

Review

Mathematical Modeling and Optimization of Platform Supply Chain in the Digital Era: A Systematic Review

Xuhui Chen, Guanghui Cheng and Yong He * 

School of Economics and Management, Southeast University, Nanjing 210096, China;
230228697@seu.edu.cn (X.C.); guanghui@seu.edu.cn (G.C.)

* Correspondence: hy@seu.edu.cn

Abstract

As supply chains rapidly digitize, platform-driven models have become central to global commerce, requiring sophisticated mathematical modeling for optimization. This systematic review comprehensively analyzes research across six critical technological domains in platform supply chains (PSCs): blockchain integration, Internet of Things applications, Industry 4.0 systems, cloud computing, live streaming commerce, and generative artificial intelligence. Our analysis finds that operational coordination and strategic decision-making under information asymmetry represent primary research focuses, with pricing strategies receiving predominant attention. Methodologically, game theory, particularly Stackelberg models, emerges as the dominant optimization framework across all domains. However, significant gaps remain in dynamic modeling capabilities, empirical validation of theoretical frameworks, and cross-technology integration. This review provides foundational insights into mathematical optimization techniques and highlights the critical need for incorporating stochastic approaches and real-world data to advance PSC management in the digital era.

Keywords: platform service; supply chain; mathematical modeling; decision optimization; digital technology; systematic literature review

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1. Introduction

In the first edition of the special issue “Mathematical Modelling and Optimization of Service Supply Chain”, Guo and He (2022) published a review article entitled “Mathematical Modeling and Optimization of Platform Service Supply Chains: A Literature Review” [1]. Their work categorized various types of platform service supply chains and identified the mathematical modeling methods used to address different research problems. A key finding indicates that research on digital platforms, particularly concerning platforms’ demand for information disclosure decisions, has attracted more researchers’ attention, especially with the development of blockchain and other novel technologies. In recent years, the rapid proliferation of digital technologies has fundamentally transformed traditional supply chain operations, giving rise to platform-based supply chain ecosystems that integrate stakeholders through cloud computing, Internet of Things (IoT), and other emerging digital technologies [2,3]. From e-commerce giants like Amazon and Alibaba to sharing economy platforms such as Airbnb and Uber, digital technology is enabling platforms to evolve beyond simple transaction facilitators into complex supply chain orchestrators [4,5]. This shift requires innovative mathematical modeling approaches to tackle the

inherent complexity, dynamism, and multi-stakeholder nature of platform supply chains (PSCs). Consequently, managers are increasingly motivated to leverage digital platforms and related novel technologies to build more efficient supply chain analytics capabilities to address the dual challenges of operational efficiency and strategic adaptability [6,7].

Modern PSCs bring unprecedented complexity to traditional supply chain management. Unlike linear structures, modern PSC ecosystems operate as non-hierarchical networks in which multiple stakeholders, including suppliers, producers, logistics partners, and consumers, interact more efficiently through digital technologies [8,9]. These interactions create complex feedback loops, network effects, and intricate data dependencies. For instance, studies on blockchain integration primarily focus on resolving information asymmetries and enhancing trust through cryptographic verification. Research on cloud computing addresses the tradeoffs between security and risk in distributed computing environments. Meanwhile, the rapid rise of live-streaming commerce has introduced new operational challenges in coordinating streamers, platforms, and manufacturers. Generative artificial intelligence (Gen AI) also shows transformative potential for predictive analytics and automated decision-making. These diverse technological features require hybrid modeling techniques that integrate game theory, stochastic programming, and machine learning. However, current literature on PSC modeling and optimization remains scattered across different fields, highlighting an urgent need for methodological advancements to better address the complexities of modern PSCs.

Recent systematic reviews have explored specific aspects of digital supply chains. For example, Culotta et al. (2024) [10] identified relevant theories within digital platforms and synthesized findings for supply chain management tasks. Tan et al. (2024) [11] considered the prevalent distribution agreement for many physical goods within the digital marketplace and cataloged the agency model in online platforms. Surucu-Balci et al. (2024) [12] discussed blockchain and cloud-based platform use cases for digital information sharing across supply chain functions, proposing future research directions for improving information sharing and processing through digital transformation. Kumar and Singh (2025) [13] reviewed current trends in Supply Chain Ambidexterity and explored its relationship with resilience, agility, and digital transformation.

While these prior reviews offer valuable insights, their scope and methodological focus remain limited. Crucially, they pay insufficient attention to how emerging digital technologies enhance PSC management. Although some studies address specific sectors, like blockchain supply chains, or broader topics, like digital supply chain management, reviews specifically focusing on the role of diverse digital technologies within PSCs are still lacking. Furthermore, as different technologies often demand distinct mathematical modeling and optimization approaches, a systematic analysis of the methods used in PSC research is essential. Previous reviews have primarily concentrated on research topics and questions, largely overlooking trends in mathematical modeling techniques and how these approaches tackle the unique challenges of PSCs by leveraging digital technologies. Furthermore, existing review articles lack a unified analysis of common PSC issues across different episode clusters, particularly a comprehensive discussion and structural comparison among technical groups. To address these gaps, this review aims to:

- Identify emerging digital technologies suitable for integration into PSCs.
- Examine the key research problems addressed within each technological domain.
- Analyze the mathematical modeling and optimization methods employed.
- Identify critical research gaps and emerging trends.
- Analyze the structural heterogeneity and methodological gaps across all technological clusters.

Specifically, we first adopted a multi-stage research design incorporating text mining to identify the technologies applied in PSCs. We then employed the Louvain community detection algorithm for topic mining to uncover technology relationships. This process clustered all discovered relevant digital technologies in four main technical communities. On this basis, we filtered out six mainstream emerging digital technologies applicable to PSCs that leverage mathematical modeling and optimization in the fields of operations management and operations research. Finally, we conducted a thematic analysis to clearly delineate the research content within each technical theme. By synthesizing insights across blockchain, IoT, Industry 4.0, cloud computing, live streaming, and Gen AI, this review provides a structured analysis of methodological trends and theoretical foundations, aiming to accelerate the development of mathematical modeling and optimization frameworks capable of matching the complexity and pace of PSCs in the digital era.

2. Methodology

Traditional bibliometric methods that rely solely on keywords or titles face significant limitations, which may overlook certain technologies operating as background infrastructure, and some technical concepts that cannot be distinguished as belonging to research methods or research objects. To address these limitations, this study implements a multi-stage, text mining-based research design to systematically identify and analyze core technologies applied within PSC research, as shown in Figure 1. Using the abstracts of all collected PSC literature, we first identified the technologies applied within this domain. Subsequently, we employed the Louvain community detection algorithm to analyze relationships among these technologies and perform topic mining based on their co-occurrence patterns. Next, we conducted manual screening to isolate publications specifically focused on modeling and optimization. Based on this refined subset of literature, we then performed a systematic review of the identified technological themes.

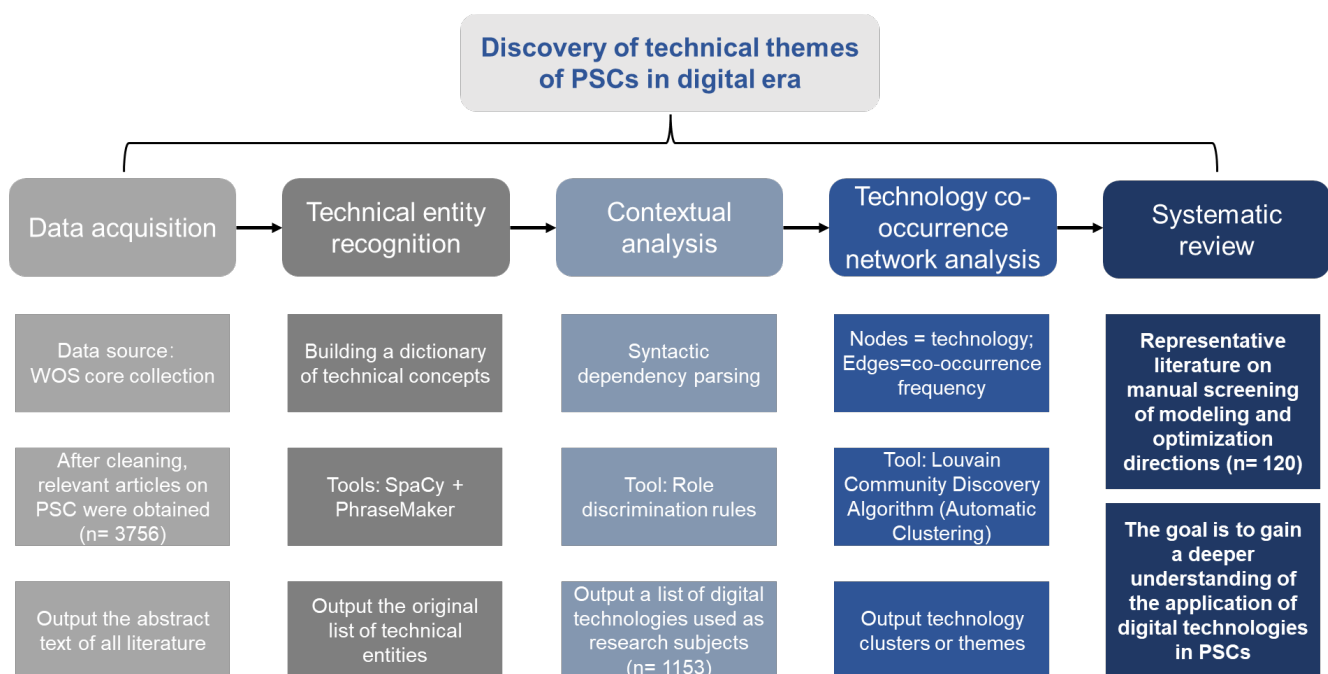


Figure 1. The overall research design.

2.1. Data Collection and Method Stages

The data for this study were sourced from the Web of Science core collection, retrieved on 30 June 2025. We performed the search using the platform's standard web interface

and exported the full records, including abstracts. Python (version 3.12) scripts were then used to process and analyze the exported data. We limited the search to journal articles indexed in the SSCI and SCI Expanded databases, with the topic “platform supply chain”. Only English-language publications were included, covering all accessible years. The initial WOS search yielded 3758 articles. After removing articles without abstracts and duplicates, 3756 articles remained for analysis. The analysis of literature abstracts involved three key stages: (1) Identifying and extracting relevant technical terms; (2) Resolving term ambiguity using syntactic dependency analysis; (3) Building technology co-occurrence networks and identifying communities through clustering.

