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# Bridging Project Management and Supply Chain Management via Optimization Method: Scenarios, Technologies, and Future Opportunities

**Liwen Zhang [1], Wanyang Zhao [1], Mingjuan Fang [1], Keke Yuan [1], Sijie Cheng [1], Wenjia Jia [1] and Libiao Bai [1,2,3,*]**

[1] School of Economics and Management, Chang'an University, Xi'an 710064, China; liwenzhang@chd.edu.cn (L.Z.); zhaowy@chd.edu.cn (W.Z.); mj.fang@chd.edu.cn (M.F.); kk.yuan@chd.edu.cn (K.Y.); sj.cheng@chd.edu.cn (S.C.); jiawenjia@chd.edu.cn (W.J.)
[2] Center for Green Engineering and Sustainable Development, Chang'an University, Xi'an 710064, China
[3] Xi'an Key Laboratory of Green Infrastructure Construction and Operation, Xi'an 710064, China
* Correspondence: lb.bai@chd.edu.cn

**Abstract**

Organizations increasingly face challenges in aligning project management and supply chain management, as project success relies on reliable supply chains while supply chain resilience hinges on effective project coordination. Despite the growing recognition of this interdependence, research remains fragmented, with most studies treating PM and SCM in isolation, limiting systematic theorization and practical guidance for integration. Addressing this gap, this review examines how optimization methods can facilitate PM–SCM integration. Through a comprehensive bibliometric analysis, incorporating co-citation, keyword co-occurrence, and cluster analysis, the study maps the intellectual structure, thematic evolution, and diverse applications of optimization within both domains. The findings uncover key trends, showing that optimization provides a methodological foundation for managing complexity and uncertainty across diverse integration scenarios, including project scheduling, resource allocation, and supply chain coordination. It further reveals that emerging technologies extend these optimization approaches by enabling real-time prediction, improved transparency, and adaptive decision-making. Theoretically, the study reframes PM and SCM as interdependent components of an adaptive system, offering a concrete and analytically tractable framework for operationalizing integration. Practically, it outlines strategies for strengthening cross-domain coordination and risk management through optimization-enabled solutions. By consolidating fragmented research, this review not only synthesizes the evolution of optimization in PM–SCM contexts but also identifies critical future opportunities, emphasizing the development of scenario-specific models, technology-driven integration mechanisms, and resilience-oriented strategies to enhance performance in project-intensive settings.

**Keywords:** project management; supply chain management; optimization methods; bibliometric analysis; management integration

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## 1. Introduction

Organizations across various industries face escalating challenges in coordinating projects and supply chains. Infrastructure and energy projects often suffer delays and cost

overruns due to an unreliable supply of critical materials [1]. Manufacturing firms experience downtime on assembly lines when production schedules misalign with component availability, creating cascading delays across the supply chain [2]. In healthcare, timely replenishment of equipment and pharmaceuticals requires coordination across procurement, logistics, and clinical operations projects [3]. In the service and fast-moving consumer goods industries, projects such as product launches or store openings inevitably trigger adjustments in sourcing, distribution, and inventory strategies, with supply chain agility depending on the simultaneous execution of multiple projects, ranging from marketing campaigns to logistics upgrades [4]. Collectively, these cases demonstrate that project success is profoundly influenced by supply chain reliability, while supply chain resilience hinges on effective project planning and coordination. This interdependence highlights that project management (PM) and supply chain management (SCM), though traditionally studied as separate domains, are, in practice, tightly intertwined. Project-intensive industries, such as aerospace [5], energy [6], and large-scale construction [7], carry national and sectoral strategic objectives. In these domains, the interdependence between PM and SCM is particularly pronounced. This interdependence extends beyond the coordination of limited timelines and scarce resources to encompass broader societal goals, thereby reinforcing the necessity of integration and driving the demand for integrated management practices. Integration is no longer optional but a critical prerequisite for ensuring operational efficiency, adaptability, and long-term success.

Despite increasing recognition of their interdependence, research on PM–SCM integration remains fragmented. Existing studies typically examine the two domains in isolation, yielding insights that lack theoretical coherence and contain limited practical guidance. This fragmentation has impeded the development of a unified framework capable of explaining how PM and SCM can operate as a cohesive system. Addressing this requires approaches that move beyond conceptualization toward systematic and operational methodologies for integration. For clarity, PM refers to the structured process of integrating knowledge, tools, and resources to achieve project objectives across the full life cycle [8], while SCM focuses on the coordinated optimization of value-chain activities to ensure efficient flows of materials, information, and finance [9,10]. Optimization provides a promising pathway by enabling structured modeling, efficient resource allocation, and informed decision-making under complexity and uncertainty [11]. Emerging technologies, such as artificial intelligence, blockchain, and digital twins, further amplify this potential by supplying data-driven tools for coordination, prediction, and adaptability [12]. Together, these advances underscore PM–SCM integration as both a practical imperative and a fertile domain for scholarly inquiry [13].

Drawing on this foundation, this review aims to explore how optimization methods can facilitate strengthening the connections between PM and SCM, two domains that have largely evolved in parallel with limited cross-fertilization. Previous syntheses rely mainly on qualitative discussion, lacking bibliometric analyses that can expose the field's structure, evolution, and research frontiers. To address this need, this review integrates optimization research across PM and SCM, incorporates the technological dimension, and employs a bibliometric approach to map the research landscape, tracing the evolution of key themes, identifying influential contributors and collaboration patterns, and clarifying how optimization has been applied and where opportunities for closer alignment may emerge. A comprehensive analysis, encompassing thematic developments, methodological applications, and collaboration structures, would not only contextualize the intellectual landscape of PM–SCM optimization but also highlight the mechanisms through which scholarly communities and interdisciplinary exchanges drive integration forward. First, we provide a comprehensive bibliometric synthesis of optimization research in PM and SCM,

revealing the core themes and their evolution. Second, we demonstrate how optimization methods have been applied across diverse scenarios, while underscoring the enabling role of emerging technologies, such as artificial intelligence (AI), blockchain, and digital twins, in enhancing coordination, prediction, and adaptability. Thirdly, we identify promising future opportunities while offering an integrative perspective to guide both scholarly inquiry and managerial practice in advancing PM–SCM integration. In line with these efforts, this review directly addresses two core objectives:

- Conduct a comprehensive bibliometric synthesis of optimization research in PM and SCM, mapping key themes, methodological applications, and their evolution;
- Identify future research opportunities and practical directions by exploring how optimization methods, along with emerging technologies can advance PM–SCM integration.

Beyond its stated objectives, this review distinguishes itself through methodological rigor and an integrative perspective. Methodologically, it combines quantitative bibliometric mapping with qualitative synthesis, thereby ensuring not only reliability and comprehensiveness but also facilitating the development of an analysis framework for understanding how optimization supports PM–SCM integration and identifying underexplored research directions. Conceptually, it moves beyond single-domain syntheses by jointly examining PM and SCM, thereby uncovering interactions and complementarities often overlooked when the two fields are studied in isolation. Taken together, these features position the review as both a comprehensive mapping of optimization research and a forward-looking lens for understanding and advancing the dynamics of PM–SCM integration.

This research provides significant contributions both theoretically and practically. Theoretically, it reframes PM and SCM as interdependent components of an adaptive system, moving beyond isolated perspectives and positioning integration as a critical mechanism for enhancing resilience and sustainability in project-intensive contexts. It also advances integration from a vague notion to a tangible and analytically tractable construct, enabling a systematic understanding of how integration can be operationalized in complex management environments. Practically, the review offers actionable insights for organizations operating in dynamic, project-based settings. Strengthening PM–SCM integration helps managers coordinate resources, schedules, and risks across organizational boundaries. In addition, the study highlights the potential of combining advanced optimization methods with emerging technologies to improve transparency, predictive capability, and decision-making. These insights provide practical guidance for balancing short-term efficiency with long-term adaptability in uncertain and competitive markets.

To synthesize the focus of this study, three key elements are outlined.

**Employ and integrate research methodologies:**

This review combines a bibliometric review with thematic analysis to capture the research landscape, trace the evolution of optimization methods, and synthesize insights into a structured framework that connects optimization, PM, and SCM.

**Answer the following research questions:**

- What is the current state of research on optimization in the domains of PM and SCM, and how has it evolved over time?
- How can optimization approaches, in combination with emerging technologies, contribute to systematic PM–SCM integration?
- What research gaps and opportunities remain for future scholarly inquiry and managerial practice?

**Ultimately generate threefold contributions:**

- Provides the first comprehensive bibliometric mapping of optimization research in PM and SCM, thereby identifying key themes, methodological applications, and their intellectual structure.
- Further clarifies the mechanisms through which optimization and emerging technologies enable integration, advancing both theoretical understanding and managerial practice.
- Identifies research gaps and future directions, providing a roadmap for scholars and practitioners seeking to enhance PM–SCM integration.

The remainder of this paper is organized as follows. Section 2 provides a review of the relevant literature and establishes the conceptual background for the study. Section 3 introduces the research methodology. Sections 4–6 present the analytical findings on PM–SCM integration, optimization techniques, and enabling technologies. Section 7 discusses the theoretical and practical implications, and Section 8 concludes with a summary of contributions, limitations, and future research directions.

## 2. Background

### *2.1. Project Management*

Project management (PM) refers to the structured approach of applying knowledge, skills, tools, and techniques to allocate limited resources and accomplish specific objectives efficiently [14]. According to the Project Management Institute (PMI), it involves guiding project activities to meet defined requirements through a systematic process [8]. PM spans the entire project life cycle, encompassing five key processes, including initiation, planning, execution, monitoring, and closure. These processes are supported by eight performance domains, such as stakeholders, team, development methodology, lifecycle, etc., forming a tailorable system for project value delivery [14]. Ultimately, effective project management ensures alignment with organizational strategy and enhances the realization of business goals. As shown in Figure 1, PM comprises three essential elements. First, PM is characterized by goal orientation, requiring strict alignment of all activities and resources with predefined objectives to ensure targeted outcomes [15]. Second, PM is a dynamic adjustment process, necessitating adaptive cycles of planning, executing, monitoring, and controlling to address project evolution and external uncertainties [16]. Third, PM operates under resource constraints. Given the limited availability of resources such as time, money, and manpower, effective resource planning and optimization are imperative for project managers [17]. This foundational PM framework provides essential mechanisms for coordinating complex systems, yet the convergence of its core elements creates inherent optimization challenges.

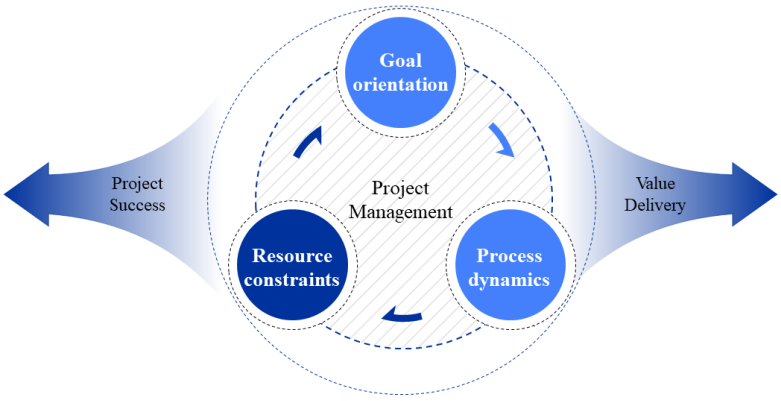



**Figure 1.** The three elements of project management.

Early PM emphasized task decomposition and execution efficiency under deterministic conditions, utilizing foundational optimization tools like Gantt charts and the Critical Path Method (CPM) to control the time–cost–quality "Iron Triangle" [18]. As business environments grow volatile, resource limitations intensify, and the urgent need for strategic implementation is gradually exposed, and PM expands from a single-project focus to program and even project portfolio management. Program management achieves scale effects through the coordinated management of related projects, subsidiary programs, and program activities, obtaining benefits not available when managing them individually. Project portfolio manages a collection of projects, programs, subsidiary portfolios, and operations together to achieve an organization's strategic objectives through integrated resource allocation and stakeholder synergy [19]. In PM practice, selecting an optimal project portfolio is critical yet challenging, as it needs to align with organizational strategic goals by maximizing benefits under limited resources while also addressing the diversity of influencing factors and complex relationships among projects [20]. The release of the new PM paradigm signaled the emergence of iterative development and adaptive planning, pushing PM from "predictive" to "adaptive" [21].

This shift spawned applications and improvements in optimization methods, including linear programming, genetic algorithms, simulated annealing algorithms, particle swarm optimization algorithms, ant colony optimization algorithms, etc. Among these, genetic algorithms are proficient at finding approximate optimal solutions for multi-objective problems such as resource allocation and schedule optimization under conflicting demand constraints. Simulated annealing algorithms effectively avoid local optima when resolving multi-phase project schedule conflicts [22]. And ant colony optimization algorithms are valuable for optimizing the sequence of interdependent project activities to reduce delays [23]. These optimization methods collectively provide data-driven and adaptive solutions to address the multifaceted challenges of evolving PM, ensuring their effectiveness remains intact even as complexity increases.

Meanwhile, the transformation of the PM paradigm raised the necessity of integrating SCM principles into the PM domain [24]. As PM complexity continues to grow exponentially, relevant concepts of SCM, networked collaboration, full-process integration, and dynamic adaptability are being increasingly introduced into this field [25]. In practice, Boeing incorporates more than 200 suppliers around the world into the project group collaboration platform, and matches project resource requirements through the visualization of the supply chain's topology, forming a two-dimensional project–supplier management model [9]. By drawing on the supply chain's end-to-end concept, PM can shift from isolated stage control to the whole life cycle of value stream optimization. The prevention and control strategy for the supply chain's bullwhip effect can inspire risk control in PM, automatically adjusting the priority of tasks according to the fluctuation of downstream demand and optimizing the allocation of resources and scheduling, so as to control and manage the project risks more effectively. Optimization methods provide precise solutions for complex PM, while SCM concepts break through the limitations of traditional PM, driving the goal of cross-project adaptive coordination to enhance organizational agility and endogenous competitiveness [10]. Therefore, these two approaches provide indispensable support for responding to increasingly complex project environments.

### *2.2. Supply Chain Management*

The supply chain is an organizational form oriented towards customer demand, aiming to improve quality and efficiency by integrating resources as a means. It is an efficient tool to achieve collaboration in the whole process of product design, procurement, production, sales, and service [26]. A supply chain contains three major flows: logistics,

information flow, and capital flow [27]. Logistics primarily involves the circulation process of materials, while information flow refers to the process of transferring information, including commodities and transactions. Capital flow, on the other hand, refers to the circulation process of cash and ownership within the supply chain. Based on the aforementioned "flows" structure, supply chain management (SCM) involves the systematic planning and control of supply, procurement, production transformation, and logistics activities throughout the entire value chain, from the supplier's supplier to the end customer [28], intending to maximize cost-effectiveness [29].

Early SCM was mainly devoted to improving logistics efficiency and reducing costs, and its focus was centered on intra-firm logistics activities. Over time, scholars began to recognize the close connection between SCM and the competitive strategies of enterprises. Among them, early research highlighted the strategic significance of supply chains, with scholars arguing that enterprises should position supply chain management (SCM) as a core element of their competitive strategies [30]. Another line of thought emphasized that supply chains must align with an enterprise's overarching goals, and that these goals should, in turn, drive the deep integration of supply chain processes [31]. This strategic positioning not only enables SCM to accurately respond to the long-term development goals of the enterprise but also allows it to play a strategic regulatory role in areas such as resource allocation, market response speed, and risk-resistance capabilities.

At present, the development of SCM can be summarized in four stages: production line management, lean manufacturing and chain management, business process re-engineering, and innovative SCM transformation, which ultimately leads to full process optimization and organizational upgrading [32,33], the specific development process is displayed in Figure 2. With the increasing market competition and diversification of consumer demand, SCM, from the internal expansion of enterprises to the entire supply chain network [34], gradually forms an integrated SCM concept. However, complexity and uncertainty exacerbate dynamic changes and unpredictability in supply chains and project execution. Against this background, subsequent research further placed emphasis on sustainable management, recognizing its growing significance in addressing the complexities and uncertainties of modern supply chain and project execution contexts [35]. In particular, risk management has always been a research hotspot, focusing on enhancing risk response mechanisms, which are expected to be increasingly flexible to cope with the growing complex global market environment [36].

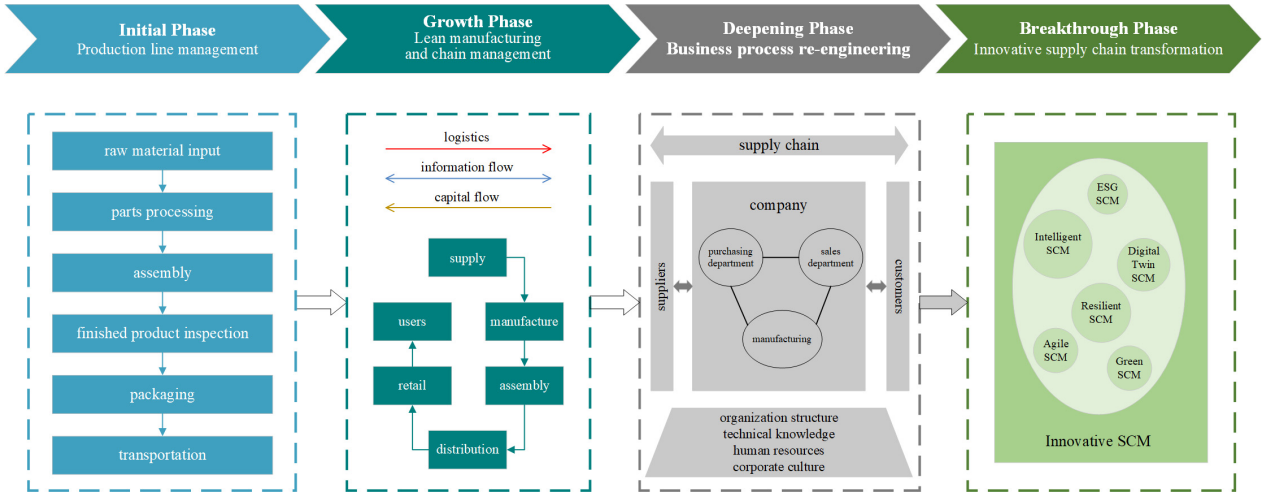



**Figure 2.** Development stages of SCM.

SCM focuses on stable, efficient process optimization, while PM excels at responding to temporary, goal-driven changes. The integration of the two has become particularly important. The application of project management methods in SCM is increasing, especially in the area of risk management. In general, PM principles are being embedded into SCM frameworks through systematic methodologies and toolsets [37,38], forming a management paradigm that combines "structured control" and "dynamic adaptability". For example, enterprises modularly decompose supply chain processes into task units with quantifiable objectives through work breakdown structure (WBS), build cross-functional collaboration mechanisms with the help of agile management thinking, and prioritize and real-time schedule delivery nodes of multi-level suppliers in globalized procurement scenarios. Through the top-level design of PM, it can realize the alignment of organizational strategy and supply chain goals [39] and establish a quantifiable, iterative, and scalable SCM system.

### *2.3. Optimization Methods*

Optimization methods play a pivotal role in addressing real-world problems, particularly in project management (PM) and supply chain management (SCM) [40]. In these domains, challenges such as resource allocation, cost control, and efficiency improvement can be formulated as single-objective or multi-objective optimization problems. The key to addressing these challenges lies in constructing appropriate mathematical models that translate real-world problems into mathematical formulations. These models can then be solved by applying specialized and effective optimization methods, and optimal or near-optimal solutions can be derived, which are critical for making informed decisions [41–43].

Methods such as linear programming, quadratic programming, and convex optimization are classical optimization methods that were widely used in the early years [44]. However, with the increase in the number of decision variables, objective functions, and some hard constraints, the problem to be solved becomes an NP-problem [45]. To address problems that are difficult to solve using classical optimization methods, researchers have begun to explore various approximation algorithms and heuristics to obtain a feasible solution or a near-optimal solution within an acceptable amount of time [46,47]. Nevertheless, in the context of the era of rapid development of big data and artificial intelligence, optimization methods are once again facing new opportunities and challenges [48], which not only need to deal with optimization tasks under massive data, but also have to cope with difficult problems such as non-convex optimization in machine learning model training, which drives optimization methods to continuously innovate and expand.

Optimization methods can be classified based on the dimensions of problem type and solution strategy. These are the terms for the types of problems. Based on the nature of the problem and the form of the objective function, it can be categorized as single-objective optimization and multi-objective optimization. According to the type of decision variables, they can be divided into continuous optimization, integer optimization, and mixed-integer optimization. Also, the problem can be classified into deterministic optimization and uncertainty optimization depending on the degree of problem determinism. In terms of solution strategy, optimization methods are usually classified into classical optimization and modern heuristic optimization. Different optimization methods are suitable for different types and scales of optimization problems. Figure 3 lists some of the common optimization methods that are currently used. When choosing optimization methods, the nature of the problem, scale, complexity, accuracy requirements, and other factors need to be considered comprehensively [49]. For simple optimization problems with clear mathematical models and structures, classical optimization methods, such as linear programming, nonlinear programming, etc., can usually find the optimal solution quickly and accurately [50]. For more high-dimensional and nonlinear problems, especially those commonly encountered

in supply chain logistics and project management, heuristic optimization methods, such as genetic algorithms and particle swarm optimization, offer better adaptability and global search capabilities [51]. In practical applications, according to the characteristics and needs of the problem, optimization methods can be improved and mixed to enhance the efficiency and quality of the solution [52].

