Supply Chain Insider
Volume 16, Issue 01, 71-93. 10-10-25
Article Received: 25-08-2025
Accepted: 15-09-2025
Available Online: 10-10-2025
ISSN: 2617-7420 (Print), 2617-7420 (Online)
DOI: **10.5281/zenodo.17284697**
supplychaininsider.org

Application of Discrete Event Simulation, AI and Machine Learning (ML) in Optimizing Supply Chain and Operations Management: A Systematic Literature Review

R.I. Nafim, S. Muntaha, N. Tasnim, A.R.M.H. Rashid
Mechanical and Production Engineering. Islamic University Of Technology, Gazipur, 1704, Dhaka

Abstract

This review paper examines the integration of Industry 4.0 technologies—specifically, artificial intelligence (AI), discrete event simulation (DES), machine learning (ML), and metaheuristics—in enhancing supply chain and operations management. By optimising manufacturing parameters, these techniques not only reduce overall costs but also increase production efficiency. Digital twins of manufacturing facilities offer additional benefits by validating optimisation results and identifying bottlenecks within existing systems. A systematic literature review (SLR) was conducted using 19 academic papers and journal articles published from 2010 to recent years. Papers were selected through thematic deduction, employing keywords such as algorithm, discrete event simulation, machine learning, artificial intelligence, supply chain, and Industry 4.0. The review first highlights how AI and ML are revolutionising supply chain management by enabling efficient decision-making, optimising process arrangements, and supporting the adoption of innovative methods through simulation-based insights derived from digital twin models. Furthermore, evidence is presented demonstrating significant improvements in production efficiency, cost management, and planning when integrating AI and ML into supply chain operations. The study also addresses the challenges hindering the implementation of these technological advancements in Bangladesh's textile and ready-made garment (RMG) industries—where, in 2023, Bangladesh ranked as the world's second-largest exporter of RMG with a revenue of $38 billion. Key challenges include data quality issues, insufficient digital infrastructure, and inadequate data documentation. Given that much of the existing research relies on case studies or reviews, this paper also suggests future research directions, including simulation-based experimentation and the exploration of additional AI techniques such as data mining (DM), long short-term memory (LSTM) networks, and natural language processing (NLP).

Keywords: Supply Chain Optimization, Discrete Event Simulation, Metaheuristics, Stochastic models.

1.Introduction

In today's competitive business world, supply chain management (SCM) has become a major focus of research, as companies look for better ways to meet growing customer demands while keeping costs under control (Khan et al., 2018). A supply chain relies on strong collaboration between companies, suppliers, and customers, requiring constant information sharing and coordinated actions (Tiwari, 2021). To keep things running smoothly and cost-effectively, organizations must make smart decisions at every level, strategic, tactical, and operational (Khan et al., 2018).

In today's increasingly automated and data-driven world, decision-making has become more strategic and complex. It requires organizations to process and analyze massive amounts of data. Traditionally, decisions were often based on intuition, experience and whatever information was available at the time. In the past, these decisions were mostly based on manual processes, experience and instinct. But this is rapidly changing with the rise of modern digital technologies (Rolf et al., 2023). With the rise of digital technologies, we have various tools to do these things. Today, tools like artificial intelligence (AI) and machine learning (ML) are transforming supply chain operations by enabling powerful data analysis, accurate forecasting and automated decision making (Mwangi, 2024; Singh, 2023). Studies have shown that advanced technologies, including artificial intelligence(AI) play a crucial role for maintaining business persistence, particularly during external disruptions. (Papadopoulos et al., 2020). Modern Supply chains are reinforced by actuators and sensors such as GPS ,POS, RFIDs, tags and various smart devices that receive and transmit data continuously. (Papadopoulos et al., 2017). Therefore, through this real-time data exchange AI can be used to develop proactive approaches to predict probabilities of risk arising and their potential impact. (Baryannis et al., 2019)
Machine learning is transforming the way organizations make decisions. It provides real-time insights that help decision makers analyze situations more accurately and make better, more informed choices. Unlike traditional methods that rely heavily on personal experience and intuition, machine learning learns from data itself. It offers a more objective, data-driven approach. In some cases, it can even perform better and replace conventional decision making methods. (Mahraz et al., 2022).

A handful of methods can be incorporated to design and analyze supply chains including predictive and analytical models, economic frameworks, stochastic models and metaheuristics (Bottani & Casella, 2024; Mustafee et al., 2021). Among various simulation techniques the most widely researched methods are Monte Carlo (MC), discrete- event simulation (DES), agent-based simulation (ABS) and system dynamic (SD). DES is broadly used for business process optimization. In general, DES is quite easy to apply in different scenarios to play out probable events in advance (Tako & Robinson, 2012a). It is known well in manufacturing industries(Vázquez-Serrano et al., 2021). Discrete event simulation (DES) models are replicated in image of any real world system or operation which in parts helps the viewer get a broader view on the operations and processes without intervening in the real model thus allowing for evaluating real world performance based on various scenarios. DES models represent the systems as a set of networks and events with state changes occurring at discrete points in time. These are inherently stochastic in nature and through the use of statistical distributions randomness is created. In the modern supply chain, in both strategic level and tactical level discrete event simulation can play a crucial role. (Tako & Robinson, 2012b).

Metaheuristics have gained traction in the past decade for optimizing sustainable supply chain management (SSCM) issues these days. Recent reviews focus on the increasing use of these algorithms in the supply chain operations across many industries. With hybrid approaches these are gaining more popularity than pure meta-heuristics (Faramarzi-Oghani et al., 2023). Among all the approaches, genetic algorithms like NSGA-II are the most frequently applied techniques (Faramarzi-Oghani et al., 2023). Metaheuristics have shown positive results in solving versatile SSCM challenges including product distribution, vehicle routing, and balancing economic and environmental factors (Abualigah et al., 2023; Faramarzi-Oghani et al., 2023). These methods have been successfully applied to various complex problems like supply chain risk management, intermodal operations, and facility location (Griffis et al., 2012). Through these approaches different alternative solutions can be found which optimize multiple objectives like minimizing cost while maximizing output whilst considering a magnitude of constraints. (Griffis et al., 2012) The accuracy of metaheuristics in SSCM depends highly on factors like algorithm selection, problem complexity, and data quality (Abualigah et al., 2023).