The purpose of the first stage was to accurately identify specific technical concepts within the unstructured abstract text. To achieve this, we built our comprehensive “Technology Lexicon” through a three-step process. First, we identified a list of seed technologies by reviewing foundational papers and major survey articles in the digital supply chain field. Second, our research team expanded this initial list by adding other relevant technologies based on our expert knowledge. Finally, we iteratively refined the lexicon. We scanned a sample of abstracts from our corpus to find and include common synonyms, abbreviations, and other variations for each term. This process ensured our final lexicon was both thorough and precise. Subsequently, we systematically identified all technical entities mentioned in each abstract using the PhraseMatcher component within the natural language processing library SpaCy, employing a case-insensitive matching approach.

The second stage, contextual disambiguation, represents a key methodological innovation in this study. Its purpose is to resolve a fundamental ambiguity: determining whether a technical concept mentioned in an abstract function as a research tool (used by the author for analysis) or as a research object (the specific technology applied or studied within the PSC context). Our analysis specifically targets the latter. To achieve this distinction, we employed syntactic dependency parsing to analyze the grammatical role of each identified technology. We developed a set of specific heuristic rules to classify each technology as either a research object (the focus of the study) or a research tool (a method used by the authors). Our classification logic was multi-layered. First, a technology was classified as a research object if it served as the grammatical subject of a sentence, such as “Blockchain” in “Blockchain enables traceability”. We also analyzed the “head” word that grammatically governed the technology term. A technology was considered a research tool if its head was a verb of application, like “use” or “propose”, or a preposition indicating instrumentality, like “using” or “by”. Conversely, it was classified as a research object if its head was a verb of investigation, such as “analyze” or “impact”, or a noun indicating focus, like “role” or “effect”. For complex cases involving prepositions like “of”, we also examined the governing noun to determine the context. If a technology could not be classified by these rules, it was defaulted to research object to ensure comprehensive coverage. This disambiguation step ensures that the final technology set analyzed consists precisely of those entities discussed or applied within the PSC domain, thereby significantly improving the accuracy of our statistics. This process identified 1153 articles from our initial set of 3756 that discussed at least one technology as a research object.

Following the precise identification of technology entities classified as research objects, we proceeded to the third analytical stage: constructing and analyzing a technology co-occurrence network. This stage aimed to uncover the interconnected structures and potential “technology ecosystems” formed by the integration of different technologies within the PSC domain. We constructed an undirected, weighted technology co-occurrence network. In this network, each node represents a distinct technology, and an edge connects two nodes if their corresponding technologies co-occur within the abstract of the same publication. The edge weight corresponds to the frequency of co-occurrence between the two

technologies. A higher weight indicates a stronger observed association, suggesting greater integration or combined application within the research literature. To uncover inherent structural patterns within this complex network, we applied the Louvain community detection algorithm. This widely recognized and efficient method identifies densely connected “technical clusters”, namely communities, within the network by iteratively maximizing the network’s modularity index. A key advantage of Louvain is that it does not require pre-specifying the number of clusters. We assessed the quality of the detected communities by calculating the network’s modularity score. Modularity quantifies the strength of connections within identified communities compared to connections between communities relative to a random null model. A positive score indicates that the detected community structure is statistically significant and non-random. Through this three-stage analytical process, our study delineates the technological landscape and its internal structure within the platform supply chain field from the abstract text. Building on this technology mapping, we then manually screened the literature associated with each identified technical topic (community) to isolate publications employing representative modeling and optimization methodologies. Finally, we conducted a systematic review focused on these selected works to synthesize findings within each technological cluster.

2.2. Statistical Analyses

Figure 2 depicts the prevalence of the top 15 digital technologies applied in PSCs, as identified through our systematic text mining and disambiguation process. Blockchain is the dominant technology, highlighting its critical role in enhancing transparency, security, and traceability within PSC operations. The IoT and AI follow closely in prevalence, demonstrating their essential contributions to real-time data acquisition, process automation, and advanced decision-making. Other prominent technologies include digital twin, cloud computing, and big data analytics. Together, these technologies constitute the core digital infrastructure underpinning contemporary efforts to model and optimize PSCs. These findings demonstrate a clear focus on technologies that enhance trust, enable data-driven intelligence, and facilitate system integration in the complex PSC management.

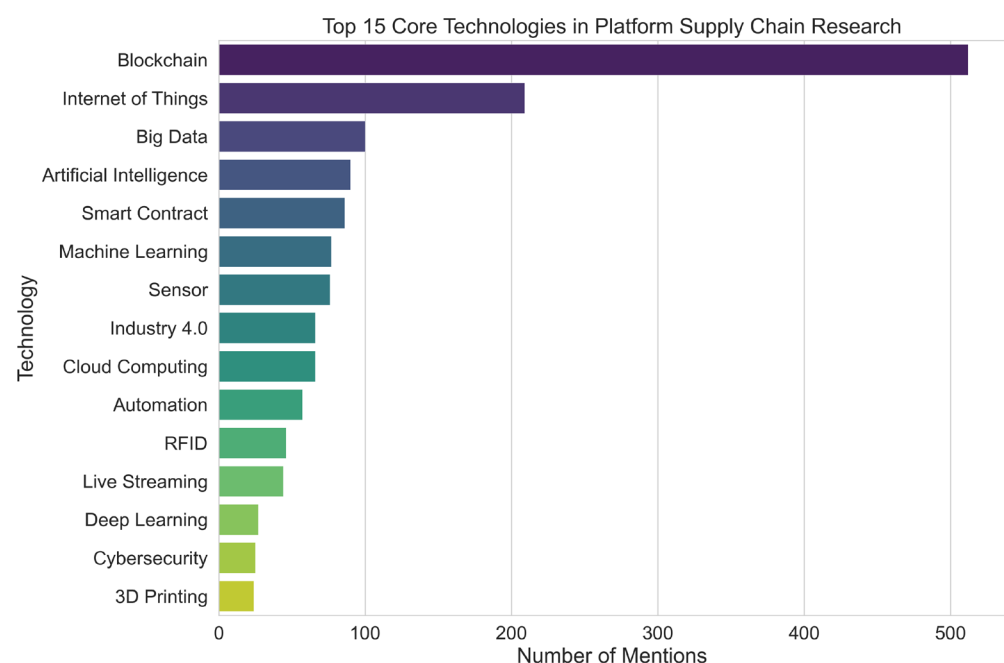


Figure 2. Top 15 digital technologies applied in PSCs.

Figure 3 illustrates the evolving research trends for key technologies applied in PSCs over time. This figure is based on the publication years of the 1153 articles that our algorithm identified as technology focused. The figure reveals a substantial increase in research focus on nearly all leading technologies, with a pronounced acceleration after 2020. Blockchain consistently shows the strongest growth, reflecting persistent and deepening research interest in its PSC applications. Research output for AI and IoT exhibits significant and parallel upward trends, underscoring their complementary and increasingly critical roles. Digital twin technology has experienced a particularly sharp rise in recent years, indicating its rapid adoption for simulation and optimization tasks. Collectively, these trends signal a shift towards research focused on integrated digital solutions. In this evolving landscape, technologies such as blockchain, IoT, and AI are increasingly combined to tackle complex mathematical modeling and optimization challenges within PSCs in the digital era.

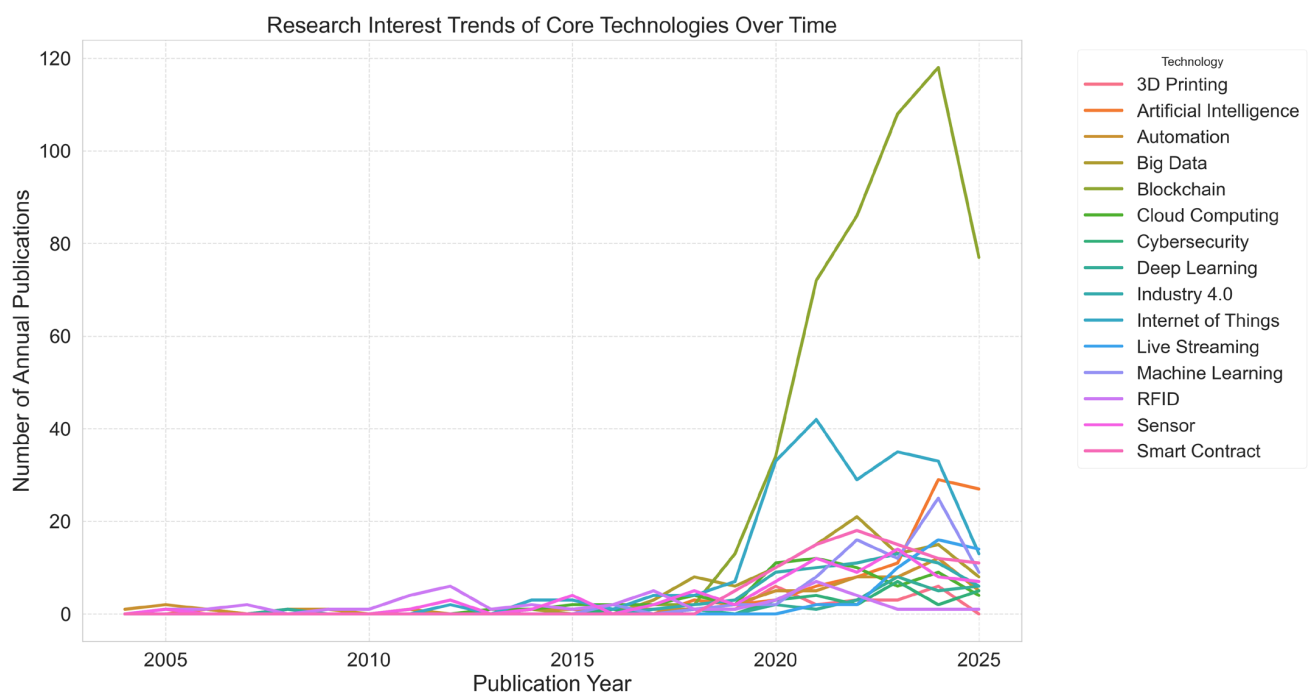


Figure 3. Research trends of technologies applied in PSCs over time.

Furthermore, we conducted community discovery analysis on technology co-occurrence networks and presented the internal correlation structure of various technologies in PSC research, shown in Table 1. This analysis revealed four primary technology communities, representing the core interconnected thematic areas in the field. The modularity score of the entire network is 0.1480. This positive value is sufficient to confirm that the detected community structure is statistically significant and non-random. We accepted this result because we also considered the interpretability of the communities, and this 4-community partition was highly coherent. However, this modest score also suggests that the boundaries between communities are not perfectly sharp and have some overlap. This is reasonable, considering that digital technologies in platform supply chains are inherently interconnected.

