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Artificial Intelligence in Disaster Supply Chain Risk Management: A Bibliometric Analysis with Financial Risk Implications

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Abstract

Disruptions caused by disasters, pandemics, and systemic crises have increased the complexity and vulnerability of global supply chains, highlighting the need for advanced analytical approaches to risk and resilience management. In this context, artificial intelligence (AI) has emerged as a promising analytical capability for improving risk assessment and decision-making in disrupted supply chains. The study follows PRISMA 2020 reporting guidelines adapted for bibliometric research and presents a bibliometric and knowledge-mapping analysis of artificial intelligence applications in disaster supply chain risk and resilience management. Using the Web of Science Core Collection, a dataset of 288 peer-reviewed publications was analyzed through keyword co-occurrence, bibliographic coupling, citation analysis, and collaboration network mapping. The findings indicate a rapidly expanding research field in which AI supports predictive risk assessment, real-time monitoring, and resilience-oriented decision-making in disaster-prone supply networks. The analysis identifies dominant thematic clusters, emerging research directions, and opportunities for integrating AI-enabled analytics into supply chain risk management frameworks. The mapped literature also suggests secondary interpretive implications for financial risk exposure and supply chain finance, rather than indicating a separately operationalized finance-specific bibliometric subfield. To enhance interpretive depth, an AI-assisted analytical layer was applied to refine thematic clusters and detect emerging trends. However, this layer operates as a complementary interpretive tool and is subject to methodological limitations, including sensitivity to keyword semantics, dependence on bibliometric outputs, and potential interpretive bias in AI-assisted thematic labeling. Consequently, the AI-assisted analysis is used to support, rather than replace, bibliometric findings. Overall, this study contributes to the emerging literature on artificial intelligence in disaster supply chain risk management and highlights future research opportunities, including improved methodological integration and enhanced analytical transparency in AI-assisted bibliometric research.

Keywords: financial risk implications; disaster supply chains; supply chain resilience; supply chain risk management; artificial intelligence; bibliometric analysis; knowledge mapping

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1. Introduction

Recent disasters, pandemics, and systemic crises have exposed the growing vulnerability of global supply chains and intensified scholarly interest in more adaptive and analytically robust approaches to risk and resilience management (Gelsomino et al., 2016; Ivanov et al., 2019) Within this context, artificial intelligence has increasingly emerged as a promising enabler of predictive, data-driven, and resilience-oriented decision support. Against this background, this introductory section first outlines the broader disaster risk and supply chain vulnerability context, then discusses the relationship between risk management and resilience in disaster supply chains, examines the role of artificial intelligence as an emerging enabler, and finally presents the study's research gap, objectives, and overall structure.

1.1. Background: Disaster Risk and Supply Chain Vulnerability

Over the past two decades, global supply chains have become increasingly interconnected, geographically dispersed, and efficiency-driven. While these developments improved cost competitiveness and responsiveness, they also increased vulnerability to disruptions from natural hazards, climate extremes, technological failures, geopolitical tensions, and public health emergencies (McGlade et al., 2019; Lucatello & Sánchez, 2022). Recent crises, including the COVID-19 pandemic and regional conflicts, have shown that highly optimized and lean supply networks often lack the adaptive capacity to cope with compound and cascading shocks, as cost-minimization strategies reduce redundancy, flexibility, and buffering capacity across interconnected production and distribution systems (Gereffi, 2020; Ivanov & Dolgui, 2020).

Beyond operational disruptions, disasters generate significant financial exposure across supply networks. Accordingly, this study treats operational disruption as the immediate disturbance affecting supply chain flows, financial risk as a consequential exposure that may arise from such disturbance, and supply chain finance as the financial management domain through which these consequences may be transmitted, monitored, or mitigated. Interruptions in production, transportation, and inventory flows frequently translate into liquidity shortages, delayed payments, and increased supplier default risk. Financial flows are tightly interconnected with material and information flows, meaning that disruptions in operational activities directly affect working-capital availability and financial stability across supply chain partners (Wuttke et al., 2013). Supply chain finance research highlights that disruptions can propagate financial distress across interconnected firms, amplifying liquidity constraints and increasing systemic risk within supply networks (Gelsomino et al., 2016). Consequently, supply chain disruptions are increasingly examined through the lens of supply chain finance and financial risk propagation across interconnected firms.

Disaster-related disruptions differ fundamentally from routine operational disturbances. They are characterized by deep uncertainty, rapid propagation, limited response time, and simultaneous impacts across multiple supply chain nodes and institutional levels (Craighead et al., 2007; Aven, 2016). Such disruptions frequently trigger ripple effects that extend beyond immediate operational losses, affecting regional economies, social stability, and environmental sustainability. In humanitarian and emergency contexts, these failures translate directly into delayed access to food, medical supplies, and critical infrastructure, with severe implications for vulnerable populations (Van Wassenhove, 2006; Kovács & Spens, 2007).

Within disaster contexts, supply chain vulnerability arises from structural concentration, dependence on critical nodes, limited data visibility, and fragmented governance, often reinforced by institutional constraints, regulatory complexity, and insufficient cross-sector coordination—particularly in humanitarian and public-sector logistics systems (Sheffi &

Rice, 2005; Dubey et al., 2021). These dynamics suggest that disaster-related supply chain failures reflect deeper systemic fragilities rather than isolated technical malfunctions, highlighting the need to understand how vulnerabilities emerge and evolve under uncertainty in order to develop adaptive, data-informed, and resilience-oriented strategies.

1.2. Risk Management and Resilience in Disaster Supply Chains

Risk management has traditionally played a central role in supply chain planning, focusing on the identification, assessment, and mitigation of potential disruptions. In disaster contexts, such approaches have primarily emphasized preventive measures aimed at reducing exposure to known hazards. While these practices remain indispensable, their effectiveness is often constrained by the unpredictable, interconnected, and evolving nature of contemporary crises (Aven, 2016; Wagner & Bode, 2008). As a result, risk management strategies that rely predominantly on ex ante planning struggle to address cascading and compound disruptions that unfold dynamically across supply networks (Ivanov, 2020).

In response, supply chain resilience has emerged as a complementary and more comprehensive framework, shifting the focus from disruption prevention toward continuity, adaptability, and long-term sustainability. Resilience encompasses the ability to prepare for shocks, respond effectively during crises, and recover or transform operations, and is commonly conceptualized as a dynamic capability involving anticipation, absorption, adaptation, and recovery (Christopher & Lee, 2004; Brandon-Jones et al., 2014; Hohenstein et al., 2015). Despite this complementarity, risk management and resilience are often treated separately in practice, with risk management emphasizing control and efficiency, and resilience emphasizing flexibility and learning. This separation may result in supply chains that are robust against known risks but vulnerable to novel disruptions, highlighting the need to integrate both perspectives through adaptive, coordinated, and data-informed governance approaches (Wieland & Durach, 2021; Hohenstein et al., 2015).