Acknowledging that this topic is still in its early stages of development, this paper seeks to provide a clear and practical understanding of the current and potential future role of artificial intelligence (AI), machine learning (ML), discrete event simulation (DES) and metaheuristics in optimizing supply chain management (LSCM) by addressing the following research questions (RQs):

RQ1: What is the current state of research on the combined application of DES, metaheuristics, AI and ML in modern supply chain optimization?

RQ2: Are there identifiable research gaps or unexplored areas in the existing literature?

RQ3: What are the synergies and trade-offs between DES modeling and ML-based optimization?

A systematic literature review (SLR) provides a thorough and structured analysis of the relevant existing academic discourse within a specific area. It enables a methodical and reliable approach to address the stated research questions. This method helps to highlight the future scopes of the technologies like AI, ML, DES and metaheuristics in further research in optimizing supply chain processes.

Comprehensive research assessing overall scopes and potential of the mentioned technologies within supply chain optimization are very limited. Therefore, the objectives of this paper are:

1. To explore how Artificial Intelligence (AI), Machine Learning (ML), Discrete Event Simulation (DES), and Metaheuristics technologies support strategic, tactical, and operational decision-making within modern supply chain management, particularly in the Bangladesh RMG and textile industries.
2. To identify thematic patterns, technological synergies, and research gaps in the current academic literature.

The methodology is described in chapter 2. A systematic literature review (SLR) protocol, data collection procedures using boolean operator and classification strategies are discussed. It also includes the conceptual framework of the analysis aligned with the research questions stated. Chapter 3 describes the findings from the analysis including the focus of the papers, peak year of publication and authors. This section also includes the potential of the future research and research gaps in this chapter.

2. Methodology

This study follows the Systematic Literature Review (SLR) methodology as proposed by Denyer and Tranfield (2009) to ensure a structured, transparent, and replicable approach to analysing existing research in the fields of AI, ML, discrete event simulation, and optimisation algorithms in supply chain and operations management in a five-step process. The SLR technique provides a systematic method to identify, evaluate, and synthesise relevant academic literature, ensuring comprehensive coverage of existing research trends, gaps, and future directions (Denyer & Tranfield, 2009). The existing literature was judged based on the aforementioned criteria after collecting them from a substantially wide database (www.dimensions.ai). Unlike traditional narrative reviews, SLR allows for an objective assessment of studies based on predefined selection criteria, making it a widely accepted method for evidence-based research. By employing this method, the study aims to provide a clear, replicable, and unbiased summary of the current state of AI-driven supply chain optimization with validation from digital twins, focusing on its application in Bangladesh's RMG sector.

It enables the synthesis of available studies on a specific area, which benefits researchers and gives scientific knowledge to strengthen practice (Tiwari, S, 2020). This paper attempts to integrate information obtained from a series of individual or multidisciplinary studies that incorporate the use of AI, ML, discrete event simulation, and optimisation algorithms in supply chain operations using SLR, as well as to identify topics that are deficient in evidence, pointing and providing new directions for future research. The five steps that will be followed in this paper for a SLR are shown in Figure 1 and comprise the following steps:
(1) Formulation of problem,

(2) Identification of studies,
(3) Selection and evaluation of studies,
(4) Analysis and synthesis and
(5) Presentation of results and discussion.

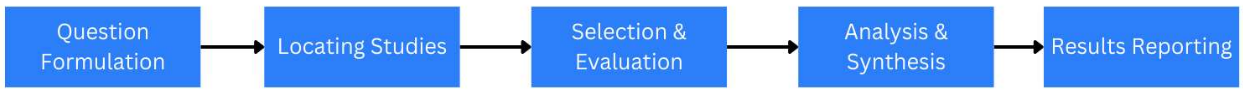


Fig 1. Research Methodology

We will go over the first three steps to illustrate how we collected and screened papers for further analysis in the results section.

2.1 Formulation of problem

Following Denyer and Tranfield (2009) principles, we begin our SLR by explicitly stating the RQ (research questions) in the introduction. The questions in this study focus on how AI, machine learning, and optimisation techniques (including discrete event simulation) are used to improve supply chain and operations management, notably in Bangladesh's textile and ready-made garment (RMG) industries. This stage determines the scope of our review and ensures that we focus on studies related to Industry 4.0 technology, manufacturing efficiency, and digital twin applications.

2.2 Identification of studies

To systematically identify and classify literature relevant to the application of AI, ML, metaheuristics, and digital twins in supply chain optimisation, with a specific focus on Bangladesh's RMG and textile industries, we conducted a structured search using Denyer and Tranfield (2009) Systematic Literature Review (SLR) methodology. The goal was to analyse global developments in Industry 4.0-driven supply chain optimisation while also determining how many studies particularly focus on Bangladesh's textile sector and whether they suggest frameworks for local industry implementation.

Our search approach was developed around three core keyword categories, ensuring that the retrieved papers cover the confluence of these themes:

1. Applying AI, ML, and Metaheuristics in Supply Chain

Keywords: ("Artificial Intelligence" OR "Machine Learning" OR "Neural Networks" OR "Deep Learning" OR "Reinforcement Learning" OR "Genetic Algorithm" OR "Ant Colony Optimization" OR "NSGA-III" OR "Swarm Intelligence" OR "Simulated Annealing")

2. Supply Chain Optimisation and Simulation.

Keywords: ("Supply Chain Optimization" OR "Demand Forecasting" OR "Production Scheduling" OR "Logistics Optimization" OR "Inventory Management" OR "Supply Chain Resilience" OR "Digital Twin" OR "Simulation Modeling" OR "Discrete Event Simulation" OR "Agent-Based Modeling")

3) Bangladesh's RMG and Textile Industry

Keywords: ("Bangladesh RMG" OR "Bangladesh Textile" OR "Garment Supply Chain" OR "Textile Production Optimization" OR "Industry 4.0 in Bangladesh" OR "AI in Textile Manufacturing" OR "ML in RMG")

Using boolean operators **(**LibGuides**)**, the keywords were combined into structured search queries to ensure only the most relevant studies were retrieved. One example search query used was:

"Artificial Intelligence" OR "Machine Learning" OR "Metaheuristics" OR "Digital Twin" OR "Supply Chain Optimisation" OR "Discrete Event Simulation" OR "Agent-Based Modelling" AND "Bangladesh RMG" OR "Bangladesh Textile" OR "Industry 4.0 in Bangladesh."