The first identified community, “Trusted Traceability”, addresses the fundamental challenges of trust and transparency within PSCs, with blockchain and IoT serving as its central technologies. This community effectively bridges the physical and digital domains. Technologies focused on data acquisition, such as IoT, sensors, and RFID, capture and digitize real-world information on goods status and location, establishing the foundation for traceability. Meanwhile, technologies enabling digital trust, including blockchain, smart

contracts, and cybersecurity, provide a secure, immutable, and verifiable environment for storing this data across multiple participants; smart contracts further facilitate the automatic execution of predefined agreements. Therefore, these technologies build the essential digital infrastructure for achieving end-to-end supply chain transparency, thereby enhancing collaboration efficiency and security.

Table 1. The topic clustering results based on Louvain community discovery algorithm (Modularity = 0.1480 > 0).

Community	Digital Technology	Community	Digital Technology
Trusted Traceability	Blockchain	Data Intelligence	Artificial Intelligence
	Internet of Things		Big Data
	Smart Contract		Machine Learning
	Sensor		Deep Learning
	RFID		Data Mining
	Cybersecurity		Drone
	Distributed Ledger		Predictive Analytics
	Edge Computing		Generative AI
	GPS		Natural Language Processing
	Fintech		Industry 4.0
Cyber-Physical Integration	Mobile Application	Smart Manufacturing	Automation
	Digital Signature		Cloud Computing
	Microservices		Robotics
	Cyber-Physical Systems		Autonomous Vehicle
	Digital Twin		Software as a Service
	Augmented Reality		3D Printing
	Virtual Reality		Reinforcement Learning
	Live Streaming		Service-oriented
	Mixed Reality		Computer Vision
	API		Chatbot

The second community, “Cyber Physical Integration”, centers on digital twin and cyber-physical systems technologies, aiming to integrate the physical and digital realms of PSCs. Its core approach involves creating real-time, synchronized digital representations of physical supply chain assets like warehouses, vehicles, and production lines. Technologies such as augmented reality and virtual reality then utilize these digital models to offer managers immersive capabilities for monitoring, simulation, and interaction. This community signifies that PSC management is progressing towards a more refined, intelligent, and predictive stage characterized by virtual-physical symbiosis.

The third community, “Data Intelligence”, functions as the cognitive core of PSC in the digital era. Driven by AI and big data, this community demonstrates the end-to-end process from data acquisition to intelligent decision-making. Here, big data provides the foundational input for analysis, while machine learning, deep learning, and data mining algorithms serve as the primary mechanisms for achieving intelligence. These technologies collectively support advanced applications like predictive analytics and Gen AI, optimizing critical platform operations, including demand forecasting, dynamic pricing, inventory management, and logistics route planning. The high centrality of this cluster underscores that data-driven intelligent decision-making has become a pivotal research focus within PSCs.

The fourth community, “Smart Manufacturing”, focuses on the digital transformation of production and operational processes within platform supply chains. Anchored by the Industry 4.0 framework, this community manifests at two distinct levels. Firstly, physical-

layer automation and flexibility, realized through technologies like robotics, automation, and 3D printing, target enhanced production efficiency and responsiveness. Secondly, innovation in digital infrastructure and business models, in which cloud computing delivers scalable computing power, enables novel digital operation models, such as service-oriented offerings. This community reflects significant scholarly attention on leveraging digital technologies to fundamentally reshape production and operational workflows.

Obviously, it is impossible to provide a detailed review of every digital technology. We excluded application-specific technologies (e.g., RFID, GPS, autonomous vehicles) as they primarily represent implementation tools rather than systemic drivers of managerial optimization. Similarly, overly broad technical categories (e.g., big data, machine learning, predictive analytics) were omitted due to conceptual vagueness and limited tractability for precise modeling. Furthermore, although the research on some technical topics already has clear and advanced mathematical modeling applications, it is still necessary to further identify these technologies in the study of management and operations research relevant fields under the PSC related issues. For instance, although extensive research has been conducted on applications related to digital twin and natural language processing, the vast majority of them are associated with strong engineering application issues. Research on management and optimization problems related to PSC is relatively scarce, and the number of articles published in mainstream management and operations research journals is also insufficient. Conversely, the chosen technologies represent clearly defined, high-impact enablers within platform supply chains: blockchain and IoT establish foundational trust and traceability; Industry 4.0 integrates cyber–physical coordination; cloud computing enables the dynamic composition of physical services into networks; and live streaming facilitates real-time product marketing and sales for supply chain members. Each possesses clear conceptual boundaries, exhibits strong compatibility with quantitative modeling approaches, and addresses core optimization challenges in PSCs, ensuring a focused and actionable synthesis for this review. Notably, Industry 4.0 represents an integrative paradigm, we note an inherent potential for conceptual overlap between this cluster and others focused on discrete technologies (e.g., blockchain, IoT, AI). For instance, a study on “Blockchain + IoT for traceability” inherently contributes to the industry 4.0 vision but was categorized based on its primary technological contribution, methodological focus, and the key issue to avoid double-counting and maintain analytical clarity. Furthermore, considering the dramatic development and increasing attention on Gen AI, such as ChatGPT and Deepseek, in recent years, it gives a valuable opportunity to conclude the current research progress, hoping to provide a reference for interested researchers. Therefore, in this review, we select six focal technologies, i.e., blockchain, IoT, Industry 4.0, cloud computing, live streaming, and Gen AI, based on their distinct suitability for mathematical modeling and optimization in PSC management.

Furthermore, we comprehensively reviewed all relevant publications and retained only those articles that meet the following criteria: (1) employ mathematical modeling and optimization methods for operational decision-making and optimization in PSCs and (2) are published in leading journals within supply chain management, operations management, operations research, economic modeling, empirical study, or other high-impact engineering fields. Following a rigorous screening process based on titles, abstracts, and methodological frameworks, we compiled a final corpus of 120 articles. Specifically, Table 2 summarizes the distribution of selected publications across technological clusters, while Table 3 details the journal publication sources. As seen, our thematic review includes 29 significant papers on blockchain applications—a mature domain warranting comprehensive analysis. For the emerging field of Generative AI in supply chains, we identified 14 relevant studies. The selected literature predominantly originates from leading operations management and

operations research journals, recognized for their scholarly impact in platform ecosystems, supply chain management, logistics, and decision sciences. These articles formed the basis for our subsequent thematic analysis.

Table 2. Number of papers selected in each technological cluster.

Technology	Number of Papers	Percentage
Blockchain in PSCs	29	24.17%
IoT in PSCs	19	15.83%
Industry 4.0 in PSCs	20	16.67%
Cloud computing in PSCs	21	17.50%
Live streaming in PSCs	17	14.17%
Gen AI in PSCs	14	11.66%

Table 3. Statistics of the journal sources of the selected papers.

Journal	Number of Papers	Percentage
International Journal of Production Economics/International Journal of Production Research	23	19.17%
Computers & Industrial Engineering/Computers & Operations Research	13	10.83%
Transportation Research Part E/Omega	13	10.83%
Annals of Operations Research/European Journal of Operational Research	12	10.00%
Industrial Management & Data Systems/IEEE Transactions on Engineering Management	9	7.50%
Technological Forecasting and Social Change	7	5.83%
Electronic Commerce Research/Electronic Commerce Research and Applications	6	5.00%
Supply Chain Management	4	3.33%
International Journal of Logistics	2	1.66%
Journal of Enterprise Information Management	2	1.66%
Journal of Retailing and Consumer Services	2	1.66%
Managerial and Decision Economics	2	1.66%
Operations Management Research	2	1.66%
Production Planning & Control	2	1.66%
Technology in Society	2	1.66%
Others	19	15.83%

3. Thematic Analysis

3.1. Cluster 1: Blockchain in PSC

The integration of blockchain in PSC has become a significant focus within operations research and supply chain management. This section systematically examines 29 studies from Cluster 1, which employ mathematical modeling and optimization to explore this intersection. We analyze their core research problems, methodologies, and emerging trends, and identify gaps.

3.1.1. Research Issue

Current research primarily tackles inherent inefficiencies and strategic challenges intensified in digital platform environments. A dominant theme is overcoming information asymmetry and its consequences. Cao et al. (2022) modeled how blockchain mitigates financing risk, counterparty risk, and trust deficits in agricultural supply chains, framing these issues as coordination failures worsened by opaque information flows [14]. Similarly, Lu et al. (2022) explicitly modeled blockchain's role in combating counterfeiting within

platform retail, where asymmetric quality information enables fraudulent sellers [15]. Zhang et al. (2023) addressed gray markets in global supply chains, analyzing the impact of blockchain on unauthorized distribution channels and manufacturer–marketer interactions under divergent market demands [16]. Li (2023) formalized the capacity of blockchain to transform multi-tier supply chains into decentralized platforms, eliminating information silos through real-time updates and automated contracts [17].

Research also addresses operational vulnerabilities unique to platform structures. Tan et al. (2023) contrasted B2C and O2O models for fresh produce, demonstrating blockchain adoption as a strategic response to COVID-19-driven quality concerns and traceability demands [18]. Dong et al. (2023) modeled channel selection (direct vs. platform) and pricing strategies (wholesale vs. agency) for capital-constrained suppliers, integrating supply chain finance with blockchain to highlight interdependencies between financing, channel choice, and information integrity [19]. Wang et al. (2024) rigorously analyzed how blockchain prevents misuse of green loans under capital constraints by verifying compliance with carbon regulations [20]. Synthesizing empirical evidence, Markus and Buijs (2022) developed a framework linking blockchain’s core features (e.g., immutability, decentralization) to supply chain operational performance pathways [21].

Platform governance and coordination represent another significant research cluster. Tao et al. (2023) examined optimal pricing and quality strategies for single versus competitive platforms, incorporating consumer acceptance of blockchain as a critical variable [22]. Wu and Yu (2023) explored hybrid platform formats (agency vs. reselling), demonstrating how blockchain reduces transaction costs and enhances transparency, which in turn requires coordination mechanisms like side-payments [23]. Shen et al. (2020) modeled platform pricing strategies (uniform vs. differential) for secondhand goods, connecting blockchain’s quality verification capabilities to competitive dynamics with new product suppliers [24]. Choi et al. (2023) proposed the ABCDE framework (Architecture, Business models, Coordination, Digitalization, Ecosystem) to organize research on blockchain-driven platform innovation, highlighting methodological gaps in multi-platform competition studies [25].

