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A systematic literature review of barriers to analytics adoption in supply chain decision-making

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ABSTRACT

The growing demand for resilient, proactive, and intelligent supply chains (SCs) has increased the adoption of analytics to support operational, tactical, and strategic decision-making. Despite the rapid growth of analytics applications in supply chain management (SCM), many initiatives remain confined to theoretical or experimental contexts and face significant challenges in real-world implementation. Existing literature has predominantly focused on methodological advancements and performance improvements, while barriers to implementation are often treated as secondary concerns rather than structural constraints that may inhibit adoption. This study examines barriers to the adoption of analytics in SCM through a systematic literature review complemented by grey literature. Based on the analysis of 464 papers, a taxonomy of barriers was developed, comprising six categories: organizational, technological, data-related, modeling, regulatory and ethical, and people-related. The findings show that these barriers are highly interdependent and generate compatibilities and trade-offs, where improvements in one dimension may mitigate or intensify constraints in another. The integration of grey literature supported the development of a multilayered framework that conceptualizes analytics adoption as holistic and interdependent process composed of three interconnected layers: (i) a strategic layer related to alignment, direction, and value orientation; (ii) a capability layer derived from the six barrier categories and representing the organizational capabilities required to support analytics adoption; and (iii) an operationalization layer associated with process integration, scalability, and effective analytics use within SC workflows. Finally, our study outlines future research directions and managerial implications to support the adoption of analytics in SCM.

1. Introduction

Modern supply chains (SCs), often referred to as Supply Chains 4.0, are characterized by seamless integration, real-time connectivity, adaptability, and a customer-centric orientation, enabled by the Internet of Things, big data, artificial intelligence, and cyber–physical systems [1]. Within this evolving paradigm, conventional optimization approaches, typically grounded in rigid assumptions and static modeling structures, are increasingly challenged to capture the complexity, volatility, and interdependencies that characterize contemporary SC environments [2]. As a result, organizations have increasingly relied on analytics to transform large volumes of data into actionable insights that support operational, tactical, and strategic decision-making. Davenport & Harris [3] defined "*by analytics we mean the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions*". More broadly, analytics involves extracting meaningful patterns, relationships, and insights from historical and current data to improve decision-making [4]. Consistent with Waller and Fawcett [5], this study adopts a broad view of analytics encompassing both data-driven approaches (e.g., artificial intelligence and machine learning) and model-driven approaches rooted in Operations Research (e.g., mathematical optimization, simulation, heuristics, and metaheuristics), as well as hybrid methods combining both paradigms. While this classification extends the original conceptualization, it is consistent with their broad perspective that effective analytics integrates diverse quantitative methods with domain knowledge to support supply chain decision-making.

The rapid expansion of analytics in supply chain management (SCM) has led to a wide range of models and methods spanning descriptive, diagnostic, predictive, and prescriptive approaches [6]. These analytical developments have enhanced visibility, improved demand forecasting, informed network design decisions, and strengthened risk management

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capabilities [6]. However, despite significant methodological progress, a gap persists between the development of analytical models and their real-world implementation. A considerable proportion of proposed solutions remains confined to simulation environments or experimental validation, with limited empirical deployment in industrial settings [7,8]. This discrepancy suggests that technical sophistication alone is insufficient to ensure successful analytics adoption.

The literature often highlights the complexity of SC environments, including high variability, environmental uncertainty, stochastic dynamics, and structural interdependencies [9–11]. In several studies, additional challenges are framed as technical modeling conditions, data requirements, operational parameters, or technological integration constraints necessary for implementing advanced analytical architectures [12,13]. While these elements significantly influence model formulation, computational feasibility, and system design, they are not necessarily treated as organizational or structural impediments to adoption. Rather, they often reflect intrinsic properties of SC systems or the analytical prerequisites for model operationalization. Similarly, many studies identify methodological limitations in existing analytical approaches and use these limitations to justify the development of novel algorithms, hybrid techniques, or enhanced computational frameworks [11–13]. Although these epistemological constraints are essential to advancing the state of the art, they do not necessarily explain why analytics solutions fail to be implemented or sustained in real-world SC environments. This distinction is critical. Challenges related to SC systems and the methodological limitations of analytical models differ conceptually from structural barriers to the adoption of analytics in SC contexts. Drawing on innovation adoption research, the successful implementation of technological and analytical innovations depends not only on their technical capabilities but also on organizational, technological, environmental, and human factors that shape adoption decisions and implementation outcomes [14,15]. In the context of SCM, analytics adoption depends not only on the quality of analytical methods but also on factors such as organizational readiness, technological infrastructure, data accessibility and quality, regulatory and ethical compliance, and the availability of human capabilities to support decision-making processes [16–18].

Existing review studies on analytics in SCM provide valuable mappings of application domains, methodological trends, and technological developments [19,20]. However, they tend to prioritize analytical techniques and computational advances while offering limited structured examination of the implementation barriers that constrain adoption. Although adoption challenges are occasionally acknowledged [20], they are rarely systematically classified or analyzed for their interdependencies and trade-offs. As a result, the literature lacks a coherent framework that distinguishes between intrinsic analytical challenges and structural implementation barriers and explains how different categories of constraints interact in practice. Therefore, this study aims to identify, classify, and conceptualize the structural barriers constraining the adoption of analytics in SCM, and to examine their interdependencies.

To address this gap, this study adopts a systematic literature review (SLR) complemented by grey literature evidence, including practitioner reports and industry analyses. Integrating these two sources enables a more comprehensive understanding of analytics adoption by bridging theoretical insights with real-world implementation challenges. While academic literature provides methodological rigor and conceptual depth, grey literature offers practice-oriented evidence on the adoption of analytics in real-world contexts, which is often underrepresented in academic research.

This study contributes to the literature in three main ways. First, based on evidence from academic literature, it proposes a taxonomy of barriers to analytics adoption in SCM, structured into six categories, and examines the interconnections. Unlike prior studies that mainly focus on methodological classifications or research trends, this work conceptualizes barriers as interdependent constraints rather than isolated implementation issues. Second, the study introduces the concept of trade-offs and compatibilities within the taxonomy, revealing that overcoming one barrier may mitigate or intensify constraints in other dimensions. This finding highlights that analytics adoption should not be approached as isolated interventions but rather through holistic, balanced management of organizational, technological, data-related, modeling, regulatory, ethical, and people-related factors. Third, by integrating insights from grey literature, the study proposes a multilayered framework for the adoption of analytics in SCs. The framework extends beyond technical implementation to encompass three interconnected dimensions: the strategic alignment of analytics with business objectives and value creation, the organizational capabilities required to support adoption, and the operationalization of analytics within SC processes and workflows. Collectively, these contributions provide a more comprehensive understanding of analytics adoption as a holistic organizational transformation process rather than a purely technological initiative.

The study is guided by the following research questions:

RQ 1. How are analytics models currently applied across different domains of SCs?

RQ 2. What are the main implementation barriers that hinder the adoption of these models in real-world SC environments?

RQ 3. How do different categories of implementation barriers interact, and what trade-offs emerge when attempting to overcome them?

By reframing analytics adoption as a holistic and multidimensional process, this study shifts the analytical focus from algorithmic sophistication to structural alignment and organizational integration. The proposed taxonomy advances theory by identifying structural barriers to analytics adoption and revealing the interdependencies and trade-offs among them, underscoring that adoption challenges should be addressed in a holistic, integrated manner rather than in isolation. Complementarily, the proposed framework advances practice by conceptualizing analytics adoption as an interconnected process that involves strategic alignment, organizational capabilities, and operationalization in real-world SCM contexts.

2. Methodology

2.1. Review protocol and design

This study adopts a systematic literature review (SLR) of academic literature and complements it with a grey literature analysis to provide a more practice-oriented understanding of the barriers to analytics adoption in supply chain management (SCM). The SLR was conducted in accordance with established methodological guidelines for evidence-based research synthesis [21], including the PRISMA 2020 guidelines [22]. Following the recommendations of Adams et al. [23], the selection of grey literature in this study was not conducted through a systematic review process. Instead, it was used to complement and extend the findings from the academic literature by incorporating practice-oriented evidence from industry reports, technology providers, consulting firms, and international organizations. The overall research process is structured into four main phases: (i) literature identification and selection, (ii) descriptive analysis, (iii) qualitative content analysis and barrier identification, and (iv) integration of academic and grey literature to support a comprehensive analysis of analytics adoption.

2.2. Academic literature review

2.2.1. Search strategy and study selection

The studies selected for review were retrieved from the Scopus database in January 2025 and filtered to include publications up to December 2024. Scopus was selected as the sole source for the systematic literature review because it is one of the largest multidisciplinary citation databases and is widely recognized for its extensive coverage

Table 1
Search string structure.

Context keyword: supply chain
AND simulation OR optimization OR programming OR queuing OR markov OR "economic method" OR "data analysis" OR "data-driven" OR "data mining" OR "data science" OR statistics OR "neural networks" OR "expert systems" OR metaheuristics OR heuristics OR "decision analysis" OR "machine learning" OR "artificial intelligence"

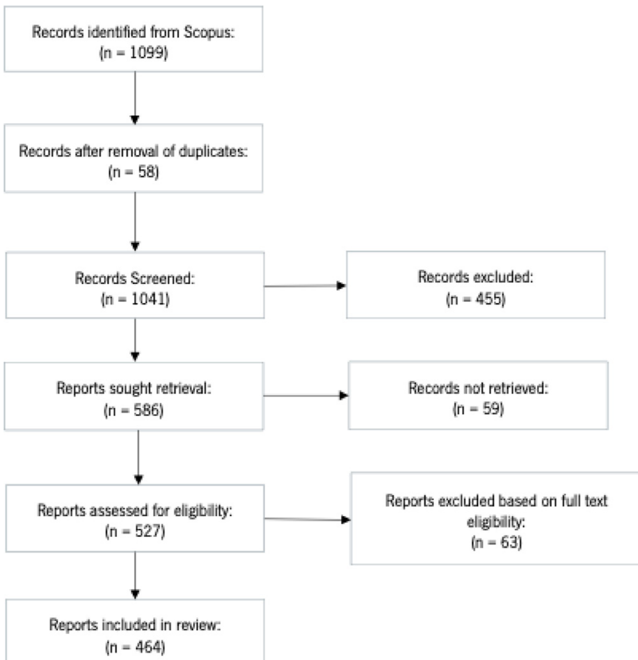

Fig. 1. Process for selecting papers in the systematic review.
Source: Adapted from the PRISMA 2020 flow diagram; [22].

of engineering, operations management, and business research, which aligns closely with the interdisciplinary nature of this study [24].

We adopted a two-layered query structure, following the approach proposed by Fahimnia et al. [25]. The first layer targeted the supply chain (SC) domain, while the second layer incorporated modeling-related keywords. The complete search string used is detailed in Table 1.

A total of 1099 records were initially identified. After removing duplicates, 1041 records remained for screening. During title and abstract screening, 455 records were excluded for not meeting the inclusion criteria, primarily because they were not relevant to SCM, lacked analytics methods, or had insufficient connection to adoption and implementation issues. Of the remaining 586 studies, 59 could not be retrieved. Full-text eligibility assessment was then conducted on 527 studies. At this stage, 63 studies were excluded because they did not directly address barriers to analytics adoption or implementation-related challenges in SCM contexts. Consequently, 464 studies were retained for the final review (Fig. 1).

