Faculty of Business Economics

Master of Management

Master's thesis

A Systematic Review of Business Optimization Techniques in Supply Chains

Selin Kiyar

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Data Science

SUPERVISOR :

Prof. dr. Mieke JANS

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De heer Shameer Kumar PRADHAN

Mevrouw Leen JOOKEN

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Abstract. Business process optimization involves analyzing and improving existing business processes to achieve enhancement in efficiency, productivity and overall productivity. Within this context, business process optimization is crucial as it impacts the efficiency and effectiveness of the entire supply chain. This emphasises the need for a comprehensive framework that categorizes the supply chain optimization techniques. However, existing frameworks often fail to address the complete supply chain. This study aims to fill this gap by presenting a systematic literature review of supply chain optimization techniques by reviewing 55 papers. The framework categorizes optimization techniques in dimensions such as techniques, supply chain levels, goals, strengths and weaknesses. An extensive systematic review was conducted that utilized a structured coding scheme to synthesize findings. Four main optimization techniques were identified, which are mathematical models, simulation models, hybrid models, and heuristic and metaheuristic models. Hybrid models, which consist of different combinations of techniques, are the most prevalent techniques. However, it is challenging to link specific strengths, weaknesses and objectives to these techniques. Some dimensions remain underexplored such as unreported weaknesses, underrepresented optimization goals, and the limited focus on the operational level of the supply chain, which requires further investigation. Future research should explore hybrid models and investigate underexplored dimensions to address the identified gaps and improve the framework. This framework is significant as it provides a structured approach to understanding business optimization techniques in supply chains, which ultimately enhances decision-making and performance.

Keywords: Business Process, Supply Chain Optimization, Optimization Techniques

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1 Introduction

Business process reengineering and business process improvement are two terms often used interchangeably in the context of business process optimization, which is a crucial element in many fields (Peng et al., 2012; Vergidis et al., 2007). Business process optimization involves analysing and improving existing business processes to achieve enhancement in efficiency, quality, productivity and overall performance. By systematically refining workflows, businesses can streamline activities, optimize resource allocation, and enhance communication and collaboration. This continuous improvement results in increased efficiency, higher productivity, reduced costs, and ultimately, enhanced customer satisfaction (Peng et al., 2012).

Supply chains consist of complex networks of businesses, individuals and processes that transform raw materials into finished products and deliver them to the end users. These networks require effective coordination and management to ensure the smooth flow of materials and products from procurement to delivery (Beamon, 1998). Therefore, business process optimization is crucial for supply chains because it directly impacts the efficiency and effectiveness of the entire supply chain. Optimized processes ensure that materials and products flow smoothly, reducing delays and bottlenecks, and enhancing overall performance. Additionally, the reliance on information technology has become paramount, with IT solutions playing a crucial role in managing and transferring vast amounts of data and information efficiently (Hyland et al., 2003).

Frameworks for categorizing optimization techniques within supply chains are indispensable tools that facilitate effective decision-making and operational improvement. These frameworks serve as guiding structures, helping practitioners select appropriate strategies tailored to specific needs and assisting researchers in identifying trends, gaps and themes in the literature for further investigation. Researchers have put significant effort into developing frameworks for categorizing optimization techniques in business processes (Tsakalidis & Vergidis, 2017; Vergidis et al., 2007). However, the literature still lacks explicit classifications tailored to the complexities of supply chain optimization. Without a cohesive categorization framework, practitioners and researchers encounter challenges in selecting appropriate techniques to address specific supply chain challenges effectively. The absence of a standardized approach also impedes the development of a comprehensive understanding of optimization strategies and their suitability across diverse supply chain environments (Abo-Hamad & Arisha, 2011).

To address this issue, a unified categorization framework is needed to encompass various optimization techniques and align them with all relevant aspects of supply chains. This study aims to construct a unifying classification framework and provide an overview of how existing literature on optimization techniques in supply chains fits into this framework. This approach facilitates a better understanding and comparison of optimization strategies, highlighting areas that have been studied in depth and identifying opportunities for future research to improve supply chain efficiency and performance.

The paper proceeds as follows: section 2 reviews related literature that attempts to create a classification framework for business process optimization within supply chains. This section examines the efforts that have been made to achieve a comprehensive classification, analysing their strengths and identifying their shortcomings. Section 3 describes the methodology used in this study. The results, including the proposed unifying classification framework, are presented in section 4 and discussed in section 5, which also offers directions for future research based on the findings. Section 6 concludes the paper.

2 Background

Developing a robust framework for categorizing business process optimization techniques is paramount in advancing understanding within the supply chain domain. An overview of related research efforts that have constructed frameworks for business process optimization within supply chains will be provided. While these classifications provide valuable insights into decision-making within supply chains, a comprehensive framework of optimization techniques that focuses on the complete supply chain is still lacking. This emphasizes the need for further research to establish a comprehensive framework that will not only organize the techniques effectively but also provide an overview of how existing literature on optimization techniques in supply chains fits into this framework.

We have provided a comparison between the works and this study in Table 1. The table compares existing studies and this study, showing that related works only focus on specific parts of the supply chain. The columns indicate different studies, while the rows represent various review dimensions addressed by these studies, such as the number of papers discussed, supply chain focus, scope, optimization techniques, supply chain level, optimization goals, strengths, and weaknesses. The ‘supply chain focus’ row indicates whether the study specifically targets supply chain optimization, while the ‘scope’ row summarizes the primary focus area of each study in a few keywords. From the table, we can infer a significant gap in existing research, as no single framework comprehensively covers the entire supply chain. This highlights the need for a more integrated approach to supply chain optimization. Each included study will now briefly be explained to provide a detailed understanding of their contributions and limitations.

Vergidis et al. (2007) explored several different classifications of business modelling techniques and developed a framework for business process models. They emphasized that developing a framework for business process models can improve our perception of business processes, which is a critical aspect of achieving business optimization. Therefore, they developed a framework focusing on the characteristics and capabilities of business process models. The framework consisted of three types: diagrammatic models, mathematical models and business process languages. Diagrammatic models provided very simple visual diagrams to represent business processes, but they lacked standardized notation. Moreover, mathematical models were described as models which included mathematical elements but could be very complex. Furthermore, it was explained that some business models were qualitative, and they were not suited to be analysed quantitatively. Business process languages were characterized as models that contained business process languages like BPML or BPEL. These models promoted standardization and reusability.

Furthermore, Vergidis et al. (2007) developed a similar framework of optimization approaches for the analysis and optimization of business processes, as identified in relevant literature. They mentioned that diagrammatic models have not provided quantitative results, which is a measure that indicates an enhancement in processes, and therefore were excluded from this framework. However, there were limited qualitative techniques for diagrammatic process models but they relied on trial and error. Business process languages were also excluded as there is no literature reference in that area. The framework of optimization approaches found in literature consisted of a combination of diagrammatic models-mathematical models, and mathematical models.

Additionally, Tsakalidis and Vergidis (2017) mentioned that business process optimization should reduce cost and lead time. They also determined that there was a need for an enhanced framework concerning business processes and also mentioned that business processes needed to be quantitively evaluated to confirm if the processes were enhanced. Authors mentioned a classification that made a distinction between two optimization types, which were single-criterion optimization and multi-criterion optimization. Optimization techniques could be classified under single-criterion if they only required one factor to achieve optimization, otherwise, it was classified under multi-criteria optimization. Despite the existence of these frameworks, there remains a need to develop a framework that includes qualitative evaluation methods that assess the effectiveness of optimization techniques in improving business processes. Moreover, both frameworks do not target supply chains.