For conceptual clarity, four related but distinct constructs should be differentiated in this study. Operational disruption refers to disturbances in the physical, informational, and organizational flows of the supply chain, such as interruptions in production, transport, inventory availability, or coordination. Supply chain resilience refers to the capacity of the supply chain to anticipate, absorb, adapt to, and recover from such disruptions. Financial risk refers to the disruption-related exposure that may emerge across firms, including liquidity shortages, delayed payments, supplier distress, working-capital pressure, and default risk. Supply chain finance refers not to disruption itself, but to the set of financial arrangements and inter-organizational mechanisms—such as reverse factoring, dynamic discounting, and inventory financing—through which financial flows are managed and may either mitigate or transmit disruption-related financial stress. In the present study, the bibliometric analysis primarily maps the literature around AI, disaster supply chains, risk, disruption, and resilience, whereas financial risk and supply chain finance are treated as secondary interpretive implications emerging from that mapped literature rather than as directly measured core constructs.

1.3. Artificial Intelligence as an Emerging Enabler

The growing complexity and uncertainty of disaster supply chains have intensified interest in analytical approaches that support timely and informed decision-making. Artificial intelligence has emerged as a central enabling technology, offering methods for processing large and heterogeneous datasets, identifying latent patterns, and generating actionable insights under uncertainty (Jordan & Mitchell, 2015). In disaster environments, decision-makers face rapidly changing conditions, incomplete information, and competing operational, social, and environmental objectives, while traditional analytical models of-

ten rely on simplified assumptions and static inputs. AI-based approaches, particularly machine learning and data-driven analytics, address these limitations by enabling continuous learning and dynamic model updating as new information becomes available (Choi et al., 2018).

Current applications of AI in disaster-related supply chains focus primarily on predictive and diagnostic tasks, such as demand forecasting, disruption prediction, hazard assessment, and vulnerability classification, enhancing situational awareness and supporting proactive risk mitigation and resource allocation (Ivanov & Dolgui, 2020). Despite these advances, AI remains only partially integrated into resilience-oriented supply chain management, often functioning as a stand-alone analytical tool rather than an embedded component of adaptive decision-support systems. Moreover, disaster response is inherently socio-technical, shaped by institutional, ethical, and organizational factors alongside analytical insights. Consequently, the transformative potential of artificial intelligence lies not in algorithmic sophistication alone, but in its integration within governance frameworks and collaborative decision ecosystems that support sustainability-oriented resilience.

1.4. Research Gap, Objectives, and Paper Structure

Despite substantial advances in disaster supply chain research, important gaps remain in how risk management, resilience, and artificial intelligence are conceptually and empirically integrated. Existing studies frequently advance resilience frameworks or demonstrate the technical capabilities of AI, yet these research streams often develop in parallel rather than in dialog (Hosseini et al., 2019).

A central gap concerns the limited incorporation of AI into learning-based and adaptive resilience frameworks. While artificial intelligence is widely applied to forecasting and optimization, its role in supporting institutional learning, coordinated response, and long-term system transformation remains underdeveloped. As a result, resilience is often treated as a strategic aspiration, whereas AI is positioned as a technical enhancement rather than as a core enabler of sustainable adaptive capacity.

The literature is further characterized by fragmentation across disciplinary, methodological, and geographical boundaries. Managerial and humanitarian logistics studies emphasize organizational coordination and governance, whereas AI-oriented research prioritizes algorithmic performance. This fragmentation constrains cumulative knowledge development and obscures opportunities for integrative theory building.

In response to these gaps, this paper systematically maps the intellectual structure of research on disaster supply chain risk and resilience through the lens of artificial intelligence. Using bibliometric and knowledge-mapping techniques, it identifies dominant thematic clusters, traces their temporal evolution, and evaluates the extent to which AI has been embedded in resilience-oriented research.

Specifically, the study addresses five research objectives:

RO1. Identify the main thematic clusters in disaster supply chain risk and resilience research.
RO2. Examine how artificial intelligence methods are positioned within these clusters.
RO3. Trace the temporal development of AI-enabled approaches.
RO4. Highlight conceptual and methodological gaps that inform future research directions.
RO5. Interpret the potential financial risk and supply chain finance implications emerging from the identified research clusters as a secondary interpretive perspective, rather than as a separately operationalized bibliometric subdomain.

By systematically mapping the intellectual structure of AI-enabled disaster supply chain research, this study contributes primarily to the resilience and operations literature, while also identifying secondary interpretive implications for the financial risk manage-

ment domain. In this sense, the study highlights how AI-driven analytics discussed in the mapped literature could potentially support financial stability and risk monitoring within supply chain finance ecosystems, without claiming a dedicated finance-specific bibliometric analysis.

2. Methodology

This section presents the methodological framework adopted to systematically map and analyze the literature on artificial intelligence in disaster supply chain risk and resilience management. The bibliometric analysis is centered on the mapped research domain of AI, disaster supply chains, risk, disruption, and resilience, while any financial risk and supply chain finance dimensions are treated only as secondary interpretive implications emerging from that broader literature. To achieve this aim, the study applies a bibliometric and knowledge-mapping approach based on a structured search and selection process, followed by data preparation, preprocessing, and network-based analysis. The section first explains the overall research design and analytical rationale, then describes the data source selection and search strategy, outlines the study selection and data cleaning procedures, and finally presents the bibliometric techniques, complementary interpretive frameworks, and methodological considerations that support the transparency and rigor of the analysis.

2.1. Research Design and Analytical Approach

This sub-section clarifies the logic of the methodological design and explains why the study is structured around distinct but complementary analytical components. Since the objective is not only to map publication patterns but also to interpret the conceptual development of the field, the research design is divided into sub-sections that separately address the overall design, the rationale for the bibliometric and knowledge-mapping approach, and the complementarity between quantitative bibliometric analysis and qualitative synthesis. This structure is intended to guide the reader from the general analytical logic of the study to the specific methodological choices that follow.