Dimensions.ai was used for the search due to its extensive academic coverage and ease of access. The search focused on peer-reviewed journal articles, conference papers, and book chapters published in English between 2017 and 2025, ensuring coverage of both foundational and contemporary research. In this way, we settled on 170 numbers of papers for the initial filtering process.

2.3 Selection and evaluation of studies

Following a set of inclusion and exclusion criteria, we screened the retrieved papers for relevance and quality. Criteria included publication in peer-reviewed journals, a focus on supply chain or operations management in a manufacturing context (with an emphasis on textiles and RMG), and the application of AI, ML, or optimisation algorithms. We ultimately selected 19 academic papers for in-depth analysis. This rigorous selection process, based on thematic deduction, helped ensure that only the most pertinent and high-quality studies were included

2.3.1 Inclusion and exclusion criteria

The inclusion and exclusion criteria were designed to focus the review on literature that is both methodologically sound and thematically relevant to the intersection of Industry 4.0 technologies and supply chain or operations management.

Inclusion Criteria:

1) Peer-reviewed journal articles, conference proceedings, or book chapters
2) Published between 2017 and 2025
3) Written in English
4) Focused on the application of AI, machine learning (ML), metaheuristics, digital twins, or discrete event simulation (DES) in supply chain or operations management
5) Studies involving optimization, forecasting, decision-making, or Industry 4.0 transformation
6) Studies relevant to Bangladesh or comparable emerging economies are especially prioritized

Exclusion Criteria:

1) Editorials, opinion pieces, or non-peer-reviewed articles
2) Studies not related to supply chain, operations, or industrial contexts
3) Articles with no clear application of AI/ML/DES/digital twin techniques
4) Duplicates or inaccessible full texts
5) Papers written in languages other than English

2.3.2 Screening and selection phases

The evaluation process consists of three sequential filtering stages:

Phase 1: Title, Abstract, and Keyword Screening
A preliminary filter will be applied to all records that are obtained from structured Boolean queries (e.g., "Artificial Intelligence" AND "Supply Chain Optimisation") by looking at their titles, abstracts, and keywords. Articles that are obviously unrelated to their stated topic, scope, or domain are eliminated in this step.

Goal: Remove obviously unrelated fields (e.g., healthcare, finance, pure AI theory)
Expected output: Reduce initial records to a manageable set for full-text screening

Phase 2: Text Review

The remaining studies will be thoroughly examined at this step. This guarantees that every manuscript offers adequate methodological depth and is in line with the review's topic focus. Unless they provide significant transferable insights, conceptual-only publications, highly theoretical models, and non-industry applications are not included.

Goal: Ensure strong relevance to your research questions

Assessment criteria:

1) Is there a clear problem statement and objective?
2) Is the methodology sound?
3) Are the results applicable to supply chain operations?
4) Is there potential for applicability in Bangladesh or similar regions?

Phase 3: Quality Assessment and Deduplication

All remaining papers are subjected to a final quality check and de-duplication process. Quality will be judged based on:

1) Clarity of research questions
2) Validity of methodology
3) Contribution to the domain
4) Relevance to the research dimensions identified in Section 2.4
5) Papers that are inaccessible or duplicated across publication venues are removed.

The final set of selected papers will be included in the Analysis and Synthesis (Section 3).

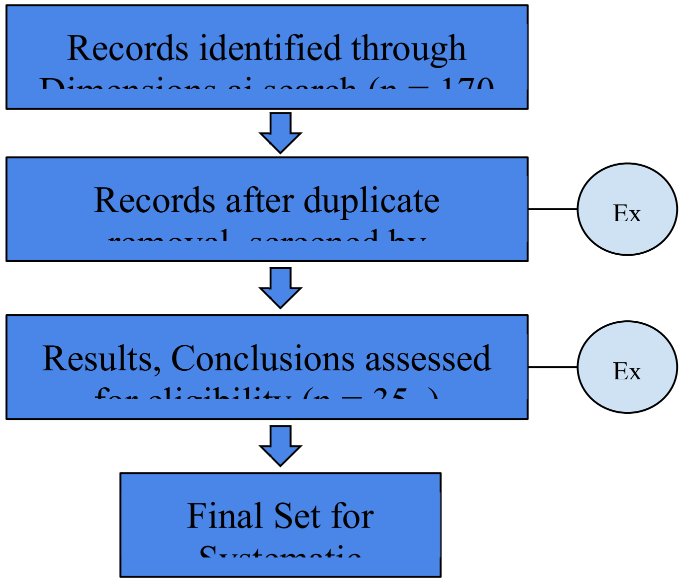


Fig 2. Screening Process

2.4 Analysis & synthesis

This section outlines the structured approach employed to synthesize and analyze the selected body of literature. Following a **thematic analysis framework**, papers were systematically categorized into coherent themes to identify patterns, methodological trends, and research gaps relevant to the integration of Machine Learning (ML), Metaheuristics, and Discrete Event Simulation (DES) in supply chain and manufacturing contexts—particularly within Bangladesh's RMG (ready-made garments) industry or similar socio-economic regions.