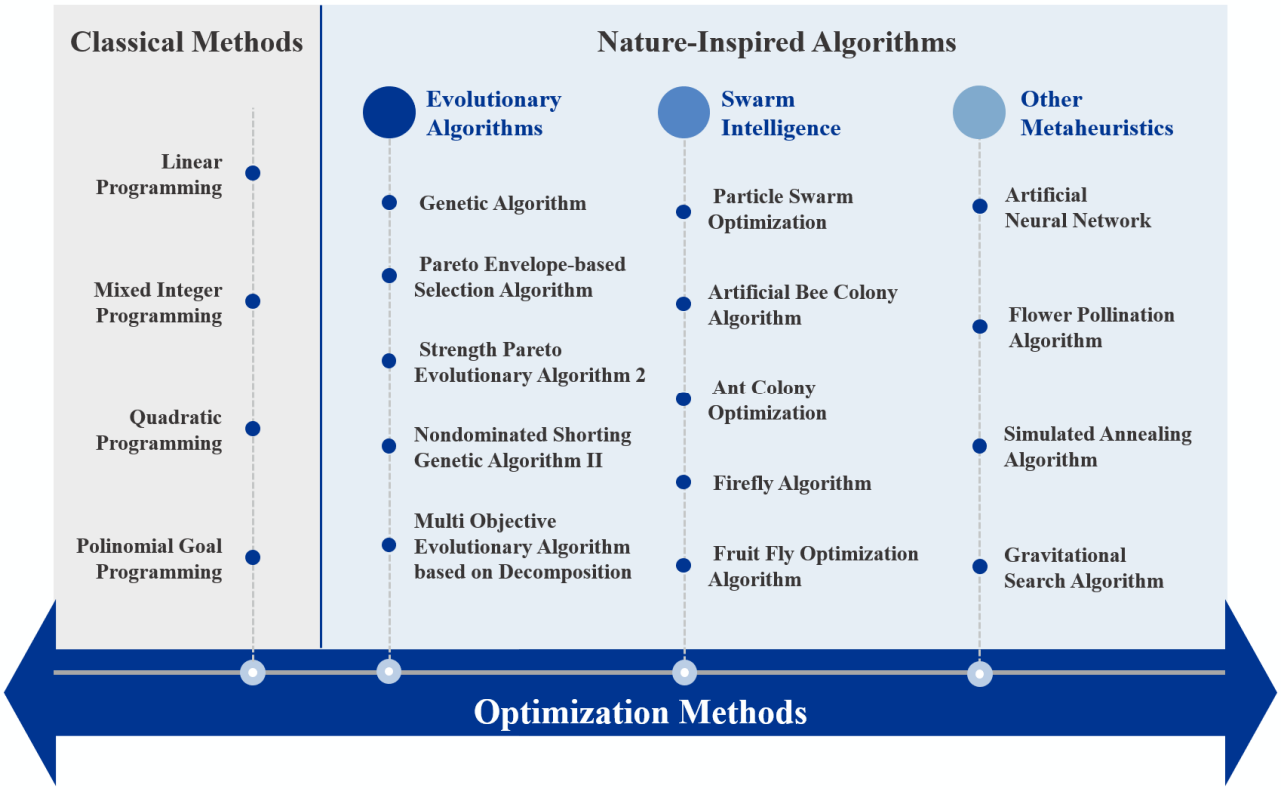



**Figure 3.** Common optimization methods.

The main value of optimization methods lies in providing structured, quantitative, optimal, or near-optimal solutions for a range of complex decision-making problems. In SCM, they are widely applied to address issues such as optimal transportation route planning [53], facility location selection [54], inventory level optimization [55], multi-level supply chain network design [56], and production scheduling and sequencing, as well as supplier selection and procurement strategies [57]. In PM, optimization methods focus on critical issues such as the optimal allocation of human resources and equipment, the trade-off between time and cost in project activities [58], cost–benefit analysis of risk mitigation strategies, and the global optimization of resource allocation in a multi-project environment with limited resources [59]. In particular, solutions in the above areas increasingly need to adapt to dynamic changes and uncertainties. A variety of multi-objective decision-making optimization problems with conflicting objectives have emerged, including task allocation [60], scheduling plans, and portfolio selection [61]. Meanwhile, complex optimization methods combining modern intelligent optimization algorithms have also demonstrated powerful capabilities and flexibility [62].

To further contextualize the application of optimization methods in PM, SCM, and their integration, Table 1 summarizes key thematic areas, corresponding optimization method categories, and representative studies. This table clarifies how different optimization approaches address domain-specific and cross-domain challenges, laying a foundation for understanding their role as a "bridge" in PM-SCM integration.

**Table 1.** Mapping of key themes, optimization method categories, and representative studies.

| Key Theme | Optimization Method Category | Typical Representative Studies | Core Application Scenario |
| --- | --- | --- | --- |
| PM Project Scheduling | Classical Optimization | CPM-based scheduling [18]; Linear Programming (LP) for time–cost trade-off [58]; | Balancing project timeline constraints and resource utilization to avoid delays. |
| PM Resource Allocation | Modern Heuristic Optimization | Genetic Algorithms (GAs) for multi-project resource sharing [59]; Particle swarm optimization (PSO) for human resource assignment [60]; | Allocating limited time, manpower, and equipment across concurrent projects. |
| SCM Supplier Collaboration | Multi-Objective Optimization | Mixed-integer programming (MIP) for supplier selection [57]; Pareto-based algorithms for multi-tier supply chain coordination [56]; | Optimizing supplier selection, order quantity, and delivery schedules to reduce costs. |
| SCM Inventory Optimization | Deterministic/Uncertainty Optimization | LP for static inventory level setting [56]; Stochastic programming for inventory under demand volatility [36]; | Maintaining optimal inventory levels to balance holding costs and stockout risks. |
| PM-SCM Risk Mitigation | Hybrid Optimization | Simulated annealing (SA) for integrated project–supply risk scheduling [24]; Ant colony optimization (ACO) for risk-driven resource reallocation [25]; | Coordinating project task adjustments and supply chain responses to mitigate disruptions. |
| PM-SCM Sustainability | Multi-Objective/Technology-Enabled Optimization | AI-integrated GAs for green project–supply network design [8]; Digital twin-assisted optimization for carbon footprint reduction [62]. | Aligning project execution with supply chain sustainability goals. |

Beyond the core themes outlined in Table 1, bottleneck detection, buffer management, and multi-actor decision-making emerge as critical dimensions in PM-SCM collaboration. The application and integration of optimization methods in these areas demonstrate significant value and complement existing research frameworks. Regarding bottleneck identification, both domains require systematic approaches to pinpoint critical nodes constraining overall efficiency. In PM, the Theory of Constraints combined with process mapping, linear programming, or discrete-event simulation precisely identifies key bottleneck activities in project schedules. In SCM, bottlenecks often manifest as weak links in supply chain networks, necessitating identification through mixed-integer programming and network topology analysis, coupled with sensitivity analysis to assess their impact on the entire chain. In buffer management, PM and SCM share the core logic of "hedging uncertainty through redundant resources", yet their application scenarios and optimization methods exhibit differentiated synergies. In PM, critical chain project management absorbs task delay risks by setting time buffers. Genetic algorithms are commonly used to optimize buffer size and placement, balancing schedule assurance and resource waste. In SCM, buffer management focuses on inventory and capacity buffers, requiring stochastic programming to address demand fluctuations and supply disruptions, while digital twin technology enables real-time dynamic adjustment of buffer levels. At the multi-agent decision-making level, the collaboration between PM and SCM fundamentally addresses cross-organizational, multi-stakeholder goal alignment. In PM, conflicts among multiple agents (e.g., owners, contractors, and supervisors) often manifest as trade-offs between schedule, cost, and quality. Game theory is employed to construct non-cooperative or cooperative game models, combined with the analytic hierarchy process (AHP) for multi-criteria decision-making. In SCM, multi-stakeholder coordination relies on contract design and distributed decision-making methods. Pareto optimization algorithms are commonly used to balance stakeholder benefits, while blockchain technology enhances decision transparency and trustworthiness.

Existing PM-SCM integration and optimization reviews often focus on single domains without cross-domain optimization links or only offer conceptual ties while lacking emerging tech like AI, digital twins, and blockchain, as well as bibliometric analysis. In contrast, this review addresses these gaps by being integration-focused, which means it breaks

single-domain limits to systematically connect PM and SCM; it is also optimization centric, as it takes methods like genetic algorithms, simulated annealing, and multi-objective programming as a core "bridge" to develop actionable integration paths, and it delivers technology-enabled synthesis by embedding the aforementioned emerging tech into the integration process. Additionally, the review uses bibliometric and qualitative methods to rectify prior reviews' methodological flaws, such as over-reliance on qualitative descriptions, thereby providing clearer insights for PM-SCM integration research.

## 3. Methodology

A literature review entails the systematic organization, analysis, and synthesis of existing scholarly works within a designated research domain. It serves to delineate the current state of knowledge, identify significant research gaps, and suggest meaningful directions for future investigation. In an era increasingly shaped by globalization, digital transformation, and operational uncertainties, the integration of project management and supply chain management has emerged not merely as a mechanism for enhancing efficiency and reducing costs, but as a strategic imperative for building resilient supply networks and advancing sustainable development objectives. The application of optimization methods, such as multi-objective algorithms including NSGA-II and classical techniques like linear programming, further strengthens the synergistic potential between these disciplines, positioning their integration as a crucial enabler of corporate digital transformation.

Accordingly, this study employs a systematic literature review to examine the interrelationship between project management and supply chain management, with a particular emphasis on how optimization methodologies can facilitate and enhance synergies between them. This section is structured into three main parts: first, an explanation of the data sources and methodological framework adopted; second, a detailed description of the literature-screening protocol and inclusion criteria; and finally, an overview of the bibliometric tools and analytical methods utilized in this research.

### *3.1. Data Sources and Collection*

Among the most commonly used databases for literature collection are Web of Science (WOS), Scopus, Google Scholar, ScienceDirect, and IEEE Xplore. For this study, Web of Science (WOS) was selected as the primary data source due to its authoritative coverage and robust citation-tracking capabilities. As one of the world's most authoritative multidisciplinary databases, WOS offers distinct advantages for systematic literature reviews. It pioneered the citation-indexing system, enabling precise tracking of citation networks for the literature published from 1900 to the present. This feature allows researchers to map the influence and evolution of academic work over time.

WOS covers approximately 12,000 high-impact core journals globally, including the Science Citation Index (SCI), Social Sciences Citation Index (SSCI), and Arts and Humanities Citation Index (A&HCI). Its rigorous selection process, based on criteria such as journal impact factor, peer-review quality, and international diversity, ensures the inclusion of authoritative and high-quality publications. Furthermore, WOS facilitates the construction of academic knowledge networks through its citation linkages, aiding in the identification of interdisciplinary research trends and hotspots. Given these strengths, WOS was deemed the most appropriate database for this research. To comprehensively capture the developmental trajectory and latest trends within the research domain, this study set the literature search time window from January 2003 to July 2025, with data download completed on 6 July 2025, ensuring the timeliness of the acquired literature. Additionally, the database index category was limited to the "Web of Science Core Collection" to ensure the credibility and high caliber of the data sources. The "topic" field was selected for retrieval to cover key

content related to the research theme, enhancing the comprehensiveness and precision of the literature screening. Furthermore, the inclusion of journal articles, review papers, and conference papers as document types effectively reflects the characteristics of core research outcomes within the field.

This study distills the following core keywords by deconstructing the research topic: "Project Management (PM)", "Supply Chain Management (SCM)", "Project Optimization", "Supply Chain Optimization", "Optimization Methods", and "Operations Optimization". Considering that the above core keywords need a more comprehensive correlation extension to cover the integration dimension, interaction interface, and specific scenarios of project and supply chain management, relevant supplementary keywords were also incorporated, including "Integration of Project and Supply Chain Management", "Project–Supply Chain Interface", "Project Logistics", "Project Suppliers", "Project Transportation Management", "Project Inventory Management", "Project-driven supply chain", "Supply Chain Project Management", "Project Management in Supply Chain Environment", "Supply Chain Optimization in Project Environment", "Project Management in Supply Chain Context", and "Supply Chain Optimization in Project Context". Based on these keywords, this research designs a three-stage keyword combination strategy for comprehensive data collection:

1. Collect data for each keyword, including all core and supplementary keywords.
2. Conduct preliminary thematic cross-searches using Boolean logic "AND" for all individual keywords. For example: ("Project Management" OR "PM") AND ("Supply Chain Management" OR "SCM") AND ("Optimization" OR "Linear Programming" OR "Genetic Algorithm").
3. Combining the aforementioned keyword screening logic with the three-stage combination strategy, the Boolean search logic ultimately determined in this study is: TS = (("project management" OR "project planning" OR "project scheduling" OR "program management") AND ("supply chain" OR "logistics" OR "procurement" OR "operations management") AND (optimization OR "mathematical programming" OR "machine learning" OR "decision support" OR simulation OR modeling OR "artificial intelligence") AND (integration OR synergy OR coordination OR collaboration OR framework OR scenario* OR application*)).

After the previous retrieval process, a separate cross-search was performed for the core thematic dimensions, resulting in 73 valid literature records. A systematic search using precise Boolean logic found an additional 416 valid records. The total of 489 valid documents created a comprehensive and reliable research dataset, providing a solid basis for subsequent bibliometric analysis and thematic exploration.

To provide a temporal perspective on the volume of literature, Table 2 breaks down the number of records at key screening steps by year.

**Table 2.** Number of records at each screening step by year.

| Year Range | Initial Hits | After Screening | Final Inclusion |
|---|---|---|---|
| 2003–2010 | 89 | 51 | 43 |
| 2011–2015 | 128 | 85 | 79 |
| 2016–2020 | 160 | 123 | 119 |
| 2020–2025 | 112 | 94 | 86 |
| **Total** | **489** | **353** | **327** |

The gold standard refers to the currently accepted benchmark or reference test that is considered the most accurate and reliable method for definitively determining a condition, against which the validity of other new or alternative diagnostic tests is measured [63].

To ensure the rigor of the literature screening, this study compared the gold standard by adopting a quantitative evaluation method based on a confusion matrix to validate the effectiveness of the search strategy [64]. The specific process is as follows.

First, a gold standard set was established through systematic manual screening. Three researchers, following clear inclusion and exclusion criteria, independently conducted title/abstract screening and full-text screening of the 456 records after duplicate removal. Through discussion and consensus, 302 publications were ultimately determined to constitute the gold standard set for this study (i.e., all genuinely relevant literature).

Subsequently, the designed keyword search strategy was executed. After applying the same screening process, this strategy finally retrieved 327 publications.

By comparing the search strategy results with the gold standard set, the following confusion matrix was constructed in Table 3.

**Table 3.** Confusion matrix of records.

| | **Gold Standard: "Relevant" (Total 302)** | **Gold Standard: "Irrelevant"** |
|---|---|---|
| **Retrieved by Search Strategy (Total 327)** | True Positives (TP) = 295 | False Positives (FP) = 32 |
| **Not Retrieved by Search Strategy** | False Negatives (FN) = 7 | True Negatives (TN) (This value is not considered in this study) |

Performance metrics of the search strategy were calculated based on the confusion matrix:

$$Recall = \frac{TP}{TP + FN} = \frac{295}{302} \approx 98\% \quad (1)$$

$$Precision = \frac{TP}{TP + FP} = \frac{295}{327} \approx 90\% \quad (2)$$

The final reported values, rounded, are recall 98% and precision 90%. This validation demonstrates that the designed search strategy achieves an excellent balance between coverage (high recall) and accuracy (high precision).

To balance these two metrics, this study initially uses broad keywords (e.g., "supply chain management" instead of "green supply chain risk assessment") and expands with synonyms (e.g., "project management" OR "program management") to maximize recall and avoid missing important information. In the mid-stage, to improve precision, filters (time range, research methods, and disciplinary fields) and Boolean logic (AND/NOT) are applied to exclude irrelevant items, refining the results to better meet research needs and enhance the quality of the retrieved literature.

### *3.2. Article Screening*

While the search strategy encompassed the literature containing keywords such as "project management", "supply chain management", and "optimization methods", it is imperative to meticulously evaluate the retrieved papers to ascertain the comprehensiveness and precision of the included research. Before formally analyzing the retrieved literature, it is imperative to meticulously screen the literature to ensure the inclusion of research literature in the search rate of completeness and accuracy. As illustrated in Figure 4, this paper delineates the screening process through the PRISMA flowchart. Given the scarcity of research on the integration of project management and supply chain management, a journal-screening phase was included to broaden the literature coverage.

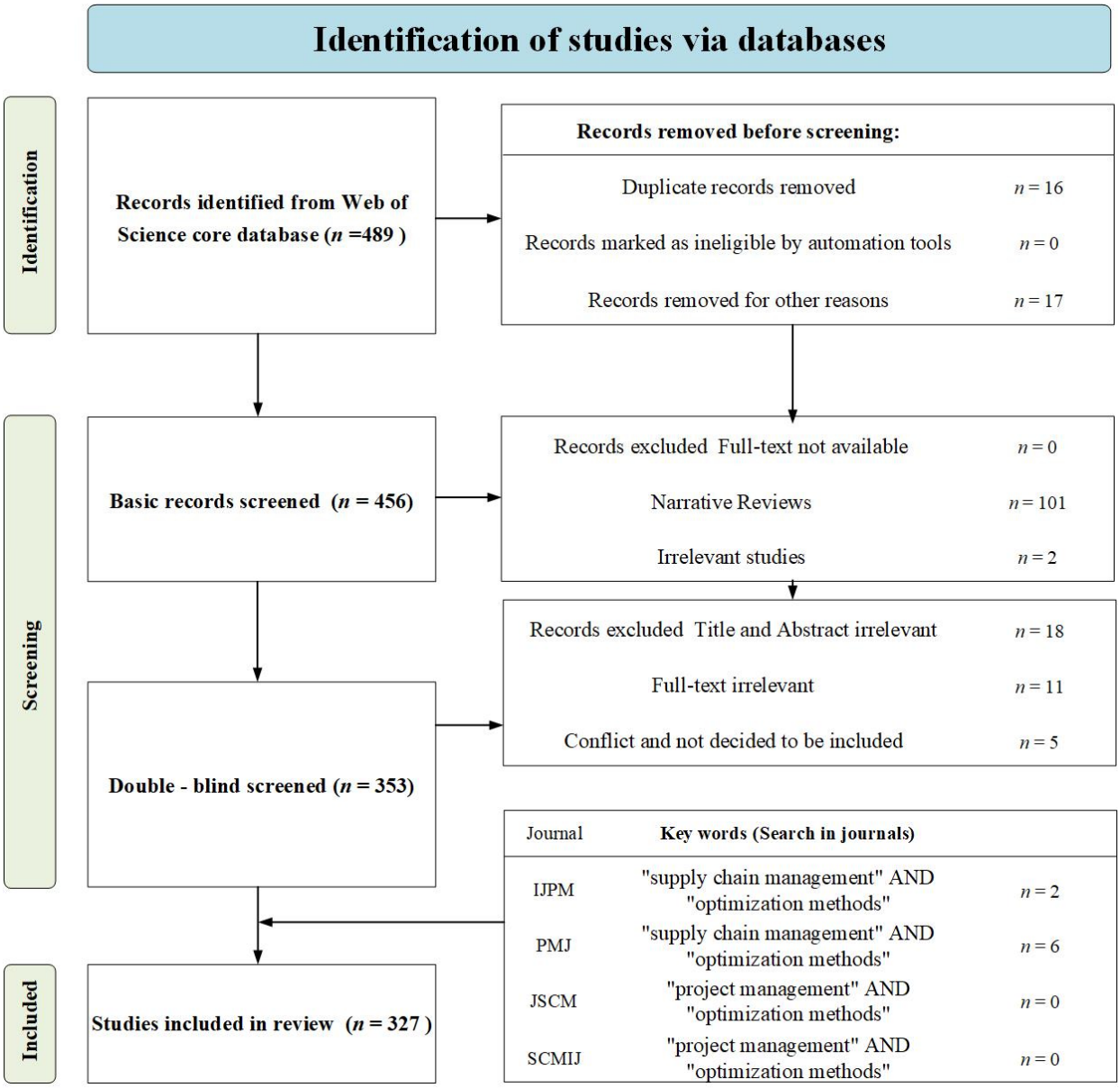



**Figure 4.** Diagram of the PRISMA process.

In the identification phase, 489 records were identified through Web of Science. After removing 16 duplicate records and 17 records due to other reasons, a total of 456 records proceeded to the screening phase. During the screening phase, 456 records underwent an initial review, excluding 101 conference papers and 2 irrelevant studies, leaving 353 records for the double-blind screening phase. In the double-blind screening phase, 353 records were subject to a more stringent review of titles, abstracts, or full texts, resulting in the exclusion of 18 records with irrelevant titles and abstracts, 11 records with irrelevant full texts, and 5 records with undecided status due to controversy. Ultimately, 319 studies were included in the review. Additionally, to further enhance the coverage of the research literature, keywords from another field were searched within journals from one field. Two studies related to "supply chain management" and "optimization methods" were found in the IJPM journal and six studies in the PMJ journal, but no relevant studies in the JSCM and SCMIJ journals. The final number of studies included was 327.