2.1.1. Overall Research Design

This study adopts a systematic bibliometric and knowledge-mapping design to examine how disaster supply chain risk and resilience research was structured through artificial intelligence-enabled analytical and decision-support approaches. The design is exploratory and integrative, combining quantitative bibliometric techniques with structured qualitative interpretation in order to map thematic patterns, collaboration structures, and influential knowledge domains within a fragmented interdisciplinary field (Donthu et al., 2021; Tranfield et al., 2003; Zupic & Čater, 2015).

Importantly, this design recognizes that bibliometric maps are not analytical endpoints. While network visualizations reveal structural relationships within the literature, scholarly interpretation remains essential for explaining their meaning and implications. For this reason, bibliometric findings are complemented by a structured qualitative framework that interprets who produces knowledge, what thematic and methodological foci dominate, when key shifts occur, where research activity is concentrated, why specific research directions gain prominence, and how artificial intelligence is employed within disaster supply chain risk and resilience research (H. Snyder, 2019).

By integrating bibliometric mapping with interpretive synthesis, the research design supports a balanced and rigorous assessment of the field. It enables dominant research streams to be identified without overstating coherence, highlights emerging areas without overstating novelty, and exposes conceptual and methodological gaps that are not readily visible through single-method or purely narrative reviews.

As shown in Figure 1, the study followed a sequential methodological process comprising research design, database selection, search strategy development, study selection, data preprocessing, bibliometric analysis, AI-assisted interpretive support, and integrated interpretation of findings.

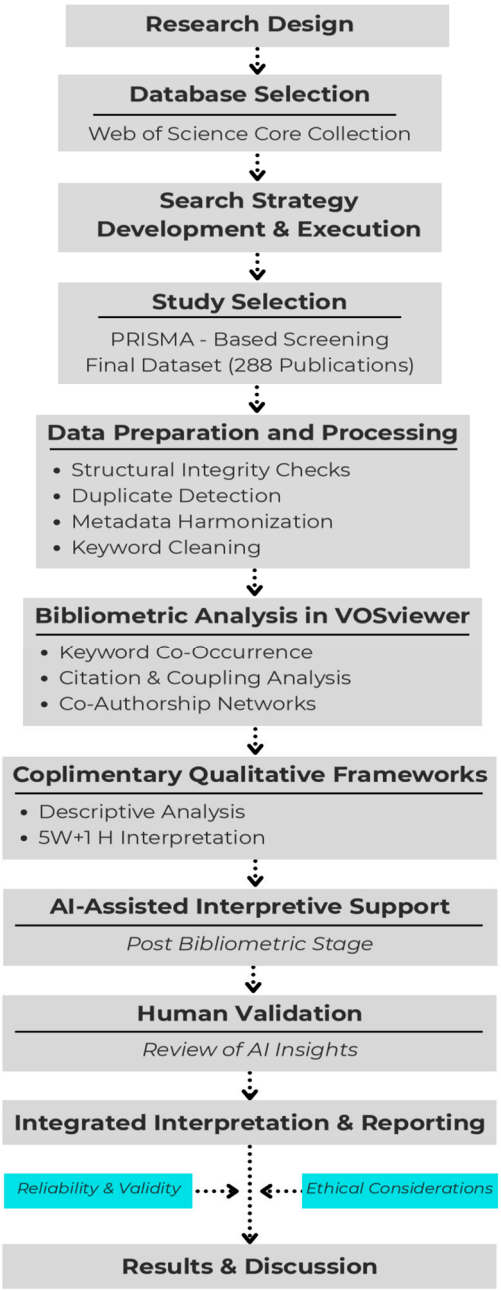


Figure 1. Methodological flow of the study.

2.1.2. Rationale for a Bibliometric and Knowledge-Mapping Approach

The rationale for adopting a bibliometric and knowledge-mapping approach is grounded in the structural characteristics of the research domain. Research on disaster supply chains, resilience, and artificial intelligence has expanded rapidly, producing a heterogeneous literature with overlapping concepts, diverse methodologies, and uneven theoretical integration. Under such conditions, conventional literature reviews risk selective coverage and limited analytical depth (Donthu et al., 2021).

Bibliometric analysis provides a systematic means of addressing this complexity by examining relationships among publications, authors, keywords, and citations. Citation-

and network-based techniques reveal thematic concentrations, influential knowledge domains, and research trajectories that are difficult to identify through manual review alone (Zupic & Čater, 2015). Knowledge mapping further emphasizes the relational structure of scientific knowledge, highlighting how research themes cluster, evolve, and converge over time (Small, 1999).

This relational perspective is particularly valuable for AI-enabled disaster supply chain research, where methodological innovation often outpaces theoretical integration, and where temporal overlay and coupling techniques help trace emerging and converging research fronts.

In addition, bibliometric approaches support theory development and research positioning by identifying dominant streams, marginal themes, and underexplored intersections, thereby clarifying where the literature has matured and where meaningful contributions remain possible (Aria & Cuccurullo, 2017). Importantly, this approach does not replace qualitative judgment but provides an empirical foundation for interpretation, enabling structural patterns to be translated into conceptual insights through careful synthesis (H. Snyder, 2019). Accordingly, only analyses directly contributing to thematic structure, temporal evolution, and collaboration patterns were retained to avoid analytical redundancy and visualization overload.

2.1.3. Complementarity of Quantitative Bibliometric Analysis and Qualitative Synthesis

While bibliometric techniques effectively reveal structural patterns within a research field, they are limited in explaining conceptual meaning. Network clusters, co-occurrence relationships, and citation linkages describe how the literature is organized but do not explain why themes emerge or how concepts are interpreted across studies (Zupic & Čater, 2015). To address this limitation, the study combines quantitative bibliometric analysis with qualitative synthesis. Quantitative techniques—such as keyword co-occurrence analysis, bibliographic coupling, citation analysis of sources, and country-level collaboration mapping—are used to identify dominant themes, influential knowledge domains, and emerging research fronts in a systematic and reproducible manner (Donthu et al., 2021). Qualitative synthesis then interprets these outputs by examining titles, abstracts, and keywords associated with identified clusters to capture conceptual intent and theoretical orientation across research streams (Tranfield et al., 2003).

This integration strengthens the identification of research gaps by distinguishing between areas of theoretical maturity and unresolved conceptual or methodological challenges (H. Snyder, 2019). By combining bibliometric mapping with interpretive synthesis, the study balances analytical rigor with conceptual depth, translating structural patterns into insights that support theory development and future research directions.

2.2. Data Source Selection

This sub-section explains the rationale for the choice of bibliographic sources used in the study. Because database selection directly affects the scope, consistency, and interpretive boundaries of a bibliometric review, this part clarifies the criteria used to evaluate data sources and justifies the decision to rely on a single curated database. Presenting this step separately helps establish the analytical foundation of the dataset before the search strategy and study selection procedures are described.