Oliveira and Machado (2021) developed a framework that categorized the supply chain optimization methods into four different types. These were deterministic, stochastic, hybrid methods and other operational research. Deterministic methods included linear programming, nonlinear programming and mathematical programming.

Stochastic methods included simulation, modelling, heuristic and metaheuristic, and robust programming. Some methods were classified as hybrid methods, which combined multiple techniques. Then methods that could not be categorized in the previous three categories were categorized as other operational research. This framework provided a foundational categorization of optimization techniques, which can be further compared with other studies to understand the broader landscape of supply chain optimization.

Furthermore, Beamon (1998) analyzed multi-stage models of supply chains and developed a framework. This framework consisted of four different types of models: deterministic analytical models, stochastic analytical models, economic models, and simulation models. This study also explored other performance measures of the supply chain, which are qualitative. The qualitative performance measures included cost minimization, maximization of profit, minimization of inventory investment, minimization of customer response time, minimization of lead time, and late delivery minimization. Beamon's framework complements Oliveira and Machado by detailing specific model types and performance measures, which can be integrated to form a more comprehensive view of optimization methods.

Mula et al. (2011) also established a framework that categorized the optimization models. This study provided five different categories, which are linear programming, nonlinear programming, multi-objective programming, network optimization, and heuristics and meta-heuristic algorithms. Previous studies combined linear programming, nonlinear programming and mathematical models as deterministic models (Beamon, 1998; Oliveira & Machado, 2021). This framework extends Oliveira and Machado's deterministic and hybrid methods by including a focus on network optimization and multi-objective programming, addressing optimization through several links of the supply chain such as manufacturing, storage and distribution by allocating resources and information effectively.

Gunasekaran et al. (2001) examined the performance measures and metrics within the supply chain. In this study, they emphasized the importance of classifying the performance metrics into three different categories: strategic, tactical and operational. This classification aligns with Mujkic et al. (2018), who examined the sustainability dimensions of supply chains, which are economic, environmental and social. Then, the authors categorized economic indicators based on decision levels: strategic, tactical, and operational. They mentioned that the dimension of economic sustainability led to cost minimization and revenue increase. The study clarified that economic indicators were classified under strategic decision if they dealt with long-term impacts of supply chains, tactical if they dealt with short-term impacts of supply chain and operational if they dealt with the day-to-day impacts of the supply chain. Both studies highlight the importance of making a clear classification for performance metrics, which influences the decision-making processes at each level (Gunasekaran et al., 2001; Mujkic et al., 2018).

Moreover, Prasad (2012) stated that it would be complex to choose the right performance measure for supply chains since the supply chain is a complex network of businesses, individuals and processes. They developed a framework to categorize the performance measures of the supply chain. These included seven different performance measures that are related to cost, quality, time, productivity, flexibility, reliability and customer service. Furthermore, these performance measures were also categorized under a specific supply chain process which was planning, sourcing, make and delivery. Authors used the SCOR model to classify the supply chain processes. This approach provides a detailed categorization that complements the performance measures mentioned by Beamon (1998) and the broader optimization models of Oliveira and Machado (2021).

Griffis et al. (2012) defined heuristics as algorithms that solved optimization problems quickly and simply but did not always achieve maximum optimization, while metaheuristic algorithms provided solutions for more complex problems. Authors also mentioned the limitations of using heuristic and meta-heuristic algorithms, such as the complexity and size of the optimization problem. This perspective on these methods adds depth to Mula et al.'s categorization and highlights practical challenges that need to be considered within the comprehensive framework.

Abo-Hamad and Arisha (2011) underlined the importance of decision-making within the supply chain. Since supply chains are very complex, managers are faced with challenges when making decisions at each level. This finding was also supported by Gunasekaran et al. (2001). Moreover, the authors developed a framework called the Optimization Techniques Map, which particularly focused on simulation methods within supply chains. The Optimization Techniques Map classified optimization techniques according to a modelling approach (mathematical model or simulation model) and methods of optimization mechanism (direct research methods or mathematical programming). This aligns with the classifications by Oliveira and Machado and further elaborates on the methods used for optimization.

Aslam and Amos (2010) developed a multi-objective optimization framework for the supply chain while making a distinction between multi-level optimization, in which optimization could be achieved at different levels and multi-objective optimization where multiple objectives are targeted to achieve optimization within the whole supply chain. Another important finding that they highlighted is the optimization goals, which are low inventory levels and lead-time, low transportation cost, lower emissions and transporting the maximum batch size. This framework adds another dimension by considering multiple objectives, complementing Mula et al.'s multi-objective programming and providing additional criteria for comprehensive optimization.

Najmi et al. (2013) examined the supply chain performance models and mentioned several studies that contributed to some parts of the supply chain. However, they emphasized that research is still lacking regarding the view of a complete supply chain. These authors defined some criteria for the assessment of the supply chain, some of these were quality, resource, effectiveness, productivity, utilization, efficiency, integration, visibility and information. This emphasis on a complete view of the supply chain performance complements the detailed frameworks provided by the other studies.

This study addresses the lack of cohesive categorization frameworks for supply chain optimization by developing a comprehensive framework that integrates optimization techniques, goals, weaknesses, strengths, and supply chain levels. Unlike previous works that focus on single aspects, this framework provides a holistic approach, incorporating elements from Vergidis et al. (2007), Oliveira and Machado (2021), and Mula et al. (2011). This new framework uniquely combines qualitative and quantitative methods, aiming to enhance understanding and comparison of optimization strategies, identifying both strengths and weaknesses, thus improving supply chain efficiency and performance.

Table 1. Overview of existing studies and their comparison with this review

	Vergidis et al. (2007)	Tsakalidis and Vergidis (2017)	Mujkic et al. (2018)	Gunasekaran et al. (2001)	Beamon (1998)	Prasad (2012)	Najmi et al. (2013)	Abo-Hamad and Arisha (2011)	Aslam and Amos (2010)	Mula et al. (2011)	Griffis et al. (2012)	Oliveira and Machado (2021)	**This paper**
#Papers discussed	88	27	50	N/A	43	6	42	100	37	15	128	354	55
Supply chain focus	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scope	Business process	Business process	Sustainability dimensions	Performance measures	Multistage models	Performance measures	Performance models	Simulation methods	Multi-objective models	Modeling approach	Metaheuristics Algorithms	Optimization Methods	Optimization Methods
Review dimensions													
Optimization techniques	●	●	●	○	●	○	◐	●	●	●	●	●	●
Supply chain level	○	○	●	○	○	○	○	◐	○	○	○	●	●
Optimization goals	○	○	○	◐	◐	◐	○	○	◐	●	◐	○	●
Strengths	◐	○	◐	◐	●	◐	◐	◐	◐	◐	◐	○	●
Weaknesses	◐	○	◐	○	○	○	○	◐	◐	◐	○	○	●

(Legend: ○ - Not mentioned in the paper. ◐ - Mentioned in the paper but not as a dimension. ● - Mentioned in the paper as a dimension.)

3 Methodology

Following the methodology provided by Xiao and Watson (2019) for conducting a systematic literature review, this paper systematically reviews published literature related to business process optimization techniques within supply chains. In this section, we describe the research questions (3.1). Section (3.2) describes the data collection method and exclusion criteria. Section (3.3) describes the coding scheme.