The preliminary literature search is typically executed by using a combination of precise keywords. As delineated in Section 3.1, the domain of project management en-

compasses various expressions such as "project portfolio" and "project environment". Conversely, the realm of supply chain management is characterized by terms including "supply chain management", "supply chain optimization", "supply chain integration", "supply chain collaboration", and "supply chain coordination." For the latter, terms such as "supply chain management", "supply chain optimization", "supply chain integration", "supply chain collaboration", and "supply chain coordination" are chosen as keywords. In the context of optimization methodologies, keywords such as "mathematical model", "linear programming", "genetic algorithm", "multi-objective optimization", and others are incorporated. The keyword search scope was set to the title, abstract, and keyword sections to ensure that all relevant publications were searched.

Following an initial review of pertinent literature, the development and implementation of inclusion and exclusion criteria are essential. The present study focuses on integrating project management and supply chain management through the application of optimization methods, exploring their application scenarios, technical tools, and future opportunities. Therefore, the following criteria are proposed: (1) At the topic level, the literature must explore the integration of project management and supply chain management and practically apply optimization methods (e.g., mathematical models, optimization algorithms, etc.). (2) In terms of research types, the literature included is limited to modeling, empirical research, case studies, or review papers. (3) In terms of data access, the literature included must be downloadable in full text and have structured data (e.g., keywords and references) for further analysis to be carried out. In addition, in terms of exclusion criteria, (1) studies focusing on a single area (i.e., only exploring project management or supply chain management, not involving the intersection of the two and optimization methods) are excluded; (2) literature focusing on purely technical optimization without combining with management scenarios should also be excluded to prevent the research scope from becoming overly broad, which would dilute the guiding theme of "PM–SCM Integration" in this paper; (3) in terms of the type of literature, non-English language literature, repetitively published literature, low-quality conference papers, and non-academic literature are excluded; and (4) literature in which keywords only appear in the reference list and are not explored in the main text is excluded. The initial screening was conducted based on the above criteria.

After the basic screening, the present study was subjected to a double-blind screening conducted independently by two researchers to ensure the accuracy and comprehensiveness of the literature screening. The double-blind screening process was meticulously structured into four stages: title and abstract review, full text review, comparison of results, and literature supplementation. During the title and abstract review stage, the two researchers excluded literature that did not contain keywords related to project management, supply chain management, and optimization methods in the title and abstract. The remaining literature was then subjected to a thorough review of the full text, and literature not related to the themes of "project management-supply chain management-optimization methods" or repetitively published or low-quality conference papers was further excluded through browsing. The two researchers, respectively, screened out 34 and 32 papers. Based on this, they conducted a comparative analysis and found that 8 documents were inconsistent. In response to this discrepancy, a third-party arbitration mechanism was introduced, and 3 pieces of divergent literature were retained. In the subsequent literature supplementation stage, the references were searched backward. First, we constrained the search to project management journals (e.g., *International Journal of Project Management* and *Project Management Journal*). Within these journals, we applied the combined keywords "supply chain management" AND "optimization methods" in the search. Similarly, we limited the scope to supply chain-focused journals (e.g., *Journal of Supply Chain Management*

and *Supply Chain Management: An International Journal*). Under this category, we searched using the keyword combination "project management" AND "optimization methods". This dual-pronged approach yielded 8 additional studies. Following a series of screening rounds, 327 sources from the literature were identified for further analysis.

To ensure the reliability of the literature screening, a sampling and validation session was established in this paper. Specifically, a quality rating scale was designed for in-depth assessment of the screened literature. Before the implementation of formal sampling, a pretest was conducted on ten randomly selected studies. The scoring criteria can be found in Appendix A Table A1.

These studies were independently scored by three researchers, and the inter-rater agreement was calculated. The results of the pretest indicated that the Kappa > 0.6, signifying substantial inter-rater agreement and thus enabling the progression of the formal evaluation. During the formal evaluation, three researchers randomly sampled 20 studies and scored each study according to the rating scale. The scoring results of the three researchers (Tables A2–A4) all indicated that over 95% of the literature had a total score exceeding 15 points, meeting the validity standards. The details can be accessed in Appendix A. This result confirms the reliability of the selected literature and the effectiveness of the screening process.

### *3.3. Bibliometric Tools and Techniques*

This study combines bibliometric tools with qualitative analysis to systematically uncover the evolutionary paths and intrinsic links in the knowledge structures of project management and supply chain management. Citespace was used as the core analytical platform, leveraging its Burst Detection to identify sudden shifts in research frontiers (e.g., technology breakthroughs or policy-driven topic shifts) and its Time Zone Evolution to visualize thematic changes over time through temporal slicing.

Keyword co-occurrence networks and cluster maps were used to quantify trends in annual publication volumes, core author/institution contributions, and cross-regional collaboration density. Methodologically, co-occurrence analysis extracts high-frequency keywords (e.g., "sustainability" and "risk management") to build similarity matrices and reveal conceptual associations. Citation analysis identifies highly cited papers and foundational knowledge (e.g., seminal theoretical frameworks). The LLR (Log-Likelihood Ratio) algorithm is applied for semantic annotation of cluster topics (e.g., "Sustainable SCM Optimization") and tracks thematic evolution (e.g., shifts from "cost optimization" to "low-carbon resilience").

To address the limitations of purely quantitative analysis, qualitative content analysis is integrated to deeply interpret clusters. For example, it refines specific application scenarios of optimization methods (e.g., "multi-objective programming in green supply chain trade-off decisions"), embedding theoretical insights into data-driven knowledge graphs. This approach enables mutual validation of macro-trends and micro-practices.

## 4. Bibliometric Analysis

To systematically trace the research trajectory of PM-SCM optimization, this paper uses CiteSpace 6.4.R1 for visual analysis of multiple elements, including authors, countries, keywords, and journals. Core parameter settings follow the logic of "first filtering nodes, then pruning networks," with all unspecified parameters using system defaults. In the temporal dimension, the time slice is set to one year to accurately capture the dynamic evolution of research hotspots on an annual scale. The node-filtering method employs the g-index with a k value set to 25. This approach emphasizes high-impact achievements within the field while accommodating the long-tail distribution characteristics of research nodes,

ensuring the integrity of core research trajectories. Link strength is calculated using cosine similarity to measure inter-document relationships, providing a more comprehensive view of internal connections. At the link-filtering stage, a threshold of 2.5 is used to retain links with sufficient strength, preventing network clutter caused by overly weak connections. During network pruning, the Pathfinder algorithm is applied only during the clustering optimization phase. This process removes redundant edges while maintaining core pathways, resulting in concise and clear knowledge networks across dimensions such as authors, countries, keywords, and journals. After setting parameters, nodes are further filtered by type based on specific criteria aligned with the research goals, preparing for subsequent visualization analysis.

### *4.1. Analysis of Publication Year*

The trend of the number of publications and the number of citations can reflect the progress and enthusiasm of a certain research field. In this paper, we focus on the topic of "PM-SCM Optimization", especially on its scenarios, technology adaptations, and future opportunities, and conduct a bibliometric analysis, aiming to provide valuable insights into the development trend of related research. By combining the relevant data from January 2003 to July 2025, a clear understanding of the evolution of research in this field can be gained, as shown in Figure 5. Generally speaking, the number of publications shows a pattern of gradual accumulation followed by accelerated expansion, and the research history can be divided into three stages: initial exploration, fluctuating growth, and rapid development.

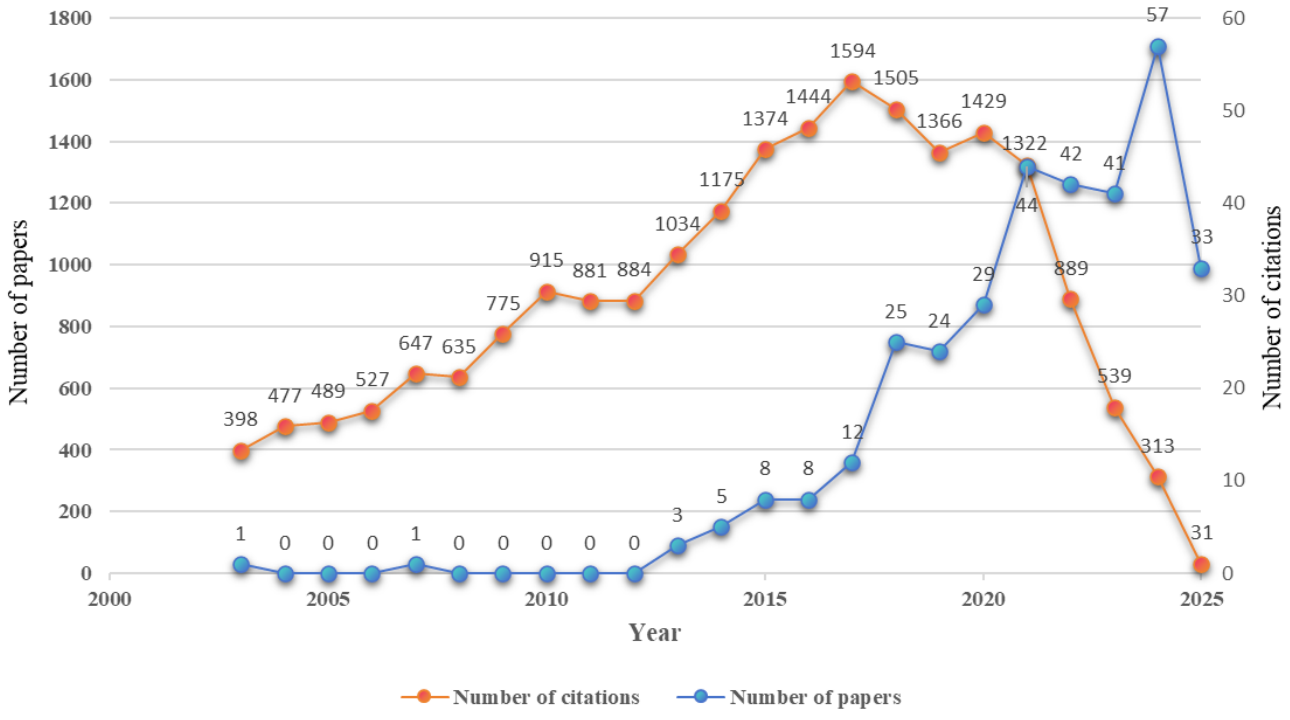



**Figure 5.** Trends in the quantity of articles and citations.

**(1) Initial exploration period (2003–2010):** The publication volume of related research has been at a low level for a long time, with the average annual output in single digits and the citation volume in a very low range. At this time, the research focusing on "PM-SCM Optimization" is still in its infancy, and most of the research tends to explore project management and supply chain management separately, and stays at the level of preliminary conceptual correlation, and there is a lack of in-depth excavation of optimization technology

in the application and landing path in the fusion scenario of the two, which has not yet formed a systematic research framework and a wide range of academic research.

**(2) Fluctuating growth period (2011–2020):** The number of publications shows a gradual growth trend, while the number of citations rises with the accumulation of publications, but with certain fluctuations. In this phase, the accelerated globalization process has led to a synergistic drive between the increased complexity of project management and the increased demand for supply chain collaboration, while the iteration of optimization algorithms and digital technology has provided solid methodological support for the research. In this context, many scholars have begun to focus on the adaptability of optimization methods in multiple scenarios (e.g., complex project resource allocation, supply chain dynamic response, etc.). However, limited by factors such as the lack of maturity of technological applications and interdisciplinary research barriers, there are certain twists and turns in the transition of research from theoretical correlation to practical exploration, but it has already accumulated a certain amount of academic influence for research in this field.

**(3) Rapid development period (2021–present):** From 2021 onward, the number of publications enters a rapid growth phase, peaking in 2023, and the number of citations also shows explosive growth. In this stage, the deep penetration of digital technology and the continuous upgrading of the industry's demands have pushed the field to become a core hotspot of cross-disciplinary research. Compared with 2020, the scale of literature output has expanded significantly, scholars' attention to "PM-SCM Optimization" has increased dramatically, and the research dimensions have covered scenario innovation (e.g., green projects and intelligent supply chain), technological breakthroughs (e.g., algorithmic optimization and system integration), practical implementation (e.g., cross-business collaboration and whole-process control) (e.g., cross-enterprise collaboration and full-process control), and other dimensions, and has become a cutting-edge direction at the intersection of project management and supply chain management. Although the citation volume has dropped after 2023, this is mainly due to the fact that the research has entered the stage of segmentation and deep cultivation, the difficulty of theoretical innovation has increased, and the results of the initial cross-field exploration have not formed a broad consensus. This fluctuation is a staged reflection of the transformation of research from "scale expansion" to "quality deepening".

### *4.2. Analysis of Authors*

The total number of authors included in the literature in this study is 1094, and Table 4 lists the top 15 core authors in terms of the number of publications. Among them, Ghannadpour SF [65–69] focuses on construction supply chain management and multi-project collaborative scheduling with five papers; for example, by designing a construction supply chain model including supplier selection and logistics optimization, forming a link between basic theory and multi-scenario application, with 108 citations in total and 22 citations on average, which demonstrates solid academic influence. Kim S [70–72], although he has only published three papers, he has solved the pain points with his research on dynamic modeling of the impact of skilled labor shortage and sustainable supply chain management in the post-epidemic era, and has become a typical representative of optimization methods adapted to complex environments, with a high impact of 144 citations in total and 48 citations on average. Hosseini, MR and Martek, I [73–75] have focused on the areas of sustainable project management and BIM-enabled project complexity by analyzing the pain points of supply chain collaboration in the Iranian construction industry and constructing a new supply chain management system for the Iranian construction industry. The above authors focus on the theme of "PM-SCM Optimization" and link optimization algorithms to project scheduling and supply chain resource allocation. In

terms of knowledge background, most of them are from the disciplines of operations research and management science, industrial engineering, and computer science, etc., and they use operations research and system optimization to promote the integration of optimization techniques into project and supply chain management processes; some of the authors have also introduced digital technologies, such as artificial intelligence, to improve the efficiency of optimization methods. The exploration of such diversified technological paths not only injects sustained momentum into the development of the field but also provides key support for cracking the core challenges in cross-domain collaboration, such as resource matching and schedule synergy.

**Table 4.** Top 15 authors.

| Authors | Number of Articles | Number of Citations | Average Citations |
|---|---|---|---|
| Ghannadpour SF [65–69] | 5 | 108 | 22 |
| Chakrabortty RK [76–79] | 4 | 35 | 9 |
| Li Y [80–83] | 4 | 34 | 9 |
| Zhang L [81,84,85] | 4 | 104 | 26 |
| Chen [86–88] | 3 | 62 | 21 |
| Ghaffa-anhoseini A [89–91] | 3 | 71 | 24 |
| Habibi F [76,77,92] | 3 | 65 | 22 |
| Hosseini MR [73–75] | 3 | 123 | 41 |
| Jolai F [93–95] | 3 | 58 | 19 |
| Kim S [70–72] | 3 | 144 | 48 |
| Kumar A [96–98] | 3 | 106 | 35 |
| Martek I [73–75] | 3 | 123 | 41 |
| Noori S [65,66,68] | 3 | 86 | 29 |
| Tabrizi BH [99–101] | 3 | 110 | 37 |
| Wang Y [102–104] | 3 | 99 | 33 |

With the help of CiteSpace visualization software and the node type "Author", the author cooperation network map in the field of "PM-SCM Optimization" is generated, as shown in Figure 6. The circular nodes represent the authors, with their size proportional to the number of publications. The more articles published, the larger the nodes. The connecting lines between nodes represent collaborative relationships among researchers. These connections collectively form co-authorship networks, the analysis of which offers valuable insights into the depth and breadth of scientific activity within a discipline. It also holds practical significance for research management, organizational coordination, and strategic guidance. As shown in Figure 6, the field of "PM-SCM Optimization" has developed several relatively stable collaborative networks. Each of these clusters is led by one or more core researchers, who play a central role in sustaining their respective research communities.

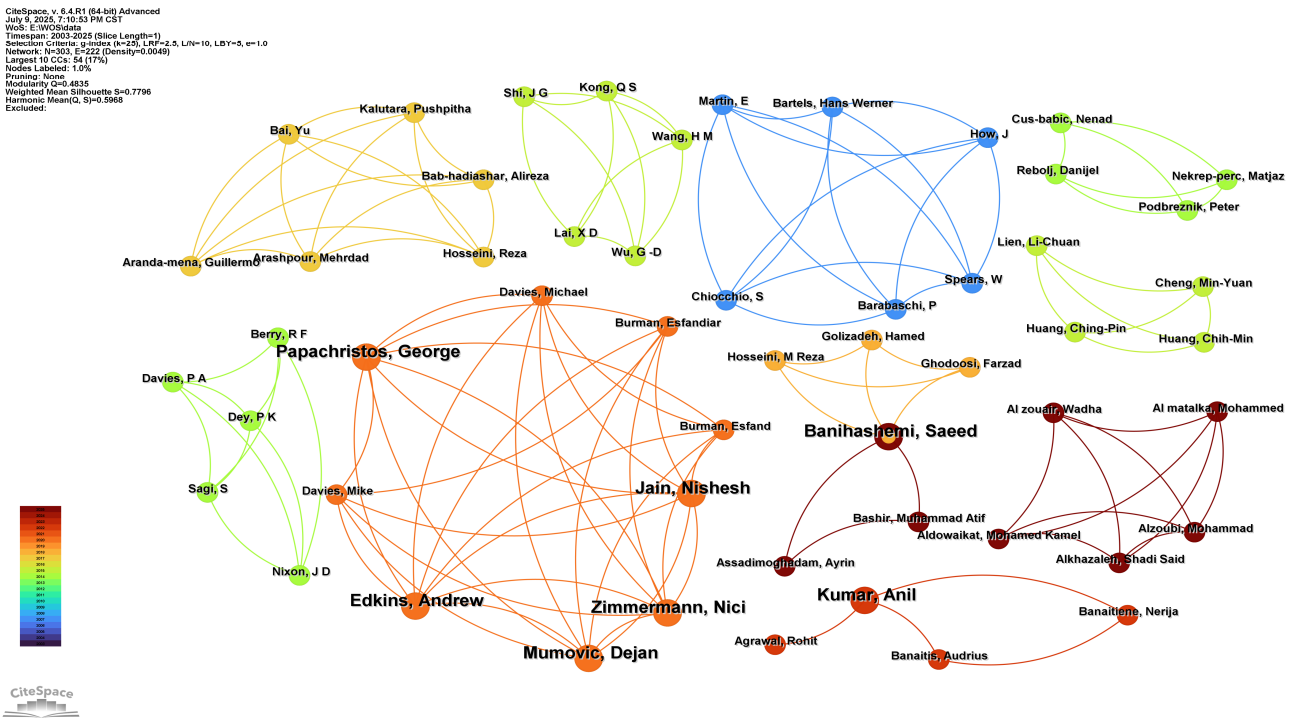



**Figure 6.** Co-authorship network map.

The core collaborative network features several prominent clusters centered around key researchers, including Papachristos, George; Banihashemi, Saeed; Jain, Nishesh; Bai, Yu; and others. Among these, Papachristos, George [75] stands out not only for his substantial number of publications, but also for his role as a collaborative hub. He maintains strong ties with researchers such as Edkins, Andrew, and Zimmermann, Nici, facilitating interdisciplinary integration of optimization methods in sustainability and construction research. This includes applications in project scheduling and enhancing supply chain resilience. The team led by Kumar, Anil [96], concentrates on supply chain resilience and sustainable development in the post-pandemic context. Their work spans resilient infrastructure, smart technology applications, and low-carbon transitions, advancing the implementation of optimization techniques in complex projects and supply chain management scenarios. Meanwhile, Banihashemi, Saeed's [74,105] group focuses on digital transformation under the "Construction 4.0" paradigm, investigating emerging technologies and optimization algorithms tailored to construction environments. This group has formed a practical, application-oriented collaborative sub-network. In addition to these cohesive clusters, the network contains numerous smaller collaborative groups, typically consisting of two to three researchers, along with many isolated nodes. These groups exhibit looser connections to the core researchers. Overall, the structure of this collaboration network indicates a field in a phase of structured development, showing a solid foundation of scholarly cooperation, yet with significant potential for further expansion and integration.

Although author analysis may appear descriptive, it provides important insights into the intellectual structure of the field. The identification of core author groups and their collaboration patterns reveals how knowledge in PM–SCM optimization has been developed, diffused, and fragmented. For example, clusters of authors working on sustainability and construction contexts indicate that integration is driven by cross-disciplinary collaborations rather than by individual researchers alone. At the same time, the prevalence of small, disconnected author groups highlights fragmentation, suggesting that greater interdisciplinary collaboration is required to advance PM–SCM integration. In this sense, Section 4.2 not

only documents the current research landscape but also provides implications for fostering collaboration and knowledge convergence in future research.