Database selection was guided by three criteria: scholarly relevance, metadata reliability, and support for citation-based analyses, consistent with best practices in bibliometric research (Donthu et al., 2021). Scholarly relevance ensured coverage of peer-reviewed publications contributing to theoretical and methodological development in disaster supply chain and resilience research. Metadata reliability—such as accurate author identification,

standardized journal titles, consistent keywords, and complete reference lists—was essential for constructing robust bibliometric networks and avoiding fragmented or distorted thematic structures (Aria & Cuccurullo, 2017). In addition, comprehensive citation data were required to support techniques such as citation analysis and bibliographic coupling, which are central to identifying influential knowledge domains and emerging research fronts (Small, 1999).

Based on these considerations, the Web of Science Core Collection was selected as the sole data source. Web of Science provides curated journal coverage, standardized indexing practices, and comprehensive citation metadata, making it suitable for bibliometric and knowledge-mapping research (*Editorial Selection Process | Clarivate*, 2023). Its strong coverage of supply chain management, operations research, risk analysis, and information systems journals ensures representation of the field's core academic discourse (Zupic & Čater, 2015; Mongeon & Paul-Hus, 2016). Using a single database ensures conceptual coherence and a more reliable interpretation of bibliometric networks.

While this choice defines the analytical boundaries of the study and excludes gray literature and non-indexed sources, it supports the objective of mapping the structured academic landscape and identifying conceptual patterns and research gaps.

Web of Science Core Collection was selected as the sole data source because of its curated journal coverage, standardized indexing, and comprehensive citation metadata, which make it well-suited to bibliometric and knowledge-mapping research (*Editorial Selection Process | Clarivate*, 2023). Its strong coverage of journals in supply chain management, operations research, risk analysis, and information systems ensures that the dataset reflects the field's core theoretical debates and methodological trajectories (Mongeon & Paul-Hus, 2016). At the same time, this choice defines the analytical boundaries of the study, as the findings represent the structured academic discourse indexed in Web of Science rather than practitioner-oriented publications, gray literature, or non-indexed conference proceedings. This boundary is appropriate given the study's objective of mapping the intellectual landscape and identifying academic research patterns and gaps.

2.3. Research Strategy and Data Collection

2.3.1. Conceptual Framing of the Research Strategy

The conceptual framing of the search strategy was guided by the need to capture a research field that is inherently interdisciplinary, conceptually fragmented, and rapidly evolving. Disaster supply chain risk and resilience research draws on theoretical foundations from supply chain management, humanitarian logistics, risk analysis, and, increasingly, artificial intelligence and data-driven decision sciences. Each of these domains employs distinct conceptual lenses and terminologies, which complicates systematic identification of the relevant literature (Tang, 2006; Christopher & Peck, 2004).

To address this complexity, the search strategy was anchored in core conceptual constructs rather than narrowly defined technical terms. Emphasis was placed on concepts that reflect the underlying research focus of the study, including risk management, resilience, disruption, adaptation, and artificial intelligence-enabled decision support. This approach helps ensure that retrieved publications engage substantively with the phenomena of interest, rather than merely referencing relevant keywords in a peripheral or incidental manner.

Importantly, conceptual framing prioritizes thematic coherence over exhaustive coverage. Bibliometric research does not seek to retrieve every potentially relevant publication, but to systematically map the dominant intellectual structure of a field in a transparent and reproducible manner (Zupic & Čater, 2015; Donthu et al., 2021). By grounding the search strategy in theory-informed constructs, the study balances breadth with analytical focus,

ensuring that the resulting dataset reflects sustained and meaningful engagement with disaster supply chain risk, resilience, and artificial intelligence.

2.3.2. Search String Development and Execution

The search string was developed through an iterative process combining deductive reasoning based on established theory with inductive refinement from empirical observation of the literature. Initial keywords were informed by seminal contributions in supply chain resilience, disaster risk management, and AI-enabled supply chain analytics, providing a theoretically grounded starting point (Ivanov & Dolgui, 2020; Tang, 2006; Christopher & Peck, 2004). These terms were subsequently refined through pilot searches, during which titles, abstracts, and author keywords of both highly cited and recent studies were examined to identify additional terminology and discipline-specific expressions. Ambiguous or overly generic terms were excluded to maintain analytical focus and avoid irrelevant results, resulting in a balanced search string that captured substantive engagement with disaster supply chain risk, resilience, and artificial intelligence (Tranfield et al., 2003; H. Snyder, 2019).

The final search string was structured around four conceptual dimensions: (i) disaster and crisis contexts; (ii) supply chain and logistics systems; (iii) risk management and resilience concepts; and (iv) artificial intelligence and data-driven analytical methods. Boolean operators, truncation symbols, and synonym groupings were used to connect these dimensions and capture variations in terminology across disciplines while maintaining thematic precision. The search was executed using the Topic Search (TS) field in Web of Science, which includes titles, abstracts, author keywords, and keywords. Plus, it ensures comprehensive and reproducible retrieval (Zupic & Čater, 2015). To maintain consistency, the finalized search string remained unchanged throughout data collection, enabling replication and validation. The full search strategy is provided in Appendix A.

2.3.3. Inclusion Criteria, Time Span, and Data Restrictions

Explicit inclusion and exclusion criteria were applied to ensure conceptual coherence and analytical integrity. Publications were included if they addressed disaster or crisis contexts in relation to supply chain or logistics systems and explicitly considered risk management, resilience, robustness, or adaptive capacity alongside artificial intelligence, machine learning, or data-driven analytical approaches. This ensured that the dataset captured the intersection of conceptual and methodological domains central to the study.

Publications were excluded if they focused on routine operations, optimization under stable conditions, or purely technical AI applications without relevance to disruption contexts. Non-peer-reviewed materials, editorials, conference proceedings, and gray literature were also excluded to maintain consistency in publication quality and citation practices (Mongeon & Paul-Hus, 2016; H. Snyder, 2019; Tranfield et al., 2003). The temporal scope spanned from the early 2000s to the most recent complete year available at the time of data collection, capturing both the emergence of resilience research and the growing adoption of artificial intelligence in supply chain management (Ivanov & Dolgui, 2020). The analysis was further limited to English-language publications to ensure comparability and coherence within citation networks. The database was last accessed on the 21 December 2025.