3.1 Research Questions

To guide our objective of exploring existing research dealing with business process optimization techniques within supply chains, we formulated the following research questions:

- **RQ 1:** What optimization techniques have been devised in the context of supply chain optimization, and what are their characteristics:
  - What are the categorizations of these techniques?
  - What are the strengths of each technique?
  - What are the weaknesses of each technique?
  - What levels does the technique target?

- **RQ 2:** What objectives do business process optimization techniques in the supply chain aim to achieve?

3.2 Collecting literature

In the pursuit of comprehensively understanding business optimization techniques within the supply chains, an initial literature search was conducted across two reputable databases: Scopus and Web of Science. To facilitate the search process, one search query was formulated based on three primary keywords: "Supply Chain", "Optimization" OR "Optimisation" and ("Technique*" OR "Method*" OR "Approach*"). This query was formulated to encompass a broad range of relevant literature.

For Scopus, searches were performed on the Article title, Abstract and Keywords and with no year of publication range limit. As for Web of Science, All field were searched within the Web of Science Core Collection. The search process considered papers published until April 2024, without imposing any specific start date for the literature search. This approach ensured that recent developments and insights in the field were captured.

Fig. 1. Paper selection strategy provides an overview of the search strategy and the number of papers included and excluded at each stage. The initial search across the two databases yielded 22,166 results, comprising 10,902 papers from Web of Science and 11,264 from Scopus. Upon removing duplicates, we screened 5,780 papers for eligibility.

To determine exclusion, papers were evaluated against the following criteria:

1. The paper offers a general overview of optimization techniques, lacking specificity for the supply chains.
2. The paper is written in a language other than English.
3. The paper is not published in a peer-reviewed scientific journal or conference proceedings.
4. The paper is a conference paper or proceedings paper that is not part of a standalone peer-reviewed conference proceedings but rather is included as a chapter in a book.
5. The paper is not electronically available or accessible.
6. The paper is a poster, one-pager, executive summary, abstract, review, book, literature review, or commentary.

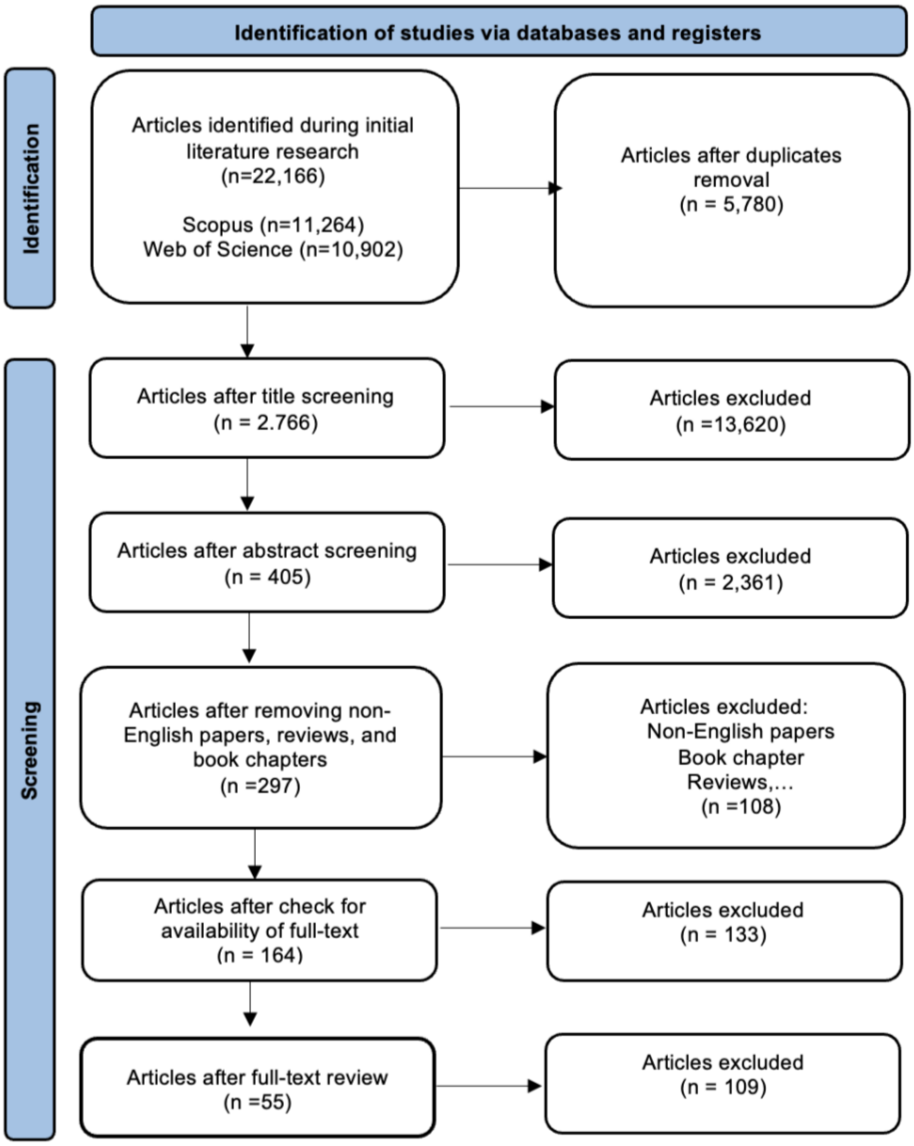

Fig. 1. Paper selection strategy

We conducted the screening process in three phases, initially filtering by the title of the paper, then by the title and abstract, and finally by the full-text. Papers lacking sufficient information for determination were advanced to the subsequent phase. The first screening phase led to the exclusion of 13,620 papers, with 2,766 papers moving to the next stage.

Screening by the title and abstract excluded an additional 2,361 papers, leaving 405 papers for the final screening phase. Among these, 108 were included as chapters in books, were reviews, and were written in languages other than English. The 133 papers were inaccessible in full-text. The remaining 164 papers underwent full-text screening, resulting in the exclusion of 109 papers due to irrelevance, leaving a total of 55 papers for inclusion in this literature review.

3.3 Coding scheme

The following section introduces a structured coding scheme meticulously developed to analyse key dimensions relevant to business process optimization. We integrated both inductive and deductive coding techniques to extract essential insights from the literature. Inductive coding involves analysing data without predetermined categories, allowing for the discovery of emergent patterns or themes directly from the data (Thomas, 2006). We used the inductive approach recommended by Thomas (2006), analysing the data and then assigning codes based on actual text or meanings found in the reviewed papers. This process generated many categories, which were then synthesized into fewer main categories, thus eliminating overlapping codes or combining them. In contrast, deductive coding begins with predefined categories or theories, with data being organized to fit these predetermined frameworks (Proudfoot, 2023). The coding scheme was developed for the following dimensions.

Optimalisation techniques. We will use inductive coding to identify the optimization techniques, present in the reviewed papers. Following the Thomas (2006) method, we extracted the paper's optimization technique based on the recurring patterns and themes found within the data. Then similar concepts are merged into fewer main categories, thus eliminating overlapping codes or combining them. This dimension supports research question 1.

Optimization goals. We employed inductive coding to identify the primary objectives pursued by optimization techniques mentioned in the papers. This categorization supports research question 2.