### *4.3. Analysis of Countries*

The research topic of "PM-SCM Optimization" has attracted a lot of attention from scholars all over the world. The literature selected in this paper comes from 63 countries, and the top 10 countries with the largest number of articles are shown in Table 5. The results show that China contributed the largest annualized volume of publications ($n$ = 82) and recorded an average citation rate of 15 counts per paper. The observed output corresponds to a mean annual growth of 7.3% over the 2015–2025 interval (Web of Science, retrieved 15 July 2025). The United States occupies the second position with 52 publications and an identical mean citation rate of 15 counts per item, indicating a comparable per-article visibility to that of China during the same period. Iran ranks third in terms of the number of papers published in this field, thanks to the continued demand for expansion of the infrastructure market in the Middle East. Its research is based on the resource constraints and autonomous development needs of local supply chains and closely follows the policy guidance of "lightweight and efficient" infrastructure projects, focusing on exploring the localized application of optimization methods in project and supply chain synergy and focusing on solving the cross-discipline synergy problems in resource-constrained environments. Among them, Ghannadpour, Seyed Farid [65–69], Mousavi, Seyed Meysam [93,94,106], and other scholars have made great efforts to adapt optimization methods to local project and supply chain collaboration scenarios, and formed research results with regional characteristics, which have made great contributions to a large number of citations in Iran. Research in the UK, Germany, France, and South Korea is characterized by in-depth explorations and groundbreaking results, and its output of high-quality literature has become an important node in promoting the dissemination of knowledge in the field.

**Table 5.** Top 10 countries.

| Country | Number of Articles | Number of Citations | Average Citations |
|---|---|---|---|
| China | 82 | 1212 | 15 |
| USA | 52 | 772 | 15 |
| Iran | 35 | 573 | 16 |
| England | 31 | 733 | 24 |
| Australia | 30 | 419 | 14 |
| India | 24 | 342 | 14 |
| Germany | 14 | 409 | 29 |
| Canada | 13 | 74 | 6 |
| France | 12 | 278 | 23 |
| Korea | 11 | 258 | 23 |

Citation data normalized per year. Source: Web of Science Core Collection, data retrieved in July 2025.

In the research field of "PM-SCM Optimization", the inter-country cooperation network shows a distinctive feature, as shown in Figure 7. As can be seen from the cooperation network that China, the United States, Iran, the United Kingdom, Australia, and India are the core nodes, which have not only published a large number of articles, but also established a close cooperation relationship with other non-core countries. Therefore, Asia, America, and Europe occupy a dominant position in the research of "PM-SCM Optimization" and have strong international influence. The fact that the authors are mainly from China, the United States, the United Kingdom, and Iran confirms the close relationship between the active countries.

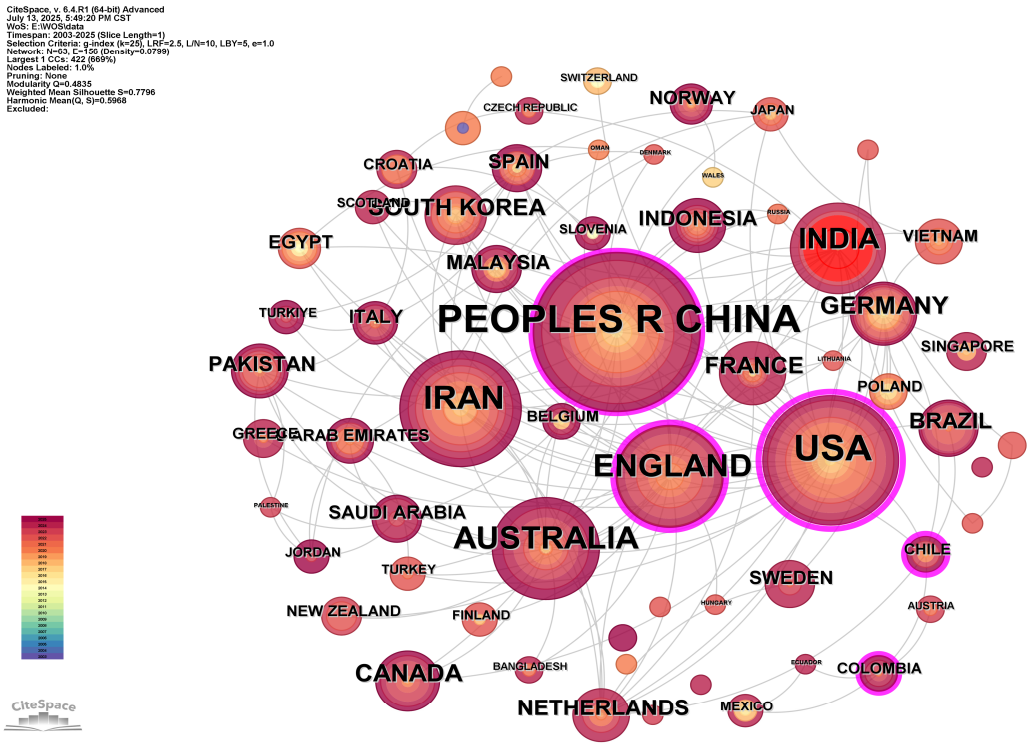



**Figure 7.** Country co-occurrence network.

### *4.4. Analysis of Journals*

Journals are the core vehicle for carrying academic results and promoting knowledge dissemination. The articles selected in this study were published in 153 journals, and Table 6 gives the publication volume, number of citations, average number of citations, and impact factor of the top 20 journals. Among them, *Automation in Construction* focuses on automation application scenarios in the construction field, with an average number of citations of 16, which has become a relatively core position for the transformation of optimization technology to engineering practice, and promotes algorithmic optimization and process reconfiguration to land in construction project–supply chain collaboration. *The International Journal of Project Management* is deeply engaged in the theoretical frontiers of project management and supply chain collaboration, with seven articles receiving 161 total citations and 23 citations per article, bringing together the research on complex project scheduling and cross-organizational supply chain collaboration, and holding the innovation in the field of basic theories. *Journal of Cleaner Production* is closely related to the demand for sustainable goals and low-carbon transformation, with a total of one article. The *Journal of Cleaner Production* is closely related to the sustainable goals and low-carbon transition needs, with an average citation intensity of 18 citations, integrating management synergy and low-carbon needs in depth, and expanding the boundaries of social value of the research. In addition, engineering management journals, such as *Engineering Construction and Architectural Management*, promote the application of optimization methods in the whole process management of infrastructure projects with 13–15 articles. Cross-disciplinary journals, such as *Computers and Industrial Engineering*, promote the application of optimization methods in the whole process management of infrastructure projects from a technical perspective. Interdisciplinary journals, such as *Computers and Industrial Engineering*, provide interdisciplinary methodological support for "PM-SCM Optimization" research from a technological perspective. And *Sustainability* has constructed a sustainable development-oriented research platform with 15 articles. The above journals together constitute the academic ecology of "theoretical innovation-technology implementation-sustainable expansion", which builds a

solid communication chain for optimization methodology from academic exploration to industrial application, helping it to become a key "technology bridge" connecting project and supply chain management. Although the number of articles and citations in the *Engineering Management Journal*, *Applied Sciences-Basel*, and other journals are different from those in some comprehensive journals, with the continuous cultivation of "PM-SCM Optimization", the number of related research articles is expected to increase rapidly. However, as "PM-SCM Optimization" continues to deepen its cultivation, the number of related research articles is expected to grow rapidly, and its future development potential is worth looking forward to.

**Table 6.** Top 20 journals.

| Journals | Number of Articles | Number of Citations | Average Citations | Impact Factor |
|---|---|---|---|---|
| *Engineering Construction and Architectural Management* | 15 | 102 | 7 | 3.6 |
| *Sustainability* | 15 | 119 | 8 | 3.9 |
| *Computers and Industrial Engineering* | 13 | 107 | 8 | 6.7 |
| *Journal of Construction Engineering and Management* | 13 | 131 | 10 | 4.1 |
| *Automation in Construction* | 9 | 144 | 16 | 9.6 |
| *International Journal of Managing Projects in Business* | 9 | 50 | 6 | 2.3 |
| *Applied Sciences-Basel* | 8 | 26 | 3 | 2.5 |
| *Engineering Management Journal* | 8 | 3 | 0 | 1.9 |
| *International Journal of Project Management* | 7 | 161 | 23 | 7.4 |
| *Journal of Cleaner Production* | 7 | 129 | 18 | 9.7 |
| *Buildings* | 6 | 41 | 7 | 2.7 |
| *Built Environment Project and Asset Management* | 6 | 22 | 4 | 1.9 |
| *Journal of Management in Engineering* | 6 | 110 | 18 | 5.3 |
| *Project Management Journal* | 6 | 76 | 13 | 5.1 |
| *Journal of Civil Engineering and Management* | 5 | 49 | 10 | 3.7 |
| *IEEE ACCESS* | 4 | 29 | 7 | 3.4 |
| *IEEE transactions on engineering management* | 4 | 53 | 13 | 4.6 |
| *Management science* | 4 | 72 | 18 | 5.4 |
| *Operations Management Research* | 4 | 36 | 9 | 6.9 |
| *Production Planning and Control* | 4 | 64 | 16 | 6.1 |

Citation data normalized per year. Source: Web of Science Core Collection, data retrieved in July 2025.

### *4.5. Analysis of Keywords*

#### 4.5.1. Analysis of Keyword Cluster

Research hotspots reflect the focal points of scholars within a specific academic field and the core issues explored in that field during a particular period. Keywords, as indispensable elements of academic papers, distill the core points of a paper and are frequently used to study and explore cutting-edge hot topics in specific fields [107]. To this end, the present study employed CiteSpace software to compare the clustered keywords generated by three mainstream tagging algorithms: LLR (Log Likelihood Ratio), LSI (Latent Semantic Indexing), and MI (Mutual Information). The findings suggest that while the three algorithms demonstrate distinctions in the particular manifestations of clustered keywords and the delineation of specific clusters, the overarching clustering framework remains constant. Core themes such as "project management", "supply chain", "risk management", and "sustainability" are consistently present, demonstrating robust stability in clustering outcomes regardless of the chosen tag-generation method. A list of relevant clustered keywords can be found in Appendix D. The LLR algorithm was selected for this study due to its demonstrated advantages in semantic distinctiveness, statistical significance, and interpretability of themes. The cluster labels it generated not only align more closely with domain terminology conventions but also effectively highlight the semantic cohesion within

each cluster. Consequently, this study undertakes a further examination of cluster analysis and discourse on the "PM-SCM Optimization" domain. Table 7 presents the complete list of 15 significant clusters obtained using the LLR label generation method, with each cluster containing at least 10 members. It is noteworthy that the contour values for each cluster exceed 0.7, indicating the reliability of the results and enabling further interpretation.

**Table 7.** Top-ranked clusters.

| Cluster ID | Size | Silhouette Value | Mean Year | Cluster Name |
|---|---|---|---|---|
| 0 | 31 | 0.897 | 2019 | optimization method |
| 1 | 26 | 0.944 | 2016 | project scheduling |
| 2 | 25 | 0.843 | 2019 | project management |
| 3 | 23 | 0.783 | 2019 | simulation |
| 4 | 22 | 0.845 | 2018 | integrated project delivery |
| 5 | 22 | 0.812 | 2020 | green supply chain |
| 6 | 21 | 0.802 | 2020 | artificial intelligence |
| 7 | 20 | 0.924 | 2013 | resiliency |
| 8 | 20 | 0.743 | 2020 | firm performance |
| 9 | 19 | 0.958 | 2016 | risk management |
| 10 | 19 | 0.908 | 2016 | supply chain management |
| 11 | 18 | 0.878 | 2021 | strategic management |
| 12 | 16 | 0.827 | 2021 | construction engineering |
| 13 | 16 | 0.966 | 2016 | supply chain disruption |
| 14 | 11 | 0.87 | 2021 | project portfolio |

Color blocks represent distinct clusters, with each block containing cluster keywords. This keyword knowledge network comprises 351 nodes and 772 connections, with a network density of 0.0128. In the CiteSpace clustering results, the clustering average contour value (S) and clustering module value (Q) serve as two critical metrics for evaluating the validity of clustering. The S value represents the closeness of samples within a cluster (i.e., homogeneity). Generally, $S > 0.5$ indicates reasonable clustering results, while $S > 0.7$ signifies high credibility. The Q value measures the closeness of connections within clusters and the sparsity of connections between clusters. Typically, $Q > 0.3$ is used as the criterion for determining significant community structure. The S-value in this study is 0.874, which is greater than 0.7, indicating high internal homogeneity within each cluster and strong reliability of the clustering partition. The Q-value is 0.7552, which is greater than 0.3, demonstrating a significant division of the knowledge network into community structures with good clustering effectiveness. This establishes a reliable foundation for subsequent cluster analysis.

According to the clustering data and the cluster diagram shown in Figure 8, "optimization method (Cluster 0)", as the core cluster, with a size of 31, a profile value of 0.897, and an average year of 2019, becomes the underlying technological logic that bridges project management and supply chain management; traditional project management clusters such as "project scheduling (Cluster 1)" and "project management (Cluster 2)", with "supply chain management (Cluster 10)", "green supply chain (Cluster 5)", and other supply chain oriented clusters, are deeply intertwined, reflecting the expansion of application scenarios of optimization methods in cross-domain collaboration. The clusters of supply chain direction, such as "green supply chain (Cluster 5)", are deeply intertwined, reflecting the expansion of application scenarios of optimization methods in cross-domain collaboration. Meanwhile, the rise in technology clusters such as "artificial intelligence (Cluster 6)" and "simulation (Cluster 3)" reflects that digital and intelligent technologies have empowered the iterative upgrading of optimization methods and pushed the research towards precision and dynamization.

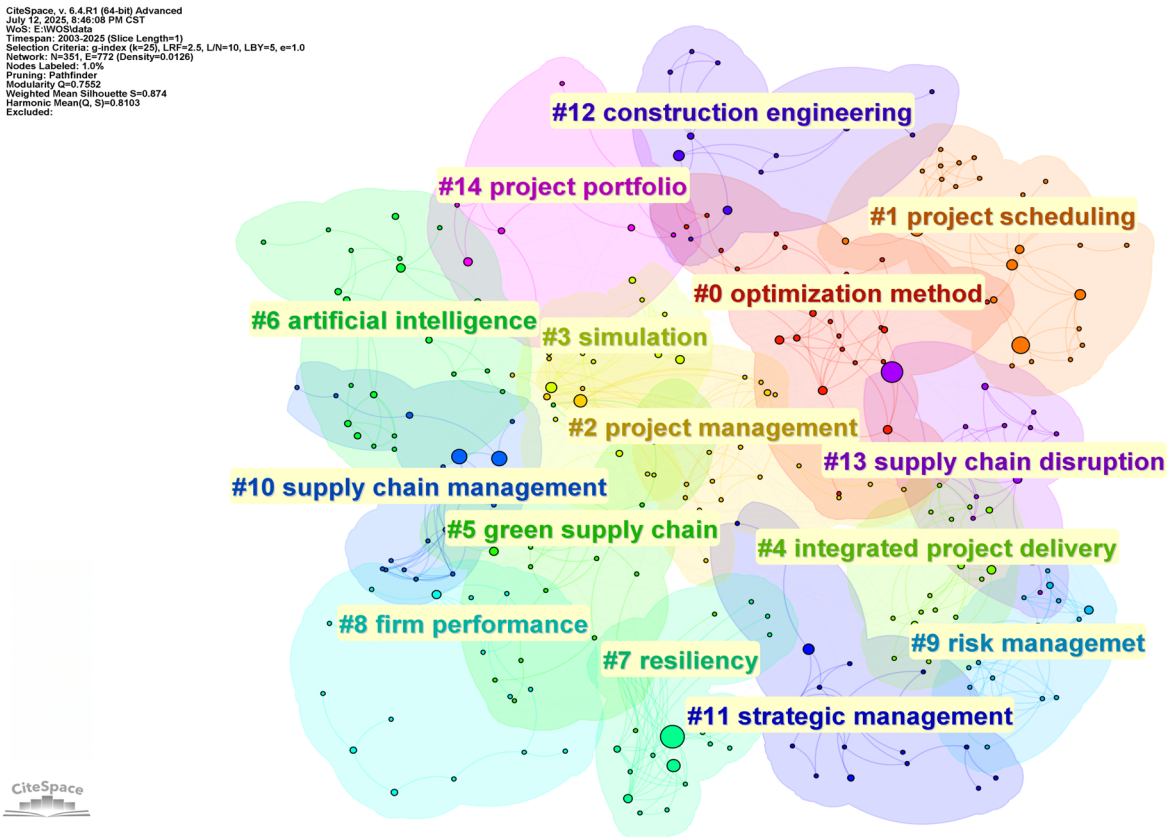



**Figure 8.** Clusters of knowledge domains within the related research.

The results of the cluster analysis indicate that research domains such as "project management" and "supply chain management" still maintain relatively independent research focuses. Although there is some degree of overlap, the scale of these interdisciplinary clusters remains small. This suggests that current research efforts in cross-domain integration are still insufficient and have yet to form a systematic theoretical framework.

The cluster mapping further shows the cluster association, with the core technology cluster (Cluster 0) radiating to the application clusters such as project management (Cluster 1, 2) and supply chain management (Cluster 5, 10), and the clusters of artificial intelligence and simulation being embedded in them, forming a "technology-scenario-innovation" linkage network. Clusters such as "supply chain disruption (Cluster 13)" and "risk management (Cluster 9)" echo the management challenges in the context of globalization and demonstrate the role of optimization methods in resilience enhancement and risk response. Clusters such as "integrated project delivery (Cluster 4)" and "project portfolio (Cluster 14)" echo the management challenges in the context of globalization and demonstrate the research value of optimization methods in resilience enhancement and risk response. Clusters such as "integrated project delivery (Cluster 4)" and "project portfolio (Cluster 14)" focus on the innovation of management mode and explore the path of optimization methods to drive the upgrading of management system.

#### 4.5.2. Analysis of Keyword Timeline

This study utilizes CiteSpace's keyword temporal analysis functionality to examine the evolution of research themes within the field of PM-SCM optimization. By leveraging the software's quantitative analysis of keyword frequency, centrality, and emergence, it further clarifies the distinctive research characteristics across different periods. This subsection presents the results of the keyword time span and emergence analysis, shown in Figures 9

and 10, which divide the knowledge evolution into three stages based on the time axis. A compact summary of the top burst terms is provided in Table A7 of Appendix D for quick reference. In the time span graph, the nodes correspond to keywords, whose size is positively correlated with the frequency, and the keywords are connected with the same-colored lines in the same year and associated with different-colored lines in different years. The burst detection of keywords has been demonstrated to be an effective method for identifying increasing trends in the attention devoted to specific research topics. This approach serves as a crucial mechanism for comprehending cutting-edge developments within a given field. In this burst detection, $\gamma$ was set to 0.5 and the minimum emergence duration to 2, which ultimately identified 21 burst keywords. In the burst analysis results graph, the beginning year is the time when the frequency increases significantly, and the end year is the time when the frequency stabilizes. The intensity of emergence reflects the significance of the frequency surge phase, and the red band corresponds to the duration.

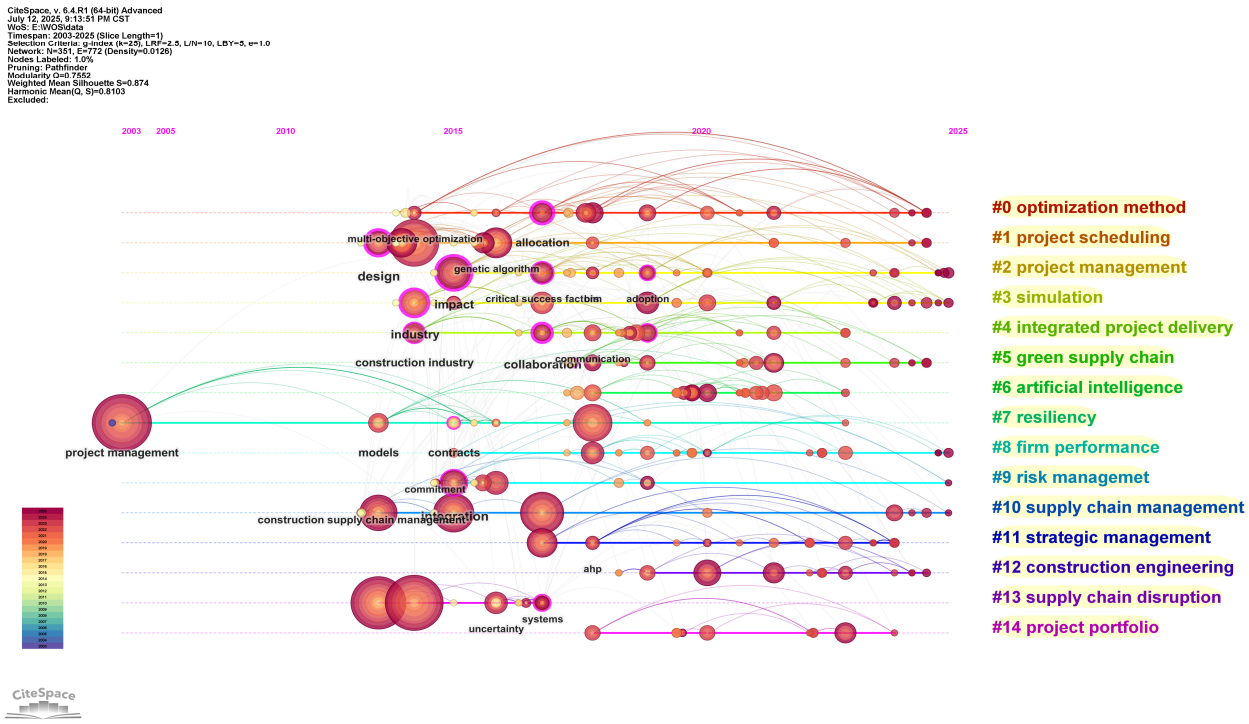



**Figure 9.** Timeline of research domains.

In the initial stage (2003–2010), "project management" and "supply chain management" emerged as basic keywords, laying the foundation of cross-domain synergy research. The research foundation of cross-domain collaboration has been laid. During this period, "optimization method" initially realizes the connection with the two management systems, and "genetic algorithm" and "multi-objective optimization" are the technical keywords. "Objective optimization" and other technical keywords emerged, marking the first step of the optimization method from theoretical concept to the exploration of algorithmic practice, building a solid technical base for the subsequent research and presenting the budding characteristics of the co-existence of management synergy demand and the introduction of basic algorithms.