Thematic analysis was selected for its ability to provide nuanced insights into qualitative patterns within large sets of research literature. According to Braun and Clarke (2006), thematic analysis is a method for "identifying, analyzing and reporting patterns (themes) within data" and is particularly suitable for reviews aiming to move beyond simple summaries toward conceptual synthesis. (Braun, V., & Clarke, V. (2006))

The analytical process followed a three-level hierarchical classification inspired by prior structured literature reviews (e.g., Rai et al., 2006; Fabbe-Costes & Jahre, 2008). These three levels included:

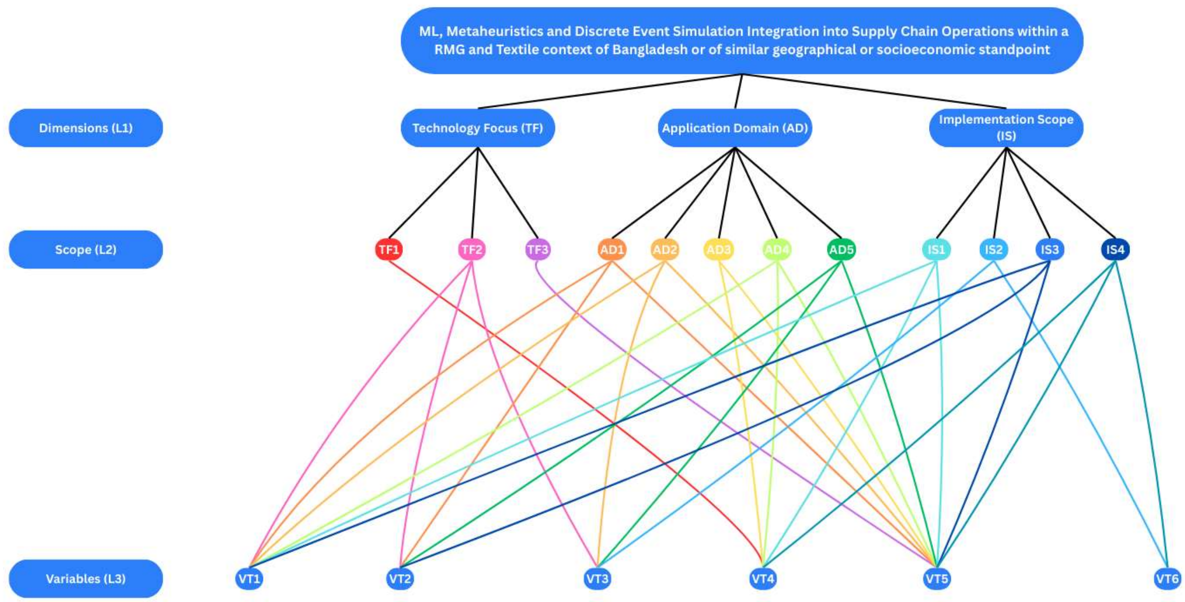


Fig 3. Thematic Classification Method

- **Level 1 (L1): Dimensions** – Major research categories such as **Technology Focus (TF)**, **Application Domain (AD)**, and **Implementation Scope (IS)**.

- **Level 2 (L2): Scopes** – Sub-categories under each dimension.

1. **TF1** – Machine Learning
2. **TF2** – Metaheuristics
3. **TF3** – Discrete Event Simulation
4. **AD1** – Production Scheduling
5. **AD3** – Demand Forecasting
6. **IS3** – Simulation-Based Evaluation
7. **IS4** – Real-World Case Study

- **Level 3 (L3): Variables** – Variables are **specific tools or techniques** mentioned in the reviewed literature. Each is assigned a variable tag (VT1 through VT6) and positioned beneath the scope(s) in which it is most commonly applied:

1. **VT1 – Genetic Algorithm (GA):** Often applied to solve scheduling, maintenance, or optimization problems using population-based search.
2. **VT2 – Particle Swarm Optimization (PSO):** Applied to production scheduling, logistics, and simulation-driven evaluations due to its convergence efficiency.
3. **VT3 – Ant Colony Optimization (ACO):** Frequently used in logistics and inventory planning, especially in inter-organizational routing or pathfinding.
4. **VT4 – Simulation Tools:** Represents platforms such as SimPy, Arena, or AnyLogic used in discrete event simulation, modeling, or scenario testing.
5. **VT5 – Digital Twin:** Refers to real-time digital models used for dynamic production, monitoring, and virtual feedback loops.
6. **VT6 – LSTM Neural Network:** A deep learning model applied primarily for time-series prediction, such as demand forecasting or maintenance anomaly detection.

Each paper was reviewed based on its title, abstract, and full text (when necessary), and then classified using this structured coding scheme. This enabled cross-sectional tagging of papers across dimensions, allowing for the analysis of:

- How frequently certain techniques (e.g., GA, LSTM) appeared across domains
- The common combinations of technology and application in real-world or simulated environments
- Thematic density and research gaps

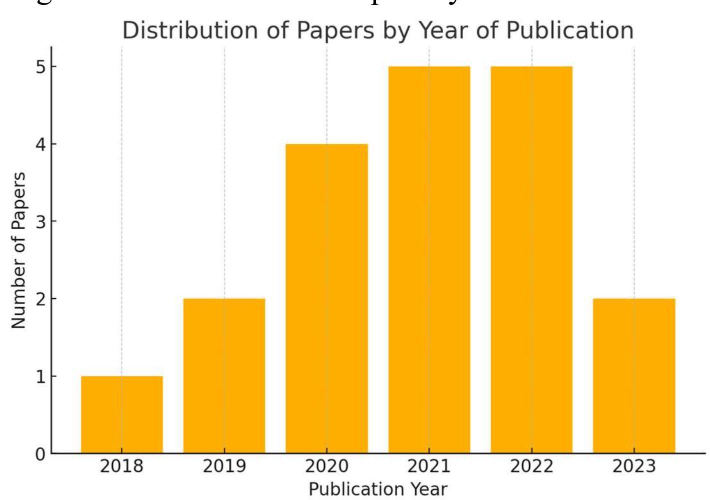
The classification framework developed in this review was adapted from the methodology used in integration studies of Industry 4.0 and supply chain systems, where multi-layered thematic deduction was applied to synthesize fragmented literature.

In addition to traditional bibliometric screening, this review used a **code-based thematic tagging** method to maintain a structured but flexible mapping of papers across intersecting research domains. This method allowed for an integrative synthesis, where themes such as "LSTM-based demand forecasting" or "GA-driven scheduling optimization in real-world RMG contexts" could be quantitatively and qualitatively analyzed.

3.Results and Discussion

The distribution of the 19 selected papers over publication years is shown in Figure X.It can be observed that the majority of the reviewed studies were published between 2020 and 2022, with peak activity in 2021 and 2022 (5 papers each year).This trend reflects a recent surge in research attention toward applying AI, digitalization, and simulation technologies in supply chain and production environments, particularly following the disruptions caused by the COVID-19 pandemic.Earlier contributions (2018–2019) were relatively sparse, indicating that this area is a newly emerging research focus.