2.3. Data extraction and classification

Inclusion criteria were limited to peer-reviewed journal articles and conference proceedings published in English up to December 2024 that directly addressed analytics models and methods in SC contexts. Studies that did not directly involve analytics approaches or were not sufficiently relevant to analytics adoption and implementation in SCM were excluded. This ensured alignment between the final sample and the research objectives, focusing exclusively on relevant analytical contributions.

To enable systematic comparison across studies and address the research questions, the selected publications were classified into four common dimensions:

1. **Application areas**. Application areas were classified using the SCOR (Supply Chain Operations Reference) framework. Following the SCOR Digital Standard, studies were assigned to one or more supply chain process categories: Plan, which covers demand and resource planning; Source, related to procurement and supplier management; Make or Transform, associated with production, assembly, and manufacturing operations; Delivery or Fulfill, covering order fulfillment, warehousing, and distribution; and Return, concerning reverse logistics and product returns. In addition, studies addressing cross-functional capabilities that support and coordinate supply chain operations, such as data management, analytics, technology infrastructure, risk management, compliance, performance measurement, and organizational integration, were classified under Orchestrate (formerly Enable) [26].
2. **Planning level**. Distinguishing between strategic, tactical, and operational decisions.
3. **Economic activity sector.** Identifying the economic sector context of application.
4. **Validation approach**. Referring to the methodological approach adopted to test and validate proposed models, following Yin [27] classification of empirical research designs. Three main types are considered:

    i. Empirical validation (Case Study): The model is evaluated through one or more case studies based on real-world SC contexts.
    ii. Experimental validation with synthetic data (SD): the model is tested using artificial or simulated datasets.
    iii. Experimental validation with real data (RD): the model is validated through controlled experiments using real-world data.

2.4. Barrier identification and barrier coding

Following the identification and classification of the final sample, a structured data extraction procedure was conducted. Each study was systematically reviewed to extract relevant information on the type of analytics, the modeling approach, the validation context, and the reported limitations or implementation challenges.

The identification of implementation barriers followed an iterative content analysis approach designed to distinguish implementation barriers from other types of constraints reported in the analytics literature. In the first stage, limitations, constraints, and challenges reported in the discussion and conclusion sections of each study were inductively identified. In the second stage, extracted elements were consolidated to harmonize terminology and eliminate redundancies, ensuring conceptual clarity and internal consistency. A subsequent deductive structuring phase organized the extracted barriers into conceptual categories. The Technology–Organization–Environment (TOE) framework [14] served as an initial theoretical lens for structuring adoption-related determinants. However, during iterative refinement, we found that the original TOE dimensions were insufficient to fully capture the analytical and modeling-specific characteristics of analytics in SCM. Consequently, the classification evolved into an extended, context-specific taxonomy developed in this study. The resulting framework integrates six interrelated categories: organizational, technological, data-related, modeling, regulatory and ethical, and people-related, reflecting both established adoption theory and empirically identified constraints. Consistent with the conceptual distinction established in Section 1, all reported limitations, constraints, and challenges to analytics adoption were initially extracted regardless of the validation context. These elements were then examined to distinguish: (i) analytical prerequisites required to implement analytical models, (ii) methodological limitations reported to motivate the development of new analytical approaches, and (iii) structural barriers that emerged during the implementation of analytics in real-world supply chain environments. Because the objective of this study is to identify barriers to analytics adoption, only the third category was retained for the implementation barrier taxonomy.

2.5. Integration of grey literature

To complement the findings of the systematic literature review and enhance the study's practical relevance, grey literature sources were included as an additional evidence base. The objective was not to conduct a separate review of grey literature, but rather to obtain practitioner-oriented perspectives on the adoption of analytics and artificial intelligence in organizational and supply chain contexts and to identify implementation experiences, barriers, and enabling factors reported in practice.

The identification of grey literature was guided by the following search string on Google: ("artificial intelligence" OR AI OR "generative AI" OR analytics OR "data analytics" OR "operational research") AND (adoption OR implementation OR deployment OR transformation OR maturity) AND (barriers OR challenges OR constraints OR readiness OR capabilities OR trust) AND ("supply chain" OR organization OR enterprise OR business). The search string was designed to capture four complementary dimensions: (i) analytics and artificial intelligence methods, (ii) adoption and implementation processes, (iii) organizational and supply chain contexts, and (iv) barriers, challenges, and readiness conditions. The search yielded practitioner reports, industry surveys, white papers, and institutional publications from consulting firms, technology providers, industry associations, and international organizations.

After the initial search, the websites of the identified organizations were reviewed to identify additional relevant publications. Related reports, documents cited in selected publications, and reports from previous years on similar topics were also considered. Candidate documents were initially screened by title and relevance to this study's objectives.

During the search process, the query was effective at identifying practitioner reports and industry surveys but less effective at retrieving corporate annual reports. To address this limitation, an additional search was conducted on AnnualReports.com, which provided access to the most recent annual reports available at the time of the study. Annual reports from organizations with significant supply chain operations and evidence of digital transformation or analytics initiatives were subsequently selected. Within the selected annual reports, keyword searches were conducted using the terms "AI", "artificial intelligence", "analytics", "digital transformation", "automation", "machine learning", "data", "innovation", "technology", and "supply chain". Only sections explicitly discussing analytics adoption, implementation initiatives, digital transformation programs, or related organizational challenges were retained for analysis.

All selected documents were reviewed in full. Only documents that explicitly addressed analytics or artificial intelligence adoption, implementation experiences, barriers, challenges, governance issues, or enabling factors were included in the final corpus. Documents consisting primarily of promotional or marketing content without supporting evidence were excluded. The final corpus comprised 20 grey literature documents, including industry surveys, white papers, practitioner reports, and corporate annual reports.

To reduce selection bias and mitigate potential commercial influence, documents were not selected solely based on the publishing organization. Priority was given to sources that provided transparent methodological descriptions, including survey designs, sample characteristics, interview protocols, case studies, or other forms of empirical evidence supporting their findings. Evidence was also collected from multiple types of organizations, including consulting firms, technology providers, international organizations, and corporate annual reports, thereby reducing dependence on a single-source perspective. The selected grey literature sources were analyzed separately from the academic sample and used exclusively to complement, validate, and contextualize findings from the systematic literature review.

3. Previous literature reviews

Before presenting the findings of the systematic review, it is important to position the present study within the existing body of review literature on analytics in SCM. This section, therefore, examines prior review studies to identify their scope, contributions, and limitations, thereby motivating the present review and highlighting its distinctive contribution.

The scientific publications analyzed and discussed in this section were identified using a combination of systematic and snowballing strategies based on the papers obtained from Scopus database using the terms "supply chain" AND "analytics" AND "review". The derived list of papers was then refined to include only peer-reviewed journal articles categorized as reviews of analytics approaches in the context of SCM, resulting in five documents selected for in-depth analysis. The selected studies are summarized in Table 2, including key information such as their objectives, methodological approach, number of articles analyzed, thematic focus, presence of a barrier to systematization, critical perspective on analytics approaches, and treatment of implementation limitations. A comparative analysis of these works allows us to identify prevailing research directions, highlight gaps in critical assessments, and situate the present study within existing literature.

Among the reviewed works, the study by Fahimnia et al. [25] stands out as the most extensive, encompassing over 1100 articles on quantitative modeling for SC risk management. Through a systematic literature review complemented by bibliometric and network analysis, the authors identify key trends and research clusters in the field. Their study provides valuable insights into the evolution of quantitative approaches, particularly optimization and mathematical modeling, for managing SC disruptions and uncertainties. However, the discussion of implementation challenges and practical barriers remains secondary to the study's primary focus on risk-related modeling.

Souza [28] adopts a more application-oriented perspective by categorizing analytical techniques according to the SCOR model and the types of analysis (descriptive, predictive, and prescriptive). While it offers a broad overview of practical applications, the work is primarily explanatory and lacks a critical framework or a structured identification of barriers to adoption. Similarly, Mishra et al. [29] provide a comprehensive bibliometric and network analysis of Big Data research in SCM, identifying six thematic clusters and emerging trends. However, the study primarily maps the field's intellectual structure rather than evaluating the practical implementation of analytics methods in real-world SC contexts. Wang et al. [19] review the literature on big data business analytics (BDBA) in logistics and SCM and propose a maturity framework that classifies analytical capabilities across levels of sophistication. While the study identifies major application areas and outlines directions for future research, it places limited emphasis on the epistemological and technical constraints of existing models and on the organizational barriers to implementation. By contrast, Pires Ribeiro & Barbosa-Póvoa [30] represent a significant advancement by integrating a conceptual analysis of SC resilience with a systematic review of quantitative approaches, particularly those grounded in operations research methods. Their work provides a detailed categorization of existing models, highlights research gaps, and outlines future directions. However, it does not propose a formal framework for systematizing the identification of implementation barriers.

Table 2
Summary of literature review studies on analytics approaches in SCM.

Review paper	Objective	Research methodology	Papers referenced	Focus	Critical analysis of analytics approaches	Barrier systematization	Barrier approach
Fahimnia et al. [25]	Review quantitative models for SC risk management; identify trends and gaps.	Systematic review	>1100	Quantitative modeling for SC risk.	Identifies trends and gaps, lacks critical assessment.	No	General limitations mentioned; no classification.
Souza [28]	Categorize analytics in SC operations (SCOR model; descriptive, predictive, prescriptive).	Not specified	N/S	Analytics applications in SC operations.	Conceptual and practical overview; no critical analysis.	No	Notes adoption challenges, but no structured or classified limitations.
Mishra et al. [29]	Review big data in SCM using bibliometric and network analysis; suggest future research.	Bibliometric analysis	286	Big data in SCM: evolution, key authors and topics.	Identifies research gaps; lacks comparative or critical analysis.	No	Mentions data/method gaps; no structure or classification of limitations.
Wang et al. [19]	Review BDBA in logistics and SCM; propose a maturity framework.	Systematic review	101	Maturity and analytics applications in SCM.	Proposes a framework, lacks methodological or epistemological critique.	No	Points out limitations (e.g., academic bias) but lacks a classification.
Ribeiro & Barbosa-Póvoa [30]	Review SC resilience models and definitions, with a focus on OR methods.	Systematic review	39	SC resilience modeling and quantitative approaches.	A critical analysis of models and gaps suggests areas for future research.	No	Discusses conceptual and practical gaps; no structured approach to barriers.
Our study	Review analytics in SCM to identify, classify, and analyze interrelations and trade-offs among implementation barriers	Systematic review	464	Analytics in SCM.	Provides a critical, structured assessment of the factors that limit the real-world implementation of analytics.	Yes	Classifies barriers into six categories and examines how trade-offs and interrelations shape their impact.

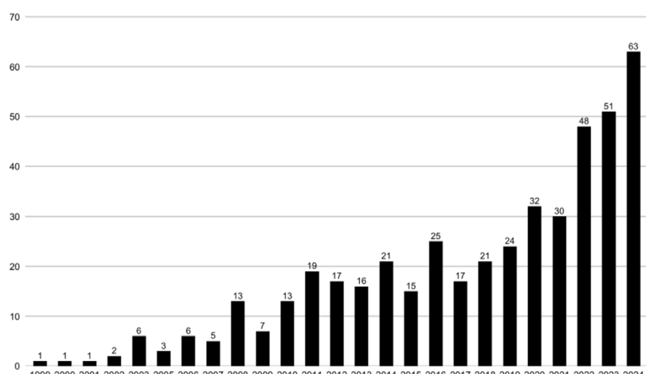

Fig. 2. Temporal distribution of studies.