During the scenario expansion period (2011–2018), the research landscape exhibited a marked proliferation of nodes, increased connectivity, and frequent emergence of new keywords, indicating the diversification of application contexts. Keywords gradually radiated into multiple domains. For instance, "construction industry" and "project scheduling" highlight the embedding of optimization techniques within infrastructure practices, resource

allocation, and construction management processes. Likewise, the prominence of "green supply chain" and "sustainability" echoes the global low-carbon agenda, underscoring the broader social and environmental value of optimization research. The growing salience of "risk management" and "collaboration" reflects an intensified focus on managerial efficiency, particularly in risk mitigation and cross-organizational coordination. In parallel, the increased frequency of terms such as "contracts" and "uncertainty" signals a shift from preliminary adaptation toward scenario-based implementation, accompanied by a trajectory of technological penetration and diversification. Nevertheless, the relatively limited maturity of digital and intelligent technologies during this period constrained their large-scale deployment.

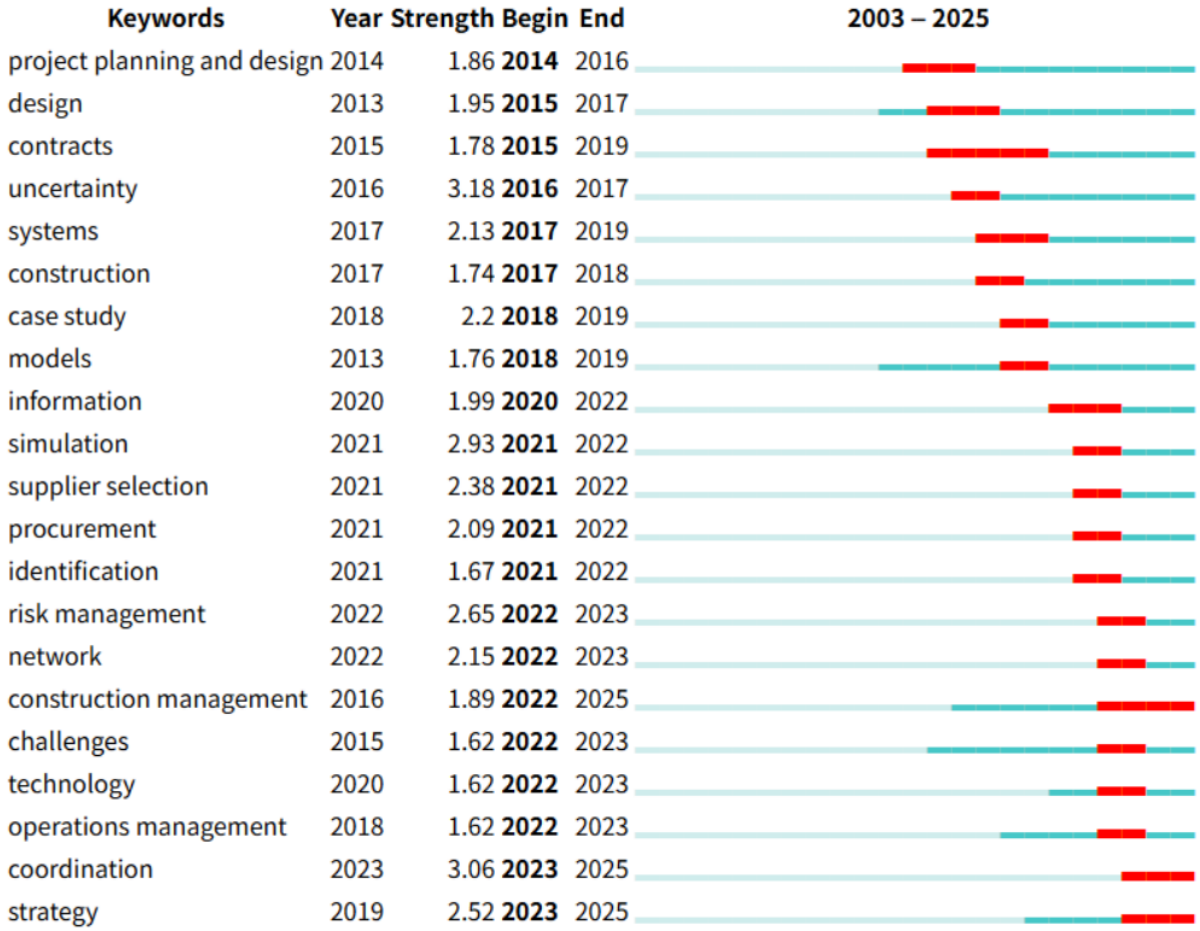



**Figure 10.** Keywords with the strongest citation bursts.

From 2019 onward, the research enters the intelligent iteration stage, and the keywords of digitalization and resilience-oriented bursts become the core of the evolution. The deep integration of "artificial intelligence" and "simulation" has injected intelligent algorithms and dynamic simulation capabilities into the optimization methodology, promoting the research to evolve in the direction of precision and predictability; the emergence of "supply chain disruption" and "resiliency" echoes the challenges of globalization, highlighting the value of optimization methods in risk resistance and system resilience construction; the rise in the keywords "integrated project delivery" and "project portfolio" explores the innovation of management mode and the empowering potential of optimization methods for systematic collaboration. At the same time, keywords such as "information" and "coordination" continue to emerge, promoting the deep integration of digital technology and optimization methods, shaping the upgrading pattern of intelligence-driven, resilience-

strengthening, and pattern breakthrough, revealing the value of this field in the construction of resilience. This reveals the research trend of the field in terms of continuous deep cultivation of practical scenarios and forward-looking layout of future trends.

The timeline diagram clearly shows the evolution of "PM-SCM Optimization" research. The optimization approach started with basic algorithmic applications, then gradually embedded into multiple management scenarios, and then achieved a significant leap in performance by relying on digital technology. The evolution of keywords indicates that research has gradually expanded from the application of fundamental algorithms to multi-scenario embedding, and now to the current focus on digitalization and resilience. This process reflects the shift in PM-SCM integration from conceptual exploration to methodological systematization. In the future, the words "information" and "coordination" will continue to emerge, which will promote the in-depth integration of AI and optimization methods, the innovation of scenarios driven by the dual goals of green development and resilience building, and the continuous breakthrough of management models in different fields, which will jointly promote the development of AI and optimization methods. However, the emergence of technologies such as "artificial intelligence" and "simulation" also suggests that current research relies heavily on emerging technologies and has yet to form a coherent theoretical integration framework. This further supports the future direction proposed in this paper, which emphasizes the development of contextualized models and technology-driven integration mechanisms. The continuous breakthrough of management mode will constitute the core direction of research deepening. These explorations will continue to promote the knowledge iteration of optimization methods in the field of project management and supply chain management integration, and provide more adaptable solutions for management collaboration in complex environments.

#### 4.5.3. Analysis of Keywords' Co-Occurrence

Keyword co-occurrence analysis forms an intuitive knowledge map by extracting keywords, abstracts, and other information from citations and analyzes and examines the development trends and research hotspots in a subject area through the study of high-frequency keywords. This section summarizes the results derived from the keyword co-occurrence analysis from 2013 to 2025. Running CiteSpace visualization software and selecting "Keyword" as the node type, a total of 445 high-frequency keywords were found, forming 1,769 links. In the hot keyword co-occurrence map of the literature, the size of the nodes and the text reflect the frequency of the keywords, the lines between the nodes indicate the correlation established in different time periods, and the thickness and density of the lines show the intensity of the keyword co-occurrence.

The keyword co-occurrence diagram (Figure 11) shows that "project management" and "supply chain management" co-occur with high frequency as the core nodes, which clearly shows the cross-field synergy nature of the research and also reflects that the application of optimization methods is based on the integration of the two management systems. This clearly demonstrates the cross-disciplinary synergy of the research, and also reflects that the application of optimization methods is based on the integration of the two major management systems; and "optimization" is closely related to the two, which not only highlights the core logic of technological empowerment, but also serves as a "methodological bridge" connecting project and supply chain management. However, several relatively independent subgroups (e.g., "Sustainable Development" and "Project Scheduling") remain within the network, suggesting that the current research has yet to form a unified integration framework.

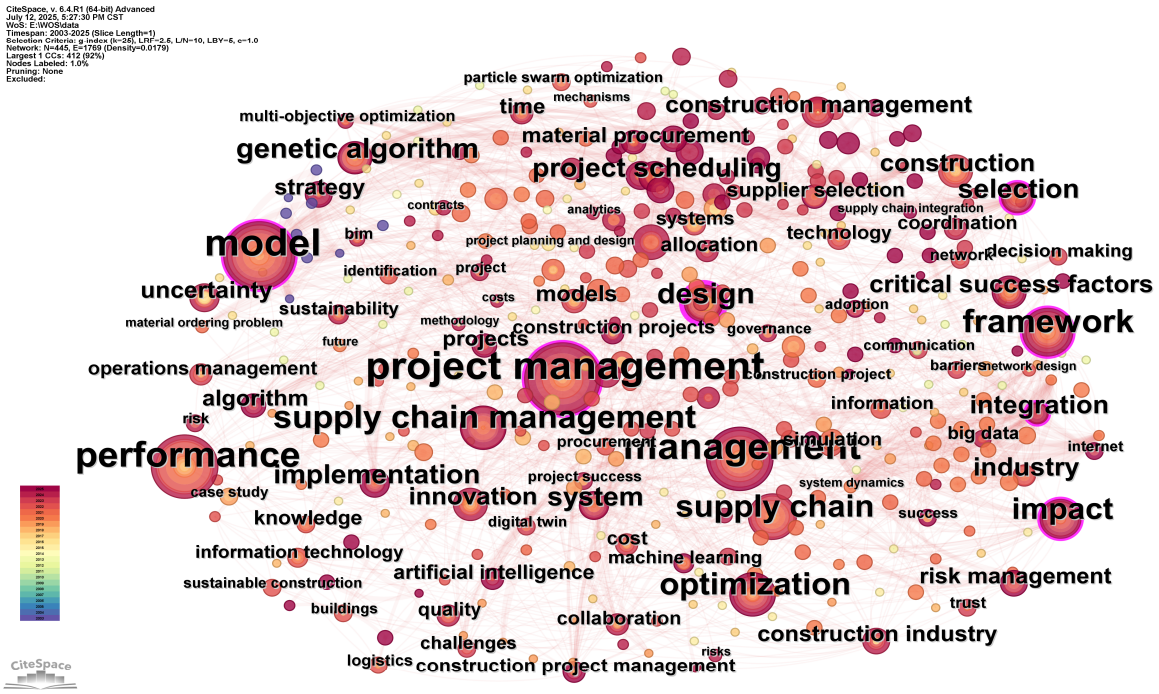



**Figure 11.** Network of keywords' co-occurrence.

Around these core nodes, the network derives multiple associated layers. In the technical dimension, the appearance of algorithm keywords such as "genetic algorithm" and "particle swarm optimization" reflects the technical support of the optimization method; in the scenario dimension, "construction management" and "scheduling" are the keywords. In the scenario dimension, "construction management" and "project scheduling" point to the practice of infrastructure projects, while "sustainability" and "green supply chain" echo the demand for low-carbon transition, further expanding the social value of the study. In the management dimension, the existence of keywords such as "performance" focuses on the enhancement of management effectiveness and risk resilience by optimization methods, deepening their application value. In addition, the co-occurrence network also presents some emerging trends, and also the incorporation of digital keywords such as "artificial intelligence" and "big data" reflects the empowering effect of technological iteration on optimization methods and promotes the research to evolve towards intelligent collaboration and accurate decision-making; keywords such as "collaboration" and "integration" strengthen cross-organizational and cross-process associations and show the potential application of optimization methods in systematic management.

Overall, the keywords show a knowledge vein of "core focus on cross-domain collaboration, technology support for methodological innovation, scenarios covering practical needs, and trends embracing digital transformation". The research on optimization methods in the integration of project management and supply chain management is taking "management synergy" as the foundation, breaking through "technological innovation", and deepening in the direction of "diversified scenarios + digital empowerment", which points out the direction for subsequent research, including strengthening the methodology of project management and supply chain management. The deepening of the research has pointed out the direction for the subsequent research, including strengthening the applicability of algorithms, expanding green and intelligent scenarios, and constructing a collaborative management system, etc., which will continue to promote the iterative development of domain knowledge.

It is noteworthy that although the keyword co-occurrence network in this study primarily emphasizes themes such as "optimization methods", "project scheduling", "green supply chain", and "risk management", a closer inspection of the inter-cluster linkages reveals implicit connections to bottleneck detection, buffer management, and multi-actor decision-making. For instance, studies on project scheduling and supply chain disruptions often focus on identifying critical paths and constrained resources, which are conceptually aligned with bottleneck detection [108]. Similarly, the frequent occurrence of keywords such as "risk management", "collaboration", and "uncertainty" suggests links to buffer management strategies, including buffer design and control as used in the critical chain methodology [109]. Furthermore, the presence of keywords such as "collaboration", "contracts", and "integration" indicates research addressing multi-stakeholder decision-making and game-theoretic approaches [110]. Thus, while these themes may not appear as standalone clusters in the visualized results, they are embedded within cross-cluster linkages and high-frequency terms, reflecting their latent significance in PM–SCM optimization research.

### *4.6. Analysis of Article Citation and Co-Citation*

#### 4.6.1. Analysis of Highly Cited Articles

The direct citation analysis evaluates the attention articles receive within a research domain based on their citation frequency in the node network. Table 8 presents the top 10 most highly cited articles, from which the most representative publications were selected for in-depth analysis. The results indicate that the most cited paper was authored by Hwang et al. (2018) [111] in *the Journal of Cleaner Production*, with 208 citations. Using the case of a prefabricated monolithic fit-out modular building in Singapore, the study systematically identifies five major constraints hindering the adoption of such structures: cross-stage coordination, pre-design complexity, over-specification in logistics, early lock-in, and high initial cost. The authors propose Building Information Modeling (BIM) and Just-In-Time (JIT) strategies as key solutions to enhance multi-party collaboration and optimize transportation. This work offers practical insights for implementing optimization methods in construction contexts and addressing complex challenges in modular building practices.

**Table 8.** Top 10 cited articles.

| Document | Title | Citations | Per Year | Normalized TC |
|---|---|---|---|---|
| Hwang, Bon-Gang et al., 2018 [111] | 'Key constraints and mitigation strategies for prefabricated prefinished volumetric construction' | 208 | 26.00 | 5.48 |
| Cubric, Marija, 2020 [112] | 'Drivers, barriers and social considerations for AI adoption in business and management: A tertiary study' | 173 | 28.83 | 6.10 |
| Teizer, Jochen, 2015 [113] | 'Status quo and open challenges in vision-based sensing and tracking of temporary resources on infrastructure construction sites' | 144 | 13.09 | 2.66 |
| Yadav, Dharmendra et al., 2021 [114] | 'Reduction of waste and carbon emission through the selection of items with cross-price elasticity of demand to form a sustainable supply chain with preservation technology' | 141 | 28.20 | 4.89 |
| Fonseca, Juan D et al., 2019 [115] | 'Trends in design of distributed energy systems using hydrogen as energy vector: A systematic literature review' | 131 | 18.71 | 3.58 |
| Brinkhoff, Andreas et al., 2015 [116] | 'All You Need Is Trust? An Examination of Inter-organizational Supply Chain Projects' | 123 | 11.18 | 2.27 |
| Lee, Dongmin et al., 2021 [117] | 'Digital Twin for Supply Chain Coordination in Modular Construction' | 122 | 24.40 | 4.23 |
| Behera, Panchanan et al., 2015 [118] | 'Understanding Construction Supply Chain Management' | 115 | 10.45 | 2.12 |
| Kim, Sungjin et al., 2020 [71] | 'Dynamic Modeling for Analyzing Impacts of Skilled Labor Shortage on Construction Project Management' | 113 | 18.83 | 3.99 |
| Sabini, Luca et al., 2019 [119] | '25 years of 'sustainable projects'. What we know and what the literature says' | 112 | 16.00 | 3.06 |

Annual citation rates serve as a valuable metric for assessing the ongoing impact of publications. Among the analyzed literature, the paper by Cubric et al. (2020) [112] holds

the highest annual citation rate of 28.83. As a representative review on the integration of intelligent technologies into management scenarios, the study emphasizes the need to strengthen interdisciplinary co-design of AI in business and management, providing forward-looking reference value for related research in the field of "PM-SCM optimization". Furthermore, the study by Yadav et al. (2021) [114], which focuses on carbon emission reduction in green supply chains, aligns closely with current sustainability demands and has garnered 28.2 citations per year. Using a project management perspective, the authors construct a two-echelon sustainable supply chain model and employ mixed-integer nonlinear programming (MINLP) to integrate and optimize key variables such as flexible production planning, investment in preservation technology, and carbon tax compliance. This approach aims to achieve dual objectives of profit maximization and environmental impact minimization. The study provides a practical decision-making framework for inventory management, transportation, pricing, and sustainability strategy formulation in green supply chain projects, thereby facilitating the application of optimization methods in low-carbon contexts.

These highly cited articles continue to shape the research direction of "PM–SCM Optimization" by exploring how optimization methods can enhance management synergy from multiple perspectives. They offer important references for subsequent theoretical advances and practical applications, promoting the in-depth development of optimization methods within integrated project and supply chain management.

Literature co-citation occurs when two articles are cited together by subsequent publications, indicating a close relationship between their research topics. A higher co-citation frequency reflects stronger academic relevance, and analyzing such networks can help identify foundational literature that has played a pivotal role in the development of a research field. Figure 12 reveals a distinct co-citation cluster comprising authors such as Habibi F [76,77,92], Zhang Y [86], Asadujjaman M [78,79], Tabrizi BH [99–101], and Akhbari M [120], among others. This pattern indicates that their publications are not only foundational but also frequently referenced together within the field, underscoring their collective role in advancing research in "PM–SCM Optimization."

The research represented by this cluster addresses several key dimensions of the field. For instance, aiming at project and supply chain collaborative management in sustainable scenarios, Habibi et al. [76,77,92] propose a two-stage framework integrating sustainable project scheduling and material ordering. Their approach quantifies supplier environmental–social value through a multi-objective model and optimizes activity time, ordering schedule, and supplier selection using NSGA-II and MOPSO algorithms, achieving a win-win outcome in terms of net present value and sustainability benefits. This study has become a highly co-cited node in sustainability-oriented research, supporting the implementation of multi-objective optimization in cross-domain management. Focusing on storage constraints at construction sites, Zhang Yan [121] developed a PSMOP dual-objective model aimed at minimizing both project duration and total cost. The model offers precise solutions to practical issues such as resource allocation and risk response in project management, serving as a typical case of embedding optimization methods into specific management scenarios and promoting further integration of related technologies into complex construction processes. Addressing information-sharing barriers among dispersed stakeholders in the construction industry, Lee Dongmin [117] proposed and validated a traceable communication framework that integrates digital twins and blockchain. By using digital twin technology to accurately map entire project processes and blockchain to ensure reliable data flow, this approach enables optimization methods to dynamically adapt to the needs of project management and supply chain collaboration based on real-time, trustworthy information. This research promotes the evolution of optimization methods

toward an intelligent, transparent, and dynamic cross-domain collaborative system. It overcomes the limitations of traditional optimization that relies on static assumptions and provides a technical foundation for adapting "PM–SCM Optimization" to the digital era.