Sustainability and circularity challenges are increasingly addressed through optimization lenses. Centobelli et al. (2022) developed a “Triple R” framework (recycle, redistribute, remanufacture) for circular supply chains, establishing mathematical relationships between blockchain’s trust, traceability, and transparency features and reverse logistics efficiency [26]. Xu et al. (2023) integrated green technology investments into platform operations (marketplace vs. reselling), modeling interactions between network effects and carbon reduction under blockchain implementation [27]. Biswas et al. (2023) explicitly modeled the trade-off between blockchain-enabled traceability and its energy-related environmental footprint, analyzing this tension [28]. Another study by Xu et al. (2023) [29] extended this analysis to remanufacturing under cap-and-trade regulations, optimizing collection rates and production quantities across different platform modes.

3.1.2. Research Methods

Game theory, particularly Stackelberg models, emerges as the dominant methodological approach, employed in 20 of the 29 studies. This prevalence reflects the hierarchical power structures and sequential decision-making inherent in PSCs. Models typically designate the platform, manufacturer, or supplier as the leader, setting key variables such as wholesale price, blockchain adoption decisions, or green investment levels. Followers (e.g., retailers) then respond with decisions like pricing, order quantity, or traceability effort. Before presenting the details, we introduce a unified operational definition of some key terms to improve the readability in methodological discussion. A model is characterized as “static” or “deterministic” when it employs frameworks like oligopolistic competition,

Stackelberg games, or single-period optimization. In contrast, the “dynamic” classification is reserved for models utilizing differential equations, optimal control, multi-period optimization, or time series analysis. Finally, we regard a model as “stochastic” solely when a random variable or stochastic process is explicitly integrated into either the objective function or the constraints. Research primarily examines three key areas using this approach:

- **Adoption and incentive analysis:** Studies use Stackelberg games to rigorously compare market equilibria with or without blockchain. For instance, Tan et al. (2023) established thresholds for blockchain adoption in B2C and O2O models, identifying critical levels of consumer traceability awareness and government subsidies needed [18]. Zhang et al. (2023) analyzed interactions between manufacturers and gray marketers under different power structures (manufacturer-led vs. simultaneous move), determining the conditions under which blockchain either promotes or prevents gray market entry [16]. Awasthy et al. (2025) modeled traceability effort and pricing within buyer–supplier relationships, finding that adoption can be driven by complementary demand-side, supply-side, and reputational factors, even when individual partners do not directly benefit [30].
- **Pricing and contract design:** Models explore complex pricing dynamics. For example, Choi (2021) incorporated agents’ risk attitudes (mean-risk theory) towards cryptocurrency volatility into a three-echelon SCF model, solving for conditions enabling all-win outcomes [31]. Lu et al. (2022) compared wholesale and agency contracts, demonstrating how commission fees influence a platform’s motivation to deploy blockchain for counterfeiting prevention [15]. Wu and Yu (2023) determined optimal wholesale/agency prices and blockchain strategies for hybrid formats, deriving side-payment contracts that achieve Pareto improvements [23]. Zhang et al. (2023) modeled dual-channel pricing under conditions of risk aversion and demand volatility, pinpointing the most cost-effective blockchain adoption scenarios (manufacturer-only, retailer-only, or joint adoption) [32].
- **Coordination mechanisms:** Several studies design coordination schemes for supply chains after blockchain adoption. For instance, Shen et al. (2020) demonstrated that blockchain enables win-win-win outcomes through horizontal integration, particularly effective for products with low uniqueness [24]. Yang et al. (2021) found that standard contracts often fail to coordinate food supply chains when blockchain is implemented, highlighting the need for tailored mechanisms [33]. Xu et al. (2023) proved that both marketplace and reselling modes can coordinate green supply chains effectively under specific network conditions, with blockchain enhancing the feasibility of this coordination [27].

While less prevalent than game-theoretic approaches, dynamic optimization methods address time-dependent processes in platform supply chains. Liu et al. (2025) applied differential game theory to model a fresh produce e-supply chain, treating product freshness and brand goodwill as state variables [34]. Their analysis derived optimal dynamic paths for supplier freshness-keeping efforts and platform advertising investments, comparing long-term equilibria under blockchain and traditional settings while incorporating the critical effect of past freshness levels on current demand.

Empirical and qualitative methods provide essential grounding and explore behavioral and complex contextual factors. Fosso Wamba et al. (2020) used structural equation modeling (SEM) on survey data from India and the US to empirically validate the impact of knowledge sharing and partner pressure on blockchain adoption, establishing links between blockchain-enabled supply chain transparency and performance outcomes [35]. Similarly, Patil et al. (2023) employed survey-based SEM to develop and validate scales measuring blockchain assimilation and network prominence based on social network

theory [36]. Case study research also plays a vital role in this domain. Sundarakani et al. (2021) utilized case studies of cross-border cargo and chemical logistics to identify critical success and failure factors in implementing integrated blockchain and big data architectures [37]. Brookbanks and Parry (2022) undertook an in-depth case study of wine supply chains, qualitatively analyzing how blockchain technology impacts established trust dynamics and introduces new intermediary roles, challenging assumptions about “trustless” disintermediation [38].

Multi-criteria decision making (MCDM) techniques address complex vendor and platform selection challenges. Azzi et al. (2019) combined theoretical analysis with real-world application studies to define key requirements for efficient blockchain-based supply chain management architectures, bridging technical specifications with operational traceability needs [39]. Bai et al. (2021) proposed a novel method integrating the DEMATEL technique with a Hierarchical Best-Worst Method (HBWM), incorporating social network theory to evaluate and select joint blockchain service vendors and platforms for multi-organizational functions [40]. This approach systematically accounts for the interplay between technological attributes, user requirements, vendor capabilities, and distributed network relationships.

3.1.3. Methodological Trends

Methodological approaches in this domain reveal several key trends:

- **Dominance of comparative statics:** Most studies rely heavily on comparing equilibrium outcomes, such as prices, quantities, profits, and adoption levels, between scenarios with or without blockchain [14–16,18–20,22–24,27–30,32,33,41,42]. This comparative approach serves as the primary method for assessing blockchain’s impact, quantifying its value through metrics like increased production quantity and total surplus [14], reduced gray market presence [16], or restricted loan misuse [20]. It also identifies critical thresholds for adoption.
- **Integration of behavioral realism:** Moving beyond assumptions of pure rationality, models increasingly incorporate behavioral factors. Choi (2021) [31] and Zhang et al. (2023) [32] explicitly modeled risk aversion using mean-risk theory and profit variance, respectively. Other studies, such as Bai et al. (2021) [40] and Patil et al. (2023) [36], applied social network theory to examine how network prominence, learning, and collaboration influence blockchain assimilation and platform choices. Key parameters frequently include consumer trust [14,33,38], awareness [18], reference effects [34], and heterogeneity [30].
- **Emphasis on coordination and contracts:** Recognizing that blockchain implementation alone does not guarantee supply chain coordination, researchers actively design and analyze contracts to achieve Pareto improvements or mutually beneficial outcomes. Prominent mechanisms investigated include side-payments [23], wholesale and agency contracts [15,27], revenue-sharing contracts [24], and coordination schemes tailored to specific operational modes [29]. Notably, Yang et al. [33] observed that blockchain can sometimes disrupt traditional coordination contracts.
- **Multi-tier and network modeling:** To capture blockchain’s inherent network effects, models increasingly extend beyond simple dyadic relationships. Three-echelon structures appear in supply chain finance (involving suppliers, manufacturers, and retailers) [31,42] and remanufacturing contexts (involving manufacturers, third-party processors, and platforms) [29]. Centobelli et al. (2022) further modeled a complex circular platform with multiple actors, including manufacturers, reverse logistics service providers, selection/recycling centers, and landfills [26].

- Incorporation of sustainability metrics: Environmental and social objectives are increasingly formalized within optimization frameworks. Key metrics modeled as objectives or constraints include carbon emissions and abatement [20,29,31], energy consumption [28], product greenness [20,41], and circular economy performance [26]. These factors often interact dynamically with blockchain implementation costs and traceability benefits.

3.1.4. Critical Methodological Gaps

Despite significant progress in current literature, several critical research gaps limit the capacity to fully guide practical implementation:

- Limited dynamic and stochastic modeling: The field exhibits a strong reliance on static, deterministic models, predominantly Stackelberg games, and only Liu et al. (2025) represent a notable exception by modeling dynamics over time [34]. This focus on static analysis overlooks the inherent volatility of real-world PSCs, including fluctuating demand, evolving technology costs, cryptocurrency value shifts, and changing consumer preferences [32]. Methodologies for modeling blockchain investment under uncertainty, such as stochastic programming, robust optimization, and real options analysis, remain significantly underutilized. Furthermore, dynamic models capable of capturing adoption diffusion, learning effects, and long-term impacts on supply chain resilience are scarce.
- Weak integration of empirical insights: A discernible disconnect exists between empirical/qualitative research findings and mathematical modeling. Rich insights derived from case studies, such as analyses of trust dynamics [38] or implementation challenges and success factors [37], and surveys investigating behavioral drivers [35,36] are rarely leveraged to parameterize, calibrate, or validate optimization models. Consequently, there is minimal empirical estimation of key parameters essential for modeling, including blockchain cost structures, consumer sensitivity to trust, and risk aversion coefficients.
- Neglect of technology stack interdependencies: Blockchain's value proposition in supply chains often critically depends on its integration with complementary technologies, particularly the IoT for reliable data capture and real-time traceability [14]. However, current mathematical models predominantly treat blockchain as an isolated technology. The crucial challenge of optimizing the combined deployment and interaction of blockchain within a broader Industry 4.0 technology stack remains largely unaddressed.
- Simplified assumptions on information and rationality: Models frequently rely on the strong assumptions that blockchain perfectly eliminates information asymmetry, and that agents exhibit perfect rationality post-adoption. These assumptions overlook potential asymmetry frictions, such as differences in data interpretation or the limited scope of smart contracts. They also neglect the realities of bounded rationality and the potential costs associated with processing vast amounts of newly available information. Furthermore, mathematically modeling the concept of "trust" beyond mere information transparency remains underdeveloped [38].
- Insufficient modeling of complex competition: While initial models exploring cross-platform competition under conditions of asymmetric blockchain adoption are emerging, they remain rare. The complex interplay between platform competition (e.g., B2C versus O2O models [18], or competition between incumbents and new entrants [41]), multi-homing behaviors, and strategic blockchain adoption decisions demands far more sophisticated game-theoretic approaches.