Figure 4 : Distribution of Papers by Year of Publication



.

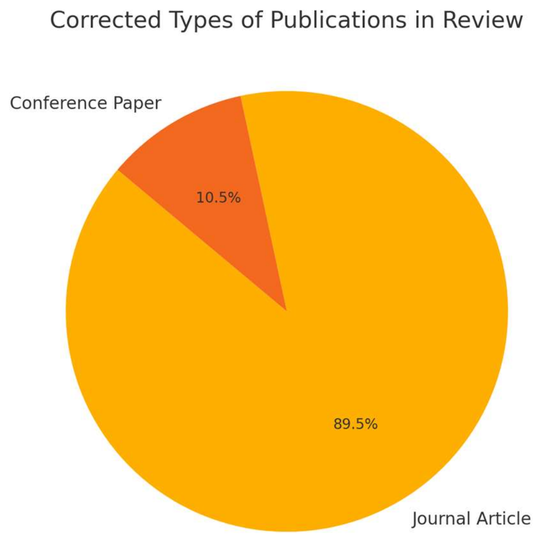


Figure 5 : Types of Publications in the Systematic Review

89% of the reviewed papers were journal articles, showing strong peer-reviewed maturity in the field. 11% were conference papers, reflecting ongoing exploration of new methods and frameworks. 0% were book chapters, indicating that this domain is largely being developed through academic journal and conference channels, rather than formalized book collections at this stage.

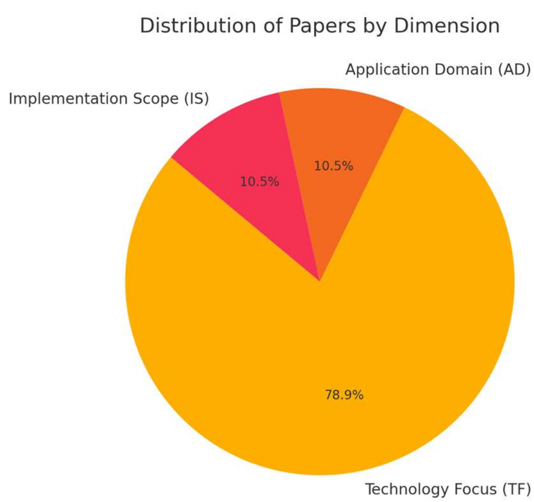


Figure 6 : Distribution of Papers by Dimension

In line with the structured classification methodology outlined in Section 2.4, the 19 selected papers were organized across three levels:

- **Level 1 (L1)**: Major Dimensions – Technology Focus (TF), Application Domain (AD), and Implementation Scope (IS).
- **Level 2 (L2)**: Specific Scopes – such as Machine Learning (TF1), Metaheuristics (TF2), Discrete Event Simulation (TF3), Production Scheduling (AD1), Demand Forecasting (AD3), Simulation-Based Evaluation (IS3), and Real-World Case Study (IS4).
- **Level 3 (L3)**: Variables – the specific methods/tools used, including Genetic Algorithm (VT1), Particle Swarm Optimization (VT2), Ant Colony Optimization (VT3), Simulation Tools (VT4), Digital Twin (VT5), and LSTM Neural Networks (VT6).

Table below presents the full categorization of the reviewed papers according to this structured three-tier framework.

No.	Paper Title	L1 (Dimension)	L2 (Scope)	L3 (Variable)
1	Exploring Sustainable Development Pathways for Agri-Food SC	IS	IS4	VT4
2	Modeling AI in Supply Chain (mathematics-10-01233)	TF	TF1	VT6
3	Navigating Tensions of Sustainable SC in Crisis	IS	IS4	(None)
4	Green SC Simulation (s10668-024-05783-z)	TF	TF3	VT4

5	Digital Twins for Production Scheduling (s12597-024-00839-0)	TF	TF3	VT5, VT4
6	Resilient Digital SC (s12652-022-04357-z)	TF	TF3	VT5, VT4
7	AI-Based Supply Chain Risk Management (sustainability-12-02641)	TF	TF1	VT6
8	Blockchain and AI in SCM (1-s2.0-S0959652624029093)	TF	TF1	(None)
9	IoT-Driven Digital Twin in Manufacturing (1-s2.0-S2666954421000089)	TF	TF3	VT5
10	Analyzing Role of Digital Twins for Resilience	TF	TF3	VT5
11	Blockchain SC Management (sustainability-13-10496)	TF	TF1	(None)
12	AI for Sustainable Production Scheduling (sustainability-14-00538)	TF	TF1	VT6
13	Six Sigma for Industry 4.0 in Textile SMEs (sustainability-15-12589)	AD	AD1	(None)
14	Garment Industry 5.0 and Digital Twins (sustainability-15-15839)	TF	TF3	VT5

15	COVID-19 Supplier Selection in Textiles (Integrated Fuzzy MSGP)	TF	TF2	(None)
16	Capacity Planning in Vaccine SC (128. paper.pdf)	IS	IS3	VT4
17	Freight Flow Optimization (liotta2015)	TF	TF2	VT1
18	SC Agility & Industry 4.0 (math-10-01635)	TF	TF1	(None)
19	Sustainable Supplier Selection (TSP_CMC_20206)	TF	TF2	(None)

As shown in Table, several patterns can be observed in the recent research landscape:

1. Dominance of Technology Focus (TF):
A significant majority of the reviewed papers (around 80%) fall under the **Technology Focus (TF)** dimension, indicating a strong research emphasis on developing and applying technological methods—such as AI, metaheuristics, and digital twin simulations—to enhance supply chain and production management.

2. Prevalence of Discrete Event Simulation (TF3) and Machine Learning (TF1) Scopes:
Within the Technology Focus category, **Discrete Event Simulation (TF3)** and **Machine Learning (TF1)** are the most common scopes. This suggests that simulation-based modeling and AI-based predictive analysis are currently the leading methodologies explored for operational improvements.