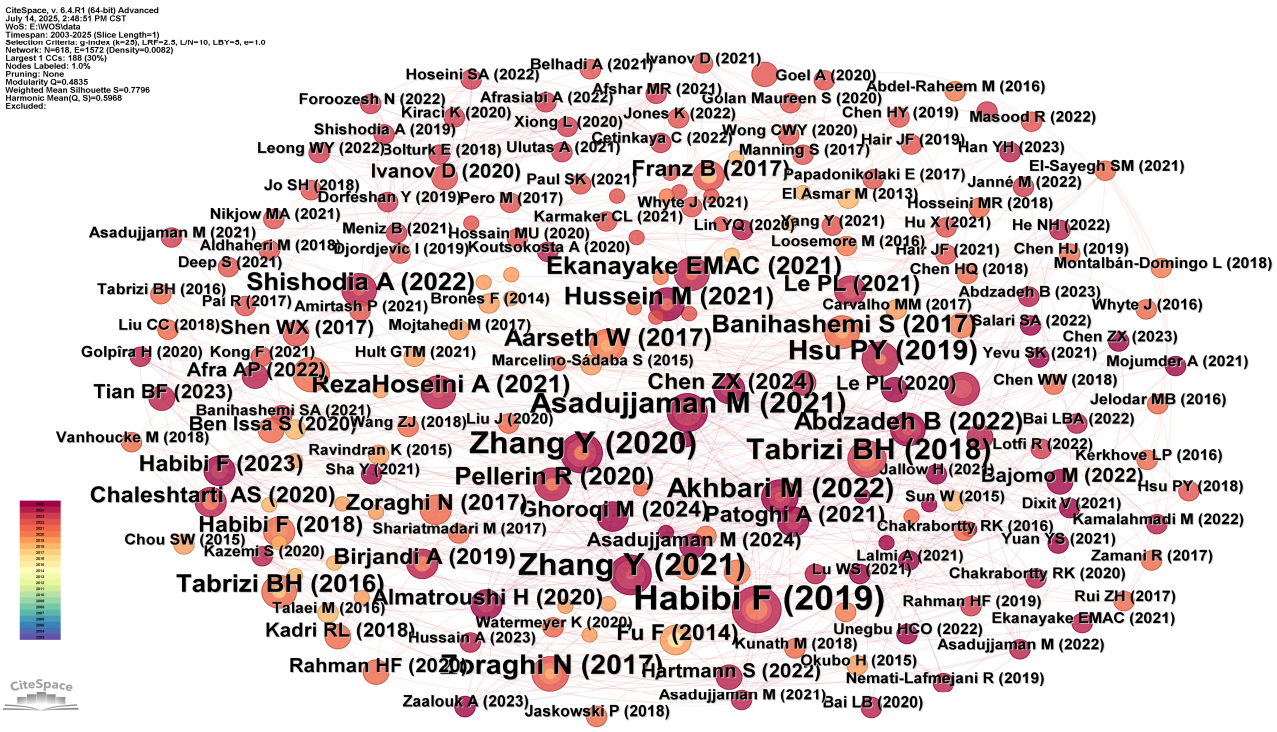



**Figure 12.** Co-citation network of articles.

Overall, the core group of authors, by virtue of their high-impact research results, has promoted the continuous iteration of optimization methods from a single model to multi-constraints, multi-value-oriented scenarios, and constructed an academic ecosystem of "technology adaptation-scenario cultivation-value expansion". This process has laid a solid knowledge foundation for solving the collaborative problems of project and supply chain management in complex environments.

#### 4.6.2. Analysis of Keywords Associated with Citation Impact

To identify the core research topics that are both frequently mentioned and highly influential in the field of "PM-SCM Optimization", this study analyzes keywords from two dimensions. On the one hand, it examines the frequency of keywords in highly cited literature to reflect current research hotspots. On the other hand, it pays attention to the coverage breadth of keywords in highly co-cited literature to reveal the academic consensus basis within the "PM-SCM Optimization" research field. Through the analysis of keywords in these two groups of literature, the core research directions that simultaneously meet the dual attributes of high frequency and high influence can be identified.

In the highly cited literature, keywords including "optimization", "sustainability", "artificial intelligence", "project scheduling", and "supply chain management" exhibit recurring patterns [111,112,114]. Furthermore, these keywords predominantly appear in publications that exert significant influence, exhibiting citation frequencies that surpass 100. This phenomenon suggests that the aforementioned themes possess significant theoretical research value and effectively address management challenges in real-world scenarios.

Secondly, in highly cited works, keywords like "project scheduling", "material procurement", "genetic algorithm", "digital twin", and "integration" have been frequently mentioned and repeatedly cited by various authors [76,77,92,117,121]. These terms have

transcended the boundaries of individual research contexts and gradually evolved into a widely recognized knowledge framework within the field. They have become common methodological elements in the field's research, providing a recognized theoretical basis and analytical framework for subsequent related studies.

In summary, the current research themes in the field of "PM-SCM Optimization" can be categorized into three core directions. The initial focus is on the methodological core, which is centered on the concept of "optimization" and its derivative models. The primary function of this field is to provide consensus-based solution logic and analytical tools for various complex management problems, thereby forming the technical foundation of research in this field. Secondly, value-driven frontiers encompassing "sustainability" and "artificial intelligence" are of particular interest. The concept of "sustainability" serves as the foundational principle that guides the field in addressing the practical demands for green development. Concurrently, the term "artificial intelligence" signifies the technological advancement that is propelling management decision-making towards an intelligent and precision-oriented transformation. Consequently, these elements collectively influence the prevailing value orientation and the subsequent developmental trajectory of research. The scenario integration hub encompasses the following: project scheduling, supply chain management, and integration. These themes function as practical application scenarios for theoretical research and as critical bridges connecting diverse fields, such as project management, supply chain management, and technological innovation. In this way, they provide essential support for cross-dimensional, systematic management practices.

## 5. Application Scenarios of PM-SCM Optimization

### *5.1. Project Management Within Supply Chain Management*

The core of SCM lies in integrating various stages, including suppliers, manufacturers, distributors, and retailers, to achieve efficient operations from raw material procurement to final product delivery. However, SCM faces numerous challenges, such as complex network structures, dynamic market demands, volatile supply environments, and disruptions caused by uncertainties. These characteristics necessitate a high degree of flexibility, adaptability, and optimization capability in SCM. PM methodologies and principles provide robust support in addressing these challenges. PM, as a goal-oriented approach, employs planning, organizing, coordination, and control mechanisms to ensure the achievement of predefined objectives under constrained resources. Its application in SCM is primarily reflected in the following aspects: First, PM emphasizes goal orientation and planning, enabling supply chain managers to clarify objectives and tasks at each stage and develop detailed plans to address complex supply chain operations. For instance, in supply chain network design, PM methodologies can optimize facility location, transportation route planning, and inventory management [25,69,122,123], thereby reducing costs and improving efficiency. Second, PM focuses on resource integration and optimal allocation, which aligns with the objectives of resource management in SCM. By incorporating PM principles, supply chain managers can better coordinate resources among suppliers, manufacturers, and logistics service providers, enhancing resource utilization efficiency. Finally, risk management methodologies in PM also offer effective tools for SCM, assisting managers in identifying, assessing, and mitigating uncertainties within the supply chain.

The integration of PM methodologies into SCM is evident across multiple management scenarios. In the construction industry, SCM must address complex project requirements and dynamic market conditions. Construction projects typically involve multiple phases, from design and procurement to construction, each requiring precise planning and coordination. By adopting PM approaches, construction supply chain managers can optimize material procurement, inventory management, and logistics distribution, thereby minimiz-

ing delays and costs. Some studies have proposed a mixed-integer linear programming (MILP) model to optimize multi-project scheduling and vehicle routing in construction supply chains, achieving a better cost balance among different project departments [65]. Another study developed a multi-product, multi-period construction supply chain model that accounts for uncertainties in supplier capacity and material demand, employing robust optimization to address model uncertainty [124]. In the realm of green and sustainable development, biomass energy supply chains utilize multi-objective optimization [123,125] to balance economic and environmental goals. Research incorporating techno-economic–environmental analysis has designed a four-tier optimized supply chain network (SCN), using a MILP model to assess the feasibility of green energy policies. In the process of supply chain optimization, project management with sustainability as the goal has become a key driving force for transforming green technological innovation and eco-design from concepts into commercial achievements. Recent studies have shown that green technological innovation, pro-environmental behavior, and eco-design can significantly increase the success rate of new green products, while the green corporate image plays a crucial moderating role in this process [126]. Emerging technological innovations further demonstrate the application of PM principles. For instance, drone logistics enhance inventory visibility through dynamic mathematical models [127], while IoT sensors combined with dynamic pricing reduce food waste [128]. Additionally, deep learning techniques (e.g., BOCNN-LSTM) are applied to demand forecasting and inventory optimization [129]. These scenarios highlight the value of PM methodologies in addressing supply chain fragmentation, resource inefficiency, and delayed responsiveness. Research has confirmed the critical role of quality integration in optimizing multi-project supply chain collaboration, demonstrating that quality integration reduces the total normalized cost by an average of 12.7%. Specifically, when the material qualification rate increases by 15%, project rework time can be reduced by 22%, while transportation distance is shortened by 18%.

To address specific challenges in SCM, PM methodologies provide a diverse set of optimization tools. Resource conflicts and scheduling issues can be resolved through mixed-integer linear programming (MILP) combined with heuristic algorithms (e.g., tabu search) for multi-project vehicle routing optimization [65]. Alternatively, mixed-integer programming (MIP) models can be applied to solve integrated resource-constrained multi-project scheduling problems in supply chains [78]. Based on research in engineering project supply chains (SC) and SC optimization, a mixed-integer nonlinear programming (MINLP) model has been developed to minimize the total SC costs in international petrochemical projects [130]. Subsequently, uncertainty management relies on robust optimization techniques. For instance, robust optimization models in construction supply chains address dual uncertainties, such as demand timeliness and transportation loss rates, during specific project periods in building material supply chains [131]. Additionally, sustainability objectives necessitate multi-objective optimization. For example, green construction supply chains utilize bi-objective models to minimize project delays while reducing logistics costs and greenhouse gas emissions [66]. Furthermore, collaborative decision-making challenges can be addressed through Stackelberg game-theoretic models to achieve equilibrium among stakeholders [132]. Applying these methodologies has significantly enhanced supply chain performance in terms of efficiency, resilience, and sustainability. In the integration of PM and SCM, risks form transmission channels through the dependencies among multiple stakeholders (e.g., a delay by one supplier can impact the entire project schedule). The contracts or principal–agent relationships established among the parties directly determine how they perceive and respond to risks. For instance, unclear responsibilities in contracts may incentivize stakeholders to conceal risks or shift blame. To block such risk propagation, effective mechanisms include setting buffers (such as allowing slack in time and resources)

and focusing on bottleneck management, thereby absorbing and mitigating risks before they spread extensively. In summary, PM approaches, leveraging mathematical models, algorithmic innovations, and other optimization techniques, provide end-to-end solutions for SCM, spanning from strategic design to operational optimization.

### *5.2. Supply Chain Management Within Project Management*

Research in Section 5.1 indicates that PM methodologies effectively enhance the supply chain capabilities in dealing with complexity and uncertainty through structured goal decomposition and dynamic control mechanisms. However, when applied to large-scale complex projects, such as international EPC engineering and spacecraft development, traditional PM models reveal considerable limitations in resource integration. Critical project resources often heavily rely on external supply networks, while risks from multi-tier suppliers may propagate through resource delays to the project's critical path. Therefore, a breakthrough in PM performance requires the deep integration of systematic optimization thinking, networked resource integration approaches, and process coordination mechanisms inherent in SCM.

In practical management scenarios, the integration of SCM principles into PM has shown significant value across multiple domains, including engineering, construction, and product development. Within the construction sector, prefabricated building projects have adopted SCM methodologies to optimize component production scheduling [133]. In product development PM, researchers have incorporated supply chain perspectives to design project-oriented supply chain networks, proposing goal programming models to address project-specific supply chain challenges [134]. At the research level, supply chain network design concepts have been introduced to large-scale PM, leading to the development of multi-level optimization models. For instance, R&D projects have employed goal programming approaches to construct supply chain networks that optimize contractor and executor configurations [134]. To address execution uncertainties, robust optimization methods from SCM have been adapted to project contexts, enabling effective resource-constrained scheduling under uncertainty [135]. These advancements transcend the localized optimization limitations of traditional PM, expanding the developmental dimensions of PM practice.

SCM provides diversified optimization methodologies to address typical PM challenges. For resource optimization in multi-project environments, mixed-integer programming [136] and genetic algorithms [137] have been effectively applied to resolve the resource allocation problem. When confronting uncertainty challenges, robust optimization approaches [135] demonstrate high effectiveness in mitigating various risk factors during project execution. Particularly noteworthy is the introduction of dynamic optimization paradigms from SCM into PM, such as cross-organizational dynamic reputation incentive models for project-based contexts [138]. The implementation of these methodologies has substantially enhanced the precision and adaptability of PM practices, while providing effective solutions to overcome the rigid constraints and fragmented optimization limitations inherent in traditional PM approaches.

### *5.3. Integration of Project Management and Supply Chain Management*

PM provides structured control capabilities for the supply chain, while SCM offers systematic optimization methods for projects. However, PM and SCM still necessitate deeper integration, specifically because of the inherent contradiction between the temporary nature of projects and the continuity of supply chains, coupled with increasing needs for flexible resource allocation driven by customer customization and the real-time collaboration foundation enabled by digital technology. A project-driven supply chain (PDSC) is a network

system centered on temporary project requirements, designed to dynamically integrate multi-tier supplier resources to achieve end-to-end collaborative optimization from design to delivery. As shown in Table 9, unlike a project-based supply chain (PBSC), PDSC is a temporary, adaptive, and goal-oriented network ecosystem dynamically configured around the unique objectives and constraints of a specific project or project portfolio. Through a systematic literature review, this study reveals that research on PDSC demonstrates a paradigm shift from unidirectional supply–demand relationships to bidirectional dynamic collaboration. Innovations in this domain are primarily manifested in three aspects: theoretical innovation, framework innovation, and research paradigm innovation.

**Table 9.** Comparison between project-driven supply chain and project-based supply chain.

| Dimension | Project-Driven Supply Chain (PDSC) | Project-Based Supply Chain (PBSC) |
| --- | --- | --- |
| Core Objective | Complete specific projects efficiently and at a low cost. | Through outstanding project management skills, I have successfully won and delivered multiple complex projects. |
| Organizational Form | Temporary and task-oriented organizations. | Permanent and capability-oriented organization. |
| Nature of Demand | Unique, one-time, and highly uncertain, driven by project-specific specifications and milestone schedules. | Repetitive or semi-repetitive across multiple projects, aiming for standardization and process improvement. |

At the theoretical innovation level, three significant contributions have emerged. Firstly, this research in this domain has pioneered project-oriented resource allocation theory. Unlike traditional SCM, which often focuses on stable demand-based allocation, PDSC tightly integrates resource allocation with dynamic project objectives and constraints. As demonstrated in studies on construction projects, optimizing material procurement, inventory management, and logistics distribution can effectively reduce delays and costs [127]. This allocation approach not only considers project requirements but also schedule and quality constraints, thereby enhancing resource utilization efficiency. Secondly, the field has enriched dynamic optimization theory. PDSC emphasizes continuous optimization throughout the project lifecycle. For example, dynamic mixed-integer linear programming models enable optimal decision-making in multi-period, multi-product environments [139]. Such dynamic optimization methods demonstrate superior capability in responding to market fluctuations and uncertainties, significantly improving supply chain flexibility and adaptability. A third theoretical advancement lies in collaborative optimization theory. PDSC highlights synergistic interactions among supply chain segments. Through collaborative optimization models, practitioners can simultaneously optimize supplier selection and project scheduling, thereby improving overall project performance [140]. This approach facilitates seamless coordination across supply chain components, enhancing both operational efficiency and economic benefits.

At the framework innovation level, the novelty lies not only in applying specific optimization models but in constructing an integrated management framework that redefines how PM and SCM interact. PDSC embeds project scheduling, procurement, supplier selection, inventory control, and logistics distribution into a unified decision-making structure, thereby transforming traditionally fragmented processes into a coordinated whole [78]. This framework innovation highlights a shift from isolated optimization to system-level integration, where project execution and supply chain operations are planned and controlled within the same architecture. Furthermore, PDSC extends this integrated framework by incorporating risk management methodologies from PM, establishing a holistic mechanism for identifying, evaluating, and mitigating uncertainties across both project and supply

chain domains. For example, robust optimization models have been developed to coordinate project scheduling and resource allocation under uncertainty [100]. Such a framework enables not only technical optimization but also systematic resilience-building, significantly enhancing the robustness and adaptability of supply chain operations.

At the research paradigm innovation level, distinctiveness lies in the redefinition of how knowledge on PDSC is generated and validated. Two paradigm shifts are particularly noteworthy. The first is the emergence of a data-driven paradigm, where the advancement of big data and digital technologies enables scholars to move from assumption-based modeling to evidence-based, real-time analysis. For example, data analytics has been applied to demand forecasting and inventory optimization in SCM [129], and similar approaches are increasingly being extended to PDSC. This transition marks a move from static, model-centric studies toward continuous, adaptive, and empirically validated research, paving the way for predictive and even prescriptive supply chain–project integration. The second is the rise in an interdisciplinary paradigm, whereby investigations no longer reside solely within the domains of PM or SCM, but increasingly integrate operations research, information systems, engineering, and even behavioral sciences. Such interdisciplinarity not only broadens the analytical toolkit but also reframes research questions, enabling holistic exploration of complex socio-technical systems. Together, these paradigm innovations point to a future in which PDSC research evolves from isolated theoretical constructs to a living, data-rich, and cross-disciplinary knowledge ecosystem, capable of continuously informing both academic inquiry and industrial practice.

Overall, PDSC represents not merely a supplement but an evolution of traditional PM and SCM theories. At the theoretical level, it pioneers project-oriented, dynamic, and collaborative optimization theories that expand the conceptual foundation of supply chain management. At the framework level, it constructs an integrated system that unifies PM and SCM processes, enabling system-wide coordination and holistic risk management. At the paradigm level, it advances a shift toward data-driven and interdisciplinary approaches, reshaping how knowledge in this field is generated and validated. Taken together, these innovations provide project-intensive industries with a comprehensive foundation to systematically govern complex, dynamic, and cross-organizational resource networks. This allows them to overcome the inherent challenges of temporary organizations, task orientation, and high uncertainty, while fostering synergistic alignment between project objectives and supply chain outcomes, ultimately enhancing efficiency, resilience, and sustainability and setting the stage for future research and practice.

As shown in Figure 13, effective integration of PM and SCM requires a clear governance structure to oversee decision-making across project and supply chain interfaces. The decision owner—typically a cross-functional steering committee comprising senior representatives from project management, supply chain, finance, and risk management—is responsible for validating optimization outcomes and approving resource allocation. This committee ensures that optimization outputs align with strategic objectives, resolves conflicts between project timelines and supply availability, and oversees risk mitigation strategies. By establishing a centralized governance body, organizations can enforce accountability and maintain alignment between temporary project goals and ongoing supply chain operations.

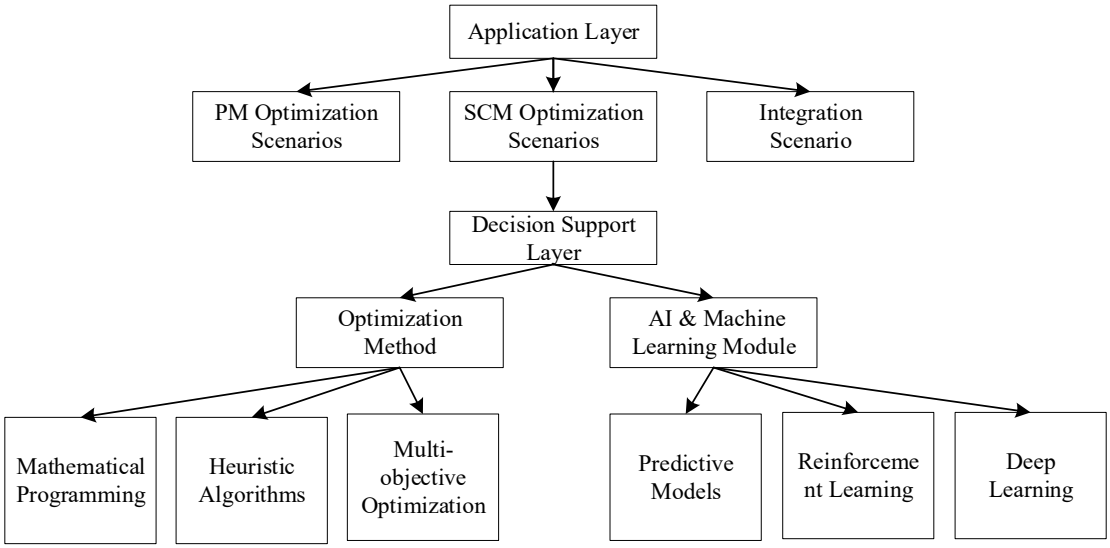



**Figure 13.** Hybrid decision reference architecture diagram.

## 6. Optimization Methods and Emerging Technologies for Bridging Project Management and Supply Chain Management

### *6.1. Mathematical Programming Approaches*

Mathematical programming is the cornerstone of operations research and management science. Its core idea is to find the optimal decision under given constraints by establishing a mathematical model and utilizing mathematical tools, primarily through steps such as problem identification and definition, model construction, and model solution, to address complex decision-making problems. Mathematical programming approaches are widely used tools for optimizing decisions through mathematical models, addressing various constraints in real-world problems [141]. Linear programming (LP), the most fundamental form of mathematical programming, is extensively applied in both supply chain management SCM and PM [66,142]. In supply chains, LP helps optimize distribution routes or minimize transportation costs by optimizing a linear objective function [143]. In PM, LP plays a vital role in task scheduling, cost control, and resource allocation, enabling project managers to achieve optimal resource allocation with limited resources [66,144,145]. As the complexity of problems increases, mixed-integer linear programming (MILP) has gained prominence, allowing for optimization with both continuous and integer variables. This flexibility makes MILP particularly effective in addressing SCM and PM challenges that involve integer decisions, such as supplier selection, production batch scheduling, and integrated project scheduling [78,114,140]. MILP's ability to handle discrete decisions more accurately ensures that solutions align closely with real-world requirements.