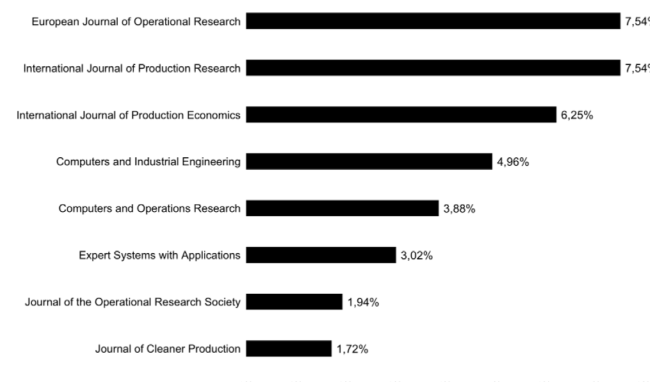

Fig. 3. Distribution of studies across the most representative journals (%).

In contrast, this study distinguishes itself by proposing a novel approach to identifying, categorizing, and systematizing barriers to the adoption of analytics in SCM. Through a systematic literature review, the selected studies were examined for the barriers reported in each study. These barriers were subsequently classified into six main dimensions: organizational, technological, data-related, modeling, regulatory, and ethical, and people-related. Unlike previous reviews, which often lack a structured critical perspective or remain confined to conceptual discussions, this study bridges a significant gap in the literature by offering a systematic understanding of implementation barriers and by developing a conceptual tool to support both decision-makers and researchers in diagnosing and overcoming them.

4. Descriptive overview of selected studies

This section presents a descriptive analysis of the 464 studies included in the final sample. The objective is to characterize publication trends, application domains, decision levels, industrial sectors, and validation approaches prior to analyzing implementation barriers.

4.1. Temporal distribution and publication outlets

As illustrated in Fig. 2, the temporal distribution shows an increase in analytics research in SCM, with accelerated growth after 2010 and a marked rise after 2020, reflecting the growing relevance of data-driven decision-making and advances in computational capabilities. The selected studies were published across 288 outlets, including journals and conference proceedings. Fig. 3 presents the most representative journals by publication volume, which together account for approximately 35% of the sample. Operations research and production-oriented journals, such as the International Journal of Production Research (Taylor & Francis), European Journal of Operational Research (Elsevier), and International Journal of Production Economics (Elsevier), are the primary journals reporting analytics applications in SCM.

4.2. Application domains and contextual characteristics

When mapped onto the SCOR framework (Fig. 4), the studies primarily focused on the Plan process (32%), followed by Deliver (25%) and Make (15%). The Source (12%) and Enable (10%) processes are examined less frequently, while Return (6%) is rarely addressed. Regarding decision-making levels (Fig. 5), the literature predominantly focuses on tactical decisions (49%), followed by strategic (32%) and operational applications (19%). The economic activity sector covered

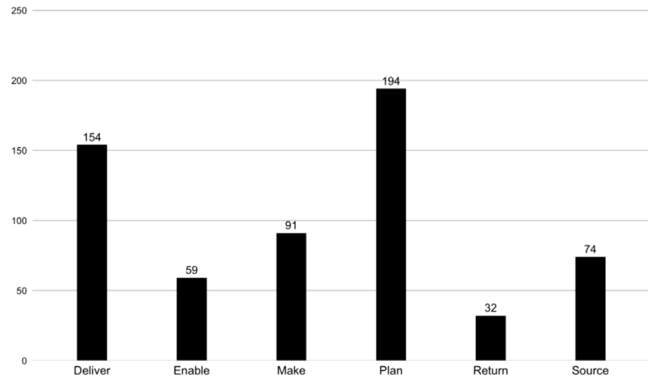

Fig. 4. Distribution of studies across SCOR processes.

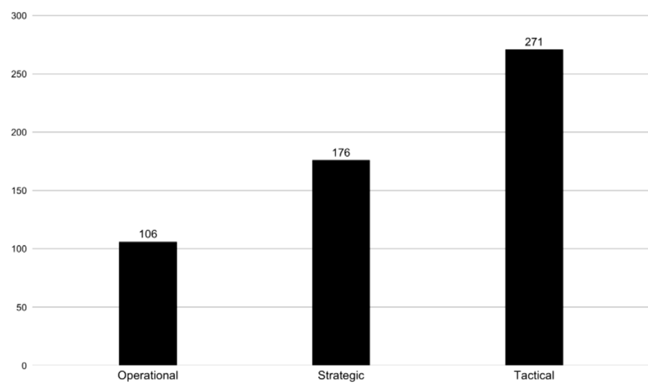

Fig. 5. Distribution of studies across decision levels.

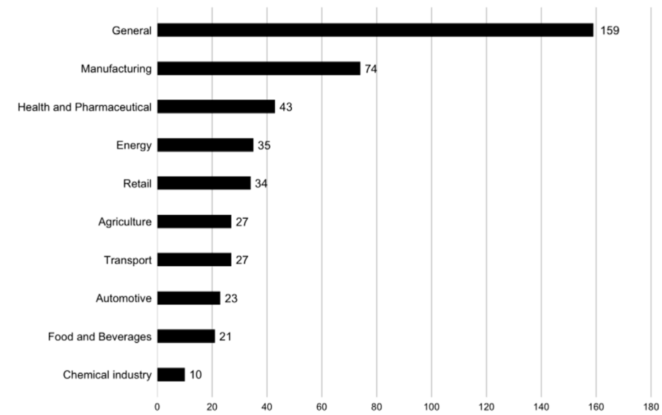

Fig. 6. Top 10 economic activity sectors in the reviewed studies.

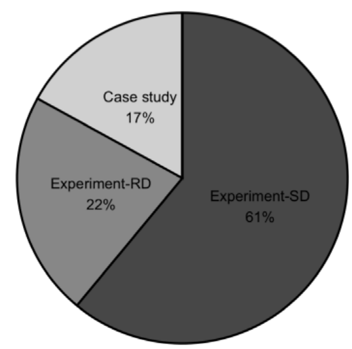

Fig. 7. Distribution of studies by validation approach.

(Fig. 6) shows that much of the literature focuses on generic SCs rather than on specific sectors. Among studies with defined domains, manufacturing is the most common, followed by healthcare and pharmaceuticals, energy, retail, and transportation. Other sectors, such as chemicals, food and beverage, and agricultural SC, are less frequently represented.

The analysis of validation approaches (Fig. 7) indicates that most models (83%) remain in the experimental stage, relying on either synthetic or real datasets (experiment-SD and experiment-RD). In comparison, only a small percentage (17%) are validated in real SC settings (case study).

5. Analytics categories

The literature on analytics applied to SC is organized into four analytical categories: descriptive, diagnostic, predictive, and prescriptive, each differing in its objectives, decision-support capabilities, and underlying analytical methods. Descriptive and diagnostic analytics are primarily based on statistical analysis, reporting, visualization, and causal inference techniques. Predictive analytics mainly encompasses statistical forecasting and machine learning methods, whereas prescriptive analytics is largely supported by operations research techniques such as mathematical programming, simulation, heuristics, and metaheuristics. Increasingly, hybrid approaches combine AI and OR methods to integrate prediction with optimization. As expected, the analysis of the reviewed studies (Fig. 8) highlights a significant imbalance: over 70% of studies focus on prescriptive analytics, about 20% adopt predictive approaches, and descriptive and diagnostic approaches account for less than 3% of the sample. Hybrid methods that combine multiple analytical techniques appear in roughly 6% of studies. This distribution aligns with the methodological patterns shown in Fig. 9, which highlight the dominance of Operations Research (OR) techniques and the prevalence of prescriptive paradigms.

These distributions largely reflect the historical evolution of analytical methods in SCM rather than an intrinsic preference for one analytical paradigm over another. Operations Research has served as the methodological foundation of SC decision support for several decades, providing effective approaches for planning, scheduling, inventory management, transportation, facility location, and network design. Consequently, the predominance of prescriptive analytics and OR-based methods is an expected feature of the literature rather than an unexpected trend. Likewise, the growing presence of AI and machine learning reflects advances in computational capabilities and data availability, expanding the analytical toolbox available to decision-makers rather than replacing existing OR approaches. Importantly, these analytical paradigms should be viewed as complementary rather than competing. Their effectiveness depends on the nature of the supply chain problem, and successful adoption of analytics continues to rely on integrating analytical outputs with human expertise, domain knowledge, and managerial judgment.

Early applications of analytics in SCM focused on descriptive reports and simple cause-and-effect analyses [18]. Subsequently, the literature shows that OR methods have become central to the modeling, analysis, and optimization of SCM problems [31]. With advances in Artificial Intelligence (AI), particularly machine learning, analytics expanded beyond predictive applications such as demand forecasting to broader decision-support domains, including inventory management, supplier optimization, and, more recently, generative AI-based simulation and sustainability applications [32,33]. In this context, analytics approaches that integrate learning-based techniques with mathematical programming have been proposed as effective hybrid frameworks, combining predictive modeling with optimization to support integrated planning, scheduling, and control decisions in SC systems [34].

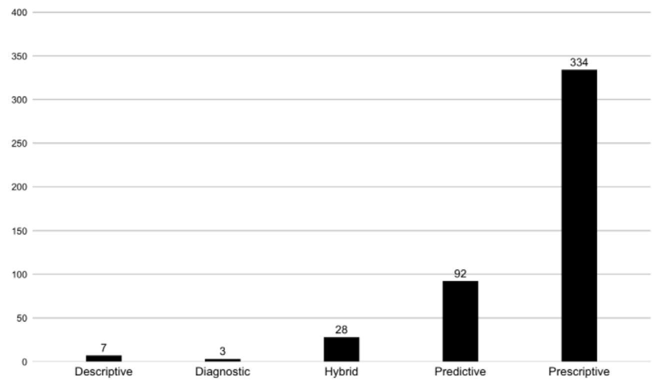

Fig. 8. Distribution of studies by type of analytics.

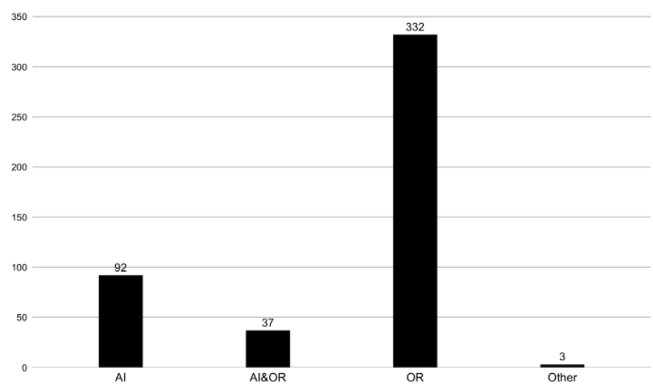

Fig. 9. Distribution of studies by analytical approach.

