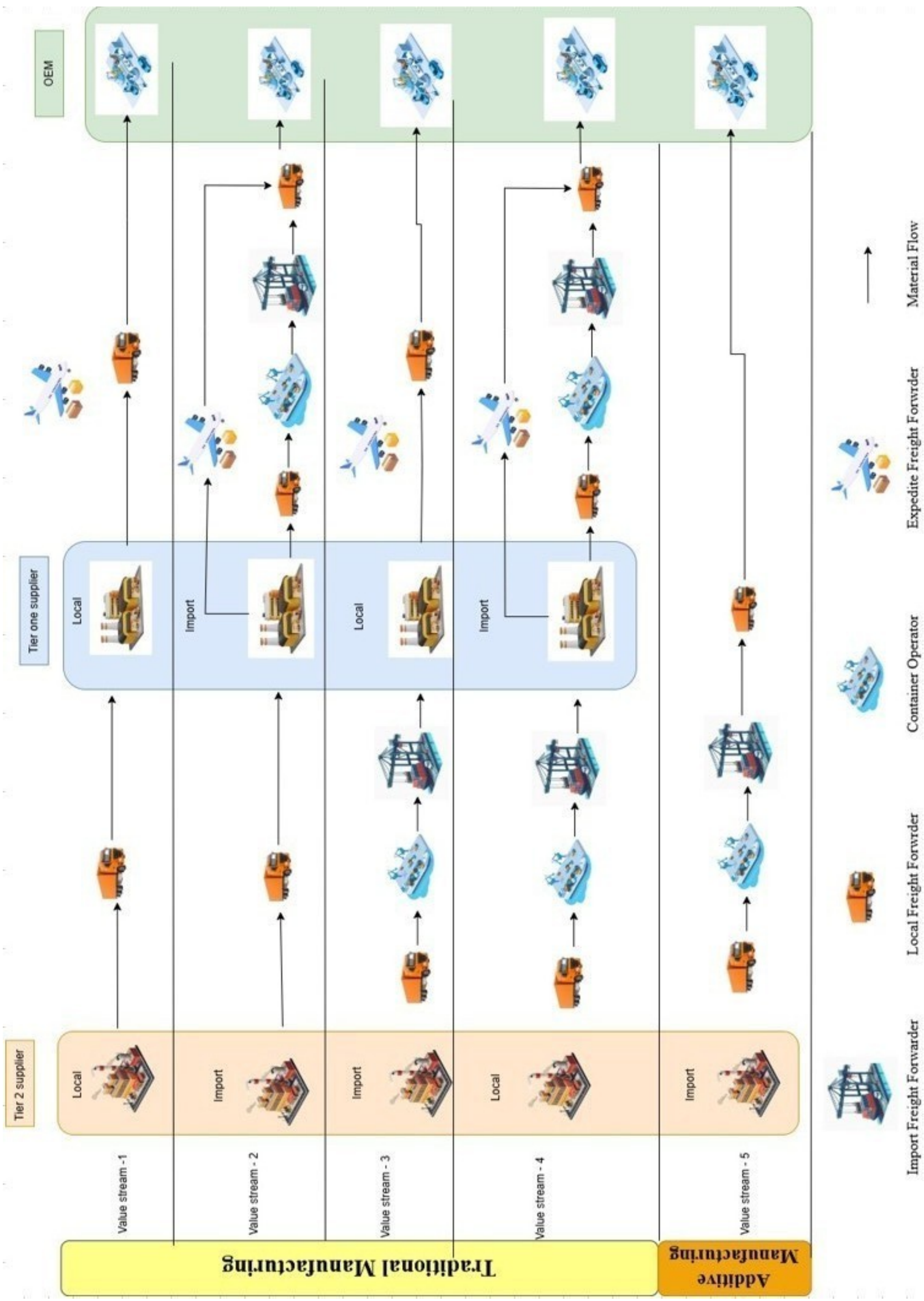
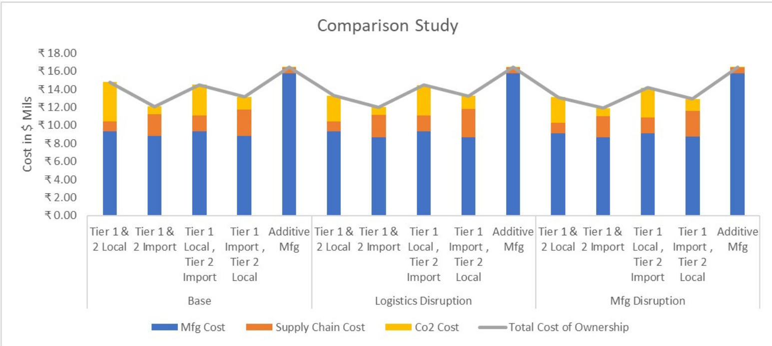
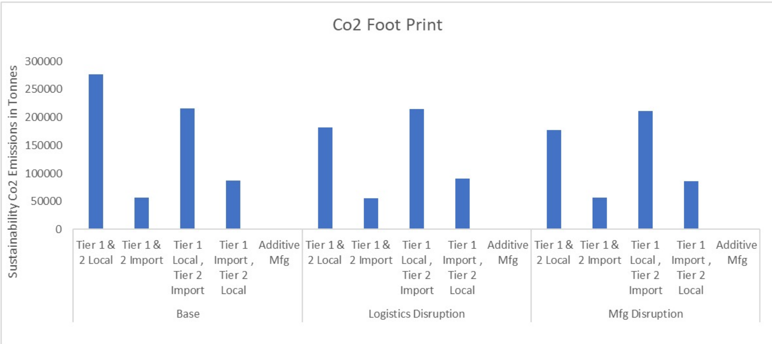