However, many real-world problems introduce nonlinear relationships, such as transportation costs that increase with the square of distance or diminishing returns in production efficiency as output grows. For these problems, nonlinear programming (NLP) provides a powerful optimization method, capable of modeling such complexities in supply chain networks [114,130]. As supply chains and projects become more volatile, uncertainty plays a crucial role. Traditional methods struggle to address unpredictable elements like demand fluctuations or transportation delays. In this context, stochastic programming becomes increasingly essential. By incorporating randomness into the model, stochastic programming enables more flexible and adaptive decision-making, allowing for better handling of uncertainty in both supply chain management and project execution [95,146,147]. Emerging technologies, such as big data analytics and cloud computing, have significantly enhanced the capability of these mathematical programming approaches. For example,

the integration of real-time data with MILP models allows for dynamic optimization, while AI algorithms help refine the accuracy of stochastic programming by improving uncertainty predictions. These technologies push mathematical programming beyond traditional, static optimization, enabling real-time, adaptive decision-making for complex and uncertain environments.

In conclusion, mathematical programming approaches have evolved significantly, from simple linear models to sophisticated methods capable of addressing nonlinear relationships and uncertainty. These methods, increasingly integrated with emerging technologies, continue to provide powerful solutions for both SCM and PM, ensuring flexibility and robustness in addressing real-world complexities.

### *6.2. Heuristic and Metaheuristic Optimization*

Heuristic and metaheuristic optimization techniques are designed to tackle complex, high-dimensional, non-differentiable, or even combinatorially explosive problems. Such problems often cannot be solved by traditional methods within a feasible time frame to obtain an exact optimal solution. Their core objective is to find a "good enough" feasible solution within a reasonable amount of time.

Heuristic and metaheuristic optimization methods have become essential in integrating PM and SCM. They provide practical solutions to complex decision-making problems that are often too difficult for exact mathematical approaches. Heuristic approaches are typically based on problem-specific rules and priority logic, offering fast computation and operational simplicity. They are widely applied in practical scenarios such as project scheduling, resource allocation, and route selection [148,149]. For example, the critical path method (CPM), priority-based scheduling, and greedy algorithms demonstrate strong responsiveness and interpretability in activity sequencing and material replenishment, particularly under dynamic and decentralized environments where rapid decision-making is critical [150,151].

Unlike heuristics, metaheuristic algorithms follow generalized search frameworks that can explore large and complex solution spaces. They combine exploration and exploitation to achieve global optimization and do not require strict mathematical assumptions [152]. Popular examples include genetic algorithms (GA), simulated annealing (SA), particle swarm optimization (PSO), ant colony optimization (ACO), and tabu search (TS) offer greater global search capabilities and scalability. GA commonly uses termination criteria such as reaching the maximum number of iterations or no improvement over a consecutive number of generations. PSO typically terminates when the maximum number of iterations is reached or the global optimal solution stabilizes. SA often stops when the final temperature reaches a threshold or the maximum number of iterations is met. ACO generally concludes when the maximum number of iterations is reached, or the solution quality meets the expected standard. Common stopping criteria for TS are reaching the maximum number of iterations or achieving the desired solution quality. These algorithms operate without the need for strict mathematical assumptions and are well-suited to solving NP-hard combinatorial optimization problems [153,154]. Following the discussion of termination criteria for metaheuristic algorithms, we now present simplified algorithmic representations of two representative optimization problems commonly encountered in integrated PM–SCM contexts. These pseudo-models (Algorithms 1 and 2) illustrate the core structure and key constraints of these problems, providing readers with an intuitive understanding of their mathematical formulation.

**Algorithm 1.** Integrated RCPSP-Inventory MILP

**Input:** Project activities, Resource capacities per period, Demand and supply data, Precedence relationships

**Output**: Optimized activity schedule and inventory levels

Initialize activity execution variables as binary
Initialize inventory level variables as nonnegative
Set objective: minimize total cost $(\text{execution} + \text{holding})$
**For** each period $t$:
    Calculate total resource usage across all activities
    **If** resource usage $>$ available capacity:
        Mark solution as infeasible
**End for**
**For** each item $i$ and period $t$:
    Update inventory: $I_{\{i,t\}} = I_{\{i,t-1\}} + supply_{\{i,t\}} - demand_{\{i,t\}}$
    **If** $I_{\{i,t\}} < 0$:
        Mark solution as infeasible
**End for**
**For** each precedence relationship $(i, j)$:
    **If** activity $j$ starts before activity $i$ finishes:
        Mark solution as infeasible
**End for**
Return optimized activity schedule and inventory levels

**Algorithm 2.** Robust Scheduling Optimization

**Input**: Set of tasks with precedence constraints, Uncertainty set $U$ for processing times

**Output**: Robust task start and completion times, Worst-case makespan estimate

Initialize task start times $S_j$ and completion times $C_j$
Define uncertainty set $U$ for processing times
**For** each scenario $\xi \in U$:
    Calculate makespan $C_{\max(\xi)}$ for scenario $\xi$
**End for**
Set objective: minimize $max_{\{\xi \in U\}}\ C_{\max(\xi)}$
**For** each precedence relationship $(i, j)$ :
    **For** each scenario $\xi \in U$:
        Ensure $S_i \geq S_i + p_{i(\xi)}$
    **End for**
**End for**
**For** each task $i$:
    **For** each scenario $\xi \in U$:
        Calculate $C_i(\xi) = S_i + p_i(\xi)$
    **End for**
**End for**
Calculate $C_{max}^{worst} = \max_{\{\xi \in U\}} max_i C_i(\xi)$
Return task start times and worst-case makespan

In PM scenarios, the application of heuristic and metaheuristic algorithms can be further enhanced by integrating network analysis perspectives to deepen optimization outcomes. For instance, Bai et al. [155] constructed a project portfolio network comprising

task and project nodes connected by collaboration and association edges. They introduced a collaboration metric to quantify the strength of resource-sharing relationships between tasks, providing precise relational weights for subsequent optimization. In integrated PM-SCM contexts, GA and PSO are frequently used to coordinate project schedules with supply plans, optimizing resource allocation and transportation routes [78,156]. ACO has shown effectiveness in logistics network design [157], while SA [158] and TS [68] are useful for time–cost trade-offs and stability in resource management.

In collaborative PM-SCM optimization, heuristic and metaheuristic methods are often used in combination to leverage their respective strengths. Heuristics may be employed to quickly generate feasible solutions or initial schedules, followed by metaheuristic algorithms for global optimization and multi-objective refinement. Some studies have proposed hybrid models that jointly optimize project scheduling, inventory control, and transportation planning [159], significantly improving overall system performance and responsiveness.

The integration of emerging technologies has further enhanced the real-time and intelligent capabilities of these optimization methods. Internet of Things (IoT) technologies and RFID enable real-time data collection from both supply chains and project sites allow algorithms to respond dynamically to unexpected disruptions [160]. Cloud computing and collaborative platforms facilitate multi-party data sharing and joint optimization [161]. Meanwhile, artificial intelligence techniques can support metaheuristic algorithms through adaptive parameter tuning, search strategy adjustment, or rule learning, thereby improving convergence speed and solution quality [162]. Furthermore, the incorporation of digital twin technologies enables simulation and adjustment of optimization plans in virtual environments, enhancing decision reliability and robustness [163]. Overall, heuristic and metaheuristic methods are evolving from computational tools into intelligent, adaptive, and technology-driven solutions that can address the growing complexity and uncertainty of integrated PM-SCM systems.

### *6.3. Machine Learning and AI-Based Optimization*

The rapid advancement of technology has enabled machine learning and AI-based optimization to provide innovative solutions for decision-making in PM and SCM. The goal of machine learning is to automatically adjust the parameters of a model by learning from data, so as to optimize the model's predictive performance. These approaches are particularly effective in dealing with large-scale data, complex uncertainties, and dynamically changing environments, with reinforcement learning, deep learning, and hybrid AI-optimization frameworks emerging as key applications.

Reinforcement learning (RL) learns optimal decision strategies through continuous interaction with the environment. In PM, RL can be applied to task scheduling and resource allocation by simulating alternative strategies to optimize project timelines and costs [164,165]. In SCM, RL has shown strong adaptability in dynamically adjusting inventory levels and optimizing transportation routes, allowing systems to respond to real-time fluctuations in demand and supply to ensure operational efficiency [166,167].

Deep learning (DL), as another powerful AI technique, is capable of recognizing patterns from large amounts of complex data. In supply chain management, deep learning can be used for demand forecasting, inventory management, and more [129]. By analyzing historical data, deep neural networks can predict future demand, which can help optimize inventory levels and improve supply chain responsiveness. In project management, deep learning can also be used to analyze historical project data to predict project schedule delays and take preventive measures [162].

Beyond standalone methods, the hybrid AI-optimization framework combines traditional optimization algorithms with modern machine learning techniques to leverage the strengths of both. It is able to handle more complex decision-making problems by combining machine learning with traditional methods such as mathematical planning and simulation optimization [163]. For example, machine learning models can be used to predict future demand, and can be combined with optimization algorithms to make decisions on resource allocation and path planning for supply chain optimization [168]. In project management, hybrid AI frameworks are able to adjust project schedules based on real-time data to ensure on-time and on-budget completion [169]. In project risk assessment and dynamic resource allocation scenarios, hybrid AI frameworks can also integrate technologies such as Bayesian networks and genetic algorithms to enhance the handling of complex interrelated risks. For instance, Bai et al. developed a fuzzy Bayesian network model that accounts for project interdependencies to address risks arising from resource sharing between projects. By optimizing network parameters through genetic algorithms, they achieved dynamic assessment and response to resource risks [170].

Collectively, these approaches signify a shift from static, rule-based optimization to adaptive and data-driven decision-making. By continuously learning and adjusting, machine learning algorithms enhance the accuracy and adaptability of optimization models. The integration of AI technologies allows for smarter and more flexible decision support in complex and uncertain environments, with frameworks that combine historical data, real-time data, and nonlinear relationships to provide robust, forward-looking solutions for both PM and SCM. A notable emerging trend is the automated detection and design of priority rules, which has been explored in recent studies [171,172]. These approaches leverage machine learning to dynamically generate or refine scheduling rules, enabling more adaptive and data-driven decision-making. Integrating such methods into PM–SCM contexts holds promise for enhancing responsiveness and robustness in complex project environments.

### *6.4. Multi-Objective and Robust Optimization*

Multi-objective optimization generates a Pareto solution set that clearly reveals the inherent trade-offs between objectives. However, translating this mathematical result into clear management decisions is a critical step during project stage-gate review meetings. To illustrate how optimization methods support this process, consider a typical scenario: a review committee for a large construction project needs to make a final choice between two conflicting objectives: “minimizing cost” and “minimizing project duration.”

Assume the optimization analysis provides three representative alternatives: Alternative A has the lowest cost but the longest duration; Alternative C has the shortest duration but the highest cost; Alternative B falls between the other two in terms of both cost and duration. These three alternatives form a classic trade-off pattern—achieving a shorter duration inevitably comes at the cost of a higher budget, and vice versa. No single alternative is optimal in both objectives simultaneously, which is precisely the challenge in decision-making.

During the stage-gate review, decision-makers must select the most suitable alternative from this trade-off landscape based on the organization’s strategic priorities. The weighted sum method plays a central role here, as it quantifies the decision-makers’ strategic preferences into specific weights. For example, when the project faces strict budget constraints, adopting a cost-priority strategy leads decision-makers to assign a higher weight to the cost indicator. Under this preference, the mathematical model automatically selects Alternative A as the optimal solution because its cost advantage far outweighs its duration disadvantage.

Conversely, if the project operates in a highly competitive market where capturing opportunities first is critical, decision-makers may shift to a time-priority strategy, assigning a higher weight to the duration indicator. In this case, the calculation results would show that Alternative C has the highest comprehensive evaluation, as its significant time value completely offsets the additional cost. Alternative B represents a balanced path, potentially becoming the ideal compromise when decision-makers consider cost and duration equally important.

This process demonstrates that the role of the optimization model is to objectively present all feasible trade-off options (the Pareto front), while the weighted sum method translates the decision-makers' subjective strategic judgments into a clear, consistent selection logic. It elevates the stage-gate review from experience-based debates to a data-driven, traceable, and rational decision-making process. This significantly enhances the transparency and scientific rigor of project governance, serving as an effective bridge connecting optimization algorithms with management practice.

Integrated decision-making in project management and supply chain management often involves conflicting objectives such as minimizing cost, shortening project duration, and reducing operational risk [121,135]. While traditional optimization approaches typically focus on single-objective solutions, multi-objective optimization (MOO) provides a more comprehensive framework that balances competing criteria and generates a Pareto-optimal solution set. In PM-SCM contexts, MOO is applied to problems like the joint optimization of project schedules and inventory costs [68], coordination of transportation timeliness and disruption risk [173], and trade-offs among time, resource, and quality in execution planning [174]. Evolutionary algorithms such as NSGA-II [175,176] and MOEA/D [177] have been widely used to handle the constraint-intensive nature of such problems.

Robust optimization, by contrast, emphasizes the stability and feasibility of solutions under uncertainty rather than nominal optimality [178]. Real-world PM-SCM systems are frequently subject to demand fluctuations, delivery delays, and uncertain resource availability. By incorporating uncertainty sets and worst-case scenarios into models, robust optimization methods ensure that solutions remain feasible across a wide range of disturbances. Applications include robust scheduling under uncertain task durations, resilient procurement strategies, and supply buffering against lead-time variability, all of which contribute to higher operational reliability and risk resistance in integrated systems [179,180].

In addition, scenario-based and game-theoretic approaches have gained prominence in recent years as valuable tools for joint PM-SCM optimization. Scenario-based optimization enhances resilience by testing candidate solutions under multiple discrete future states, such as market fluctuations or supply disruptions [181,182]. Game theory, on the other hand, is particularly suitable for decentralized environments involving multiple autonomous stakeholders, such as contractors, logistics providers, and suppliers [183]. It allows for the modeling of strategic interactions where cost, time, and risk must be negotiated or balanced in competitive settings [184]. When combined with multi-objective techniques, these approaches can facilitate collaborative planning and equilibrium-seeking strategies, providing strong decision support for distributed project–supply ecosystems.

## 7. Future Opportunities and Challenges

### *7.1. Research Opportunities*

Building on the insights synthesized from Sections 2–6, this section identifies several research opportunities at the intersection of PM and SCM. These opportunities address both theoretical and practical challenges and reflect the evolving demands for more robust, flexible, and sustainable approaches in these fields.

First, future research could focus on developing hybrid optimization frameworks that combine mathematical programming, metaheuristics, and AI-driven techniques. This approach seeks to integrate the strengths of various methods, enabling more comprehensive solutions for complex and uncertain project–supply ecosystems. As discussed in Section 3, single-method optimization models often fail to capture the dynamic nature of real-world systems. Hybrid models can overcome these limitations by leveraging complementary strengths, offering greater adaptability in fluctuating environments. Furthermore, these frameworks can enhance decision-making processes in PM-SCM by facilitating better resource allocation, risk management, and scheduling efficiency.

Second, the concept of the PDSC requires further refinement and empirical validation. Research can focus on its application across diverse sectors, such as construction, healthcare, and aerospace, where project complexity and inter-organizational coordination present unique challenges. As highlighted in Section 5, cross-sector collaboration in project supply networks requires dynamic optimization and multi-agent systems. Integrating these tools with the PDSC model could lead to more efficient and resilient project execution, addressing the persistent gaps in supply chain coordination and response to unforeseen disruptions.

Finally, the integration of multi-objective and robust optimization models deserves greater attention, particularly in the context of resilience, sustainability, and carbon neutrality in PM-SCM systems. This focus aligns with the contemporary need for systems that not only optimize cost and time but also contribute to sustainability goals. As noted in Section 6, the growing emphasis on environmental impact and sustainable development in PM and SCM necessitates models that can simultaneously balance multiple objectives. Interdisciplinary collaboration with environmental science, policy research, and engineering could enrich these models, ensuring they are responsive to modern industry expectations and regulatory demands.

### *7.2. Practical Implications*

The integration of PM and SCM originates from practical needs, develops through systematic research, and ultimately guides managerial practice. This dual orientation ensures that theoretical insights not only enrich academic discourse but also inform industry applications, creating a feedback loop between research and real-world implementation. As highlighted in Sections 2–6, by translating theoretical insights into managerial action, organizations can achieve improvements in efficiency, resilience, and sustainability.

One important implication lies in the adoption of hybrid optimization frameworks. By combining mathematical programming, metaheuristics, and AI-driven techniques, such frameworks move beyond the limitations of single-method approaches noted in Section 3. For managers, they enable adaptive, real-time decision support in uncertain environments, helping anticipate disruptions, reallocate resources, and synchronize project schedules with supply capacities. Organizations that embrace these tools gain a strategic advantage, making hybrid optimization a managerial priority rather than an optional enhancement.

Another implication concerns the project-driven supply chain (PDSC) model, which is particularly relevant for industries such as construction, aerospace, and energy. PDSC supports alignment of project and supply chain objectives, addressing the coordination challenges emphasized in Section 5. The incorporation of technologies like digital twins, AI, and blockchain can enable real-time monitoring, predictive analysis, and enhanced supply chain transparency. These tools also foster greater collaboration among stakeholders, reducing inefficiencies and boosting performance. In particular, AI and blockchain can enable smarter contract management and enhanced traceability, while digital twins simulate real-world supply chain scenarios, enabling predictive maintenance and risk management.

Another implication involves the outputs from optimization models serving as critical, data-driven inputs to stage-gate reviews, transforming managerial decision-making from subjective judgment to objective evaluation. At each gate, decision-makers assess optimization-derived metrics against predefined project objectives and tolerances. This process ensures that optimization results are not merely technical exercises but are directly embedded into the governance framework, enhancing the transparency, agility, and rigor of project and supply chain decisions.

A further implication involves multi-objective and robust optimization models, especially in relation to sustainability and resilience. As underscored in Section 6, organizations face growing regulatory and societal pressure to achieve carbon neutrality and resource efficiency. Embedding sustainability metrics into optimization processes allows firms to balance cost, time, and environmental performance simultaneously. These models also inform policymakers by enabling incentive programs and carbon tracking, highlighting that sustainability-oriented optimization is not merely a technical refinement but a necessity for sustainable practices.

### *7.3. Challenges and Barriers*

Despite the significant potential offered by the integration of PM and SCM, various challenges and barriers impede its effective realization and implementation in practice. Technological limitations and organizational inertia are two primary barriers.

Technological barriers represent a fundamental challenge to the integration of PM and SCM. As discussed in Section 4, the application of advanced technologies such as AI, blockchain, and digital twins requires not only the development of sophisticated algorithms and systems but also seamless integration with the existing infrastructure. Issues such as data interoperability, system compatibility, and scalability often hinder the effective deployment of these technologies. Moreover, the reliance on real-time data and advanced analytics introduces significant concerns regarding data privacy and cybersecurity, particularly within industries that handle sensitive information or critical infrastructure. These technological constraints limit the scalability and practical implementation of the integrated models.

Organizational and cultural challenges further complicate the integration process. In many organizations, PM and SCM operate in silos, resulting in misaligned goals, inefficient workflows, and fragmented communication. The lack of a cohesive organizational culture that promotes cross-functional collaboration creates substantial barriers to integration. As emphasized in Sections 2 and 5, effective PM-SCM integration requires a fundamental shift in organizational culture, which often necessitates restructuring and realigning leadership priorities. However, such transformations are frequently met with resistance, as entrenched organizational habits and hierarchies can be difficult to overcome. The need for leadership realignment, resource reallocation, and reconfigured decision-making processes further complicates organizational adaptation.

## 8. Conclusions

This study has systematically explored the integration of PM and SCM through bibliometric analysis and literature synthesis. The findings indicate that PM–SCM integration is particularly critical in complex and uncertainty-prone domains, such as large-scale infrastructure, aerospace, and energy systems, indicating that integration is not incidental but increasingly necessary in project-intensive industries. Within these contexts, advanced technologies are emerging as critical enablers, while optimization approaches ranging from mathematical programming to hybrid frameworks provide the analytical foundation. The bibliometric mapping further revealed major trends, notably a growing emphasis on

resilience and sustainability, alongside enduring challenges in methodological coherence, organizational alignment, and technological feasibility.

This research provides significant contributions both theoretically and practically. Theoretically, it reframes PM and SCM as interdependent components of an adaptive system, moving beyond fragmented perspectives and highlighting integration as an important vehicle for resilience and sustainability in project-intensive contexts. Also, the concept of integration is transformed from a vague idea into a tangible, actionable, and modelable analytical object. This shift allows for a deeper understanding of how integration can be operationalized and systematically applied within complex management environments. Practically, the research provides valuable insights for organizations operating in dynamic, project-based settings. The integration of PM and SCM could facilitate managers seeking to better coordinate resources, time, and risk across organizational boundaries. Furthermore, the study elucidates the potential of combining advanced optimization methods with emerging tools to improve transparency, predictive capabilities, and decision-making in complex management environments. It provides practical guidance for balancing efficiency and long-term adaptability in uncertain and dynamic markets.