5.1. From descriptive monitoring to diagnostic explanation

Descriptive analytics address the question "what happened?", providing basic monitoring and visibility across SC processes. Typical applications include product traceability and supplier mapping [35,36]. Later, spatial clustering techniques were introduced to extract patterns directly from data, marking the integration of AI concepts into descriptive analytical contexts [37].

As data matures, diagnostic analytics have emerged to address the question *"why did it happen?"*, often integrated with descriptive analytics [38]. Its primary role in identifying root causes and bottlenecks sets it apart. Analytics methods in this domain are frequently implemented as statistical decision rules, including threshold-based tests for causal identification or as causal inference frameworks such as Lasso–Granger models [39]. Furthermore, AI techniques, including decision trees, random forests, and neural networks, are employed to uncover hidden determinants within complex datasets, supporting applications such as facility location optimization in the SC [40]. Despite their limited representation, diagnostic analytics play a key role in supporting causal reasoning.

5.2. Predictive analytics and the growing role of machine learning

Predictive analytics address the question "what will happen?", supporting anticipatory decision-making in SCM, particularly in applications such as demand forecasting, lead-time estimation, and disruption anticipation [33]. While early approaches relied on statistical forecasting models, the field has increasingly shifted towards machine learning techniques that capture complex and nonlinear patterns [41,42]. Despite these advances, predictive performance remains highly dependent on data availability and quality [43], highlighting the need for integration with descriptive and diagnostic layers and the resulting limitations in translating forecasts into proactive decisions.

5.3. Prescriptive analytics and the historical dominance of operations research

Prescriptive analytics dominate the literature, accounting for more than 70% of the reviewed studies, a pattern closely associated with the central role of OR in SC decision-making. While early formulations relied primarily on exact optimization methods [44], the NP-hard nature of many large-scale problems has driven the widespread adoption of heuristic and metaheuristic approaches to achieve tractable solutions within realistic decision times [45,46]. More recently, prescriptive analytics has increasingly incorporated AI [47], giving rise to hybrid AI-OR frameworks that combine learning-based models with optimization and simulation to better handle uncertainty, scalability, and dynamic decision environments [48].

Across all analytical paradigms, the ultimate objective remains to support rather than replace human decision-makers. The effectiveness of analytics, therefore, depends not only on analytical performance but also on its integration with domain expertise and organizational decision-making processes.

6. Implementation barriers with empirical validation

Building on the structured extraction and coding procedure described in Section 2.4, this section presents the implementation barriers identified across the reviewed studies. Although limitations and challenges were extracted from all reviewed studies, only those corresponding to structural barriers that emerged during the implementation and operationalization of analytics in real-world supply chain environments were retained for the taxonomy. We acknowledge that general challenges to analytics adoption are frequently reported in the broader analytics literature. Yet, when they are reported solely as analytical prerequisites (e.g., data requirements, computational resources, or technological integration conditions) or as methodological limitations motivating the development of new analytical approaches (e.g., scalability limitations of exact methods or modeling assumptions), they cannot be interpreted as empirically demonstrated barriers to implementation. Hence, restricting the taxonomy to empirically observed implementation barriers ensures conceptual consistency with the scope of this study while strengthening the practical relevance and validity of the proposed framework. This decision follows the conceptual distinction established in Section 1 and it is further supported by the descriptive findings in Section 4.2. Although 83% of the reviewed studies validated their methods using synthetic or real datasets in experimental settings, only 17% examined empirical implementation through real-world case studies. Experimental research offers valuable insights into analytical capabilities, technical requirements, and methodological limitations. However, studies involving actual implementation provide stronger evidence for identifying the practical barriers that emerge as constraints on analytics adoption.

Hence, Table 3 synthesizes only barriers that were empirically observed and explicitly reported as impediments to analytics adoption in operational settings.

6.1. Barrier categories

The barriers identified in Table 3 can be grouped into distinct analytical categories. Their structure is informed by the TOE framework [14], which has been widely used to explain the adoption and implementation of technological innovations, including supply chain technologies and analytics-related systems [49,98]. The findings further suggest that analytics implementation should not be viewed solely as an information technology adoption process. Rather, analytics create value by transforming data into actionable insights for decision-making through the complementary interaction among data resources, analytical technologies, human expertise, and organizational knowledge [4,99].

Table 3
Barriers to the adoption of analytics approaches reported in the academic literature.

Barrier	Description	Studies
Organizational resistance	Cultural or structural opposition to analytics adoption	[49,50]
Fear of losing organizational control	Perceived loss of managerial autonomy due to analytics uses	[49,50]
Distrust towards new technologies	Skepticism about the reliability or transparency of analytics systems	[49,50]
Inconsistent decision-making	Misalignment between analytics outputs and managerial actions	[50]
Lack of institutional coordination	Insufficient governance or alignment among SC actors	[51–53]
High implementation cost	High financial requirements for model deployment and integration	[54]
Lack of infrastructure in the organization	Insufficient IT or computational infrastructure for model support	[55,56]
Need for expertise	Requirement of advanced technical knowledge	[43,53,57,58]
Training requirement	Need for continuous training to operate analytical tools effectively	[59]
Simplified model	Simplified model assumptions	[51,60,61]
High complexity of modeling	High methodological complexity	[62,63]
High complexity of the environment	Environmental volatility and interdependencies complicate modeling	[64,65]
Parameter sensitivity	Sensitivity to parameter calibration	[66]
Solution instability	Instability of optimization outcomes across scenarios	[67]
Low accuracy	Insufficient predictive or optimization performance	[68,69]
Judgment dependency	Excessive reliance on human intervention	[70]
Lack of technological capabilities	Inadequate IT infrastructure or digital maturity	[57,71,72]
Non-integrative technology	Isolated solutions not embedded in core systems	[57,73]
Lack of system interoperability	Technical incompatibility between information systems	[74]
High computational time	The model is solvable, but computationally too slow for practical or large-scale use	[75–81]
Computational scalability	Computational limitations for large-scale problems	[10,76,82–85]
Concerns about data privacy and security	Risks of unauthorized access, misuse, or leakage of sensitive data	[59,86]
Lack of data	Insufficient or unavailable data for reliable model estimation	[57,87–92]
Poor quality data	Presence of incomplete, inconsistent, inaccurate, or noisy data	[57,87,93,94]
High data variability	Temporal instability in data patterns	[61]
Regulatory and Compliance Constraints	Legal or regulatory constraints that restrict data access, sharing, modeling, or deployment of analytical solutions	[59]
Impractical solution in the real world	Mathematically valid models that are operationally infeasible due to excessive complexity, computational intractability, or impractical solution times	[11,12,57,62,75,95]
Ethical issues	Explicit concerns regarding fairness, discrimination, bias, accountability, or societal harm	[20]
Lack of practical validation	Absence of real-world organizational testing or implementation	[60,88,96]
Black box	Lack of model transparency, limiting explainability, and decision trust	[43]
Low generalization	Poor out-of-sample performance reduces model robustness	[97]

This distinction provides the rationale for extending the original TOE framework. First, data-related barriers constitute a separate category because many implementation challenges stem from the data characteristics rather than from the technologies used to manage them. The reviewed studies consistently report issues with data availability, quality, completeness, accessibility, representativeness, and trustworthiness. Although technological infrastructure enables data collection and processing, data constitutes a distinct organizational resource whose contribution to analytics depends on its interaction with analytical technologies and human capabilities [4,99]. A similar argument applies to modeling-related barriers. Traditional TOE studies conceptualize the technological context in terms of infrastructure, compatibility, and technical capabilities [98]. However, analytics introduces an additional layer through analytical models, whose formulation and characteristics (e.g., explainability and interpretability) directly influence adoption and decision support [100]. Accordingly, the reviewed studies identify barriers such as model simplification, representation of reality, parameter sensitivity, solution instability, transparency, limited generalizability, and practical applicability. These challenges stem from the analytical model itself rather than from the technological infrastructure needed to run it.

Human factors further justify extending the TOE framework. Drawing on multilevel theory [101], organizational barriers capture structural capabilities such as resources, infrastructure, and analytical readiness, whereas people-related barriers reflect individual-level cognitive and behavioral mechanisms. While traditional TOE studies incorporate managerial support and absorptive capacity within the organizational context [102], recent research emphasizes that organizational decisions are fundamentally shaped by managers' cognitive processes, attention allocation, and interpretation of available information [103]. In analytics, these cognitive capabilities become particularly important because the value of analytical outputs depends on decision-makers' ability to understand, interpret, critically evaluate, and integrate analytical insights into organizational decision-making [99,104]. Consequently, barriers such as limited analytical literacy, difficulties in interpreting model outputs, cognitive resistance to new decision-making approaches, and low confidence in analytical insights warrant conceptual distinction from organizational resources.

Regulatory and ethical barriers constitute a distinct category because analytics-based systems are subject to requirements related to privacy, data protection, transparency, explainability, accountability, auditability, and algorithmic fairness. Unlike the environmental dimension of the TOE framework, which primarily captures external regulatory pressures, these requirements directly constrain the design, implementation and use of analytics systems throughout the analytics lifecycle [100,105].

Based on these findings, this study proposes an extended taxonomy comprising six categories of implementation barriers:

- **Organizational barriers:** organizational culture, organizational infrastructure, coordination and information sharing, financial resources, skills, and analytical capabilities.
- **Technological barriers**: appropriate technology, integration and interoperability, computational complexity.
- **Data-related barriers**: data availability, data quality and trust, representativeness.
- **Modeling issues:** representation of reality, model stability and robustness, transparency, and applicability.
- **Regulatory and ethical barriers.**
- **People-related barriers.**

6.1.1. Organizational barriers

Organizational barriers are among the most persistent obstacles to adopting analytics methods in SCM. Rather than reflecting isolated issues, these barriers are structural and span organizational culture, infrastructure, coordination mechanisms, financial resources, and human capital resources [18,106].

Organizational culture. Organizational resistance is frequently rooted in limited trust in analytical models and concerns transparency and decision-making autonomy. Managers and decision-makers often prefer familiar, interpretable tools and rely on experience or intuition when confronted with complex models [20,50]. When model outputs conflict with expectations, credibility is questioned, potentially hindering implementation efforts [107]. This resistance is reinforced in organizational cultures that privilege stability over experimentation and perceive automated systems as risky in critical SC contexts.

Organizational infrastructure. Inadequate digital infrastructure and poor system integration constrain effective data management, traceability, and deployment of analytics [108]. Data fragmentation across isolated systems and the absence of standardized data collection processes limit organizations' ability to embed analytics into routine decision-making, resulting in reactive rather than systematic planning practices [50].

Coordination and information sharing. Limited coordination among SC partners, both internally and externally, is a recurring barrier. Data sharing is often limited by a lack of trust and concerns about competitive advantage [74], while heterogeneity in data formats and analytical capabilities further weakens collaboration [58,74]. Internally, insufficient information sharing across functional units or departments prevents analytical insights from translating into coordinated organizational action [18].

Financial resources. The adoption of analytics is typically constrained by high implementation and maintenance costs, as well as indirect costs associated with training, organizational restructuring, and change management [33]. These constraints are particularly noticeable in SMEs or organizations facing budgetary constraints, often leading them to prioritize short-term cost minimization over long-term analytical maturity [12].