Supply chain level. To code the level of optimization techniques within the supply chain framework, we will use a predefined set of codes defined by Matinrad et al. (2013). The codes include *strategic, tactical* and *operational.* These codes are fitting as they comprehensively cover the different layers of decision-making within supply chains. Papers coded as 'Strategic' involve decisions aimed at long-term objectives in supply chain management. 'Tactical' decisions are directed towards mid-term planning to support strategic goals. Meanwhile, 'Operational' decisions handle short-term tasks and daily management. The codes, discovered through deductive coding, along with their descriptions, can be found in Table 2. This dimension supports research question 1.

Subcode	Explanation
Strategic	Papers coded as ‘strategic’ emphasize optimization techniques that involve decisions aimed at long-term objectives in supply chains (Matinrad et al., 2013).
Tactical	Papers coded as ‘tactical’ highlight optimization techniques that involve decisions which are directed towards mid-term planning to support strategic goals (Matinrad et al., 2013).
Operational	Papers coded as ‘operational’ emphasize decisions that handle short-term tasks and daily management within supply chains (Matinrad et al., 2013).

Table 2. Supply chain level codes

Strengths. To determine the effectiveness of the optimization techniques behind the papers, we employed inductive coding to identify the strengths of the reviewed papers. This dimension also supports research question 1.

Weaknesses: To determine the limits of the optimization techniques behind the papers, we employed inductive coding to identify the weaknesses of the reviewed papers. This dimension also supports research question 1.

4 Results

This section presents the findings of the systematic literature review. Section 4.1 explains the process of identifying and categorizing the codes for the framework. The remaining sections discuss the results of each dimension in detail.

4.1 Framework

This framework of optimization techniques within supply chains was meticulously developed by extracting and synthesizing codes from existing literature. This section explains the process of identifying and categorizing these codes for each dimension, which resulted in the comprehensive framework presented here.

Various techniques were extracted from the reviewed studies and grouped into categories for the optimization techniques dimension. These codes include mathematical models, simulation models, hybrid models, and heuristic and metaheuristic models. It involved identifying the methods used in each study and categorizing them based on the nature of the techniques and their problem-solving approaches. Mathematical models involve the use of mathematical frameworks to represent real-world problems systematically. These models can be utilized when multiple conflicting objectives in production and planning, such as minimizing total delivery time and total costs, need to be achieved (Badhotiya et al., 2019). In addition, simulation models provide optimization through simulation that assesses the performance of different scenarios (Vieira et al., 2023). Simulation models can be utilized to control and reduce inventory variance, in which several scenarios will be created and compared. It improves decision-making and enables them to understand the impact of several factors within supply chains (Carotenuto et al., 2014). Hybrid models are combinations of different optimization techniques (Tordecilla et al., 2023). These models can be utilized when targeting cost and resilience objectives within supply chains, which allows them to combine a mathematical model and a simulation model. Several combinations of models can be employed, it ultimately depends on the optimization problem itself. Moreover, heuristic and metaheuristic models aim to optimize processes by using simple rules or algorithms. While metaheuristic models provide near-optimal solutions within a short time frame, heuristic models may not provide the most optimal solution (Kumanan et al., 2007). These models can be utilized to minimize the total cost of production and distribution, in which genetic algorithm and particle swarm optimization methods can be combined.

For the optimization goal dimension, various objectives were extracted from the reviewed studies and grouped into categories. These include financial optimization, efficiency, sustainability, resilience, performance, decision enhancement, customer satisfaction and time optimization. These codes were identified by systematically reviewing each paper to understand the primary goal it aimed to achieve and categorizing them based on shared characteristics. Financial optimization refers to techniques aimed at optimizing the financial situation of supply chains, which include minimizing cost and maximizing profits (Askary et al., 2024; Vieira et al., 2023). However, efficiency aims to enhance operational efficiency by maximizing resource utilization, combining multiple techniques, and enhancing the distribution process, which results in optimization within the supply chain (Carotenuto et al., 2014; Durmaz & Bilgen, 2020). Moreover, some papers aimed to reduce environmental impacts, like lowering emissions, which were categorized as sustainability (Abir et al., 2020). Resilience refers to the aim of optimization techniques that quickly recover and adapt to disruptions, which will allow the supply chain operations to operate further with minimized disturbances (Tordecilla et al., 2023). In addition, performance goals refer to optimization objectives that aim to improve the overall performance and productivity within the supply chain. These techniques effectively optimize processes, resulting in enhanced performance across various supply chain domains (Park, 2020). Decision enhancement goals aim to improve the quality of the decision-making processes within the supply chain (Evans et al., 2007). Moreover, customer satisfaction refers to optimization techniques that aim to increase customer satisfaction. These techniques aim to increase customer satisfaction through timely demand fulfilment and price adjustments (Belil et al., 2019; Özkır & Başlıgil, 2013; Zhao & Wang, 2018). Lastly, optimization techniques categorised as time optimization, aim to improve time across the entire supply chain, including objectives aimed at minimizing delivery time and computational efforts (Bagherinejad & Dehghani, 2015).

For the supply chain level dimension, a predefined set of codes defined by Matinrad et al. (2013) was used. These codes include strategic, tactical, and operational levels.

Strategic-level decisions involve long-term objectives and planning within supply chain management (Askary et al., 2024). Tactical decisions focus on mid-term planning to support strategic goals (de Faria et al., 2024). Operational decisions handle short-term tasks and daily management activities (Osorio et al., 2017). These predefined codes effectively cover the different layers of decision-making within supply chains.

For the strengths dimension, several strengths of optimization techniques were extracted from the reviewed studies and grouped into categories. These codes include efficiency, multi-objective optimization, resilience, parameter insensitivity, flexibility and scalability. This categorization was done by assessing the characteristics highlighted in each paper and grouping them based on their functional advantages. The category efficiency involves the ability of optimization techniques to handle complexities and uncertainties efficiently within supply chains. These optimization techniques can be efficient in terms of computational time but also through solving complex supply chain problems (de Faria et al., 2024; He et al., 2015). These also easily combine multiple methods and enhance transportation capacity (Yoshizumi & Okano, 2007). In addition, multi-objective optimization addresses multiple goals simultaneously (Avci & Selim, 2018). Resilience refers to optimization techniques that have the ability to enhance the adaptability and efficiency of supply chain operations in uncertain environments. This enables supply chains to effectively respond to disruptions, fluctuations in demand, and other unpredictable factors (Li & Chen, 2013). Parameter insensitivity refers to the potential of optimization techniques to withstand parameter variations within the supply chain without significantly impacting its performance, which ensures reliability in decision-making. This strength effectively reduces the risk during the decision-making processes within the supply chain (Bagherinejad & Dehghani, 2015). Flexibility refers to the capability of optimization techniques to adapt to different problem types, which allows them to address various areas within the supply chain (Badhotiya et al., 2019). Furthermore, scalability specifies the capability of the optimization techniques to handle problems of various sizes, from small-scale to large-scale, without significant loss of efficiency (de Faria et al., 2024; Yoshizumi & Okano, 2007).