Looking forward, further progress requires strengthened interdisciplinary collaboration, drawing on operations research, information systems, and sustainability studies to develop more comprehensive models of PM–SCM integration. While this review provides significant insights, it remains limited by its reliance on bibliometric data from a single database and English-language publications. Additionally, while the focus on applications within management scenarios provided the necessary scope, it may have excluded insightful methodological advances from purely technical optimization studies. Future research should, therefore, complement these findings through empirical studies, longitudinal case analyses, and mixed-method approaches. Such efforts are crucial for deepening the understanding of the mechanisms that shape PM–SCM integration and for addressing key operational challenges and theoretical gaps in the field.

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**Conflicts of 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.

## Abbreviations

The following abbreviations are used in this manuscript:

| | |
|---|---|
| PM | Project management |
| SCM | Supply chain management |
| AI | Artificial intelligence |
| PMI | Project management institute |
| CPM | Critical path method |
| WBS | Work breakdown structure |
| LLR | Log-Likelihood Ratio |
| LP | Linear programming |
| NLP | Nonlinear programming |
| MIP | Mixed-integer programming |
| MILP | Mixed-integer linear programming |
| MINLP | Mixed-integer nonlinear programming |
| SCN | Supply chain network |
| PDSC | Project-driven supply chain |
| GA | Genetic algorithms |
| SA | Simulated annealing |
| PSO | Particle swarm optimization |
| ACO | Ant colony optimization |
| TS | Tabu search |
| RL | Reinforcement learning |
| DL | Deep learning |
| MOO | Multi-objective optimization |

## Appendix A. Literature Rating Scale and Three Researchers' Rating Scale

**Table A1.** Rating Scale.

| Evaluation Dimension | Scoring Criteria | Points |
|---|---|---|
| Research Design | Are the research questions clear, are the methods highly applicable, and is the logic sound? | 1–5 |
| Methodological Rigor | Are scientific, transparent, and reproducible research methods used? | 1–5 |
| Data Reliability | Is the data source reliable, is the processing rigorous, and is it verifiable? | 1–5 |
| Validity of Conclusions | Are the conclusions based on data analysis? Do they have practical or theoretical contributions? Are they generalizable? | 1–5 |

**Table A2.** First researcher's literature quality rating scale.

| Literature Number | Research Design | Methodological Rigor | Data Reliability | Validity of Conclusions | Total Score | Evaluations |
|---|---|---|---|---|---|---|
| 1 | 4 | 5 | 3 | 4 | 16 | validity |
| 2 | 3 | 4 | 4 | 3 | 14 | not valid |
| 3 | 4 | 4 | 5 | 4 | 17 | validity |
| 4 | 4 | 3 | 4 | 5 | 16 | validity |
| 5 | 4 | 5 | 5 | 3 | 17 | validity |
| 6 | 5 | 4 | 4 | 4 | 17 | validity |
| 7 | 4 | 5 | 5 | 3 | 17 | validity |
| 8 | 3 | 3 | 5 | 4 | 15 | validity |
| 9 | 3 | 5 | 4 | 4 | 16 | validity |
| 10 | 4 | 4 | 5 | 4 | 17 | validity |

**Table A2.** *Cont.*

| Literature Number | Research Design | Methodological Rigor | Data Reliability | Validity of Conclusions | Total Score | Evaluations |
|---|---|---|---|---|---|---|
| 11 | 5 | 5 | 4 | 4 | 18 | validity |
| 12 | 5 | 5 | 5 | 3 | 18 | validity |
| 13 | 4 | 5 | 3 | 5 | 17 | validity |
| 14 | 4 | 3 | 3 | 5 | 15 | validity |
| 15 | 5 | 3 | 4 | 4 | 16 | validity |
| 16 | 3 | 5 | 4 | 5 | 17 | validity |
| 17 | 5 | 5 | 4 | 5 | 19 | validity |
| 18 | 5 | 3 | 5 | 5 | 18 | validity |
| 19 | 5 | 3 | 4 | 3 | 15 | validity |
| 20 | 5 | 5 | 3 | 3 | 16 | Validity |

Validity Threshold: The total score is 20. A total score $\geq$ 15 is defined as valid literature; literature scoring below 15 is considered invalid and excluded.

**Table A3.** Second researcher's literature quality rating scale.

| Literature Number | Research Design | Methodological Rigor | Data Reliability | Validity of Conclusions | Total Score | Evaluations |
|---|---|---|---|---|---|---|
| 1 | 3 | 5 | 4 | 4 | 16 | validity |
| 2 | 3 | 4 | 4 | 5 | 16 | validity |
| 3 | 4 | 3 | 5 | 5 | 17 | validity |
| 4 | 4 | 3 | 4 | 4 | 15 | validity |
| 5 | 4 | 5 | 3 | 3 | 15 | validity |
| 6 | 3 | 5 | 5 | 5 | 18 | validity |
| 7 | 5 | 4 | 5 | 5 | 19 | validity |
| 8 | 4 | 5 | 3 | 3 | 15 | validity |
| 9 | 3 | 5 | 4 | 4 | 16 | validity |
| 10 | 4 | 3 | 4 | 4 | 15 | validity |
| 11 | 3 | 3 | 5 | 5 | 16 | validity |
| 12 | 3 | 5 | 3 | 5 | 16 | validity |
| 13 | 3 | 4 | 5 | 3 | 15 | validity |
| 14 | 5 | 3 | 4 | 4 | 16 | validity |
| 15 | 4 | 5 | 3 | 3 | 15 | validity |
| 16 | 3 | 5 | 5 | 5 | 18 | validity |
| 17 | 5 | 4 | 5 | 5 | 19 | validity |
| 18 | 3 | 4 | 5 | 5 | 17 | validity |
| 19 | 3 | 4 | 5 | 5 | 17 | validity |
| 20 | 4 | 5 | 5 | 3 | 17 | validity |

Validity Threshold: The total score is 20. A total score $\geq$ 15 is defined as valid literature; literature scoring below 15 is considered invalid and excluded.

**Table A4.** Third researcher's literature quality rating scale.

| Literature Number | Research Design | Methodological Rigor | Data Reliability | Validity of Conclusions | Total Score | Evaluations |
|---|---|---|---|---|---|---|
| 1 | 4 | 4 | 4 | 3 | 15 | validity |
| 2 | 3 | 3 | 5 | 4 | 15 | validity |
| 3 | 4 | 5 | 4 | 5 | 18 | validity |
| 4 | 4 | 5 | 4 | 5 | 18 | validity |
| 5 | 4 | 4 | 5 | 4 | 17 | validity |

**Table A4.** *Cont.*

| Literature Number | Research Design | Methodological Rigor | Data Reliability | Validity of Conclusions | Total Score | Evaluations |
|---|---|---|---|---|---|---|
| 6 | 4 | 4 | 5 | 5 | 18 | validity |
| 7 | 5 | 4 | 5 | 5 | 19 | validity |
| 8 | 5 | 3 | 4 | 4 | 16 | validity |
| 9 | 5 | 5 | 3 | 5 | 18 | validity |
| 10 | 3 | 5 | 4 | 4 | 16 | validity |
| 11 | 4 | 5 | 3 | 4 | 16 | validity |
| 12 | 5 | 4 | 5 | 5 | 19 | validity |
| 13 | 5 | 4 | 3 | 4 | 16 | validity |
| 14 | 5 | 5 | 3 | 3 | 16 | validity |
| 15 | 4 | 3 | 3 | 4 | 14 | not valid |
| 16 | 5 | 5 | 5 | 4 | 19 | validity |
| 17 | 5 | 4 | 5 | 4 | 18 | validity |
| 18 | 3 | 4 | 5 | 4 | 16 | validity |
| 19 | 4 | 4 | 3 | 5 | 16 | validity |
| 20 | 3 | 4 | 4 | 4 | 15 | validity |

Validity Threshold: The total score is 20. A total score $\geq$ 15 is defined as valid literature; literature scoring below 15 is considered invalid and excluded.

## Appendix B. Bibliometric Parameter Setting and Execution Process

**Search Database and Time Range:**

Database: Web of Science (WOS) Core Collection

Time Range: January 2003 to July 2025 (Actual search date: 6 July 2025)

**Complete Search Strategy:**

Boolean logic combinations of keywords were used, including the following:

TS = ((“project management” OR “project planning” OR “project scheduling” OR “program management”) AND (“sup-ply chain” OR “logistics” OR “procurement” OR “operations management”) AND (optimization OR “mathematical programming” OR “machine learning” OR “decision support” OR simulation OR modeling OR “artificial intelligence”) AND (integration OR synergy OR coordination OR collaboration OR framework OR scenario* OR application*))

Search Field: Topic (Title, Abstract, Keywords)

**Screening Process:**

1. Identification Stage:

A total of 489 records were identified in Web of Science. Some records were removed for the following reasons:

Duplicate records: 16.

Other reasons for removal: 17.

Records marked as non-compliant by automation tools: 0.

Final number of records entering the screening phase: $489 - 16 - 17 - 0 = 456$.

2. Screening Stage:

A total of 456 records underwent initial screening. The records excluded at this stage included the following:

Conference papers: 101.

Irrelevant studies: 2.

Records without full text available: 0.

Remaining records entering the next round of double-blind screening: 456 − 101 − 2 − 0 = 353.

3. Double-blind Screening Stage:

A total of 353 records underwent more rigorous screening of titles, abstracts, and full texts. The records excluded at this stage included the following:

Irrelevant titles and abstracts: 18.

Irrelevant full texts: 11.

Records with unresolved controversy: 5.

Final number of studies included in the review: 353 − 18 − 11 − 5 = 319.

4. Final Inclusion Analysis:

The distribution of included studies was listed based on specific journals and keyword combinations:

In IPM journal, there were two studies with the keyword combination "supply chain management" AND "op-timization methods."

In PMJ journal, there were six studies with the same keyword combination.

In JSCM and SCMIJ journals, there were no studies with the keyword combination "project management" AND "optimization methods."

Final number of included studies: 319 + 2 + 6 = 327.

**CiteSpace Analysis Parameters:**

Version: CiteSpace 6.4.R1.

Time Slices: 1 year.

Node Types: Year, Authors, Countries, Journals, Keywords, Article Citation.

Algorithm Selection: LLR (Log-Likelihood Ratio) for cluster naming.

Other Parameters: g-index (k = 25).

## Appendix C. Sample of Included and Excluded Papers with Reasons

**Table A5.** Literature Screening Criteria and Results.

| Literature Number | Author and Year | Decision | Reason |
|---|---|---|---|
| 1 | Du et al., 2023 [133] | Include | The study explicitly integrates PM and SCM, using VBM and JIT optimization methods. The methodology is rigorous, and the conclusions have practical value. |
| 2 | Wicaksana et al., 2022 [185] | Exclude | Focuses solely on SCM risks, without addressing project management or optimization methods. |
| 3 | Forozandeh et al., 2019 [134] | Include | The multi-objective optimization model clearly integrates PM and SCM. The method is innovative and the data is reliable. |
| 4 | Wu et al., 2023 [186] | Exclude | A study on a purely technical optimization algorithm, not combined with practical application in a management scenario. |

# Appendix D. Burst Keyword Categories and Cluster Labels Comparison Supplement

**Table A6.** Comparison of cluster labels among LLR, MI, and LSI algorithms.

| Cluster ID | Size | Silhouette | Label (LSI) | Label (LLR) | Label (MI) |
|---|---|---|---|---|---|
| 0 | 31 | 0.897 | multi-objective optimization; project management; resource constraint; evolutionary computation; main path analysis \| greenhouse gases; mathematical models; task analysis; project; sustainable construction management | multi-objective optimization (14.95, 0.001); carbon emissions (11.13, 0.001); constructability (11.13, 0.001); optimization (8.79, 0.005); scheduling (7.44, 0.01) | iot (0.23); planning (0.23); ready-mix-concrete delivery (0.23); integrated design-build (0.23); cluster analysis (0.23) |
| 1 | 26 | 0.944 | project scheduling; primary supplier selection; back-up supplier selection; project networks; shipping modes \| project management; simulation; control methodology; framework; disruption | project scheduling (30.89, 0.0001); material procurement (18.37, 0.0001); material ordering (13.76, 0.001); construction project (9.47, 0.005); disruption (5.55, 0.05) | activity crashing (0.42); quantity discount problem in material ordering (0.42); prefabricated prefinished volumetric (0.42); multi-site context (0.42); scenario-based stochastic programs (0.42) |
| 2 | 25 | 0.843 | project management; existing buildings; renovation projects; building information modeling; bim challenges \| scope elements; decision making; making trial; interpretive structural modeling; scope management | project management (11.09, 0.001); cost overruns (7.4, 0.01); optimized dismantling (5.53, 0.05); integrated collaboration model (5.53, 0.05); public sector supply chain (5.53, 0.05) | optimized dismantling (0.23); integrated collaboration model (0.23); public sector supply chain (0.23); renovation projects (0.23); automated 3d building reconstruction (0.23) |
| 3 | 23 | 0.783 | project management; cultural dimensions; simulation; heterarchical framework; waste factors \| project performance; agile project management; quality performance; lean project management; cost performance | simulation (7.64, 0.01); project management system (5.66, 0.05); quality performance (5.66, 0.05); heterarchical framework (5.66, 0.05); innovation performance (5.66, 0.05) | project management system (0.21); quality performance (0.21); heterarchical framework (0.21); innovation performance (0.21); improvement (0.21) |
| 4 | 22 | 0.845 | project management; integrated project delivery; supply chain integration; relational contracting; systemic innovation \| construction industry; supply chain management; construction supply chain; sustainable construction; research questions | integrated project delivery (6.24, 0.05); partnership (6.24, 0.05); erp (6.24, 0.05); sharing economy (6.24, 0.05); it outsourcing (6.24, 0.05) | information technology (0.15); partnership (0.15); erp (0.15); sharing economy (0.15); it outsourcing (0.15) |

**Table A6.** *Cont.*

| Cluster ID | Size | Silhouette | Label (LSI) | Label (LLR) | Label (MI) |
|---|---|---|---|---|---|
| 5 | 22 | 0.812 | project management; green supply chain; project success; project risk management; fuzzy theory \| learning capabilities; knowledge management; dynamic capabilities; information systems; focus group | green supply chain (13.5, 0.001); leadership styles (6.73, 0.01); predict cash flow (6.73, 0.01); cfa (6.73, 0.01); material transportation (6.73, 0.01) | leadership styles (0.11); predict cash flow (0.11); cfa (0.11); material transportation (0.11); relationship quality (0.11) |
| 6 | 21 | 0.802 | project management; operations management; open innovation; tertiary study; search schedule \| artificial intelligence; sustainable food systems; child nutrition; school food programs; information management | machine learning (18.46, 0.0001); artificial intelligence (15.38, 0.0001); school food programs (6.12, 0.05); project-based data. project management (6.12, 0.05); search schedule (6.12, 0.05) | school food programs (0.16); project-based data. project management (0.16); search schedule (0.16); variation orders (0.16); sustainable food systems (0.16) |
| 7 | 20 | 0.924 | project management; dynamic capabilities; dematel method; environmental strategy; green supply management \| supply chain; risk management; project scheduling problem; bi-level multi-objective programming; particle swarm optimization | project management (16.31, 0.0001); supply chain (8.03, 0.005); project scheduling (6.19, 0.05); game theory (4.76, 0.05); resiliency (4.15, 0.05) | resiliency (0.55); fuzzy set (0.55); graph decomposition (0.55); environment (0.55); time-dependent resource availability (0.55) |
| 8 | 20 | 0.743 | firm performance; market orientation; balanced agile project management; strategic agility; innovation diffusion \| relational governance; formal governance; collaborative contracting; innovation diffusion; public procurement | firm performance (14.16, 0.001); relational governance (8.73, 0.005); innovation diffusion (7.06, 0.01); concurrent scheduling (7.06, 0.01); strategic agility (7.06, 0.01) | innovation diffusion (0.09); concurrent scheduling (0.09); strategic agility (0.09); capabilities (0.09); public procurement (0.09) |
| 9 | 19 | 0.958 | project management; risk management; decision making; continuous improvement; cost performance \| portfolio management; indicators; procurement; success; integration | risk management (7.37, 0.01); indicators (6.36, 0.05); unmanned aerial vehicles (6.36, 0.05); success (6.36, 0.05); construction schedule (6.36, 0.05) | indicators (0.14); unmanned aerial vehicles (0.14); success (0.14); construction schedule (0.14); supply chain projects (0.14) |

**Table A6.** *Cont.*

| Cluster ID | Size | Silhouette | Label (LSI) | Label (LLR) | Label (MI) |
|---|---|---|---|---|---|
| 10 | 19 | 0.908 | supply chain management; operations management; inter-organizational relationships; experiential learning; serious game \| project management; risk management; financial performance; supply chain risk; internal logistics | supply chain management (20.71, 0.0001); construction supply chain management (5.65, 0.05); bi-level programming (5.65, 0.05); inventory buffer (4.62, 0.05); construction site (4.62, 0.05) | inventory buffer (0.41); construction site (0.41); inter-organizational relationships (0.41); quarantine level (0.41); information system success model (0.41) |
| 11 | 18 | 0.878 | critical path method; maritime logistics; business process analysis; business process management; resource-constrained project scheduling problem \| supply chain management; soft computing; neuro-fuzzy analytic network process; group decision-making; fuzzy judgments | critical path method (13.9, 0.001); strategic management (7.36, 0.01); dynamic critical path (6.93, 0.01); group decision-making (6.93, 0.01); resilience index (6.93, 0.01) | dynamic critical path (0.09); group decision-making (0.09); resilience index (0.09); soft computing (0.09); risk quantification method (0.09) |
| 12 | 16 | 0.827 | project management; quadruple helix; agile mindset; urgent projects; agile project \| risk management; subsea gas pipeline; cost overrun; risk analysis; fuzzy Bayesian belief networks | construction engineering (6.45, 0.05); bioethanol (6.45, 0.05); supply chain network design (6.45, 0.05); subsea gas pipeline (6.45, 0.05); fuzzy Bayesian belief networks (6.45, 0.05) | construction engineering (0.13); bioethanol (0.13); supply chain network design (0.13); subsea gas pipeline (0.13); fuzzy Bayesian belief networks (0.13) |
| 13 | 16 | 0.966 | project management; supply chain management; supply chain disruption; smart contracts; construction supply chain \| construction supply chain; incentive coordination; sustainable development; robust optimisation; bi-level programming | supply chain disruption (3.79, 0.1); stochastic optimization (3.79, 0.1); multi-criteria decision-making (3.79, 0.1); synergy benefits (3.79, 0.1); whole life cycle (3.79, 0.1) | stochastic optimization (0.69); multi-criteria decision-making (0.69); synergy benefits (0.69); whole life cycle (0.69) |
| 14 | 11 | 0.87 | risk management; operations management; project management; project portfolio; innovation capability \| social sustainability; construction project management; conceptual framework; social responsibility; conceptual modeling | project portfolio (13.66, 0.001); program (13.66, 0.001); decision making (9.91, 0.005); risk management (9.48, 0.005); operations management (8.78, 0.005) | procurement procedure (0.1); organizational flexibility (0.1); a systematic literature review (0.1); digitisation (0.1); quality professionals (0.1) |

**Table A7.** Major burst keywords categories and corresponding periods.

| Cluster ID | Cluster Name | Size | Mean Year | BurstBegin | Burst | Main Cutting Keywords (After 2020) |
|---|---|---|---|---|---|---|
| 0 | optimization method | 31 | 2020 | 2014 | 2018 | particle swarm optimization, project, megaproject |
| 1 | project scheduling | 26 | 2016 | 2013 | 2014 | search, material ordering, chance-constrained programming |
| 2 | project management | 25 | 2020 | 2015 | 2015 | supply chain integration, benefits, cost overruns |
| 3 | simulation | 23 | 2019 | 2014 | 2014 | barriers, analytics, internet |
| 4 | integrated project delivery | 22 | 2019 | 2014 | 2014 | digital twin, systematic review, data analytics |
| 5 | green supply chain | 21 | 2018 | 2012 | 2016 | carbon neutrality, circular economy, sustainability |
| 6 | artificial intelligence | 20 | 2017 | 2011 | 2017 | machine learning, predictive analytics, artificial intelligence |
| 7 | resiliency | 19 | 2015 | 2003 | 2015 | disruption management, risk assessment, resilience |
| 8 | firm performance | 18 | 2019 | 2010 | 2020 | big data, blockchain, supply chain risk |
| 9 | risk management | 17 | 2018 | 2009 | 2017 | project portfolio, resource allocation, simulation |
| 10 | supply chain management | 16 | 2020 | 2015 | 2022 | agile, stakeholder management, collaboration |
| 11 | strategic management | 15 | 2017 | 2011 | 2016 | hybrid methods, optimization model, scheduling |
| 12 | construction engineering | 14 | 2019 | 2012 | 2021 | sustainability, green supply chain, environmental performance |
| 13 | supply chain disruption | 13 | 2018 | 2014 | 2017 | multi-objective optimization, robustness, uncertainty |
| 14 | project portfolio | 12 | 2016 | 2008 | 2014 | knowledge management, decision support, governance |

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