2.3.4. Study Selection Process and PRISMA Flow Diagram

The study selection process followed the logic and reporting principles of the PRISMA 2020 framework, adapted for a bibliometric review based on structured metadata rather than full-text systematic procedures (Page et al., 2021). The objective was to ensure transparency and reproducibility in identifying and selecting studies for bibliometric

and knowledge-mapping analyses. The following supporting information is available in the Supplementary Materials.

The initial search of the Clarivate Web of Science Core Collection yielded 427 records. Prior to screening, 10 records were removed for other reasons, while no duplicates were identified, and no records were excluded through automated tools, resulting in 417 records for screening. Titles, abstracts, and keywords were reviewed using predefined inclusion and exclusion criteria. Full-text screening was not conducted, as bibliometric reviews rely on structured metadata. Given the structured and metadata-based nature of bibliometric screening, single-reviewer selection was considered appropriate. Although this approach is methodologically acceptable in bibliometric reviews based on structured metadata, it may still introduce subjective judgment in borderline inclusion or exclusion decisions, particularly in interdisciplinary research domains. To mitigate this risk, predefined inclusion and exclusion criteria were applied consistently, and exclusion reasons were documented transparently.

During eligibility assessment, 129 records were excluded due to insufficient alignment with the inclusion criteria. Most exclusions related to the absence of a clear supply chain or logistics focus (n = 102) or the lack of artificial intelligence or data-driven analytical methods (n = 18), while additional records were excluded for lacking a disaster context (n = 6) or risk and resilience perspective (n = 3). Following this process, 288 studies were retained for bibliometric and knowledge-mapping analyses. The complete selection procedure is summarized in the PRISMA 2020 flow diagram (Figure 2).

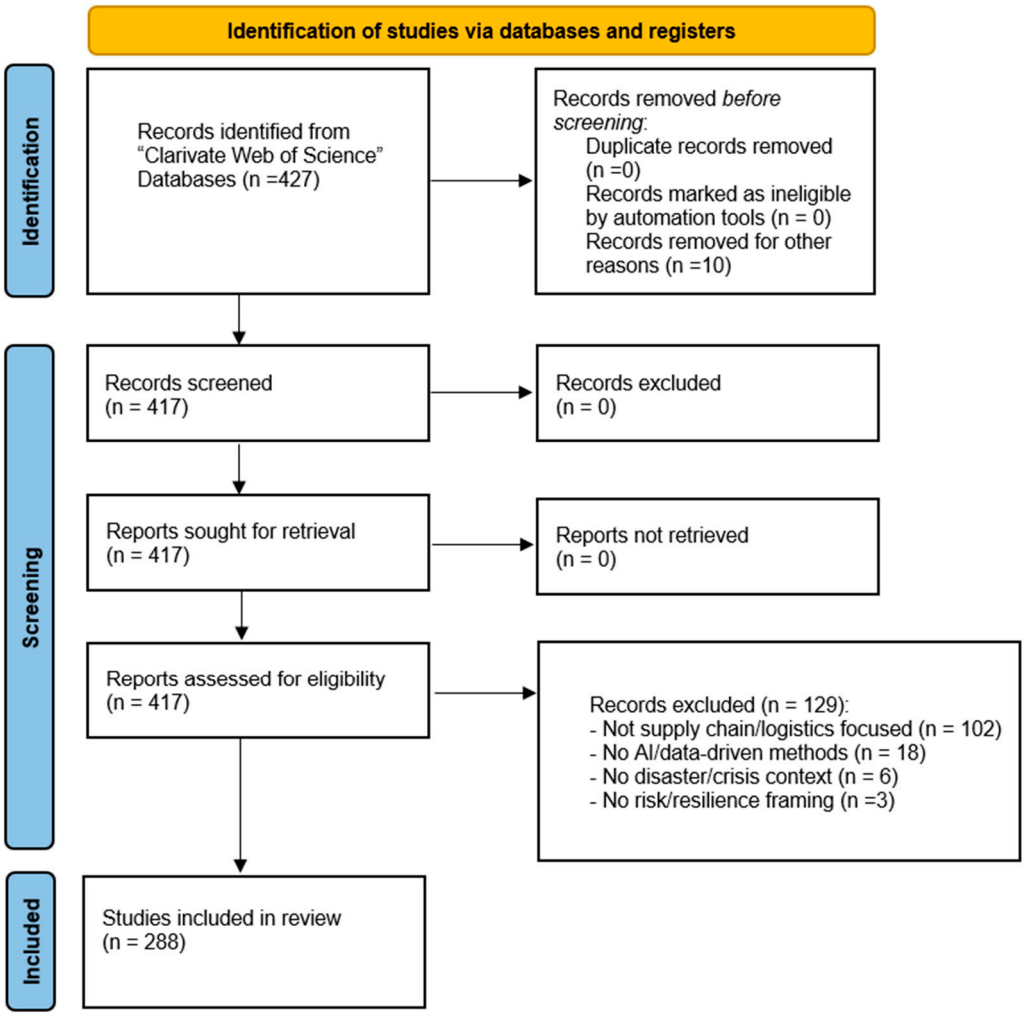


Figure 2. PRISMA flow-chart.

2.3.5. Final Dataset Characteristics

The final dataset comprises peer-reviewed publications that collectively represent the core academic discourse on disaster supply chain risk and resilience with the application of artificial intelligence. The dataset captures both foundational research streams and more recent methodological and analytical developments, thereby providing a balanced empirical basis for subsequent bibliometric and knowledge-mapping analyses.

At this stage, the dataset is considered analytically stable and suitable for further processing. Summary characteristics of the dataset, including publication volume, temporal distribution, and disciplinary coverage, are reported to support interpretation of the results. The dataset subsequently serves as input to the data preparation, keyword harmonization, and network construction procedures described in the following section.

2.4. Data Preparation and Preprocessing

Before conducting bibliometric analyses, the dataset required careful preparation to ensure consistency, analytical reliability, and interpretive validity. For this reason, this sub-section is divided into distinct parts that address structural integrity checks, duplicate and metadata consistency control, keyword cleaning and semantic harmonization, and validation procedures. Organizing the material in this way makes clear that preprocessing is not merely a technical step, but a necessary analytical stage that directly affects the robustness of the resulting bibliometric networks.

2.4.1. Methodological Rationale for Data Preparation

Data preparation represents one of the most consequential yet often underreported stages of bibliometric and knowledge-mapping research. Although bibliographic databases provide curated and standardized records, raw datasets frequently contain inconsistencies, redundancies, and semantic ambiguities that can substantially affect network-based analyses. In bibliometric studies, such imperfections do not merely reduce analytical precision; they can actively distort thematic structures, artificially inflate or fragment clusters, and misrepresent intellectual relationships within the literature (Zupic & Čater, 2015).