Various weaknesses of optimization techniques were extracted from the reviewed studies and grouped into categories for the weaknesses dimension. These codes include uncertainty, multiple objective complexity, scalability issues, time-consuming processes, complexity and sensitivity. This categorization was done by assessing the recurring issues highlighted in each paper and grouping them according to how they affected the optimization techniques and their implementation. Uncertainty refers to the difficulties that optimization techniques face due to uncertain parameters such as costs and shipping that vary or are not considered. These parameters such as demand fluctuations, market conditions, and data, make it complex and unpredictable (Papageorgiou et al., 2001; Wu et al., 2018; Xu et al., 2019). Multi-objective complexity underlines the challenges that are associated with managing multiple objectives and the potential conflicts that may occur while trying to achieve multiple goals (Chen et al., 2021). Scalability issues refer to optimization techniques that face challenges when scaling up to handle larger or more complex scenarios (Abouelrous et al., 2022). Moreover, time-consuming refers to optimization techniques that require significant computational resources or implementation time (Kabiri et al., 2022). Another weakness was complexity, which referred to difficulties in finding optimal solutions in the global supply chain and computational complexity (Pan et al., 2012). The weakness sensitivity refers to optimization techniques that are susceptible to variations in parameters and assumptions, which is crucial to understanding the impact of factors like demand or pricing (Mele et al., 2005). Some studies did not report any weaknesses, which were noted accordingly.

The framework, which encompasses all the reviewed articles, provides a structured and detailed understanding of the diverse aspects of supply chain optimization. This comprehensive inclusion ensures that the framework accurately reflects the current state of research and practices in the field. The complete framework can be found in Table 3.

Table 3. Classification of reviewed studies in supply chain optimization framework

Papers	Optimization techniques				Optimization goals								Supply chain level			Strengths						Weaknesses						
	Mathematical model	Simulation model	Hybrid model	Heuristic & Metaheuristic model	Financial optimization	Efficiency	Sustainability	Resilience	Performance	Decision enhancement	Customer satisfaction	Time optimization	Strategic Level	Tactical Level	Operational Level	Efficiency	Multi-objective optimization	Resilience	Parameter insensitivity	Flexibility	Scalability	Uncertainty	Multiple objective complexity	Scalability issues	Time-consuming	Complexity	Sensitivity	Not reported
Askary et al. (2024)			x		x	x	x						x			x	x		x			x	x					
de Faria et al. (2024)		x			x		x							x		x					x	x						
Vieira et al. (2023)		x			x		x						x				x			x		x						
Tordecilla et al. (2023)			x		x			x					x					x										x
Kabiri et al. (2022)			x		x		x						x			x						x		x				
Chen et al. (2021)			x		x								x	x		x		x			x	x	x		x			
Avci and Yildiz (2020)			x		x								x	x		x		x			x				x			
Abir et al. (2020)			x	x	x	x	x		x		x		x	x		x	x					x			x			
Durmaz and Bilgen (2020)			x		x	x							x	x			x			x		x					x	
Park (2020)			x		x				x				x			x												x
Ransikarbum et al. (2020)			x		x				x				x	x			x					x			x	x		
Belil et al. (2019)			x							x			x	x		x				x					x	x		
Badhotiya et al. (2019)	x				x							x		x		x	x		x	x		x				x		
Xu et al. (2019)		x			x									x		x						x			x			
Wu et al. (2018)			x		x	x	x						x	x	x	x	x					x						
Avci and Selim (2018)			x		x			x		x				x		x	x			x					x			

Papers	Optimization techniques				Optimization goals								Supply chain level			Strengths						Weaknesses						
	Mathematical model	Simulation model	Hybrid model	Heuristic & Metaheuristic model	Financial optimization	Efficiency	Sustainability	Resilience	Performance	Decision enhancement	Customer satisfaction	Time optimization	Strategic Level	Tactical Level	Operational Level	Efficiency	Multi-objective optimization	Resilience	Parameter insensitivity	Flexibility	Scalability	Uncertainty	Multiple objective complexity	Scalability issues	Time-consuming	Complexity	Sensitivity	Not reported
Zhao and Wang (2018)			x		x			x			x			x		x		x										x
Yildizbaşi et al. (2018)	x				x					x			x				x			x		x					x	
Díaz-Madroñero et al. (2017)	x				x	x								x			x	x				x		x	x			
Grossmann et al. (2017)	x					x						x		x		x		x				x			x			
Osorio et al. (2017)			x		x				x				x		x	x						x						
He et al. (2015)	x				x									x		x				x		x		x	x	x		
			x		x									x		x		x		x		x				x		
Güller et al. (2015)			x		x					x				x		x					x	x			x			
Ye and You (2015)			x		x								x	x		x	x								x			
Bagherinejad and Dehghani (2015)				x	x							x	x			x	x		x	x		x						
Carotenuto et al. (2014)		x			x	x								x		x		x		x	x							x
Li and Chen (2013)			x		x			x	x					x			x	x				x				x		
Pan et al. (2012)			x						x	x				x		x										x		
Mirzapour Al-E-Hashem et al. (2011)			x		x						x		x				x	x								x		
Wang et al. (2008)			x		x								x			x		x			x							x

Papers	Optimization techniques				Optimization goals								Supply chain level			Strengths						Weaknesses						
	Mathematical model	Simulation model	Hybrid model	Heuristic & Metaheuristic model	Financial optimization	Efficiency	Sustainability	Resilience	Performance	Decision enhancement	Customer satisfaction	Time optimization	Strategic Level	Tactical Level	Operational Level	Efficiency	Multi-objective optimization	Resilience	Parameter insensitivity	Flexibility	Scalability	Uncertainty	Multiple objective complexity	Scalability issues	Time-consuming	Complexity	Sensitivity	Not reported
Gao and Wang (2008a)			x		x									x		x						x				x		
Gao and Wang (2008b)			x		x						x				x	x							x					
Merkuryeva et al. (2007)			x		x						x			x		x										x		
Evans et al. (2007)			x		x					x				x		x		x						x		x		
Yoshizumi and Okano (2007)			x		x				x			x	x			x					x		x					
Jian-ming and Li-wen (2007)	x				x	x			x				x			x										x		
Kumanan et al. (2007)				x	x	x							x			x	x				x				x			
Gupta and Evans (2006)		x			x		x	x					x				x	x										x
dos Santos Coelho and Lopes (2006)				x	x	x			x				x			x									x			
Mele et al. (2005)			x		x	x	x		x	x	x		x	x			x	x								x	x	
Chen and Lee (2004)	x				x				x	x			x				x	x										x
Ding et al. (2004)			x		x				x				x				x	x								x		
Papageorgiou et al. (2001)	x				x				x				x			x				x		x		x				
Brinza (2012)			x		x	x									x	x						x						
Özkır and Başlıgil (2013)	x				x		x		x		x		x			x		x										x
Sbai and Berrado (2023)		x			x				x		x					x										x		

Papers	Optimization techniques				Optimization goals								Supply chain level			Strengths						Weaknesses						
	Mathematical model	Simulation model	Hybrid model	Heuristic & Metaheuristic model	Financial optimization	Efficiency	Sustainability	Resilience	Performance	Decision enhancement	Customer satisfaction	Time optimization	Strategic Level	Tactical Level	Operational Level	Efficiency	Multi-objective optimization	Resilience	Parameter insensitivity	Flexibility	Scalability	Uncertainty	Multiple objective complexity	Scalability issues	Time-consuming	Complexity	Sensitivity	Not reported
Abouelrous et al. (2022)			x		x					x				x		x								x	x			
Gansterer et al. (2014)			x		x					x			x	x		x								x	x		x	
Yang et al. (2012)				x	x							x		x		x								x	x			
He et al. (2013)			x			x			x					x		x					x	x						
Zhang et al. (2015)			x		x		x		x					x		x	x			x		x			x			
Varthanan et al. (2012)			x		x	x							x			x	x								x			
Chu and You (2014)		x			x				x				x			x										x		
Aghajani et al. (2016)			x		x				x				x			x					x						x	
Gupta and Mohanty (2015)	x				x									x		x				x			x					

4.2 Optimization techniques

While analysing the optimization techniques, four main techniques were identified within the supply chain field: *mathematical models, heuristic and metaheuristic models*, *simulation models* and *hybrid models*. However, it should be noted that Fig. 2 does not reflect the total number of papers reviewed. Some papers compared two methods without combining them. The categorization of optimization techniques for each paper can be found in Table 3. *Mathematical models*, mentioned in ten papers (18,2 %), involve the use of mathematical frameworks.