Human capital resources. The shortage of internal technical and analytical skills is a transversal barrier [106]. Effective implementation requires hybrid profiles that can translate business problems into analytical models and interpret results for decision support [18]. In their absence, organizations become dependent on external expertise, limiting knowledge retention and reducing the practical impact of analytics on decision-making [12].

6.1.2. Technological barriers

Technological barriers are a major constraint on the adoption of analytics models and methods in SCM. Rather than reflecting isolated technical limitations, these barriers relate to the adequacy of the technological infrastructure, system integration, and computational feasibility required to operationalize analytical solutions under real-world conditions [18,33].

Appropriate technology. The literature consistently highlights that effective analytics adoption depends on adequate technological infrastructure, including computing capacity, network connectivity, data acquisition technologies, and integrated data management systems [33,109]. However, many SC contexts still rely on outdated ERP systems, fragmented workflows, and limited hardware resources, which undermine the scalability and reliability of analytics applications [33]. Insufficient computational capacity and weak integration between analytics tools and operational platforms constrain the practical deployment of advanced methods, particularly in time-sensitive decision environments.

Integration and interoperability. A recurring technological barrier is the limited integration and interoperability of information systems across SC functions and among partners [110]. Studies report that the absence of standardized data models, interoperable interfaces, and shared data governance mechanisms hampers seamless data exchange and synchronization between planning and operational systems [111]. As a result, analytics components often operate in isolation, requiring manual intervention to ensure consistency, which reduces reliability, visibility, and traceability across the SC [33].

Computational complexity. Computational complexity is widely reported as a critical technological barrier in SCM analytics. Many decision problems are NP-hard, and exact optimization approaches often become intractable as the problem size increases [45]. Even when models are theoretically solvable, large-scale instances may involve many variables and constraints, leading to excessive solution times [77]. To address these limitations, the literature documents the widespread use of heuristic and metaheuristic approaches, which improve tractability at the expense of guaranteed optimality [31]. Nevertheless, several studies emphasize that analytics solutions remain impractical when computational time exceeds the operational decision window, thereby limiting their applicability in real-world SC settings [112].

6.1.3. Data-related barriers

Data-related barriers are a critical limitation to the adoption of analytics methods in SCM, as analytical effectiveness depends on the availability of complete, reliable, and timely information [33]. The literature consistently reports that analytics research and practice in SCM are constrained by limited data availability, fragmented data sources, and insufficient data governance, which hinder the transition from analytical prototypes to operational deployment [108,113].

Data availability. Data availability is a recurring limitation for analytics [56], particularly in contexts where management systems such as ERP are absent, incomplete, or poorly integrated [114]. Studies report that datasets available for model development are often limited in size, costly to obtain, and insufficiently diverse in features, posing significant challenges for model training, validation, and robustness, especially in machine learning applications [115]. Even when large volumes of data exist within SCs, access is often restricted by privacy, compliance requirements, and the need to protect strategic information, rendering relevant data unavailable for analysis [116]. Furthermore, data scarcity also stems from the lack of analytically usable data, as information is often dispersed across heterogeneous systems and requires extensive preprocessing and consolidation before it can support analytical models [117].

Data quality and trust. When data are available, concerns shift to data quality, which directly affects model reliability and the effectiveness of decision-making [56]. The heterogeneity of SCs across products, markets, operational policies, and environmental conditions introduces noise, gaps, and inconsistencies that hinder pattern identification and reduce predictive accuracy [87]. The literature indicates that fragmented, outdated, or inconsistent records compromise model performance and may lead to unreliable or misleading outcomes [20]. Data quality issues are often linked to inadequate data integration and management practices, resulting in limitations in accuracy, completeness, consistency, and timeliness [118]. These deficiencies further constrain tasks such as anomaly detection, risk identification, and performance evaluation.

Representativeness. Beyond availability and quality, studies emphasize representativeness as a critical barrier to data [119]. Short, temporally biased, or spatially limited datasets limit models' ability to generalize to new conditions. Structural changes and rare events, such as disruptions or market shifts, can further reduce the relevance of historical data and limit the construction of representative samples [43]. In performance evaluation contexts, data heterogeneity and the presence of interval or ordinal information also require methodological adaptations to avoid biased or unreliable conclusions [120].

6.1.4. *Modeling issues*

Modeling issues constitute a significant barrier to the adoption of analytics in SCM, as they directly affect the realism, robustness, transparency, and practical applicability of analytical solutions. The literature consistently reports challenges in representing complex SC dynamics [121], ensuring model stability, achieving interpretability, and ensuring external validity, which collectively limit the transfer of analytical models from theoretical development to real-world implementation [33,122,123].

Representation of reality. A recurring modeling challenge concerns accurately representing real-world SCs, which are inherently dynamic, stochastic, and highly complex [121]. Studies report that analytical models often rely on simplifying assumptions and reduced sets of variables to remain tractable, as fully detailed representations can lead to excessive mathematical and computational complexity. As a result, many models capture only a partial view of operational reality, limiting their ability to reflect the uncertainty, variability, and interdependence observed in industrial environments [60,124].

Model stability and robustness. Model stability and robustness are widely recognized as critical issues in modeling. The literature highlights that analytical solutions are often highly sensitive to parameter settings, initial conditions, and stochastic elements embedded in optimization and learning algorithms [60,125]. In machine learning applications, model performance depends heavily on hyperparameter selection [126], whereas in metaheuristic and evolutionary algorithms, small parameter variations can lead to substantially different outcomes [127]. This sensitivity reduces reproducibility and reliability, particularly in long-term or dynamic decision contexts, and often requires frequent recalibration and specialized expertise to maintain acceptable performance [128].

Transparency. Lack of transparency is a prominent modeling issue, particularly in analytics approaches that rely on complex machine learning architectures. Many models, especially deep learning methods, are characterized by limited explainability because their internal decision-making mechanisms are not directly accessible to human understanding [123]. The literature reports that this opacity constrains validation, hampers trust among decision-makers and complicates the integration of analytical outputs into operational and managerial decision-making processes [116]. As a result, limited explainability remains a significant barrier to the broader adoption of advanced analytics models in SC contexts.

Applicability. Practical applicability presents a further modeling challenge, as many analytical models remain confined to experimental or highly specific settings. Studies indicate that proposed solutions are often tailored to SC configurations, limiting their generalizability and transferability to other contexts [60]. Moreover, the lack of empirical validation under real-world conditions undermines confidence in analytical models and reduces practitioners' perceived business value [129]. These limitations are particularly pronounced for small and medium-sized enterprises, where implementation costs, data availability, and operational complexity often render advanced models infeasible [130].

6.1.5. *Regulatory and ethical barriers*

Regulatory and ethical barriers are important constraints on the adoption of analytics in SCM, particularly in sectors operating under strict legal and compliance frameworks [60]. The literature reports that fragmented and heterogeneous regulatory environments, combined with the absence of harmonized standards across jurisdictions, limit the transferability and scalability of analytics solutions, especially in cross-border SC contexts [131]. As a result, analytical approaches that are feasible in one regulatory setting may become legally or operationally infeasible in others.

Furthermore, ethical concerns related to data use and algorithmic decision-making are increasingly reported as barriers to analytics adoption. Studies highlight issues with data privacy, confidentiality, and transparency, particularly in distributed SC environments that require information sharing across multiple actors [132]. Moreover, concerns about algorithmic bias, fairness, and accountability often arise when advanced machine learning models are used, as they may generate opaque or difficult-to-justify decisions in sensitive contexts [33]. The literature also identifies ethical considerations extending beyond technical compliance, including social and labor implications of automation, environmental responsibility, and the broader societal impact of analytics-driven decisions [133]. These regulatory and ethical constraints are therefore considered structurally significant barriers because they influence data governance practices, limit permissible data use, and affect an organization's willingness to deploy analytics solutions in real-world SC environments.

6.1.6. *People-related barriers*

People-related barriers constitute a distinct yet cross-cutting dimension of analytics adoption in SCM. The literature consistently emphasizes that managerial mindsets, decision-making habits, and professional trajectories shape how analytical insights are interpreted, accepted, and incorporated into organizational routines [134]. In this sense, analytics adoption is not merely a technological upgrade but also a managerial and organizational transformation. Even in data-rich environments, organizations often struggle to integrate analytical evidence into established decision-making processes [135].

A recurring challenge is the persistence of experience-based and relationship-oriented decision-making practices. SCM has traditionally relied on domain expertise, tacit knowledge, managerial experience, and long-standing business relationships [136]. While these elements remain fundamental to effective decision-making, difficulties arise when analytical insights are not effectively integrated with existing managerial practices and routines. As a result, analytics tools may be formally implemented but only partially incorporated into strategic, tactical, or operational decisions [137].

Leadership and top management support also play a critical role. Senior managers and executives often determine organizational priorities, allocate resources, and shape decision-making cultures. Consequently, analytics initiatives may struggle to gain organizational legitimacy when leaders do not actively promote evidence-informed decision-making or fail to align analytical initiatives with business objectives [135,137]. Several studies further suggest that analytics projects frequently underperform not because of technological limitations, but because they remain disconnected from managerial processes and organizational practices [137].

Behavioral and cognitive constraints further influence analytics adoption. Supply chain environments are characterized by high levels of information complexity, uncertainty, and time pressure. Decision-makers are frequently required to process large volumes of information within limited timeframes, which may create cognitive overload and reduce decision effectiveness [138]. Consequently, the value of analytics depends not only on model performance but also on the ability to present information in a manner that supports human cognition and facilitates its integration into decision-making processes [138].

Overall, people-related barriers highlight that successful analytics adoption depends not only on technological capabilities but also on leadership, managerial mindset, decision-making practices, and user-centered system design. Analytics creates value when analytical insights, domain expertise, and managerial judgment are effectively combined to support organizational decision-making. If these human and organizational factors are not adequately addressed, organizations may struggle to translate analytical capabilities into improved supply chain performance [134,135].

6.2. Classification and systematization of barrier categories

Table 4 consolidates the barriers identified in the reviewed literature by mapping each barrier to its corresponding category, providing a structured overview of their distribution across the six analytical dimensions.

6.3. Interdependencies, compatibilities, and trade-offs

The categories presented in Table 4 should not be treated as independent dimensions. Drawing on the trade-off and compatibility literature [139–141] barriers are viewed as interconnected constraints that influence one another throughout the implementation process. Actions to mitigate a particular barrier may generate complementary effects that facilitate improvements in other categories while creating new challenges elsewhere. Fig. 10 illustrates some of these interdependencies, highlighting how analytics adoption is shaped by a network of reinforcing and constraining relationships rather than by isolated implementation factors.

Although Fig. 10 illustrates the interdependence among the six barrier categories, these interactions can take different forms. Based on the evidence extracted from the reviewed studies, three main relationship types were identified: compatibility relationships, interdependencies, and trade-offs. Table 5 summarizes the main relationships observed across categories.

7. Structural dynamics of analytics adoption

The relationships presented in the previous section suggest that implementation barriers do not operate in isolation. Instead, they form an interconnected system in which changes in one category frequently influence the behavior and effectiveness of others. Building on these relationships, this section examines how interdependencies, compatibilities, and trade-offs shape analytics adoption in SCM and discusses their implications for implementation.