3. Widespread Adoption of Digital Twin and Simulation Tools:
At the variable level, **Digital Twin (VT5)** and **Simulation Tools (VT4)** appear most frequently. Their repeated appearance highlights the industry's growing reliance on real-time dynamic modeling and virtual scenario testing for strategic decision-making.

4. Relatively Lower Emphasis on Application Domain (AD) and Implementation Scope (IS):
Only a small fraction of studies fell into the **Application Domain (AD)** and **Implementation Scope (IS)**

categories. This indicates that while many technologies are proposed and modeled, fewer studies directly address real-world implementation or operationalization challenges in production and logistics environments.

5. Underutilization of Metaheuristics and LSTM Models:
Although metaheuristic techniques (TF2) and deep learning methods like LSTM (VT6) were identified, they were less frequently employed compared to simulation models and digital twins, suggesting potential future research opportunities to explore these approaches more extensively in supply chain optimization.

Discussion:

The visualizations below were created using Vosviewer. For the analysis, 35 papers were chosen and two conditions were established. The first criterion is that the minimum keyword co-occurrence threshold is set to three. The second criteria was configured to select 60% (the default) of the most relevant keywords.

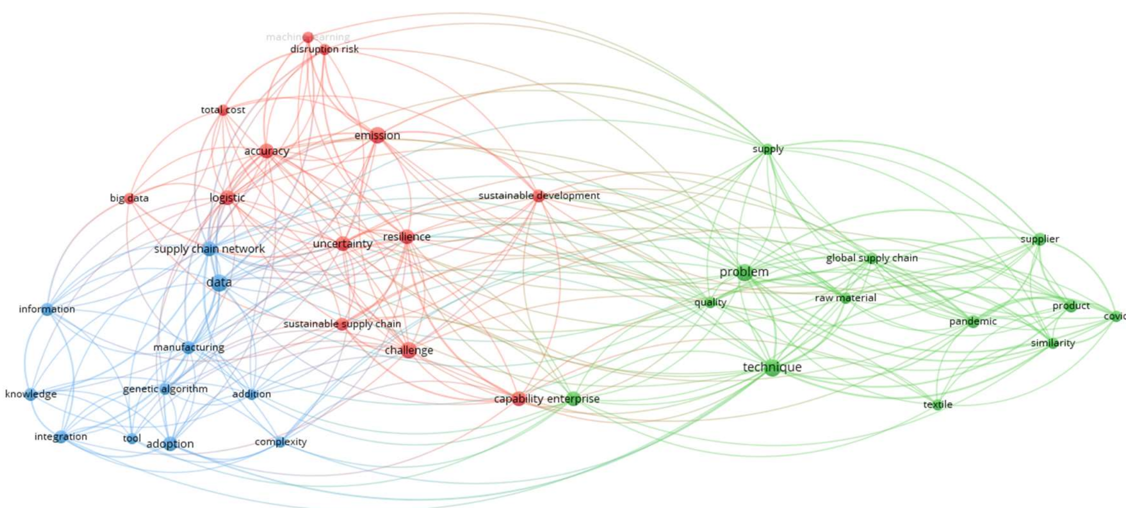


Fig 7: Keyword relevance graph

The first network graph depicts the most relevant keywords and the relationships between them. The distance between keywords and the thickness of the connecting lines show connection strength, which can assist in determining which keywords should be prioritized or which areas require additional research. We can see that there are 3 clusters - blue, red and green. The blue cluster includes keywords like data,genetic algorithm, integration, manufacturing etc. The red cluster includes logistics, sustainable development, resilience, disruption risk etc. And lastly the green cluster keywords includes supply chain, covid, pandemic, textile etc. We can conclude that the blue cluster focuses on technological approaches, for instance the role of machine learning (ML) , AI . While the red cluster shows the challenges in logistics and supply chain. And the green cluster focuses on real-life applications and the effect of the pandemic in the supply chain.

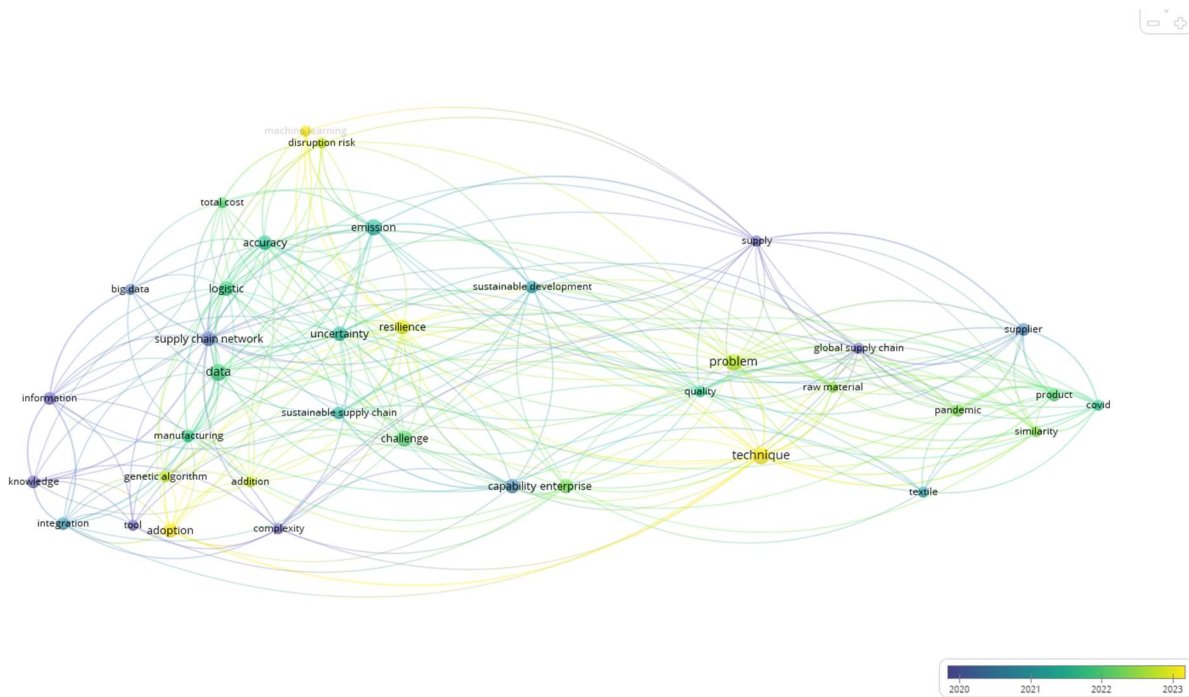


Fig 7: Keyword trend graph

The second graph depicts the keyword trend throughout the years 2020–2023. The yellow nodes are the most current, while the blue nodes are from prior years. This helps to determine the emerging trend of study topics and their scopes.