Additionally, five papers (9,1 %) are categorized as *heuristic and metaheuristic models*, which aim to optimize processes by using simple rules or algorithms. Furthermore, seven papers (12,7 %) are classified as *simulation models*. Notably, the most prevalent optimization technique was *hybrid models*, which is mentioned in 34 papers (61,8 %). The relatively low number of papers categorized as mathematical, heuristic and metaheuristic and simulation models suggests that within supply chain optimization, these models may not be sufficient enough to achieve optimization compared to hybrid models. In addition, this explains the inclination towards hybrid models that combine multiple methods according to the nature of the optimization problem, which can handle the multifaceted nature of supply chains.

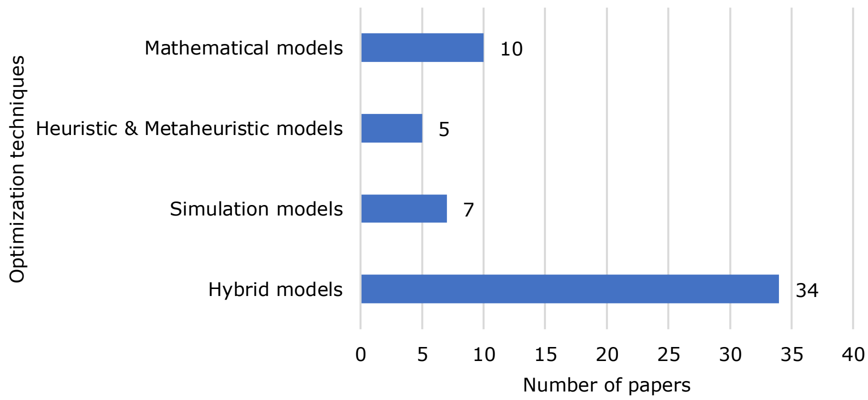

Fig. 2. Optimization techniques in the supply chain field

4.3 Optimization goals

This section presents the goals of optimization techniques identified during the literature review, which are grouped into eight main categories – *financial optimization, performance, efficiency, decision enhancement, customer satisfaction, sustainability, time optimization,* and *resilience,* as illustrated in Fig. 3. It should be noted that papers can mention multiple goals of optimization techniques simultaneously. As a result, the total number of papers illustrated in Fig. 3 may exceed the total number of papers included in the full-text review. The categorization of optimization goals for each paper can be found in Table 3.

The category *financial optimization* mentioned in 52 papers (94,5%), was the most prominent goal in the reviewed papers. Nineteen papers (34,5%) are dedicated to the goal of *performance*. Furthermore, fourteen papers (25,5 %) of the reviewed papers are classified under objective *efficiency*.

Moreover, the category of *decision enhancement* was mentioned ten times (18,2 %), which was higher compared to papers mentioning the goal of *customer satisfaction* eight times (14,5 %). Ten papers (18,2%) are dedicated to the goal of *sustainability,* which is higher compared to the category *time optimization* that is mentioned in five papers (9,1 %). The remaining category *resilience* is mentioned in five papers (9,1%). These findings suggest that the goal of financial optimization is a crucial goal for supply chain optimization, which focuses on minimizing cost and maximizing profits. Furthermore, the performance goal also indicates that improving the overall performance of supply chains is a key concern. In addition, the relatively low number of papers dedicated to the goal of time optimization, customer satisfaction and resilience indicates that the reviewed literature does not mainly cover these objectives. Moreover, this emphasises that the literature does not explore these objectives thoroughly and there is a need for more research. Future research may reveal more insights concerning these objectives.

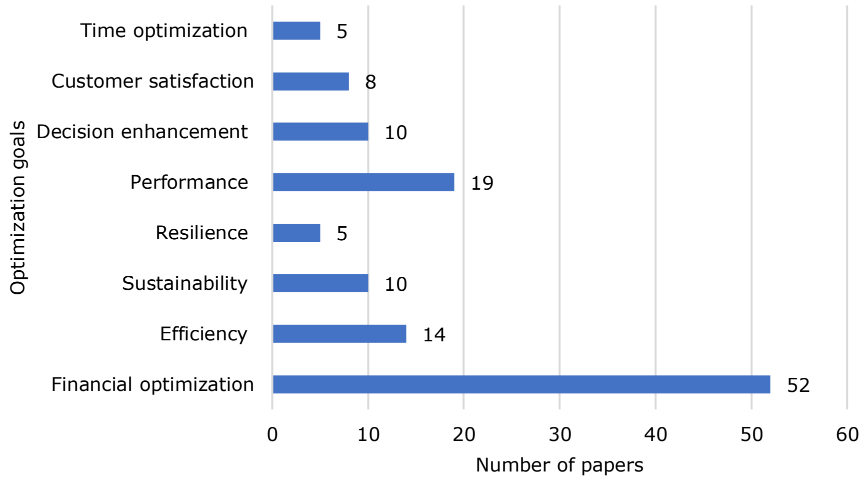

Fig. 3. Goals of optimization techniques

4.4 Supply chain level

Some papers can contribute to all three supply chain levels simultaneously. Therefore, the total number of papers in Fig. 4 may be higher than the total number of papers included in the full-text review. The categorization of supply chain levels for each paper can be found in Table 3. The category *strategic level*, mentioned in 32 papers (58,2 %) focuses on the optimization of the long-term objectives and decision-making within supply chains. Moreover, the *tactical level* is mentioned in 31 papers (56,4%), which aim to provide optimization to the mid-term objectives and decision-making in supply chains. In addition, only four (7,3%) papers are categorized at the *operational level*. The relatively high number of papers on the strategic and tactical levels indicate that optimization techniques target long-term and mid-term decision-making within supply chains. It suggests that the reviewed paper focuses more on high-level optimization compared to day-to-day operations. Furthermore, this also reveals that there is a limited number of papers dedicated towards short-term objectives in supply chains.