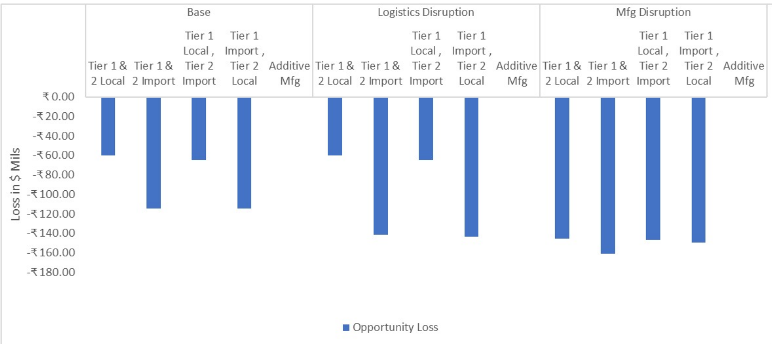
Figure 3: Multi-Echelon Supply Chain Value Stream



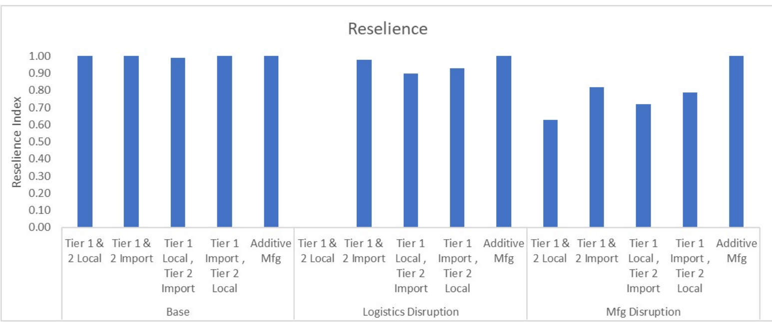
(a) Comparison of TCO between Scenarios



(b) Comparison of CO_2 between Scenarios

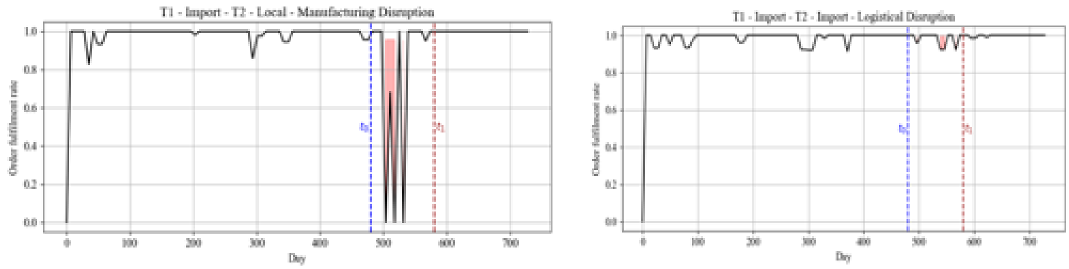


(c) Comparison of Opportunity Loss between Scenarios

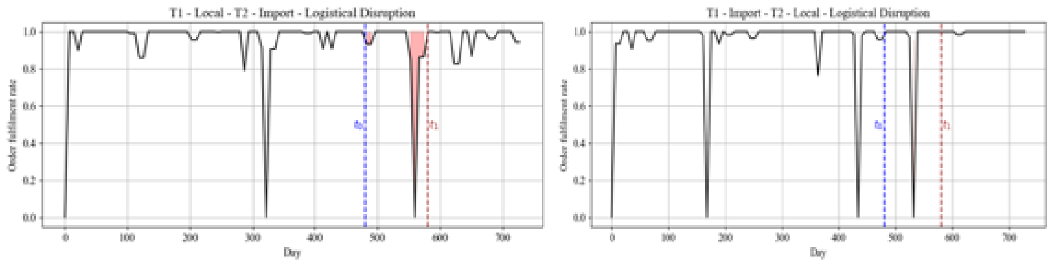


(d) Comparison of Resilience Index between Scenarios

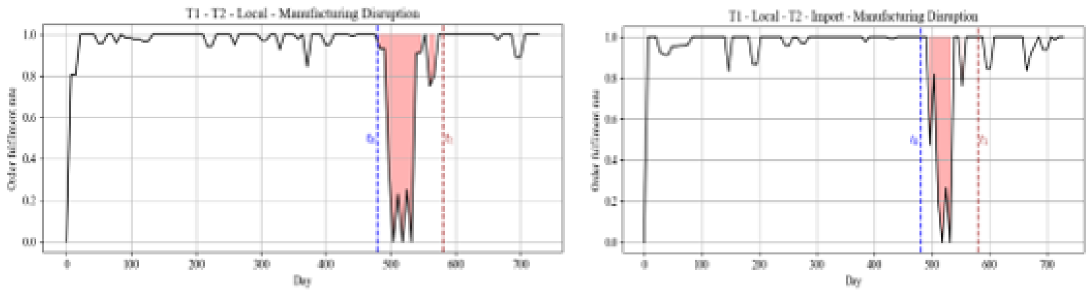
Figure 4: Cost, Emissions, Opportunity Loss, and Resilience Comparison Across Manufacturing Scenarios



(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

Figure 5: Order Fulfilment Rate of Supplier Agents Under Different Scenarios

5.4 Proposing AM as a Postponement enabler for Automotive SC

To establish Additive Manufacturing (AM) as a postponement enabler (Boone *et al.* (2007)), this study formulates a facility location optimization model to determine the optimal number and geographic placement (latitude and longitude) of AM hubs within the supply chain (Figure. 6). The model strategically positions AM hubs closer to end customers and farther from production plants, while simultaneously minimizing total transportation cost and the number of AM facilities required (Figure. 7). The problem is formulated and solved using Genetic Algorithm and Simulated Annealing for large and complex datasets while ensuring the model accuracy closeness to exact solvers for smaller datasets.