4.Conclusion

This study presents a comprehensive systematic literature review (SLR) on the integration of Artificial Intelligence (AI), Machine Learning (ML), Discrete Event Simulation (DES) and metaheuristics in optimizing supply chain operations. This study particularly focuses on the textile and RMG sector of Bangladesh. The results reveal that these technologies have huge potential in future research and especially in the context of Bangladesh RMG and Textile sector these technologies are underexplored. Especially the optimization of the supply chain through DES using digital twins can be explored more.

Most of the reviewed literature falls under the TF dimension which is in the Technology Focused sector. These are mostly emphasized on DES and ML in their methodologies for optimization process. Despite this, the real-time implementation is very limited. On the other hand, the Application Domain (AD) and Implementation Scope (IS) dimensions are underexplored as well. This yells a significant research gap between the theoretical advancements and their practical adaptation in industrial environments. Developing countries like Bangladesh struggle to adopt these technologies because of poor data quality, limited digital infrastructure and insufficient documentation.

In conclusion, further research needs to be done to bridge the gap especially in Bangladesh's RMG and textile industry between conceptual models and industrial application. Further studies should aim to develop integrated frameworks which validate the simulation based organizational barriers to technology adoption.

Reference:

Akbari, M., & Do, T. N. A. (2021). A systematic review of machine learning in logistics and supply chain management: Current trends and future directions. *Benchmarking: An International Journal, 28*(10), 2977–3005. https://doi.org/10.1108/BIJ-10-2020-0514

Andrianandrianina Johanesa, T. V., Equeter, L., & Mahmoudi, S. A. (2024). Survey on AI applications for product quality control and predictive maintenance in Industry 4.0. *Preprints, 202401.1596.v1*. https://doi.org/10.20944/preprints202401.1596.v1

Bojic, S., Maslaric, M., Mircetic, D., Nikolicic, S., & Todorovic, V. (2023). Simulation and genetic algorithm-based approach for multi-objective optimization of production planning: A case study in industry. *Advances in Production Engineering & Management, 18*(2), 250–262. https://doi.org/10.14743/apem2023.2.471

Bottani, E., & Casella, G. (2024). Discrete-event simulation in logistics and supply chain management: A scientometric perspective. *Production & Manufacturing Research, 12*(1), 2415038. https://doi.org/10.1080/21693277.2024.2415038

Fukuzawa, M. (2020). Function of value stream mapping in operations management journals. *Annals of Business Administrative Science, 19*(5), 207–225. https://doi.org/10.7880/abas.0200909a

Ghasemi, P., Goli, A., Goodarzian, F., & Ehmke, J. F. (2025). Simulation-based genetic algorithm for optimizing a municipal cooperative waste supply chain in a pandemic. *Engineering Applications of Artificial Intelligence, 139*, 109478. https://doi.org/10.1016/j.engappai.2024.109478

Habib, Md. M., Sabah, S., Chowdhury, F., Raisa, R., & Shuvo, T. F. (2024). Technology-enabled ready-made garments supply chain management: A literature review. *Revista de Gestão Social e Ambiental, 18*(10), e08842. https://doi.org/10.24857/rgsa.v18n10-188

Hamja, A., Maalouf, M., & Hasle, P. (2019). The effect of lean on occupational health and safety and productivity in the garment industry: A literature review. *Production & Manufacturing Research, 7*(1), 316–334. https://doi.org/10.1080/21693277.2019.1620652

Hsu, C. H., He, X., Zhang, T. Y., Chang, A. Y., Liu, W. L., & Lin, Z. Q. (2022). Enhancing supply chain agility with Industry 4.0 enablers to mitigate ripple effects based on integrated QFD-MCDM: An empirical study of new energy materials manufacturers. *Mathematics, 10*(10), 1635. https://doi.org/10.3390/math10101635

Huang, M. C., & Huang, H. H. (2019). How transaction-specific investments influence firm performance in buyer-supplier relationships: The mediating role of supply chain integration. *Asia Pacific Management Review, 24*(2), 167–175. https://doi.org/10.1016/j.apmrv.2018.03.001

Kao, H. (2022). Integrated fuzzy-MSGP methods for clothing and textiles supplier evaluation and selection in the COVID-19 era. *Mathematical Problems in Engineering, 2022*, 9433454. https://doi.org/10.1155/2022/9433454

Khan, S. A., Chaabane, A., & Dweiri, F. T. (2018). Multi-criteria decision-making methods application in supply chain management: A systematic literature review. In V. A. P. Salomon (Ed.), *Multi-Criteria Methods and Techniques Applied to Supply Chain Management* (pp. 1–22). InTech. https://doi.org/10.5772/intechopen.74067

Liotta, G., Stecca, G., & Kaihara, T. (2015). Optimisation of freight flows and sourcing in sustainable production and transportation networks. *International Journal of Production Economics, 164*, 351–365. https://doi.org/10.1016/j.ijpe.2014.12.016

Logožar, K. (2024). The role of artificial intelligence in supply chain management: A systematic literature review. *ENTRENOVA - ENTerprise REsearch INNOVAtion, 10*(1), 328–337. https://doi.org/10.54820/entrenova-2024-0027

Muthaluri, J. (2024). Optimizing supply chain management and marketing strategies: AI and ML integration for competitive advantage. *Educational Administration: Theory and Practice, 30*(5), 8990–8997. https://doi.org/10.53555/kuey.v30i5.4494

Mwangi, J. (2024). Analyzing the role of artificial intelligence and machine learning in optimizing supply chain processes in Kenya. *International Journal of Supply Chain Management, 9*(1), 39–50. https://doi.org/10.47604/ijscm.2322