Research captured in Cluster 1 reveals substantial progress in mathematically modeling blockchain's role within PSCs. Game theory, particularly Stackelberg models, offers a powerful and predominant framework for analyzing strategic interactions, adoption incentives, pricing dynamics, and coordination mechanisms under conditions of enhanced information transparency. These studies successfully address critical challenges, including information asymmetry, financing risks, counterfeiting, traceability deficits, sustainability trade-offs, and platform governance issues, yielding nuanced insights into when and how blockchain generates value. This value creation is often shown to depend heavily on factors such as cost structures, consumer behavior, and power dynamics. Methodologically, the field shows increasing sophistication through the incorporation of behavioral factors, multi-tier interactions, and sustainability goals, alongside a strong focus on designing effective coordination mechanisms.

Despite these advances, the field faces significant methodological constraints. A heavy reliance on static, deterministic models that consider blockchain in isolation creates a substantial disconnect with the dynamic, uncertain, multi-technology, and multi-objective realities of digital supply chains. The underutilization of methodologies like dynamic optimization, stochastic programming, robust optimization, and formal multi-objective frameworks limits the capacity to develop actionable long-term strategies for navigating uncertainty or managing complex trade-offs. The lack of integration between rich empirical findings and prescriptive models hinders both realism and practical applicability.

Moving forward, research must prioritize several critical areas to bridge these gaps: developing dynamic and stochastic models that incorporate learning effects, adoption diffusion patterns, and market volatility; employing rigorous multi-objective optimization techniques to address inherent trade-offs; integrating empirical data to calibrate models and validate key assumptions; modeling blockchain as part of broader technology ecosystems involving IoT, AI, and big data analytics; incorporating more realistic behavioral and informational assumptions that account for bounded rationality and residual information frictions; and advancing sophisticated game-theoretic network models capable of analyzing complex multi-platform competition. Addressing these imperatives is essential for generating genuinely actionable insights to guide the optimized design and operation of blockchain-enabled PSCs in the digital era.

3.2. Cluster 2: IoT in PSCs

3.2.1. Research Issues

Integrating IoT into PSCs introduces distinct challenges and opportunities for mathematical modeling and optimization research. The selected 19 studies within this cluster collectively explore how IoT-enabled data transparency can enhance strategic coordination, improve operational efficiency, influence competitive dynamics, and advance sustainability within PSC ecosystems.

A significant research stream examines strategic decisions surrounding IoT adoption. This includes modeling how platform vertical integration, such as a platform's entry into smart device markets, affects manufacturer innovation, pricing strategies, and profitability under various contractual frameworks like subscription models, usage-based fees, or quantity discounts [43,44]. These studies also analyze optimal IoT investment levels and their cascading effects on pricing decisions, profit distribution (including challenges like double marginalization), and overall channel performance, frequently revealing counterintuitive outcomes [45–48].

Equally important is research on designing coordination mechanisms and mitigating risks enabled by IoT data. Studies develop and analyze contracts such as enhanced revenue-sharing agreements or hybrid consignment-revenue sharing models to align incentives

across multi-echelon or circular supply chains [49,50]. This issue is further extended to design IoT architectures and optimization models that bolster traceability, reduce spoilage and waste in perishable goods supply chains, and mitigate financial or operational risks through real-time monitoring [51–55].

Additionally, leveraging IoT to optimize sustainability and enable circular economy practices represents a growing focus. Researchers formally model the role of IoT in reducing waste and improving resource utilization, often employing multi-objective frameworks to capture the complexity of these goals [49,54,56,57]. This kind of mathematical modeling and optimization studies address critical applications, including optimizing vaccine distribution under infrastructure constraints [58] and managing pandemic-related waste streams [54].

3.2.2. Research Methods

The analytical techniques, primarily game theory and mathematical optimization, dominate the methodological approaches in this research domain. Game theory serves as the principal method for modeling strategic interactions, with Stackelberg games being extensively applied. These models analyze leader–follower dynamics, such as those between platforms and manufacturers or retailers and distributors under conditions of IoT-enabled information transparency. They determine optimal decisions regarding market entry, pricing, investment, and contract design [43,44,47,49]. Game theory also facilitates comparisons of outcomes under different pricing structures (e.g., wholesale vs. agency models, subscription vs. usage-based fees), particularly when IoT investment decisions are involved [44,45]. Furthermore, game-based analytical models are constructed to assess the design and effectiveness of coordination contracts, such as revenue-sharing or hybrid agreements, leveraging IoT data availability [49,50].

Within mathematical optimization, most studies focus on improving operational efficiency by formulating and solving programming models. Several build deterministic models addressing network design, tracking architecture optimization, and cost balancing, typically relying on known parameters [48,51,52,55]. For sustainability-focused research, multi-objective optimization is essential to balance competing economic, environmental, and social goals [54,56]. To tackle the complex, often NP-hard optimization problems arising from IoT integration, metaheuristic approaches are employed, such as the colonial competitive algorithm [48] or multi-objective algorithms like MOGWO [54].

Beyond these analytical and mathematical methods, empirical and conceptual approaches constitute another significant field. Examples include leveraging SEM to test hypothesized relationships between IoT capabilities and performance outcomes [57–59], employing case studies for model validation and contextual understanding [51,60], and developing conceptual frameworks like the 6C model for ecosystem analysis [61]. Risk modeling also utilizes specialized techniques, such as the Peaks Over Threshold method for market risk assessment [53].

3.2.3. Critical Methodological Gaps

Despite methodological diversity, significant gaps persist in current research approaches. A primary limitation is the scarcity of robust models accounting for the inherent uncertainty in real-time IoT data, such as sensor errors, transmission delays, and data volatility. Most optimization models remain deterministic [48,50–52], and even studies utilizing real-time data often lack stochastic foundations in their core models [54]. Furthermore, empirical validation using actual operational IoT data is critically limited. Current validation predominantly relies on simulations, hypothetical datasets, or qualitative case studies, with a pronounced absence of testing analytical models against large-scale, real-world IoT data streams. This gap significantly hinders practical applicability. Integration

challenges also exist. The explicit mathematical modeling of IoT, combined with complementary technologies such as AI/machine learning for prediction or blockchain for security and trust within game-theoretic or optimization frameworks, remains nascent and underdeveloped [56,60]. Additionally, there is a dearth of sophisticated system dynamics or agent-based models capable of simulating emergent behaviors and long-term dynamics within complex IoT-enabled platform ecosystems, a need previously highlighted [61]. Finally, the mathematical representation of environmental and social sustainability pillars within optimization models often lacks the sophistication applied to economic objectives.

Research has effectively applied game theory and deterministic optimization to model IoT's impact on platform supply chain strategies (e.g., market entry, pricing, contracts) and operations (e.g., traceability, waste reduction, coordination), demonstrating methodological effectiveness. However, key limitations still exist: the dominance of deterministic models overlooks IoT data uncertainty, empirical validation with operational data is scarce, and modeling the integration of IoT with complementary technologies or complex ecosystem dynamics is immature. To advance this field, future research should address the inherent uncertainty in IoT data streams by incorporating stochastic programming and robust optimization techniques. Moreover, a crucial direction involves modeling IoT not simply as a conventional sensor network, but as a Software-Defined IoT (SD-IoT). This approach separates control logic from physical hardware, allowing centralized and programmable management of network resources and IoT devices through software. Such a shift offers transformative potential for supply chain optimization, enabling dynamic resource allocation to prioritize critical data flows (e.g., real-time monitoring of perishable goods) and dynamic reconfiguration of sensor networks in response to demand fluctuations or disruptions. Additionally, emerging paradigms such as the Software-Defined Internet of Multimedia Things, which supports high-bandwidth video and audio streams, create new opportunities for applications like live quality inspection, automated compliance checks, and immersive remote auditing in PSC management. Future modeling should therefore evolve beyond treating IoT as a fixed data source and instead formalize decision processes within this software-defined control layer.

3.3. Cluster 3: Industry 4.0 in PSC

3.3.1. Research Issues

Research at the intersection of Industry 4.0 technologies and platform supply chains focuses on overcoming systemic, operational, and strategic barriers to achieve digital circularity, resilience, and performance optimization. A primary theoretical challenge involves PSCs, where traditional linear models struggle to integrate value-capturing return flows and coordinate multiple stakeholders. Mahdiraji et al. (2022) addressed this gap to some extent by examining the disruptive impacts of Industry 4.0 technologies on pharmaceutical PSCs within emerging economies, using Pythagorean fuzzy methods to identify interventions [62]. Similarly, Taddei et al. (2024) developed a conceptual model to bridge systemic and firm-specific barriers in the supply chain transition, grounding their approach in gap analysis and expert validation [63].

Achieving effective coordination in digitally enabled platform supply chains presents another critical issue. Kumar et al. (2023) applied game theory to model coordination conflicts and pricing strategies for e-commerce platforms under extended producer responsibility, comparing centralized and decentralized channel structures [64]. Complementing this, Biswas et al. (2024) analyzed contract design and innovation incentives for manufacturers introducing Industry 4.0 products alongside traditional lines using a two-period game-theoretic model [65].

Enhancing visibility and resilience constitutes a third core research focus. Brookbanks and Parry (2024) and Ali et al. (2024) empirically demonstrated how IoT and blockchain mitigate information asymmetry and disruptions in cross-border and food processing supply chains, respectively [66,67]. Gyarmathy et al. (2025) further explored how Industry 4.0 technologies overcome visibility barriers in e-commerce platform supply chains through data-sharing platforms, framing their analysis within innovation diffusion theory and complex adaptive systems [68]. Furthermore, the impact of these technologies on dynamic capabilities and performance also receives significant attention. Li et al. (2020) investigated how digital technologies mediate economic and environmental performance through supply chain platforms under environmental dynamism [69], while Eslami et al. (2024) modeled how Industry 4.0 capabilities moderate relationships between supply chain integration, agility, and financial performance [70].