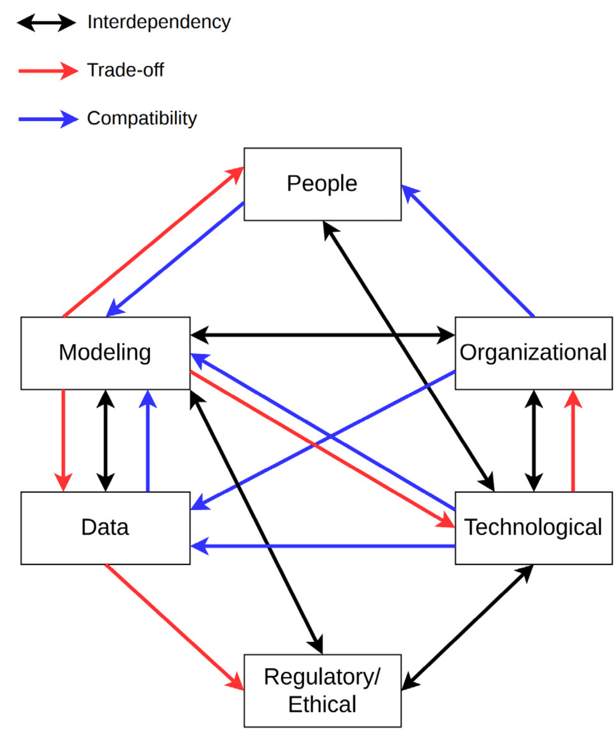

Fig. 10. Compatibility and trade-off relationships among barriers categories.

7.1. Structural interdependencies among barrier categories

The finding that over 70% of the reviewed studies adopt prescriptive analytics based on Operations Research (OR) approaches, together with the rapid growth of AI-driven predictive analytics, intensifies structural interdependencies among barrier categories. Prescriptive models require scalable formulations and robust computational capacity [19], increasing exposure to technological and modeling-related constraints. Predictive models, in turn, depend not only on data availability but also on data sufficiency, stability, and structural reliability [143], reinforcing structural data-related barriers. As organizations increasingly adopt predictive and prescriptive analytics to support managerial decision-making, analytical sophistication rises, placing concurrent demands on data governance, technological readiness, and human capabilities [53]. When analytical ambitions exceed organizational and operational maturity, implementation challenges may arise, constraining sustainable and effective deployment.

7.1.1. Modeling sophistication vs. technological capacity

The predominance of prescriptive models and continued reliance on OR-based approaches suggest that the field remains strongly oriented towards methodological rigor and optimal decision-making. However, the evidence also indicates that increasing modeling sophistication systematically intensifies technological requirements. As models attempt to incorporate higher levels of structural detail, uncertainty, and integration across SC echelons, their computational burden grows disproportionately, making technological capacity a binding constraint [10,144]. In this context, the issue is no longer solely whether exact methods fail and heuristics succeed, but whether the adopting organization's technological environment can sustain the level of sophistication embedded in the model. Advanced prescriptive and hybrid AI-OR architectures often require scalable computing infrastructure, high-quality data pipelines, and interoperability across the enterprise systems [20,53]. When such conditions are absent, even theoretically robust models become impractical, not because of modeling weakness but

Table 4
Proposed systematization of barrier categories identified in the literature.

Category	Subcategory	Barrier
Organizational (O)	Organizational culture	(1) Organizational resistance (2) Misaligned organizational culture
	Infrastructure	(1) Lack of infrastructure in the organization
	Coordination and information sharing	(1) Lack of institutional coordination (2) Lack of stakeholder collaboration
	Financial resources	(1) High implementation cost
	Human capital capabilities	(1) Need for expertise (2) Training requirement
Technological (T)	Lack of adequate technology	(1) Need for specific technology
	Integration and interoperability	(1) Non-integrative technology (2) Lack of system interoperability
	Computational complexity	(1) High computational time (2) Scalability
Data (D)	Availability	(1) Lack of data (2) Insufficient data
	Quality	(1) Poor quality data (2) Inconsistencies in the data from different sources (3) High data variability
	Representativeness	(1) Insufficient temporal granularity
Modeling (M)	Representation of reality	(1) Simplified model (2) High complexity of the real environment (3) Modeling complexity
	Stability and robustness	(1) Parameter sensitivity (2) Solution instability (3) Low accuracy
	Transparency	(1) Black-box approaches
	Applicability	(1) Low generalization (2) Lack of practical validation (3) Impractical solution in the real world
Regulatory and ethical (R/E)	Legal barriers/compliance	(1) Legal issues (2) Concerns with regulatory compliance (3) Data privacy and security concerns
	Ethical	(1) Ethical issues
People (P)		(1) Intuition-based and experience-driven decision logic
		(2) Low trust and acceptance of analytics to support decision-making Cognitive and behavioral resistance to analytics integration

because of infrastructural misalignment. This reveals a structural imbalance: modeling ambition often advances faster than organizational technological readiness. As analytical ecosystems become more integrated and data-intensive, the feasibility of implementation depends less on algorithmic design alone and more on the alignment between model complexity and technological capacity. Thus, effective deployment requires aligning modeling sophistication with infrastructure maturity, ensuring that computational intensity and system integration demands remain proportionate to the organization's technological capabilities [1].

7.1.2. Data enrichment vs. model robustness

Data availability and quality constitute structural constraints in many SC contexts, directly affecting the robustness of analytical models. Advanced predictive and prescriptive approaches typically assume access to large, consistent, and granular datasets. However, real-world SC environments are often characterized by data separation, heterogeneous storage formats, limited interoperability, and uneven analytical governance structures [74]. This misalignment between modeling requirements and data reality weakens model stability and limits the reliability of analytical outputs. To address data scarcity, studies often use synthetic data generation or transfer learning [145]. Although these strategies mitigate data scarcity, the literature highlights associated risks, including overfitting, instability, sensitivity to hyperparameters, and limited generalization, particularly in small-data regimes [119]. Thus, data enrichment strategies interact with model robustness. In particular, expanding datasets may improve apparent model performance while simultaneously increasing structural distortions if assumptions remain insufficiently validated. In prescriptive analytics, robustness depends not only on data volume but also on data integrity, consistency, and traceability. Enhancing these dimensions typically requires standardizing processes, integrating systems, and redesigning governance [53]. Such efforts entail financial investment and organizational restructuring, revealing a trade-off between strengthening data foundations and intensifying organizational and economic constraints. This interaction highlights a critical balance: initiatives to enrich data resources can enhance analytical performance, yet without corresponding governance maturity, they risk undermining modeling robustness and managerial trust. Effective implementation, therefore, depends on aligning data expansion efforts with validation mechanisms and organizational capacity, ensuring that improvements in data inputs translate into robust analytical outcomes [18].

7.1.3. Regulatory constraints vs. data-driven integration

Regulatory and ethical constraints exert a cross-cutting influence on data-driven SC integration, shaping how data are collected, shared, and used. Advanced predictive and prescriptive models rely on granular, multi-actor datasets to improve accuracy and decision quality [90]. However, increased data integration across SC partners intensifies exposure to privacy risks, cybersecurity vulnerabilities, and compliance obligations [59].

Table 5
Structural relationships identified among the six barrier categories.

Compatibilities	Simultaneous improvement of two or more dimensions without a distinguishable loss of performance between them [141]	
Paper	Relationship[a]	Description
[58,59,70,73]	T → D	Improving technological capabilities enhances data access, sharing, and availability
[58]	D → M	Higher-quality data leads to more accurate and robust models
[52,56,59,60]	O → D	Improving organizational coordination ensures more consistent data across partners
[67,81]	T → M	Greater computational capacity enables the implementation of more complex analytical models.
[43,85,91]	P → M	Human expertise enhances model interpretation, acceptance, and practical utilization.
[58,91]	O → P	A supportive organizational culture facilitates capability development and the adoption of analytics.
Interdependencies	Improvement in one dimension requires the concurrent development of another dimension [141]	
Paper	Relationship	Description
[50,58]	O ↔ T	Technological investments require complementary organizational adaptation and support.
[43,91]	O ↔ M	The adoption of new analytical models requires complementary organizational adaptation and support
[89,93]	D ↔ M	Analytical models depend on data inputs, while model requirements determine data needs
[60]	T ↔ R/E	Regulatory and ethical requirements influence technological design and implementation choices
[60]	M ↔ R/E	Regulatory constraints shape model formulation, assumptions, and applicability
[58,59]	P ↔ T	Technological advancement and human capabilities evolve jointly and reinforce one another
Trade-offs	Improvement in one dimension is achieved at the expense of lower performance in another dimension [141]	
Paper	Relationship	Description
[50,58]	T → O	Technological advancement often requires substantial organizational investments and associated costs
[51,82,142]	M → T	Increased model realism leads to higher computational complexity and resource requirements
[43,57]	M → P	More sophisticated models require higher levels of analytical expertise.
[43]	M → D	Increased model realism requires more extensive and detailed data
[43,57]	M → P	Increased model sophistication may reduce interpretability and user understanding
[58,59]	D → R/E	Increased data sharing and integration create privacy, security, and compliance challenges.

[a] T: Technological; D: Data; M: Modeling; O: Organizational; P: People; R/E: Regulatory/Ethical.

A structural trade-off therefore arises between analytical performance and regulatory conformity. Expanding data accessibility strengthens predictive and prescriptive capabilities but also increases legal and ethical exposure. Data sharing is often limited by confidentiality concerns and regulatory requirements, which constrain the scope of integration and reduce model comprehensiveness [59]. While governance frameworks, anonymization strategies, or alternative modeling architectures may mitigate these risks, they introduce additional technological complexity, organizational coordination requirements, and financial costs [59]. These interactions illustrate that regulatory constraints do not merely operate as external limitations but also actively reshape model design and data strategies. Efforts to maximize analytical depth may conflict with compliance requirements, while strict regulatory adherence can limit data richness and scalability. The balance between data-driven integration and regulatory accountability thus becomes a central design consideration, influencing not only model feasibility but also long-term acceptance and trustworthiness of analytics in SCM [43].

7.1.4. Modeling issues trade-offs: explainability vs. model performance

A recurring tension in SCM analytics concerns the balance between explainability and analytical performance. Decision-making in supply chain environments often involves multiple stakeholders, regulatory oversight, and cross-functional accountability. Under such conditions, low-explainability "black-box" models may face resistance because decision makers may struggle to understand, justify, or audit model-driven recommendations [116]. Explainability, therefore, becomes an important condition for organizational trust, accountability, and adoption. Prior studies have shown that, in some applications, more complex models may achieve higher predictive performance while providing limited transparency, creating potential tensions between interpretability and model effectiveness [116]. However, this relationship is not deterministic. Recent advances in explainable AI and neuro-symbolic approaches demonstrate that predictive performance and explainability can often be pursued simultaneously, reducing the need to treat them as inherently conflicting objectives [100]. Consequently, the challenge for organizations is not choosing between accuracy and explainability per se but identifying an appropriate balance that aligns analytical performance with governance, regulatory, and decision-making requirements. Model selection, therefore, is both a technical and a governance decision. In highly regulated or risk-sensitive contexts, explainability may be prioritized to facilitate accountability, stakeholder acceptance, and model adaptability, whereas in operational settings, predictive performance may receive greater emphasis, provided that appropriate mechanisms exist to interpret, monitor, and validate model outputs. Effective implementation, therefore, depends on aligning model complexity, transparency requirements, and organizational objectives to ensure that analytical insights remain actionable and trustworthy [43].