These risks are amplified in interdisciplinary research domains such as disaster supply chain risk and resilience, where terminology evolves rapidly, and concepts are frequently transferred across disciplinary boundaries. Differences in naming conventions, keyword preferences, and indexing practices often reflect disciplinary traditions rather than substantive theoretical distinctions. As a result, treating data preparation as a purely technical or mechanical task risks embedding methodological artifacts into subsequent analyses and compromising interpretive validity.

In this study, data preparation is therefore conceptualized as an analytical intervention rather than a procedural necessity. The objective is to ensure that bibliometric outputs capture meaningful intellectual structures and research dynamics, rather than noise introduced by inconsistent metadata or fragmented terminology. This perspective aligns with established best practices in bibliometric research, which emphasize the central role of preprocessing in safeguarding the validity, reliability, and interpretability of network-based findings (Donthu et al., 2021).

2.4.2. Data Export and Structural Integrity Checks

All bibliographic records were exported from the Web of Science Core Collection in plain text format, including full publication metadata and cited references. This export format was selected because it preserves citation linkages and supports advanced citation-based analyses, including citation analysis and bibliographic coupling.

Following export, an initial structural integrity check was conducted to assess dataset completeness and internal consistency. Records were examined for missing or incomplete bibliographic fields, such as absent author information, incomplete cited reference lists, or truncated abstracts. Publications lacking essential metadata were excluded at this stage, as incomplete records can introduce systematic bias into network construction and compromise the reliability of citation-based analyses (Aria & Cuccurullo, 2017).

This preliminary screening stage serves two complementary purposes. First, it ensures that all retained records are analytically usable across the full range of bibliometric techniques employed in the study. Second, it establishes a consistent and reliable baseline from which subsequent cleaning, harmonization, and normalization procedures can be applied without propagating structural errors through later stages of analysis.

2.4.3. Duplicate Detection and Metadata Consistency

Although duplicate removal was initiated during the PRISMA-based study selection process, an additional duplicate detection step was conducted during data preparation. Duplicate records may arise from indexing updates, journal reclassification, or batch export procedures, and their presence can artificially inflate citation counts and distort co-authorship and co-citation networks.

Beyond duplicate detection, metadata consistency was addressed through systematic harmonization of author names, journal titles, and institutional affiliations. Minor variations—such as abbreviated versus full journal titles or inconsistent use of author initials—can fragment networks and obscure collaboration patterns if left uncorrected. Harmonization was conducted conservatively, prioritizing standardized forms provided by the database and avoiding subjective reinterpretation of records (Zupic & Čater, 2015).

This step is particularly important for co-authorship and institutional collaboration analyses, where accurate representation of relationships depends on consistent identification of entities across records.

2.4.4. Keyword Cleaning and Semantic Harmonization

Keyword processing constitutes one of the most analytically sensitive stages of bibliometric preprocessing. Author-provided keywords reflect disciplinary backgrounds, research traditions, and editorial practices, resulting in substantial semantic overlap and lexical variation across the dataset. If left unaddressed, such variation can fragment thematic clusters and dilute the interpretability of keyword co-occurrence networks.

In this study, keyword cleaning involved the systematic identification and consolidation of synonymous terms, spelling variants, and plural forms. Examples include harmonizing "supply chain" and "supply chains," "artificial intelligence" and "AI," and "machine learning" and related algorithmic descriptors, where conceptually appropriate. At the same time, deliberate care was taken to preserve meaningful conceptual distinctions between related but non-identical terms, such as "risk," "resilience," and "robustness."

To document and operationalize these decisions, a thesaurus file was developed and applied during analysis. The thesaurus records all keyword substitutions, mergers, and exclusions, providing a transparent and reproducible account of the semantic harmonization process. Thesaurus-based keyword cleaning is widely recognized as a best practice in bibliometric research, as it enhances analytical validity and supports methodological transparency (Donthu et al., 2021; Van Eck & Waltman, 2014).

2.4.5. Validation and Quality Assurance Procedures

To assess the robustness of the data preparation process, a set of validation and quality assurance procedures was implemented. First, random samples of records were manually inspected to verify that keyword harmonization preserved conceptual meaning and did

not inadvertently merge analytically distinct concepts. Second, preliminary trial networks were generated to visually inspect unexpected fragmentation, isolated nodes, or anomalous clustering patterns that could signal unresolved data quality issues.

These validation procedures are not intended to eliminate interpretive judgment, but to reduce the likelihood that methodological artifacts influence substantive conclusions. Such quality assurance practices are increasingly emphasized in bibliometric research as a means of strengthening analytical credibility, enhancing transparency, and increasing reviewer confidence in the robustness of the findings (Donthu et al., 2021).

2.4.6. Summary and Transition to Bibliometric Analysis

The cleaned and validated dataset was then used for bibliometric and knowledge-mapping analyses.

By explicitly documenting data preparation and validation procedures, the study enhances methodological transparency and reproducibility, ensuring that subsequent bibliometric results can be interpreted with confidence. The following section builds directly on this foundation by detailing the bibliometric analysis techniques and parameter settings applied in the study.

2.5. Bibliometric Analysis Using VOSviewer

This sub-section presents the bibliometric techniques applied in the study and explains why each method is included as part of the overall analytical strategy. The individual sub-sections are organized according to the different dimensions of the field that the analysis aims to capture, including thematic structure, temporal development, intellectual foundations, current research fronts, and collaboration patterns. This structure allows each analytical technique to be introduced and justified separately while also showing how the combined outputs contribute to an integrated interpretation of the literature.

2.5.1. Rationale for the Selected Bibliometric Techniques

Bibliometric analysis encompasses a range of complementary techniques, each suited to addressing different analytical dimensions of a research field. In the context of disaster supply chain risk and resilience research, no single bibliometric method is sufficient to capture thematic structure, temporal evolution, and collaboration dynamics. For this reason, the present study adopts a multi-technique bibliometric strategy, combining complementary approaches to provide a coherent and holistic representation of the literature.

The selection of techniques is guided by the study's objectives: to identify dominant thematic streams, trace their temporal development, detect emerging research fronts, and examine patterns of scholarly collaboration. Keyword-based techniques are employed to explore conceptual structure, citation-based techniques are used to examine influential publication venues and convergence among documents, and authorship-based techniques are applied to investigate collaboration dynamics across countries. This layered strategy is consistent with established bibliometric practice, which emphasizes methodological triangulation to enhance analytical robustness and interpretive depth (Zupic & Čater, 2015; Donthu et al., 2021).