3.3.2. Research Methods

The integration of Industry 4.0 paradigm into PSCs presents distinct methodological challenges, owing to its inherent breadth and complexity. Unlike discrete technologies such as blockchain or IoT, Industry 4.0 represents a holistic cyber–physical system. As a result, the mathematical modeling literature in this cluster does not treat Industry 4.0 as a single entity, but instead translates its core principles into model parameters through several distinct yet complementary approaches. Most commonly, Industry 4.0 is conceptualized as a set of technological capabilities, in which technologies such as IoT, AI, and blockchain are represented by the enhanced functionalities they enable, including perfect information transparency, automated coordination, and traceability. These functionalities are incorporated into game-theoretic and optimization models as parameters that influence cost structures, demand functions, or information sets. Another approach frames Industry 4.0 as a strategic investment, modeling it either as a binary adoption decision or as a continuous effort that affects operational performance. In empirical studies using SEM, Industry 4.0 is treated as a latent construct, measured through observable indicators of its technological components to examine mediating or moderating effects on performance outcomes. Finally, in conceptual and MCDM frameworks, Industry 4.0 often serves as a contextual factor that shapes evaluation criteria and system boundaries for optimizing sustainability and resilience, rather than as an explicit decision variable.

Research methodologies in this domain reflect the multifaceted nature of Industry 4.0 in PSCs. Mathematical modeling and optimization are prominent approaches, with game theory frequently applied to coordination and contract design challenges. For instance, Kumar et al. (2023) used Stackelberg games to derive optimal decisions across different contracting scenarios [64], and Biswas et al. (2024) employed game theory to model manufacturer–retailer dynamics involving Industry 4.0 products, identifying critical market thresholds [65]. SEM serves as another key methodology for examining complex relationships with mediating or moderating effects. Sharma et al. (2022) used SEM to confirm the mediating role of Industry 4.0 technologies between supply chain management practices and performance [71], Qader et al. (2022) applied SEM to model Industry 4.0-enabled resilient supply chains [72], and Huang et al. (2023) applied SEM within a dynamic resource-based framework to analyze impacts on supply chain capabilities [73]. MCDM techniques address sustainability optimization challenges. Mastrocinque et al. (2022) developed a novel Sustainability Index 4.0 using fuzzy inference systems to assess renewable energy supply chains [74], and Mahdiraji et al. (2022) combined Pythagorean fuzzy Delphi with simultaneous evaluation of criteria and alternatives methods to prioritize interventions for disruptive Industry 4.0 impacts [62]. Moreover, system dynamics modeling captures complex driver–barrier interactions, exemplified by Ghadge et al. (2020),

who simulated the impact of Industry 4.0 on supply chain parameters to develop an implementation framework [75]. Qualitative and mixed-methods provide complementary depth: Ralston and Blackhurst (2020) derived resilience insights through semi-structured interviews [76], Bellini et al. (2022) presented technical solutions for plant control integration [77], and Centobelli et al. (2023) employed a multiple case study grounded in Industry 4.0 for the shipbuilding PSC [78]. Technical modeling also extends to interoperability platforms, as demonstrated by Cimino et al. (2023), who integrated simulation tools for SME optimization [79].

In general, methodological trends reveal three areas: (1) Strong empirical validation through surveys [67–73], case studies [68,78,80], structured or semi-structured analyses [66,81], and fuzzy decision [62,63,74], often within specific sectors; (2) Integration of theoretical frameworks like dynamic capabilities and innovation diffusion theory [68–70,73,78]; and (3) Growing application of fuzzy methods and uncertainty-handling techniques for sustainability trade-offs [62,74]. Studies increasingly model mediation and moderation effects to elucidate how and when Industry 4.0 impacts manifest [70–72].

3.3.3. Critical Methodological Gaps

Current optimization approaches are predominantly static and deterministic, failing to capture real-time disruptions and evolving supply chain dynamics. Limited progress has been made in developing dynamic, stochastic models that integrate real-time operational data for adaptive decision-making, with technical solutions often lacking formal optimization frameworks [77,79]. While interoperability challenges are acknowledged, few models specifically address data harmonization costs or platform compatibility issues. Scalability concerns for SMEs also persist, as solutions like integrated platforms or MCDM frameworks require validation across diverse contexts and simplified implementation pathways [62,74]. Quantitative modeling of cyber–physical risks and resilience trade-offs associated with Industry 4.0 adoption remains notably underdeveloped. Ali et al. (2024) highlighted the non-significant impact of Industry 4.0 on mitigating transportation risks [67], pointing to an area needing deeper analytical exploration. Furthermore, though emerging multi-objective frameworks attempt to balance economic, environmental, social, resilience, and circularity goals, they require more sophisticated mathematical formulations applicable to complex PSC networks.

Research methodologies for studying Industry 4.0 in PSCs demonstrate both robustness and ongoing evolution, effectively combining theoretical rigor with empirical validation. Game theory provides effective coordination modeling, SEM analyzes complex performance pathways, and innovative MCDM techniques address sustainability optimization. Qualitative and technical studies further enrich this landscape with crucial contextual insights. Nevertheless, advancing more sophisticated mathematical optimization approaches remains imperative—particularly dynamic models capable of real-time adaptation. Future research should prioritize the following: developing stochastic optimization techniques that incorporate live Industry 4.0 data streams; explicitly modeling interoperability challenges and costs within platform ecosystems; creating scalable optimization tools tailored for SMEs; rigorously quantifying risk-resilience tradeoffs from Industry 4.0 adoption; and advancing multi-objective frameworks that balance efficiency, circularity, sustainability, and resilience goals in digital supply chains.

3.4. Cluster 4: Cloud Computing in PSCs

3.4.1. Research Issues

Research in this domain primarily addresses three interconnected challenges: optimizing cloud platform integration, overcoming adoption barriers, and enhancing performance

in digital supply chains. Central to these efforts is evaluating supply chain coordination and pricing under security risks, where aligning stakeholder incentives (cloud providers, manufacturers, users) amid data security concerns proves critical. Studies have examined coordination failures stemming from security vulnerabilities [82], pricing-security trade-offs in AI cloud models [83], and profitable channel selection for software vendors [84], alongside hybrid cloud procurement under demand uncertainty [85]. Designing resilient cloud-based supply chains must contend with demand volatility, cost fluctuations, capacity constraints, and disruptions. Key work includes integrated product-supply chain design using real-time cloud data [86], robust global network design balancing agility and resilience [87], and optimizing inventory allocation in complex cloud-enabled structures [88]. Additional challenges involve evaluating cloud provider performance within supply chain contexts [89], managing specialized cloud resource demands [90], developing conceptual frameworks for hybrid cloud integration [91], and environmental footprint considerations of cloud computing [92].

Previous research explored the determinants of implementation intent [93], identified drivers (e.g., IT capabilities) and consequences (e.g., enhanced integration) of cloud assimilation [94], examined its role in reducing SME financing risks [95], and assessed impacts on information sharing and operational performance [96]. Barriers affecting cooperative resilience—particularly security and trust concerns between logistics and cloud providers [97]—and links between cloud adoption and supply chain responsiveness [98] require further investigation. Additionally, cloud-based PSCs face unique disruptions necessitating specialized recovery strategies. Current work focuses on optimizing recovery from operational and cyber disruptions [99], formalizing multi-structural dynamics [6], and refining service matching in specialized contexts like healthcare [100]. Foundational research establishing definitions, characteristics, and reference models for cloud-enabled PSCs completes this methodological landscape [6,101].

3.4.2. Research Methods

Game-theoretic models dominate coordination conflict resolution, exemplified by Liu et al. (2024) employing Stackelberg games to design security-constrained revenue-sharing contracts [82]. Similarly, Guo et al. (2025) applied analytical modeling to optimize security investments and pricing across hybrid AI cloud environments [83]. Researchers typically apply stochastic and fuzzy MCDM methods for uncertain decision contexts. For instance, Hasani (2021) implemented fuzzy MCDM with augmented ε -constraint for resilient network design [87], and Li et al. (2023) derived optimal capacity decisions under stochastic conditions [85]. Algorithmic and simulation approaches enable dynamic solutions, such as Jianjia et al. (2021) deploying time-contextual singular value decomposition for medical service recommendations [100], and Chen and Chang (2021) used cellular automata to simulate disruption recovery strategies [99]. Data-driven techniques leveraging real-time analytics represent another significant methodology. Specifically, Ali et al. (2021) integrated live cost data into mixed-integer linear programming with genetic algorithm frameworks [86], and Tan et al. (2024) combined machine learning forecasting with empirical error distributions for cloud-based inventory optimization [88]. Performance evaluation includes Azadi et al.'s (2024) stochastic two-stage DEA model assessing cloud service efficiency with undesirable outputs [89]. There are relatively few studies related to empirical theoretical frameworks. Manuel Maqueira et al. (2019) identified key determinants of cloud adoption levels in PSCs [94], whereas Lin and Lin (2019) integrated elaboration likelihood and commitment trust theories within SEM frameworks to examine adoption drivers [93]. Conceptual advances include the formalization of cloud-based processes [101], SEM analysis of security-trust dynamics in logistics-cloud partnerships [97],

hybrid cloud integration framework [91], and characterization of cloud supply chain in the multi-structural dynamics [6].

Methodological trends reveal three prominent developments. First, hybrid approaches combining optimization with AI and machine learning techniques are proliferating [86,87], often enhanced by advanced uncertainty handling through stochastic capacity modeling [85,89]. Second, sector-specific adaptations have emerged as a defining characteristic, with notable applications in healthcare [100], medical device manufacturing [87], and retail supply chains [88]. Third, research increasingly emphasizes real-time data integration for dynamic decision-making [86,88], life cycle assessment methodologies for cloud service PSCs [92], and empirical validation of technology adoption drivers using structural equation modeling [93,94,96]. This evolution reflects the field's progression toward context-sensitive, data-driven methodologies that address both operational complexity and domain-specific requirements.

3.4.3. Critical Methodological Gaps

Significant methodological gaps persist in current research. Most models remain static or deterministic [82,83,85], lacking dynamic optimization capabilities that incorporate real-time data streams for adaptive decisions like pricing adjustments or security updates. Quantitative modeling of interoperability costs across hybrid cloud environments remains underdeveloped despite recognized barriers [84], and available conceptual frameworks [6,91,101], with technical constraints rarely integrated into optimization approaches. Research also shows sparse investigation of trade-offs between cybersecurity investments, operational resilience, and cost efficiency. For instance, Guo et al. (2025) optimized security measures without considering disruption impacts [83], while Chen and Chang (2021) modeled recovery processes but omitted proactive investment strategies [99]. Additional urgent gaps include scalability limitations in SME-focused tools [84,95] and insufficient multi-objective frameworks that holistically balance sustainability, economic performance, resilience, and security [82,92].