7.1.5. Analytical complexity vs. human capabilities

People emerge as structural constraints on SCM analytics adoption, interacting with modeling, technological, data, and organizational dimensions. Human capabilities and behavior influence not only model development but also interpretation, validation, and long-term operationalization. As analytical systems become more sophisticated, the cognitive and technical demands on organizations rise accordingly [138].

A central trade-off arises between analytical complexity and human readiness. Advanced prescriptive, hybrid AI-OR, and machine learning models enhance predictive accuracy and solution performance, yet they require specialized technical, analytical, and interpretive skills to translate business problems into formal structures and to contextualize the outputs [20]. Although automation is often presented to reduce reliance on human expertise, empirical evidence indicates that skilled professionals remain critical throughout the analytical lifecycle, particularly where regulatory, financial, or infrastructural constraints prevent full automation [146]. Rather than replacing human expertise, automation shifts its role towards higher-value analytical and decision-support activities. This trade-off is reinforced by strong interaction effects across barrier categories. Technological infrastructure yields limited value when users lack the capability to configure or interpret systems effectively [53]. Conversely, insufficient technological maturity limits opportunities for skill development [58], generating negative complementarities between human and technological readiness. Data-related processes, such as governance, validation, and integration, also depend heavily on human judgment, so limited analytical literacy can exacerbate data quality challenges and undermine trust in model outputs. Opaque, high-performing models may encounter resistance when interpretability is low [116].

These interdependencies suggest that analytical ambition must remain aligned with organizational human capital. Increasing model sophistication without a parallel investment in skills development risks undermining implementation, even when data and technological conditions appear favorable.

7.2. From isolated barriers to holistic maturity

The identified trade-offs demonstrate that analytics adoption cannot be conceptualized as simply eliminating isolated barriers. Instead, implementation reflects a holistic balancing process across interdependent dimensions, including technological readiness, organizational alignment, data governance maturity, modeling feasibility, regulatory compliance, and human capabilities and behavior [20]. Weakness in any single dimension may constrain overall performance, even when other conditions appear favorable, because of reinforcing interactions across barriers.

The prevalence of prescriptive, methodologically sophisticated models in the literature signals significant analytical progress. However, methodological advancement alone does not ensure effective implementation. Organizational maturity is compromised when advances in modeling sophistication are not matched by proportional development of technological infrastructure, governance mechanisms, regulatory coherence, and absorptive human capabilities [118], generating structural asymmetries between analytical potential and institutional preparedness. These imbalances can reduce scalability, undermine trust, and limit long-term adoption.

This interpretation aligns with empirical evidence indicating that analytics generates performance effects only when it is fully assimilated through organizational routines and managerial orchestration, rather than merely adopted at a technical level [147]. Accordingly, analytics maturity should be understood as a holistic capability rather than a purely technical achievement.

7.3. Bridging conceptual barriers and real-world implementation: insights from grey literature

The integration of grey literature reinforces and extends the academic review's findings by providing practice-oriented evidence on barriers to the adoption of analytics in SCM. While academic literature conceptualizes adoption as a holistic process shaped by interdependent barriers, the grey literature confirms that these constraints are pervasive in real-world organizational settings and become particularly critical during implementation and scaling.

7.3.1. Convergences with academic literature

A strong convergence emerges on the multidimensional nature of barriers. The six category taxonomy proposed in this study (organizational, technological, data-related, modeling, regulatory and ethical, and people-related) is consistently reflected in reports from Deloitte [148,149], Gartner [150,151], OECD [152,153], IBM [154], IDC [155], Accenture [156], KPMG [157], McKinsey [158,159], and BCG [160]. These sources highlight a combination of skill shortages, weak strategic alignment, fragmented infrastructure, data limitations, governance gaps, and organizational resistance, reinforcing the interpretation that analytics adoption depends on coordinated development across multiple structural dimensions rather than on analytical sophistication alone. In particular, the grey literature places strong emphasis on organizational and people-related constraints, which often emerge as the dominant limiting factors. The lack of skills limited analytical literacy, weak leadership support, and insufficient management capabilities are repeatedly identified as critical barriers [149,154,156,157]. These findings reinforce the argument developed in this study that human and organizational factors shape not only the adoption decision but also the interpretation, acceptance, and operational use of analytical outputs.

Technological and data-related constraints also align strongly across both literatures. Integration challenges, data silos, poor data quality, and insufficient infrastructure are consistently reported as limiting factors that constrain model applicability and scalability [149,152, 154,155,160,161]. These observations support the structural role of data governance, interoperability, and technological readiness that this study highlights. Similarly, regulatory, ethical, and governance-related issues, such as privacy, security, compliance, and trust, are identified as key constraints affecting both feasibility and organizational acceptance [154,156–159], reinforcing their classification as structural barriers.

7.3.2. Extensions from grey literature

The grey literature offers additional insights that deepen the analysis of trade-offs and interdependencies. In fact, it emphasizes the pilot-to-scale gap, highlighting that organizations often initiate analytics or AI projects but struggle to embed them in operational processes and generate sustained value (Deloitte, [149]; McKinsey, [158]; BCG, [160]; MIT NANDA, [162]; KPMG, [157]). This observation complements the gap identified in the academic literature between model development and real-world implementation by showing that the key challenge lies in scaling, integration, and organizational transformation rather than in initial technical feasibility. A second important extension concerns the role of value capture and return on investment (ROI) uncertainty. Practitioner sources consistently report difficulties in defining, prioritizing, and measuring the value generated by analytics initiatives (Deloitte, [148]; BCG, [160]; McKinsey, [158,159]). This suggests that financial ambiguity acts as a cross-cutting constraint, weakening strategic alignment, limiting investment, and reducing organizational commitment, thereby reinforcing multiple barrier categories simultaneously. In this sense, ROI uncertainty can be interpreted as a practical manifestation of deeper structural misalignment across organizational, technological, and data-related dimensions. Furthermore, grey literature highlights the importance of workflow integration and process redesign, indicating that analytics solutions fail when they are

Table 6
Barriers to the adoption of analytics approaches, based on grey literature (GL) sources and cross-checked against the academic literature (AL).

Barrier	AL	GL	Source
Lack of skills, talent, and analytical/AI literacy	X	X	Deloitte [148,149]; Gartner [150,151]; OECD [152,153]; IBM [154]; IDC [155]; Accenture [156]; KPMG [157]; McKinsey [158,159]; BCG [160]; ASML [164]; Walmart [165]
Difficulty in scaling pilot projects to production		X	Deloitte [149]; Gartner [151]; McKinsey [158,159]; MIT NANDA [162]; KPMG [157]; BCG [160]; Walmart [165]
Lack of a clear strategy and organizational alignment		X	Deloitte [148,149]; Gartner [151]; McKinsey [158,159]; BCG [160]; IBM [154]; KPMG [157]; Walmart [165]
Difficulty in measuring value and return on investment (ROI)		X	Deloitte [148,149]; McKinsey [158,159]; BCG [160]; KPMG [157]
High costs of implementation, maintenance, and scaling	X	X	Deloitte [149]; OECD [152,153]; IBM [154]; McKinsey [158]; IDC [155]; AWS [161]; Accenture [156]; KPMG [157]; Walmart [165]
Insufficient digital infrastructure	X	X	Deloitte [149]; OECD [152]; AWS [161]; DHL [166]; ASML [164]; Maersk [163]; Walmart [165]
Challenging integration with existing and legacy systems.	X	X	Deloitte [149]; Gurobi [167]; IBM [154]; AWS [161]; BCG [160]; DHL [166]; Maersk [163]; IDC [155]; MIT NANDA [162]; Walmart [165]
Data silos and a lack of end-to-end integration	X	X	AWS [161]; KPMG [157]; Maersk [163]; Deloitte [149]; OECD [152]
Challenges related to data access, quality, and preparation	X	X	Deloitte [148,149]; OECD [153]; Gurobi [167]; McKinsey [158]; BCG [160]; IBM [154]; IDC [155]; KPMG [157]; AWS [161]; Accenture [156]; Walmart [165]
Lack of data and AI governance	X	X	Deloitte [148,149]; IBM [154]; McKinsey [158,159]; KPMG [157]; Accenture [156]; IDC [155]
Privacy, security, and compliance	X	X	Deloitte [149]; OECD [152,153]; IBM [154]; McKinsey [158,159]; AWS [161]; Accenture [156]; KPMG [157]; Maersk [163]; Walmart [165]
Lack of trust in outputs	X	X	Accenture [156]; KPMG [157]; IDC [155]; IBM [154]; McKinsey [158]; Deloitte [149]
Organizational and cultural resistance to change	X	X	Gartner [150,151]; Deloitte [148]; McKinsey [158]; MIT NANDA [162]; Accenture [156]; KPMG [157]; AWS [161]; Walmart [165]
Lack of executive sponsorship and leadership		X	Deloitte [148]; MIT NANDA [162]; KPMG [157]
Need for process and workflow redesign		X	Gartner [150]; MIT NANDA [162]; McKinsey [158]; AWS [161]; Maersk [163]
Dependence on the digital maturity of partners and the broader ecosystem	X	X	Gartner [150]; AWS [161]; DHL [166]; Maersk [163]; ASML [164]; Walmart [165],
Technological and computational complexity.	X	X	Gurobi [167]; Deloitte [149]; Accenture [156]; ASML [164]; AWS [161]; Walmart [165]
Challenges in UX, user adaptation, and integration into workflows	X	X	MIT NANDA [162]; IDC [155]
Regulatory uncertainty and difficulty in interpreting digital legislation	X	X	OECD [152]; [153]; KPMG [157]; IBM [154]
External pressures and contextual volatility		X	Gartner [150]; DHL [166]; Maersk [163]; ASML [164]; Walmart [165]

AL — Academic literature; GL — Grey literature.

not aligned with operational routines, user requirements, and decision-making processes (Gartner, [150]; AWS, [161]; Maersk, [163]). This provides a more operational interpretation of the applicability and organizational alignment challenges identified in this study, emphasizing that implementation success depends on embedding analytics into existing workflows rather than treating it as a standalone technological barrier.

To further consolidate evidence from grey literature and provide a structured overview of the main barriers identified in practitioner-oriented sources, Table 6 summarizes these barriers, their categorization, and the supporting references.

Taken together, these findings suggest that certain barriers operate as cross-dimensional leverage points, influencing multiple dimensions of the adoption process simultaneously. Rather than introducing entirely new barrier categories, the grey literature reveals recurring cross-cutting implementation dynamics including: (i) skills and analytical literacy gaps, (ii) scaling analytics initiatives beyond pilot stages, (iii) data and integration limitations, (iv) strategic alignment and governance weaknesses, and (v) uncertainty regarding value realization and trust.