All bibliometric analyses were conducted using VOSviewer 1.6.20, which provides integrated support for network construction, normalization, clustering, and visualization within a unified analytical environment. The software is widely adopted in bibliometric research due to its transparency, reproducibility, and suitability for large-scale network analysis (Van Eck & Waltman, 2014).

2.5.2. Software Environment and General Parameter Settings

All bibliometric analyses were conducted in VOSviewer to ensure analytical consistency across techniques. The software was selected because it applies a unified mapping and clustering framework, allowing direct comparison of results from keyword co-occurrence, citation analysis of sources, bibliographic coupling, and co-authorship networks. Full counting was used throughout, assigning equal weight to each co-occurrence or linkage regardless of the number of co-authors or references involved. This choice is consistent with the exploratory nature of the study and avoids down-weighting interdisciplinary or highly collaborative publications, which are common in disaster and resilience research (Van Eck & Waltman, 2014). Network normalization was performed using the association strength measure, and threshold values for keyword occurrences, citation counts, and node inclusion were adjusted iteratively to balance readability and analytical inclusiveness.

To enhance methodological transparency and reproducibility, a detailed summary of the VOSviewer software environment, common analytical settings, and analysis-specific parameters is provided in Appendix B. In particular, Table A1 reports the analysis-specific parameter matrix for the keyword co-occurrence, overlay visualization, bibliographic coupling, source citation, and country co-authorship maps. Table A2 presents the common settings applied across the different bibliometric analyses, including the software version, counting method, normalization approach, and threshold logic. Finally, Table A3 provides illustrative examples from the thesaurus file used for keyword cleaning and semantic harmonization before network construction. Together, these Tables in the Appendix complement the methodological description in the main text and provide additional detail regarding the operational implementation of the bibliometric mapping procedure. This fits the manuscript's existing discussion of VOSviewer, full counting, association-strength normalization, threshold setting, and thesaurus-based preprocessing.

2.5.3. Keyword Co-Occurrence Analysis

Keyword co-occurrence analysis was employed to identify the thematic structure of the literature. This technique examines how frequently keywords co-appear within the same publications, thereby revealing clusters of concepts that represent dominant research themes.

In this study, author-provided keywords were used as the primary unit of analysis, as they reflect authors' intentional conceptual framing. A minimum occurrence threshold was applied to construct a co-occurrence network that balanced network density with interpretability.

Clusters generated through keyword co-occurrence analysis were interpreted as thematic research streams rather than rigid categorical groupings. Each cluster was examined in relation to its most central keywords and representative publications, enabling qualitative interpretation of its conceptual focus. This approach recognizes that bibliometric clusters do not automatically correspond to coherent theoretical schools and therefore require interpretive synthesis to extract meaningful insights (Zupic & Čater, 2015).

2.5.4. Overlay Visualization for Temporal Analysis

Overlay visualization was applied to examine the temporal evolution of research themes by assigning each keyword an attribute corresponding to the average publication year of the documents in which it appears. This technique enables the identification of shifts in thematic emphasis over time and supports the distinction between established and emerging research topics (Van Eck & Waltman, 2014).

In the context of disaster supply chain risk and resilience research, overlay visualization facilitates temporal comparison between long-established concepts, such as traditional

risk management and robustness, and more recent themes related to artificial intelligence, machine learning, and data-driven decision support. To avoid purely descriptive interpretation, temporal patterns identified through overlay visualization were contextualized through qualitative examination of representative publications, ensuring that apparent novelty reflects substantive conceptual development rather than transient terminological trends (Zupic & Čater, 2015).

2.5.5. Density Visualization Analysis

Density visualization was employed selectively to assess the concentration of research activity within the bibliographic coupling analysis. In density maps, regions of high density indicate areas of sustained scholarly attention, while lower-density regions suggest underexplored or emerging research directions (Van Eck & Waltman, 2014).

In this study, density visualization was used to support the interpretation of thematic saturation and emerging focal points within the contemporary research front, rather than as a stand-alone analytical tool. Density patterns were interpreted in conjunction with co-occurrence and citation-based results to avoid overinterpretation of visual intensity as a proxy for conceptual maturity (Zupic & Čater, 2015; Donthu et al., 2021).

2.5.6. Bibliographic Coupling Analysis

Bibliographic coupling analysis was employed to identify contemporary research fronts by examining publications that share similar reference bases. Unlike citation analysis of sources, which reflects accumulated influence, bibliographic coupling is forward-looking and well-suited to detecting active and emerging research streams (Kessler, 1963). In the present study, bibliographic coupling was applied at the document level to explore how artificial intelligence is currently being integrated into disaster supply chain risk and resilience research. Only documents with a minimum of 10 citations were included in the visualization, using full counting and association strength normalization, in order to retain analytically meaningful linkages while preserving map readability and interpretability. Clusters derived from this analysis were interpreted as areas of active methodological experimentation and conceptual development, providing insight into the evolving structure of the field (Donthu et al., 2021).

2.5.7. Citation Analysis of Sources

Citation analysis was conducted at the source (journal) level to identify influential publication venues shaping the development of disaster supply chain risk and resilience research. By examining citation relationships among journals, this analysis reveals how different disciplinary domains contribute to and interact within the field.

The resulting citation network was interpreted as an indicator of intellectual anchoring and interdisciplinary convergence, rather than as a measure of journal quality or impact. This approach supports understanding of how supply chain management, operations research, risk analysis, and information systems journals collectively structure the academic discourse.

2.5.8. Co-Authorship Network Analysis

Co-authorship network analysis was conducted to examine patterns of scholarly collaboration at the country level. Collaboration networks provide insight into how knowledge production is organized geographically and how research capacity is distributed across regions.

In disaster-related research, collaboration patterns are often shaped by access to data, funding structures, and exposure to hazard-prone environments. Accordingly, co-authorship networks were interpreted not as indicators of research quality, but as structural

contexts that may influence thematic focus and the diffusion of AI-enabled approaches within the field (Zupic & Čater, 2015).

2.5.9. Integrative Interpretation of Bibliometric Outputs

The final analytical step involved integrating insights across all bibliometric techniques. Keyword co-occurrence, overlay, and density analyses informed understanding of thematic structure and temporal evolution, while bibliographic coupling and source-level citation analysis revealed contemporary research fronts and intellectual anchoring. Co-authorship analysis provided additional context regarding the organization of knowledge production.