Polo-Triana, S., Gutierrez, J. C., & Leon-Becerra, J. (2024). Integration of machine learning in the supply chain for decision making: A systematic literature review. *Journal of Industrial Engineering and Management, 17*(2), 344–372. https://doi.org/10.3926/jiem.6403

Singh, P. K. (2023). Digital transformation in supply chain management: Artificial intelligence (AI) and machine learning (ML) as catalysts for value creation. *International Journal of Supply Chain Management, 12*(6), 57–63. https://doi.org/10.59160/ijscm.v12i6.6216

Tako, A. A., & Robinson, S. (2012). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems, 52*(4), 802–815. https://doi.org/10.1016/j.dss.2011.11.015

Tariq, S., Mahmood, K., & Moeen, R. (2023). Smart supply chain strategies: Determinants and relationship with supply chain integration and sustainable supply chain performance. *International Journal of Transport Economics, 50*(1–2), 115–142. https://doi.org/10.19272/202306702004

Wang, C. N., Pan, C. F., Nguyen, V. T., & Husain, S. T. (2022). Sustainable supplier selection model in supply chains during the COVID-19 pandemic. *Computers, Materials & Continua, 70*(2), 3005–3019. https://doi.org/10.32604/cmc.2022.020206

Yadav, P. K., Singh, S., Tripathi, C. M., & Bhushan, R. (2023). Supply chain schedule management with genetic algorithm. In *2023 International Conference on Evolutionary Algorithms and Soft Computing Techniques (EASCT 2023)*. https://doi.org/10.1109/EASCT59475.2023.10393211

Abualigah, L., Hanandeh, E. S., Zitar, R. A., Thanh, C.-L., Khatir, S., & Gandomi, A. H. (2023). Revolutionizing sustainable supply chain management: A review of metaheuristics. *Engineering Applications of Artificial Intelligence*, *126*, 106839. https://doi.org/10.1016/j.engappai.2023.106839

Baryannis, G., Validi, S., Dani, S., & Antoniou, G. (2019). Supply chain risk management and artificial intelligence: State of the art and future research directions. *International Journal of Production Research*, *57*(7), 2179–2202. https://doi.org/10.1080/00207543.2018.1530476

Bottani, E., & Casella, G. (2024). Discrete-event simulation in logistics and supply chain management: A scientometric perspective. *Production & Manufacturing Research*, *12*(1), 2415038. https://doi.org/10.1080/21693277.2024.2415038

Faramarzi-Oghani, S., Dolati Neghabadi, P., Talbi, E.-G., & Tavakkoli-Moghaddam, R. (2023). Meta-heuristics for sustainable supply chain management: A review. *International Journal of Production Research*, *61*(6), 1979–2009. https://doi.org/10.1080/00207543.2022.2045377

Griffis, S. E., Bell, J. E., & Closs, D. J. (2012). Metaheuristics in Logistics and Supply Chain Management. *Journal of Business Logistics*, *33*(2), 90–106. https://doi.org/10.1111/j.0000-0000.2012.01042.x

Khan, S. A., Chaabane, A., & Dweiri, F. T. (2018). Multi-Criteria Decision-Making Methods Application in Supply Chain Management: A Systematic Literature Review. In V. A. P. Salomon (Ed.), *Multi-Criteria Methods and Techniques Applied to Supply Chain Management*. InTech. https://doi.org/10.5772/intechopen.74067

Mahraz, M., Benabbou, L., & Berrado, A. (2022). Machine Learning in Supply Chain Management: A Systematic Literature Review. *International Journal of Supply and Operations Management*, *Online First*. https://doi.org/10.22034/ijsom.2021.109189.2279

Mustafee, N., Katsaliaki, K., & Taylor, S. J. E. (2021). Distributed Approaches to Supply Chain Simulation: A Review. *ACM Transactions on Modeling and Computer Simulation*, *31*(4), 1–31. https://doi.org/10.1145/3466170

Mwangi, J. (2024). Analyzing the Role of Artificial Intelligence and Machine Learning in Optimizing Supply Chain Processes in Kenya. *International Journal of Supply Chain Management*, *9*(1), 39–50. https://doi.org/10.47604/ijscm.2322

Papadopoulos, T., Baltas, K. N., & Balta, M. E. (2020). The use of digital technologies by small and medium enterprises during COVID-19: Implications for theory and practice. *International Journal of Information Management*, *55*, 102192. https://doi.org/10.1016/j.ijinfomgt.2020.102192

Papadopoulos, T., Gunasekaran, A., Dubey, R., & Fosso Wamba, S. (2017). Big data and analytics in operations and supply chain management: Managerial aspects and practical challenges. *Production Planning & Control*, *28*(11–12), 873–876. https://doi.org/10.1080/09537287.2017.1336795

Rolf, B., Jackson, I., Müller, M., Lang, S., Reggelin, T., & Ivanov, D. (2023). A review on reinforcement learning algorithms and applications in supply chain management. *International Journal of Production Research*, *61*(20), 7151–7179. https://doi.org/10.1080/00207543.2022.2140221

Singh, P. K. (2023). Digital Transformation in Supply Chain Management: Artificial Intelligence (AI) and Machine Learning (ML) as Catalysts for Value Creation. *International Journal of Supply Chain Management*, *12*(6), 57–63. https://doi.org/10.59160/ijscm.v12i6.6216

Tako, A. A., & Robinson, S. (2012a). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems*, *52*(4), 802–815. https://doi.org/10.1016/j.dss.2011.11.015

Tako, A. A., & Robinson, S. (2012b). The application of discrete event simulation and system dynamics in the logistics and supply chain context. *Decision Support Systems*, *52*(4), 802–815. https://doi.org/10.1016/j.dss.2011.11.015

Tiwari, S. (2021). Supply chain integration and Industry 4.0: A systematic literature review. *Benchmarking: An International Journal*, *28*(3), 990–1030. https://doi.org/10.1108/BIJ-08-2020-0428

Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas-Barrón, L. E. (2021). Discrete-Event Simulation Modeling in Healthcare: A Comprehensive Review. *International Journal of Environmental Research and Public Health*, *18*(22), 12262. https://doi.org/10.3390/ijerph182212262