7.3.3. Integrated multi-layer framework for analytics adoption in SCM

Building on the taxonomy and the complementary grey literature analysis, this study proposes a multi-layer conceptual framework for analytics adoption in SCM. The taxonomy developed from the systematic literature review primarily captures the capability conditions required for implementation, including organizational, technological, data-related, modeling, regulatory and ethical, and people-related capabilities. These dimensions indicate what must be in place for analytics methods to be adopted in practice. However, the complementary grey literature analysis highlighted two additional dimensions that are less visible in academic literature. First, analytics adoption must be strategically aligned with organizational objectives and linked to value creation and value measurement. Second, adoption must move beyond pilot development towards operational scalability, workflow integration, and effective use in routine decision-making. Accordingly, the

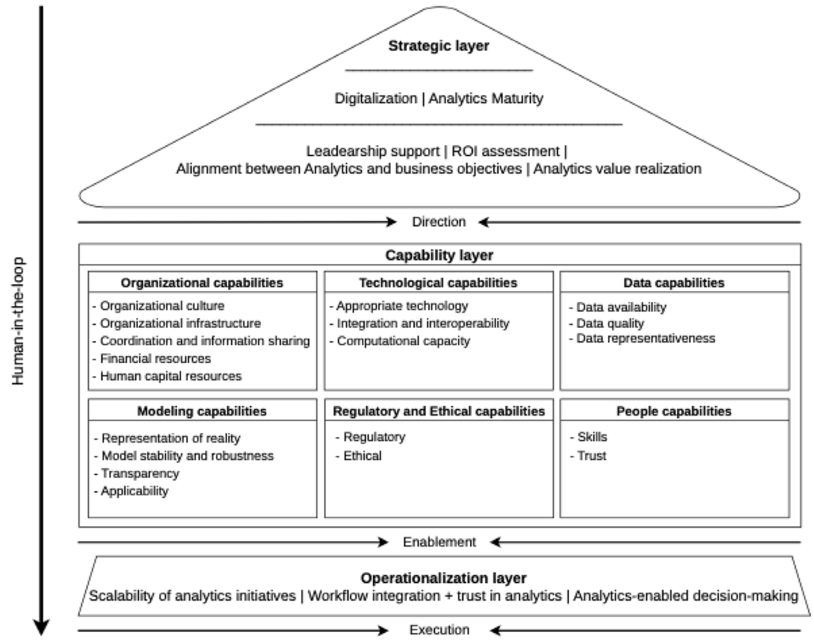

Fig. 11. Multi-layer framework for analytics adoption in supply chain management.

proposed framework organizes analytics adoption into three interrelated layers: strategic, capability, and operationalization (Fig. 11).

Strategic layer. The strategic layer represents the directional and value-oriented dimensions that guide analytics adoption within organizations. It encompasses elements such as digitalization strategy, analytics maturity, leadership support, alignment between analytics and business objectives, and the realization of analytics value [149,150]. This layer reflects the extent to which analytics initiatives are embedded within organizational priorities and long-term decision-making processes [158]. The findings suggest that analytics adoption depends not only on technological feasibility but also on strategic coherence and organizational commitment.

Capability layer. The capability layer represents the organizational capabilities required to enable analytics adoption. It is structured around six capability dimensions derived from the taxonomy developed in this study: organizational, technological, data, modeling, regulatory and ethical, and people capabilities. These dimensions capture the foundational conditions necessary to develop, integrate, and sustain analytics solutions in practice. Rather than representing isolated barriers, this layer conceptualizes the organizational readiness needed to support analytics implementation across different functional and operational contexts.

Operationalization layer. The operationalization layer translates analytical capabilities into effective organizational use. It captures the extent to which analytics solutions are integrated into workflows, scaled beyond pilot initiatives, and embedded in routine decision-making practices [154,159,160]. The findings indicate that many analytics initiatives fail not during model development but during operational deployment and organizational integration [162]. Consequently, successful adoption depends not only on analytical performance but also on the ability to operationalize analytics within existing processes, systems, and decision structures.

8. Managerial implications and future work

8.1. Implications for decision-makers

Our findings provide structured insights for decision-makers seeking to operationalize advanced analytics in SC contexts. Our results provide evidence that analytics adoption should not be framed as a purely technological investment but as a holistic organizational transformation process that requires alignment across modeling sophistication, technological infrastructure, data governance maturity, regulatory compliance, and human capabilities and behavior [147]. When methodological ambition advances without parallel institutional development, implementation asymmetries may emerge, reducing scalability and limiting realized value.

From a strategic perspective, analytics initiatives should be aligned with broader organizational priorities and long-term value objectives rather than driven solely by technological trends or methodological sophistication. The findings suggest that many organizations struggle not with technical feasibility itself, but with defining how analytics initiatives create operational and strategic value within SC processes [149,158,160]. Establishing clear objectives, governance structures, and alignment between analytics initiatives and business priorities may therefore be essential to improve scalability, organizational commitment, and long-term impact.

Model selection decisions should therefore be contingent on organizational readiness rather than methodological novelty. While the integration of descriptive, predictive, and prescriptive analytics, combining artificial intelligence techniques with simulation and optimization models, enhances data-driven decision-making capabilities and supports SC resilience [20,53], their successful deployment depends on the feasibility of integration, interpretability requirements, computational scalability, and long-term maintainability within existing systems. In many SC environments, analytically robust and interpretable solutions may be more sustainable than highly complex but opaque architectures, particularly where accountability and stakeholder trust are central [43].

Data governance is a foundational enabler of analytics maturity. Fragmented information systems and weak interoperability structures not only constrain model robustness but also increase exposure to regulatory and cybersecurity risks [59]. Strengthening data traceability, standardization, and cross-partner integration enhances both analytical reliability and compliance resilience. At the same time, sustained investment in human capital, through analytical literacy development, interdisciplinary collaboration, and change management, remains essential to ensure that technological capabilities translate into effective decision-making practices [58].

Our findings also suggest that organizations should pay greater attention to the operationalization of analytics initiatives. Many analytics projects demonstrate technical feasibility during pilot stages but struggle to achieve scalable deployment due to integration challenges, process misalignment, unclear mechanisms for value realization, and insufficient organizational absorption capacity [149,158,160,162]. Embedding analytics into operational workflows, therefore, requires not only technological readiness but also process redesign, cross-functional coordination, governance structures, and continuous organizational adaptation.

Taken together, these implications indicate that competitive advantage through analytics is less a function of algorithmic sophistication alone and more a reflection of balanced capability development across interdependent strategic, technological, organizational, and operational dimensions.

8.2. Implications for researchers

Future research should move beyond isolated evaluations of analytical methods and focus on the interdependent conditions required to adopt sustainable analytics in real-world SC contexts. Although the literature demonstrates significant advances in prescriptive analytics and AI-enabled predictive approaches [19,168], prior review studies have consistently highlighted the fragmented nature of research on analytics adoption across diverse SC environments [169,170]. The findings of this study suggest that implementation success depends less on methodological sophistication alone and more on the organization's ability to strategically align, operationalize, and institutionalize analytics within existing workflows and decision-making structures.

From a strategic perspective, future studies should further investigate how organizations govern, prioritize, and capture value from analytics initiatives. Elements such as leadership support, digitalization strategy, analytics maturity, ROI assessment, and alignment between analytics initiatives and business objectives remain comparatively underexplored despite their central role in shaping organizational commitment and long-term resource allocation. Greater attention is therefore needed to the mechanisms through which analytics initiatives generate operational and strategic value, as well as the organizational conditions that enable sustained value realization over time [149,158,160].

Future research should also examine how organizations transition from pilot initiatives to large-scale operational deployment. Practitioner-oriented studies indicate that many analytics initiatives fail not during model development, but during process integration, scalability, cross-functional coordination, and long-term organizational embedding [149,158,160,162]. Greater empirical attention is therefore needed regarding workflow integration, organizational absorption capacity, operational redesign, and the institutionalization of analytics within SC processes and routines. Moreover, further research is needed on the dynamic interactions and trade-offs among technological infrastructure, data governance, modeling sophistication, regulatory compliance, and people-related capabilities. Rather than treating these dimensions as independent variables, future studies should conceptualize them as interdependent capabilities that collectively determine operational feasibility, scalability, and long-term sustainability. This is particularly important given the practical integration constraints and organizational limitations highlighted in recent SCM analytics studies [171]. Further research is also needed on hybrid analytical architectures that balance predictive accuracy, prescriptive capability, interpretability, and operational feasibility. Rather than maximizing predictive performance in isolation, future studies should address the practical constraints, data limitations, explainability requirements, and organizational integration challenges associated with real-world SC environments

Furthermore, advancing the empirical validation of the proposed taxonomy is essential. Future research should rigorously examine its robustness, applicability, and explanatory power across different industries, levels of analytical maturity, and SC configurations. Such efforts would not only assess its generalizability but also refine its dimensions and strengthen its theoretical and practical relevance.

Finally, advancing SCM analytics ultimately requires stronger cross-disciplinary integration. Bridging operations research, artificial intelligence, information systems, and organizational theory will enable the development of holistic frameworks capable of capturing the structural interdependencies identified in this study [118]. Such integration is essential to shift the discourse from isolated methodological advancements towards holistic maturity in analytics.

9. Conclusion

This study provides an overview of barriers to the adoption of analytics in SCM. While prior reviews have primarily focused on methodological advancements and application domains, this study shifts the analytical lens towards the structural conditions that constrain real-world implementation. By conceptually distinguishing between intrinsic SC complexity, methodological limitations, and structural implementation barriers, the study clarifies what constitutes an effective obstacle to analytics adoption. We propose an extended taxonomy comprising six interrelated barrier categories: organizational, technological, data-related, modeling, regulatory and ethical, and people-related.

Although comparative analyses have reported substantial overlap between Scopus and Web of Science, with Scopus covering most journals indexed in Web of Science within these disciplines, thereby reducing the likelihood of omitting highly relevant studies [172], relying on a single database may have excluded studies indexed exclusively in other sources (e.g., Web of Science or ABI/INFORM), particularly older publications or specialized regional journals. This limitation is acknowledged and should be considered when interpreting our findings.

Our findings reveal a pronounced dominance of prescriptive and OR approaches in the literature, reflecting substantial methodological progress. However, the analysis of trade-offs shows that increased analytical sophistication often amplifies exposure to multiple structural constraints. Implementation success, therefore, depends not solely on modeling capability but also on balanced development across technological readiness, data governance maturity, organizational alignment, regulatory compliance, and human capabilities and behavior. Rather than viewing barriers as isolated impediments, this study conceptualizes the adoption of analytics as a holistic process of balancing interdependent dimensions characterized by trade-offs, compatibilities, and reinforcing interactions.

We further propose a multilayered adoption framework that integrates strategic alignment, organizational and technological capabilities, and operationalization challenges. While the proposed taxonomy identifies the core categories of implementation barriers, the framework explains how these barriers interact across different layers of the adoption process, influencing scalability, integration into operational routines, and long-term value realization. In this sense, analytics adoption is conceptualized not merely as a technical implementation problem but as an organizational transformation process that requires simultaneous alignment among strategic priorities, capability development, and operational execution.

We argue that improving analytics adoption in SCM depends not only on modeling innovation but also on aligning analytical design with organizational realities. By systematically identifying implementation barriers, examining their interdependencies and trade-offs, and proposing an integrated adoption framework, this study helps bridge the gap between analytical research and sustainable real-world deployment in SCM contexts.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors used ChatGPT (OpenAI, GPT-5.2) to assist with language editing and clarity improvement. The tool was used solely for linguistic refinement. All content was critically reviewed and approved by the authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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