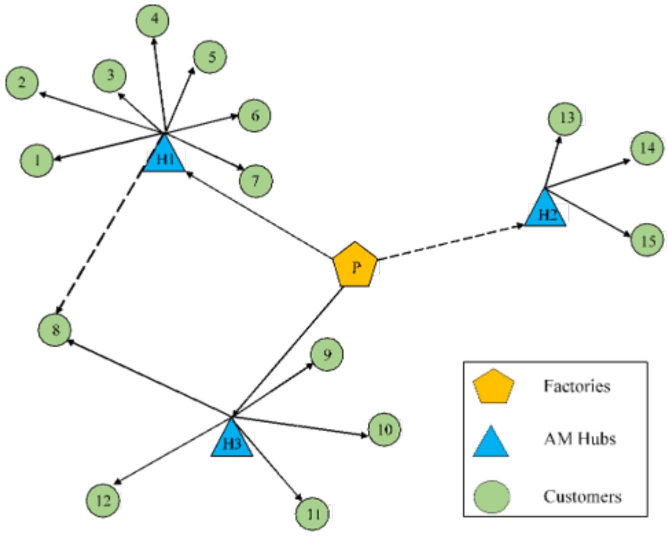


Figure 6: AM hub integration in the Value Chain

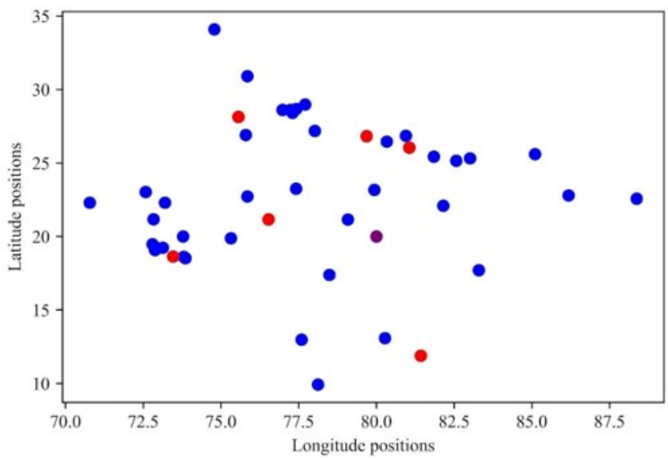


Figure 7: MCDM workflow for Part Prioritization

6 Conclusion

This research establishes Additive Manufacturing as a strategic lever for building resilient and sustainable automotive supply chains when guided by a structured, system-level decision framework. By integrating AI-enhanced multi-criteria decision-making, Design for Additive Manufacturing, agent-based simulation, and spatial optimization, the study provides a practical roadmap for informed AM adoption.

The results demonstrate that AM-enabled supply chains can improve order fulfillment performance and enhance disruption resilience, while achieving balanced trade-offs between total cost, carbon footprint, and operational flexibility. Overall, the framework enables OEMs to move from reactive risk mitigation to proactive supply chain design, positioning Additive Manufacturing as a key enabler of agile, disruption-ready, and sustainability-driven automotive supply chains.

7 Organization of Thesis

The present thesis is organized into eight chapters, and the summary of each chapter is given here:
Chapter 1 : Introduction
Chapter 2 : Review of the literature
Chapter 3 : Multi stage decision making framework for stakeholders to adopt Additive Manufacturing in Automotive Supply Chain
Chapter 4 : Generative AI enabled Multi-Criteria Decision Making Model for Critical Parts Selection in Automotive Supply Chain
Chapter 5 : A Quantitative Cost Benefit Analysis of integrating Design for AM advantages in Automotive Supply Chain via Part Unification
Chapter 6 : Fostering Automotive Additive Manufacturing: A simulation driven decision making approach to optimize supply chains
Chapter 7 : Redesigning for Resilient and Agile Supply Chain: Additive Manufacturing's Role in Automotive Postponement Strategies
Chapter 8 : Conclusions, Limitation and Future Research Directions

8 List of Publications

Journal Publications