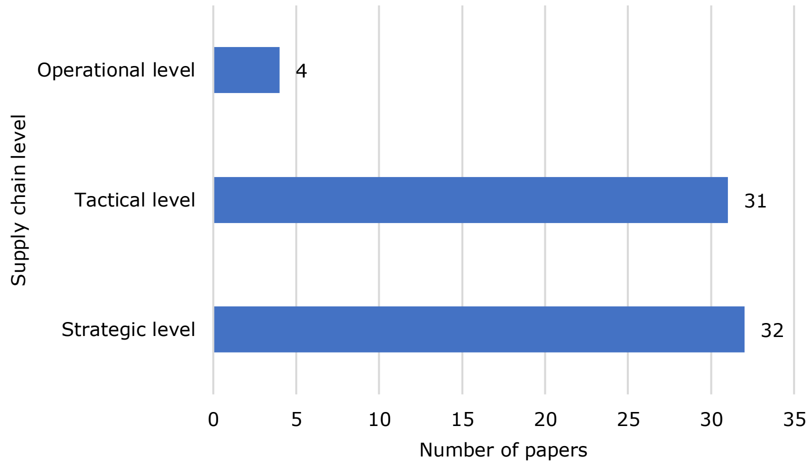

Fig. 4. Supply chain level of optimization techniques

4.5 Strengths

This section presents the strengths of the optimization techniques identified during the literature review, grouped into six main categories – *efficiency, multi-objective optimization, resilience, scalability, flexibility and parameter insensitivity*, as illustrated in Fig. 5. It should be noted that papers can mention multiple strengths of optimization techniques simultaneously. As a result, the total count of papers depicted in Fig. 5 may exceed the number included in the full-text review. The categorization of strengths for each paper can be found in Table 3. The category efficiency, mentioned in 44 papers (80%) was the most prevalent goal in the reviewed papers. Furthermore, the goal of multi-objective optimization is mentioned 21 (38,2%) times. Seventeen papers (31%) are dedicated to the category of resilience.

Moreover, the category of scalability was mentioned in ten papers (18,2%), which was lower compared to papers mentioning the category of flexibility thirteen times (23,6%). Only three papers (5,5%) mention the category parameter insensitivity, which is significantly lower compared to the other four categories. These findings suggest that the strength of efficiency is a critical strength of optimization techniques, which focuses on efficiently handling the uncertainties and complex nature of supply chains. Furthermore, strengths such as multi-objective optimization and resilience also are of critical importance as optimization techniques need to be resilient in uncertain environments considering the nature of supply chains to be capable of achieving multiple objectives simultaneously. The relatively low number of papers categorized as parameter insensitivity suggests that this aspect is not explored enough and needs more research.

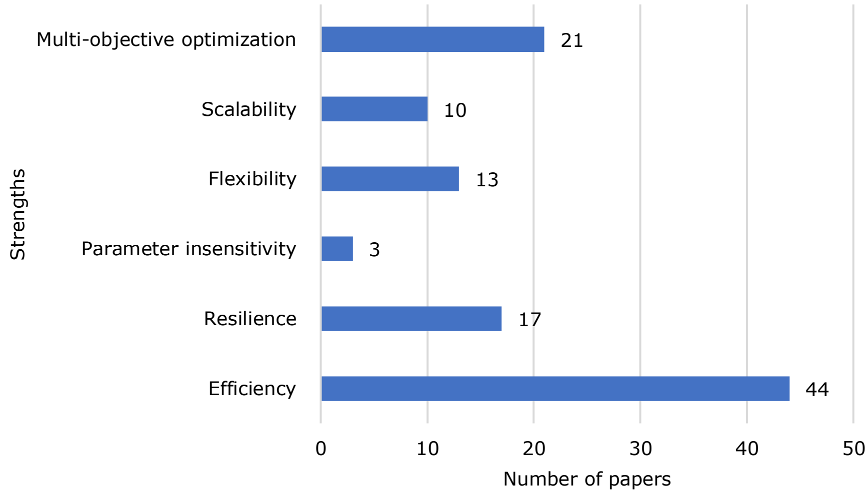

Fig. 5. Strengths of optimization techniques

4.6 Weaknesses

This section presents the weaknesses of optimization techniques identified during the literature review, which are grouped into six main categories – *uncertainty*, *time-consuming*, *complexity*, *scalability issues*, *multi-objective complexity and sensitivity*, as illustrated in Fig. 6. It should be noted that papers can mention multiple weaknesses of optimization techniques simultaneously. As a result, the total number of papers depicted in Fig. 6 may exceed the number included in the full-text review. The categorization of weaknesses for each paper can be found in Table 3.

The category uncertainty, mentioned in 25 papers (45,5%) was the most prevalent weakness in the reviewed papers. Moreover, the category of *time-consuming* is mentioned in nineteen papers (34,5%), which was higher compared to papers mentioning the category of *complexity* sixteen times (29,1%).

Eight papers (14,5%) did not report any weakness regarding the optimization techniques and therefore are categorized as *not reported*. In addition, eight papers (14,5%) are dedicated to the weakness of *scalability issues*, which is higher compared to the papers mentioning *multi-objective complexity* five times (9,1%). The remaining category of *sensitivity* is mentioned in five papers (9,1%). The relatively high number of papers reported uncertainty suggests that optimization models still face challenges concerning uncertain parameters or not considered data. It indicates that unpredictability within the supply chains remains a significant challenge to achieve efficient optimization. Weaknesses such as time-consuming and complexity reveal that some optimization techniques often require computational efforts, which can be time-consuming. These models also can perform poorly due to the complexity of the optimization problem. In addition, the relatively low number of papers categorized as multi-objective complexity and sensitivity reveals that optimization techniques experience difficulties while trying to achieve multiple objectives and are vulnerable to parameters. The low number of papers in these categories indicates that there is not enough research done. Additionally, some papers did not report any weaknesses, which indicates the need for future research. Future research may reveal more insights concerning underexplored weaknesses.

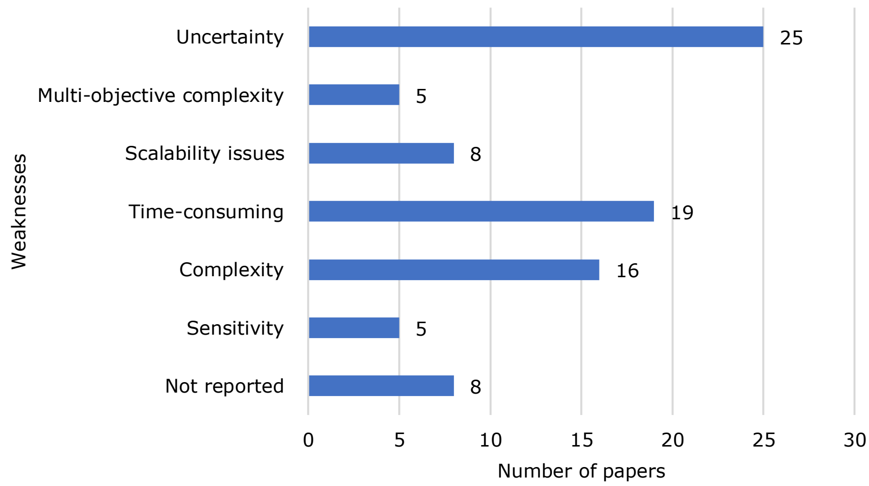

Fig. 6. Weaknesses of optimization techniques

5 Discussion

This section discusses the results and explores the implications for practitioners and researchers. Among the optimization goals identified, most papers aimed to achieve financial optimization, as shown in Fig. 7. Efficiency and performance are consistently mentioned throughout the years, which is emphasises their importance in supply chains. In recent years, there has been an increase in papers on sustainability, likely due to growing concerns about sustainable practices within supply chains. Additionally, decision enhancement is regularly mentioned, reflecting the industry's focus on decision-making. However, goals like resilience, time optimization, and customer satisfaction are less frequently addressed, indicating a need for future research in these areas. Furthermore, majority of the reviewed papers focus on strategic and tactical levels of supply chains, with only a minimal number addressing the operational level, as shown in Fig. 4. This indicates that the operational level is often underrepresented, highlighting a gap in the literature.