While Cluster 4 demonstrates methodological diversity for cloud-enabled supply chains, game theory addresses competitive coordination, stochastic/fuzzy optimization handles uncertainty, simulation captures dynamic interactions, data-driven methods enable operational optimization, and SEM studies validate adoption pathways. Critical advancements remain needed. Future work should develop dynamic optimization using live cloud data, create interoperability models quantifying technical constraints, establish unified cybersecurity-resilience-cost frameworks, scale optimization tools for SMEs, and build holistic models co-optimizing sustainability, efficiency, and resilience in cloud-driven PSCs.

3.5. Cluster 5: Live Streaming in PSCs

3.5.1. Research Issues

Integrating live streaming commerce into supply chains creates complex operational and strategic interdependencies among manufacturers, platforms, streamers, and other stakeholders. The 17 articles in this cluster employ rigorous mathematical modeling to analyze these relationships, primarily examining optimal decision-making across different structural configurations and market conditions. Research predominantly focuses on strategic channel design and operational coordination, addressing key questions such as: (1) choosing between agency selling and reselling arrangements [102–106]; (2) deciding whether to adopt or integrate live streaming channels [107–113]; selecting appropriate platform selling modes [114,115]; and managing unique risks like supply disruptions [107] and greenwashing concerns [106]. A critical theme emerging across multiple studies

explores how live streaming commerce reshapes power dynamics and profit distribution within PSCs [105,116–118].

3.5.2. Research Methods

The Stackelberg game still serves as the primary analytical approach. In these models, manufacturers typically act as leaders setting wholesale prices or channel strategies, while platforms, streamers, or retailers respond as followers determining retail pricing, commission rates, effort levels (e.g., marketing or freshness-keeping), or disclosure policies. For instance, Zhang et al. (2023) compared centralized versus decentralized decision-making (supplier-led vs. streamer-led) in fresh produce supply chains while incorporating consumer freshness preferences [117]. Similarly, Hao and Yang (2023) modeled the interaction between sales formats (resale/agency) and pricing strategies under consumer return policies to derive equilibria [104]. Zhu et al. (2025) further extended this analysis to brand–platform–streamer interactions across power structures and selling formats [102], collectively capturing sequential decision-making and inherent conflicts of interest.

Optimization techniques frequently complement these game structures or operate independently to determine constrained optimal decisions. Xu et al. (2023) optimized production quantities and coordination mechanisms under cap-and-trade regulations across platform modes [103], while Li et al. (2025) determined optimal selling formats when introducing live streaming to mitigate supply risks [107]. In agricultural contexts, Xu et al. (2025a, 2025b) developed optimization models to evaluate blockchain adoption against greenwashing and live streaming channel viability, incorporating quality investments and technology costs [106,112]. Stochastic elements feature prominently in such analyses, as when Li et al. (2025) modeled random supply viability for risk-adjusted channel decisions [107] and Zhang et al. (2024) compared operational strategies to derive optimal revenue-sharing terms [110]. Equilibrium analysis remains central to game-theoretic studies for comparing optimal decisions (prices, efforts, channel structures) and profit outcomes across scenarios. Most incorporate sensitivity analysis of key parameters, such as commission rates, consumer preferences, cost structures, and power dynamics, to extract managerial insights and define strategic boundaries. Ma et al. (2024) enhanced this approach through multi-agent simulation validation [108].

3.5.3. Critical Methodological Gaps

A striking absence of empirical validation leaves insights reliant on analytical derivations and numerical examples, untested against real-world platform operations or consumer behavior in live streaming supply chains [116,118]. Most models depend heavily on deterministic demand functions that are often linear and price-dependent or effort-dependent, overlooking the stochastic volatility influenced by streamer performance, real-time interactions, and platform algorithms [102,105,108]. Consumer behavior is frequently oversimplified through basic utility functions (price/quality/effort-based), neglecting critical behavioral dimensions like impulse purchasing, trust dynamics unique to live streaming, and social influence within digital rooms that drive platform appeal [117]. The predominance of static, single-period frameworks fails to capture the inherent dynamic evolution of platform ecosystems, such as streamer reputation building, long-term contracts, or consumer learning [107,109,111]. Operational complexities like algorithm-driven visibility, content moderation costs, and multi-homing streamers are rarely incorporated [114,115]. While some studies consider coordination mechanisms [103,110], sophisticated contract designs beyond basic revenue sharing remain underexplored for aligning incentives among manufacturers, platforms, and streamers.

This cluster demonstrates how mathematical modeling (primarily game theory and optimization) effectively unravels strategic complexities introduced by live streaming. Researchers have addressed diverse problems spanning channel structures, sales formats, risk mitigation, and coordination across power dynamics. However, the field remains largely theoretical. Future work should prioritize empirical validation while incorporating stochastic demand, behavioral richness, dynamic multi-period modeling, operational realities, and advanced contracts to enhance practical relevance. Grounding research in empirical observations of platform dynamics and consumer behavior will be crucial for advancing this evolving domain.

3.6. Cluster 6: Gen AI in PSCs

3.6.1. Research Issues

This thematic cluster examines the emerging integration of GenAI into PSCs, focusing on research problems and methodological approaches. Researchers primarily investigate four areas: the implications of GenAI adoption (benefits, challenges, trends) [119–121]; critical enablers and capabilities for implementation [122–124]; impacts on performance outcomes like sustainability, resilience, and risk management [125–129]; and conceptual frameworks [130–132]. A recurring theme highlights the empirical gap concerning GenAI's practical value mechanisms within complex platform environments.

3.6.2. Research Methods

Methodologically, empirical and analytical techniques dominate, with growing use of multi-method approaches. Survey-based studies employing statistical analysis prevail for examining practitioner perceptions and adoption factors across sectors [119,120,125–128]. Several studies employ MCDM techniques to structure complex decision problems. For instance, Sharma and Rathore (2024) combined Delphi methods with an analytic hierarchy process for enabler prioritization [122]. Kurrahman et al. (2025) integrated fuzzy Delphi with DEMATEL to identify key GenAI capabilities for green supply chains [124]. Similarly, Fontoura et al. (2025) utilized fuzzy DEMATEL to analyze causal relationships in energy efficiency frameworks [131].

Innovative methods include sentiment analysis and LDA topic modeling of social media data for enabler identification [122]. Content analysis of site visit transcripts using a generative large language model forms the basis for a novel firm-level supply chain risk measurement proposed by Fan et al. (2025) [129]. Akhtar et al. (2024) applied SEM to test their framework linking smart product platforming, big data analytics, machine learning, and the circular economy in a Gen AI environment [132]. Dubey et al. (2024) specifically proposed a “theoretical toolbox”, synthesizing ten organizational theories to benchmark PSC management practices using GenAI [130], while Jackson et al. (2024) offered a comprehensive capability-based framework for GenAI analysis and implementation in supply chain and operations management [123].

3.6.3. Critical Methodological Gaps

Current research exhibits a notable scarcity of formal mathematical modeling and optimization techniques directly addressing GenAI integration in supply chains. While methods like DEMATEL and AHP offer analytical rigor for problem structuring, they cannot prescribe optimal configurations, resource allocations, or deployment policies under constraints. For instance, the LLM-based risk measurement approach remains descriptive and correlational [129], lacking optimization capabilities for mitigation strategies. Simulation modeling, which could capture dynamic interactions in AI-driven supply chains and test resilience scenarios, is similarly absent. Existing frameworks [123,130–132] often stay conceptual or rely on correlation-based validation, missing the algorithmic development

needed to transform them into actionable tools. Furthermore, studies frequently examine capabilities or outcomes in isolation rather than developing integrated models that simultaneously optimize potentially conflicting objectives like efficiency, resilience, and sustainability inherent to platform supply chains.

This cluster effectively maps the diverse landscape of research problems surrounding GenAI in platform supply chains, heavily utilizing empirical surveys and sophisticated analytical methods like MCDM. The integration of fuzzy logic addresses uncertainty, while the generative large language model for risk quantification represents methodological innovation. Theoretically grounded frameworks provide valuable adoption lenses. However, critical gaps remain in developing prescriptive mathematical optimization, simulation, and algorithms tailored to GenAI-enhanced PSCs. Future work should prioritize such models to generate implementable solutions for operating AI-enabled PSC management under real-world constraints.

3.7. Cross-Cluster Comparison

Based on the comprehensive review and discussion above, we propose a cross-cluster comparison (summarized in Table 4) that integrates core issues, applicable digital technologies, mainstream methodologies, and potential directions within PSCs. This framework illustrates how specific technologies address particular problems and highlights shared modeling paradigms across applications.

Table 4. Mapping the cross-cluster overall comparison.

Research Issue	Technology Cluster	Methodology	Potential Direction
Coordination and Incentive Alignment	Blockchain: Addressing coordination failures caused by information asymmetry. Live streaming: Managing profit distribution conflicts among manufacturers, platforms, and live-streamers. Cloud computing: Coordinating cloud providers and users under security risks.	Stackelberg game	1. Integrate empirical behavioral insights (such as trust and fairness preferences) into the utility function. 2. Design a coordination mechanism suitable for multiple entities. 3. Contract design under dynamic repetitive games.
Pricing and Revenue Management	Blockchain: Channel pricing under transparent information. Live streaming: Pricing under different sales models (agency/resale). IoT: Service pricing based on IoT data (subscription/usage). Cloud computing: Pricing of cloud resources and AI model services.	Stackelberg game Optimization theory	1. Introduce randomness in demand (such as fluctuations in demand in live streaming rooms). 2. Dynamic pricing algorithm under competitive platforms. 3. Bundled pricing for multiple products/services.
Strategic Adoption and Investment Decision	All clusters: Blockchain adoption, IoT investment, cloud migration, GenAI deployment, etc.	Stackelberg game Programming MCDM	1. Dynamic uncertainty modeling of technical costs and benefits. 2. Endogenous modeling of network effects (positive/negative). 3. Portfolio optimization of joint investment in multiple technology stacks.

Table 4. Cont.

Research Issue	Technology Cluster	Methodology	Potential Direction
Operations and Resource Optimization	IoT: Inventory, route, and traceability Optimization. Cloud computing: Resource allocation, capacity planning. Industry 4.0: Sustainable manufacturing, circular logistics.	Programming Robust optimization Heuristic algorithm	1. An online optimization algorithm integrating real-time data streams. 2. Data sharing and collaborative optimization across enterprise boundaries. 3. The combination of explainable AI and optimized models.
Risk Management and Resilience	Blockchain: Alleviating financing and counterfeiting risks. Cloud computing: Cybersecurity, disruption recovery. Live streaming: Supply disruption, green washing risks. Gen AI: New algorithmic risks.	Game Stochastic simulation	1. Quantify the trade-off between cybersecurity investment and operational resilience. 2. Model the propagation effect of multi-node interrupts. 3. Incorporate resilience as a clear objective into multi-objective optimization.
Sustainability and Circularity	Blockchain: Green traceability, carbon footprint tracking. IoT: Reducing waste and recycling. Industry 4.0: Sustainable manufacturing. Gen AI: AI-driven sustainable management.	Game Multi-objective optimization MCDM	1. Develop unified measures and weights (such as the comprehensive sustainability index). 2. Model the uncertainty of consumers' green preferences. 3. Dynamic modeling of circular economy systems for long life cycle products.