Arvindkumar S, Ragunanthan, & Pitchaimani, K. (2025). Fostering automotive additive manufacturing: A simulation-driven decision-making approach to optimize supply chains. *Journal of Simulation*, 1–25. `https://doi.org/10.1080/17477778.2025.2588282`

Manuscripts Under Review

- Arvindkumar., & Pitchaimani, K. *A multi-phase framework for integrating additive manufacturing in automotive supply chains: Bridging the gap from theory to practice*. Production Planning & Control (Manuscript ID: TPPC-2025-0891). - Working on Comments Received from the Journal

- Arvindkumar S, Ragunanthan., & Pitchaimani, K. *Redesigning for resilient and agile supply chains: Additive manufacturing's role in automotive postponement* *strategies*. International Journal of Production Research (Manuscript ID: 269693047). - Waiting for Reply form the Journal

International Conference

- S.Arvindkumar , Kalpana P . "Case Study Additive Manufacturing's influence on Postponement strategy in supply chain" ICBAI ORSI Conference, 2023, IISC Bangalore.

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1. **Alavi, M.**, **D. Leidner**, and **R. Mousavi** (2024). Knowledge management perspective of generative artificial intelligence (genai). *Alavi, Maryam*, 1–12.

2. **Boone, C. A.**, **C. W. Craighead**, and **J. B. Hanna** (2007). Postponement: an evolving supply chain concept. *International Journal of Physical Distribution & Logistics Management*, **37**(8), 594–611.

3. **Carvalho, H.**, **A. P. Barroso**, **V. H. Machado**, **S. Azevedo**, and **V. Cruz-Machado** (2012). Supply chain redesign for resilience using simulation. *Computers & Industrial Engineering*, **62**(1), 329–341.

4. **Deiva Ganesh, A.** and **P. Kalpana** (2022). Supply chain risk identification: a real-time data-mining approach. *Industrial management & data systems*, **122**(5), 1333–1354.

5. **Kmiecik, M.** and **D. Skórnóg** (2025). Impact of generative ai on logistics companies' business models. *International Journal of Logistics Research and Applications*, 1–25.

6. **Saaty, T. L.** (1977). A scaling method for priorities in hierarchical structures. *Journal of mathematical psychology*, **15**(3), 234–281.