Fig. 7. Distribution of optimization goals across years (Note: that the data for 2024 does not reflect the entire year)

The weaknesses of each model are shown in Fig. 8

Fig. 8, with uncertainty being the most prominent weakness for most models. For mathematical models, uncertainty is the most notable weakness, with additional issues in scalability, complexity, and time consumption. Simulation models also face significant weaknesses in uncertainty, complexity, and scalability. This suggests that mathematical and simulation models may perform poorly in handling larger scenarios, which can be complex and time-consuming due to uncertainty. Heuristic and metaheuristic models primarily struggle with time consumption and uncertainty, indicating that despite being less complex, they can be time-consuming, which introduces unpredictability to the model.

Hybrid models have a lot of reported weaknesses, with uncertainty, complexity and time consumption being the most prevalent. As hybrid models often combine multiple optimization techniques, determining which combination contributes to particular weaknesses can be challenging. For example, Mele et al. (2005) utilized the genetic algorithm, classified as heuristic and metaheuristic models, to optimize the performance of the entire supply chain. However, due to the nature of supply chains, heuristic and metaheuristic models were insufficient for handling uncertainty. Therefore, they utilised a simulation model that achieved optimized solutions with minimal computational effort. This indicates the pressing need to discover the advantages and disadvantages of combining multiple techniques.

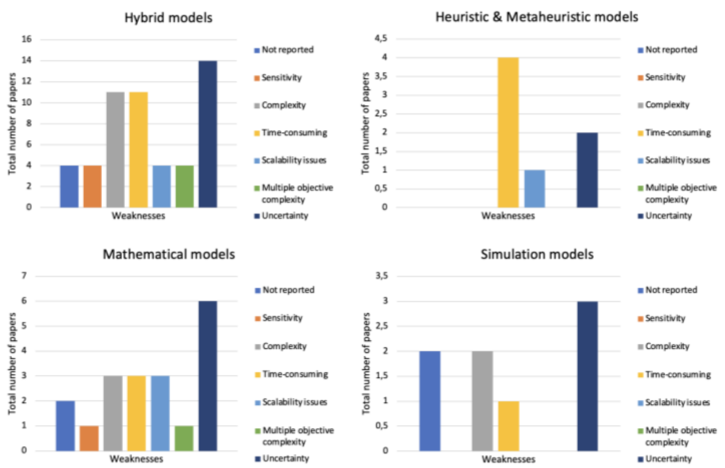

Fig. 8. Weaknesses of optimization techniques

Furthermore, the strengths of each model are shown in Fig. 9, with efficiency being the most prominent strength for most models. Mathematical models show strengths in flexibility, resilience, and multi-objective optimization. Moreover, simulation models show evenly distributed strengths in scalability, flexibility, multi-objective optimization and resilience, making them valuable for supply chain optimization.

Furthermore, the strength of multi-objective optimization is the most notable in heuristic and metaheuristic models after efficiency. However, the strength resilience is not present in heuristic and metaheuristic models, which indicates that this model may not perform well in uncertain environments or disruptions.

The most notable strengths in hybrid models are resilience and multi-objective optimization, while efficiency remains the highest. However, hybrid models consist of several different combinations of optimization techniques therefore it is difficult to determine which combination of techniques contributes to particular strengths. This emphasises the need for further research to uncover which combinations of techniques lead to particular strengths and weaknesses.

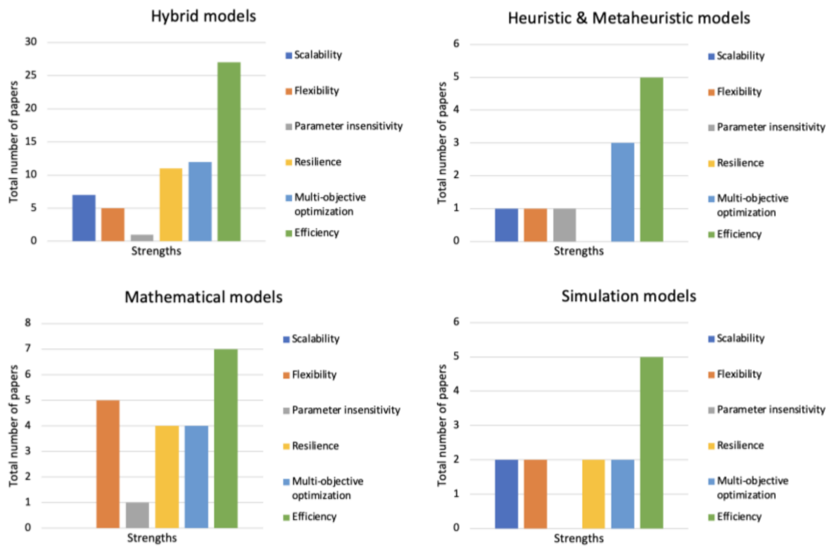

Fig. 9. Strengths of optimization techniques

This framework has implications for research in the field of supply chain optimization, as it provides a structured approach to categorizing and comparing optimization techniques in supply chains, identifying common themes, trends, and gaps in the literature to target new areas for investigation. It also simplifies finding related models, allowing easy comparison of different approaches.

Furthermore, practitioners can benefit from the framework by utilising it as a practical tool to navigate supply chain optimization techniques, categorizing them by goals and methods to select suitable strategies tailored to specific needs. Using our framework, practitioners can improve decision-making by linking techniques to specific supply chain levels, ensuring alignment with organizational objectives.

Despite its comprehensive approach, the research has several limitations. One major limitation is the subjectivity introduced by the inductive coding process used for optimization goals, techniques, strengths, and weaknesses, which could affect the categorization and completeness of these dimensions. Additionally, the study's limited time frame restricts its ability to capture long-term trends and developments in supply chain optimization, suggesting that longitudinal studies are necessary to validate and refine the framework. The insufficient exploration of hybrid models, particularly in understanding their strengths, weaknesses and optimization goals at different supply chain levels, is another notable limitation. Moreover, the study identifies underexplored dimensions, such as unreported weaknesses, underrepresented optimization goals like customer satisfaction, resilience, and time optimization, and the limited focus on the operational level of the supply chain, which requires further investigation.

Therefore, continued research on supply chain optimization techniques will be critical in refining the framework to address these identified gaps and enhance overall supply chain efficiency.

6 Conclusion

This paper presents a systematic literature review of papers focusing on supply chain optimization techniques. This study provides a comprehensive framework regarding optimization techniques within the supply chain. By synthesizing the findings from various research papers, we have shed light on the current state of the art of optimization techniques, objectives, supply chain levels, weaknesses and strengths within the supply chain field. Using insights from this study, researchers can categorize and compare supply chain optimization techniques to identify key themes, trends, and gaps in the literature. Practitioners can utilize the framework to navigate these techniques, enhancing decision-making by aligning strategies with specific supply chain levels and organizational objectives.

We have discussed the limitations and future research in section 5. As for future research, further exploration could be conducted to explore hybrid models, particularly to better understand their strengths, weaknesses, and optimization goals at different supply chain levels. Additionally, investigating unreported weaknesses, underrepresented optimization goals such as customer satisfaction, resilience, and time optimization, as well as focusing more on the operational level of the supply chain, will be essential to address the identified gaps and improve the framework.

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