A systematic comparison across thematic clusters reveals both methodological commonalities and distinctive characteristics among digital technologies used in PSC related problems. By linking technologies, problems, and methods, this overall comparative table offers scholars and practitioners a structured perspective for developing more comprehensive, realistic, and instructive mathematical models, supporting deeper and more integrated research of PSCs in the future.

Although the research contexts differ across technology clusters, an analysis of their methodological limitations reveals a number of common and structured challenges. Rather than presenting these gaps within isolated technological silos, we distill and summarize them into five core dimensions in Table 5, which concludes systematically how each dimension manifests within different clusters.

As shown in Table 5, the methodological gaps in current research are not isolated, but rather form a set of systematic and structured challenges facing the entire field in addressing digital complexity. Future research should shift from static to dynamic randomness, from simplified to behaviorally realistic models, from isolated to integrated collaboration, from bilateral to network ecosystems, and from single-objective to multi-objective trade-offs. Addressing these five common challenges is essential to developing supply chain management practices that can effectively guide the future of intelligent, resilient, and sustainable platforms.

Table 5. Mapping the cross-cluster comparison on methodological gap.

Gap Dimension	Manifestation Across Clusters	Unified Core Challenge
Inadequate dynamic and stochastic modeling	Blockchain: Research in this area relies heavily on comparative static analysis and seldom explores dynamic diffusion or cost fluctuations. IoT: Optimization models remain largely deterministic and often overlook sensor data noise and transmission delays. Cloud computing: Current models lack dynamic pricing and adaptive security mechanisms that utilize real-time data. Industry 4.0: There is a shortage of dynamic stochastic models to handle real-time operational disruptions. Live streaming: Studies employ deterministic demand functions and neglect fluctuations driven by host performance and viewer interactions. Gen AI: The inherent uncertainty and dynamic nature of AI-generated outputs remain largely unaddressed.	Existing research is difficult to capture and optimize the decision-making process that evolves over time and random events in real PSCS, resulting in models being unable to provide long-term and anti-interference strategies.
Oversimplified behavioral and realistic factors	Blockchain: Existing studies often assume that the “trust” issue is fully resolved, overlooking bounded rationality and information processing costs. Live streaming: Current models oversimplify key behavioral factors such as viewer–host trust, impulse buying, and social influence. All clusters: Rich case studies and empirical findings, such as implementation challenges and behavior-driven evidence, have not been sufficiently incorporated into mathematical models for parameterization, calibration, or validation, leading to a significant gap between theory and practice.	The current models fail to incorporate the key behavioral and psychological factors that influence decision-making and are not combined with empirical observations, which weakens the explanatory power and predictive accuracy.
Isolated technology treatment	Blockchain: Current models fail to capture the collaborative value arising from integration with enabling technologies like IoT and AI. IoT: Integration with AI (for prediction) or blockchain (for security) remains largely conceptual, with limited modeling advances. Cloud computing: Quantitative models assessing interoperability costs and constraints in hybrid cloud environments are still underdeveloped. Industry 4.0: While technological integration is central to its vision, existing models do not thoroughly optimize integrated configurations. Gen AI: Its role as an enabler alongside technologies such as IoT and blockchain has yet to be formally modeled.	The current research perspectives do not align with the way digital technologies work collaboratively in practice, and thus cannot provide optimized guidance for strategic decisions involving joint investment in multiple technologies.
Limited complex ecosystem modeling	Blockchain: Current models do not adequately address cross-platform competition or multi-homing user behavior. Cloud computing: Ecosystem-level modeling of multi-cloud and multi-vendor competition remains underdeveloped. Live streaming: Existing studies often oversimplify platform operations, such as algorithmic traffic allocation and cross-platform host agreements. Gen AI: The new competitive landscape shaped by Gen AI has not been fully explored in modeling efforts. All clusters: Most models are restricted to dyadic or triadic interactions and lack a comprehensive multi-agent network perspective.	Previous studies have failed to capture the complex network effects and competitive dynamics of multilateral and cross-platform in the platform ecosystem, and have been unable to analyze the emergent behaviors of the ecosystem.

Table 5. Cont.

Gap Dimension	Manifestation Across Clusters	Unified Core Challenge
Insufficient multi-objective optimization	Blockchain and IoT: Environmental objectives are often treated merely as constraints or simplified multi-objective optimizations, lacking more sophisticated modeling frameworks. Cloud computing: A unified framework that simultaneously optimizes cybersecurity, economic efficiency, operational resilience, and environmental impact is still missing. Industry 4.0: More sophisticated models are required to balance competing objectives such as circularity, resilience, and operational efficiency. All clusters: Quantitative models that incorporate social responsibility considerations, such as fairness and ethics, remain underdeveloped.	The current optimization framework is insufficient to support managers in making scientific and quantitative trade-off decisions among conflicting goals such as efficiency, resilience, sustainability (environmental and social), and safety.

4. Conclusions

Platform supply chains (PSCs) represent a critical frontier in digital transformation, fundamentally altering how enterprises operate and deliver value. This systematic review synthesizes 120 articles from leading journals across six pivotal technological domains, i.e., blockchain, IoT, Industry 4.0, cloud computing, live streaming, and Gen AI, to consolidate research issues, methodologies, and critical gaps. Our analysis indicates that while substantial progress has occurred in formalizing PSC operations, significant challenges persist in integrating digital technologies with the dynamic interconnectivity inherent to PSC ecosystems.

The review highlights strategic coordination and operational performance as predominant research objectives. Game theory, particularly Stackelberg models, constitutes the dominant analytical framework across all six domains. These models extensively dissect complex multi-stakeholder interactions: resolving pricing conflicts between platforms and suppliers, quantifying adoption incentives for blockchain or IoT technologies, designing coordination contracts for cloud services, and analyzing power dynamics among manufacturers, platforms, and live streamers. Mitigating information asymmetry emerges as a consistent priority. Blockchain research rigorously model capabilities for building trust, combating counterfeiting, and ensuring traceability. IoT studies leverage real-time data transparency to enhance traceability and reduce waste, notably in perishable goods supply chains. Cloud computing research emphasizes optimizing data-driven resilience against disruptions. Additionally, sustainability has garnered significant scholarly attention. Multi-objective optimization frameworks are increasingly adopted, especially in Industry 4.0 and blockchain-enabled PSCs, seeking optimal trade-offs among economic profitability, environmental impact, and social considerations.

Furthermore, this review identifies critical methodological limitations in current research. First, all six technological domains exhibit overreliance on static and deterministic assumptions. The predominance of equilibrium-based models, primarily Stackelberg games, fails to capture the inherent volatility of PSCs in the digital era. Such volatility includes fluctuating consumer demand driven by live streamer influence or algorithmic trends, evolving technology costs (e.g., blockchain implementation, cloud computing), and dynamic learning effects among stakeholders. This creates a significant disconnect from real-world PSC operations. Second, a persistent gap exists between empirical insights and quantitative modeling. While rich qualitative findings from case studies (e.g., on blockchain trust dynamics or IoT deployment challenges) and empirical surveys (e.g., on technology adoption drivers) offer valuable managerial insights, key parameters remain

empirically underexplored. These include realistic technology cost structures, consumer trust sensitivity to information disclosure, and practical risk aversion coefficients. Third, technologies are predominantly modeled in isolation. Current research largely neglects synergistic interdependencies such as IoT sensors feeding immutable data to blockchain ledgers, AI algorithms analyzing cloud-based data streams for predictive optimization, or Gen AI enabling adaptive coordination. Integrated frameworks that holistically optimize multi-technology deployment within Industry 4.0 ecosystems are notably absent. Finally, platform-specific complexities are frequently oversimplified. Live streaming models inadequately capture behavioral nuances (e.g., impulse purchasing driven by real-time interaction, deep influencer trust) and operational dynamics (e.g., algorithm-driven visibility impacts, content moderation costs, multi-homing streamer strategies). Similarly, emerging Gen AI research focuses heavily on conceptual frameworks but lacks prescriptive optimization models for deployment in complex PSC operations.

To advance this field and realize the potential of digital technologies in PSC management, future research should address several critical priorities. First, embracing dynamism and uncertainty is crucial. Moving beyond static equilibria requires adopting stochastic programming, robust optimization, simulation techniques, and dynamic game theory to capture technology adoption dynamics, demand volatility, and evolving system parameters over time. Second, strengthening empirical-quantitative integration is essential. Leveraging operational data (e.g., IoT sensor streams, platform transaction logs, blockchain records) combined with behavioral experiments can significantly improve model calibration and validation, enhancing practical applicability. Third, explicit integration of digital technologies must be prioritized. Developing comprehensive frameworks that model interdependencies among blockchain, IoT, Gen AI, and cloud computing within PSCs will yield actionable insights. Fourth, advanced analytical methods are needed to address PSC complexity. This includes mathematical modelling incorporating bounded rationality, system dynamics simulations, algorithmic approaches, and multi-agent reinforcement learning. Finally, sophisticated multi-objective optimization should advance to simultaneously balance competing goals: economic efficiency, cybersecurity, operational resilience, environmental sustainability, and social responsibility.

In conclusion, this review highlights the critical role of leveraging digital technologies for mathematical modeling and optimization in advancing PSC management. While existing research establishes a robust foundation for analyzing strategic interactions and technological impacts, its practical applicability remains constrained by methodological limitations. Future studies must therefore bridge gaps in dynamic modeling, empirical validation, technological integration, and complexity management. By addressing these challenges, researchers can develop agile, realistic, and holistic frameworks capable of navigating intricate digital-era challenges and leveraging transformative opportunities for PSCs. This necessitates a concerted shift from isolated static analyses toward interconnected, adaptive, and dynamic optimization approaches. Additionally, although discussions on the separation of digital technologies in terms of problems and methods can ensure the depth of the analysis, we acknowledge that there is some inherent conceptual overlap between industries such as Industry 4.0 and other specific technologies. Future research can adopt more detailed bibliometric techniques, such as topic evolution analysis or co-citation network analysis, to further unravel and quantify these synergies.

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