Such an integrative interpretation is essential, as individual bibliometric techniques capture distinct but complementary dimensions of a research field. Combining them supports a more nuanced and conceptually meaningful synthesis, moving beyond visualization toward analytical insight that directly addresses the study's research objectives (Donthu et al., 2021).

2.5.10. AI-Assisted Analytical Support and Human Validation

To enhance interpretive depth in the post-bibliometric stage, the study employed an AI-assisted analytical support process using ChatGPT (OpenAI, GPT-5.4 Thinking, accessed 27 December 2025). The tool was used only after completion of the core bibliometric procedures and did not generate, modify, weight, or cluster the bibliometric networks. Its role was limited to supporting semantic interpretation of already derived outputs, including thematic refinement of cluster content, provisional labeling of conceptually related keyword groups, and identification of emerging topics and weak signals across the bibliometric maps.

The operational use of the AI tool followed a structured and iterative prompting strategy applied exclusively at the post-bibliometric interpretation stage. Prompts were designed to support the semantic refinement of cluster-level keyword sets, propose candidate thematic labels, identify latent sub-themes within broad bibliometric clusters, explain the conceptual logic underlying cluster composition, and compare temporally recent keywords with more established themes in order to detect emerging topics and weak signals. The prompting process was iterative rather than one-step, and all outputs were repeatedly constrained to the specific bibliometric material generated in this study, including keyword clusters, overlay visualization patterns, bibliographic coupling information, and representative titles, abstracts, and author keywords. The AI system was not used to retrieve references, introduce external evidence, generate empirical findings, alter the bibliometric structure, replace bibliometric software outputs, or make final analytical judgments. The exact prompt applied is described in detail in Appendix C.

Human validation was applied at each stage of AI-assisted interpretation. First, all AI-generated thematic suggestions were reviewed manually against the original VOSviewer outputs, including keyword co-occurrence maps, overlay visualizations, bibliographic coupling results, and source-level citation patterns. Second, candidate labels and interpretations were checked against the titles, abstracts, and author keywords of representative publications within each cluster to confirm conceptual consistency. Third, outputs judged overly broad, semantically ambiguous, unsupported by the bibliometric evidence, or interpretively redundant were discarded or reformulated by the authors. Final thematic labels, trend interpretations, and narrative synthesis were therefore determined by the authors and not by the AI tool.

This AI-assisted layer should be understood as a complementary interpretive support mechanism rather than an autonomous analytical method. It remains methodologically constrained by the quality and granularity of the bibliometric inputs, by sensitivity to

prompt formulation and keyword semantics, and by the risk of plausible but unsupported thematic generalization. For this reason, AI-assisted outputs were retained only where they were directly corroborated through human review and bibliometric evidence.

2.6. Complementary Analytical Frameworks

While bibliometric software provides powerful tools for visualizing structural relationships within the literature, network-based maps alone are insufficient for capturing the full conceptual and interpretive depth of a research field. For this reason, the present study complements bibliometric analyses with additional analytical frameworks that support descriptive insight, qualitative synthesis, and theory-oriented interpretation (Zupic & Čater, 2015).

2.6.1. Descriptive Bibliometric Analysis

Descriptive bibliometric analysis was conducted to provide an overview of the publication landscape prior to network-based interpretation. This analysis examines publication trends over time and the distribution of publications across journals and subject areas, offering essential contextual information for interpreting subsequent bibliometric results.

Temporal trends were analyzed to identify periods of accelerated research activity and to situate the emergence of artificial intelligence within the broader evolution of disaster supply chain risk and resilience research. In addition, the distribution of publications across journals and subject categories was examined to assess the degree of disciplinary concentration and interdisciplinary integration within the field (Donthu et al., 2021).

2.6.2. 5W + 1H Analytical Framework

To complement quantitative bibliometric outputs with qualitative insight, the study employs the 5W + 1H analytical framework (Who, What, Why, When, Where, and How). This framework is widely used in qualitative analysis to structure interpretation and synthesize complex information in a systematic manner.

The conceptual rationale for applying the 5W + 1H framework lies in its ability to translate bibliometric patterns into interpretable research narratives. While bibliometric networks reveal structural relationships among concepts and publications, they do not directly explain who is producing knowledge, what specific problems are being addressed, why certain approaches are adopted, or how methods are applied in practice.

In this study, the framework was applied to titles, abstracts, and keywords associated with the main bibliometric clusters. The “Who” dimension captures dominant contributing actors and research communities; “What” identifies the core problems and themes under investigation; “Why” reflects stated motivations and contextual drivers such as disaster risk, uncertainty, or operational vulnerability; “When” situates thematic developments temporally; “Where” highlights contextual or geographic focus; and “How” examines the methodological and analytical approaches employed.

By synthesizing insights across these dimensions, the 5W + 1H framework enables a structured qualitative interpretation that complements network-based findings and supports the identification of nuanced research gaps that may not be visible through bibliometric visualization alone (H. Snyder, 2019).

2.6.3. Theory–Method Alignment Analysis

Beyond thematic description, the study conducts a theory–method alignment analysis to examine the extent to which artificial intelligence methods are meaningfully aligned with resilience-oriented research objectives. This analysis addresses a critical concern in the literature, namely, the tendency for advanced analytical methods to be adopted without corresponding theoretical integration.

AI methods identified in the dataset—such as machine learning, predictive analytics, and optimization-based approaches—were mapped against resilience objectives, including anticipation, absorption, adaptation, and recovery. This mapping enables assessment of whether AI applications primarily support narrow predictive tasks or contribute more broadly to resilience as a dynamic capability.

Through this alignment analysis, conceptual and methodological gaps were identified. In particular, the analysis highlights areas where AI is used extensively for forecasting and classification but remains underutilized in supporting adaptive decision-making, learning, and system-level resilience. This framework thus provides a bridge between bibliometric description and theory-driven critique, informing the discussion of future research directions.

Across this theory–method alignment analysis, artificial intelligence was employed exclusively as an interpretive support tool and did not intervene in the construction, weighting, or clustering of bibliometric networks.

2.7. Reliability, Validity, and Methodological Rigor

Ensuring reliability, validity, and methodological rigor is essential in bibliometric and knowledge-mapping research, particularly given the interpretive role of the researcher in selecting parameters and synthesizing results. This study addresses these concerns through a combination of procedural transparency, analytical triangulation, and explicit acknowledgment of limitations.

Reliability is supported through the use of a stable and reproducible search strategy, a single curated bibliographic database, and consistent application of bibliometric techniques. The search string, inclusion and exclusion criteria, and analytical procedures are fully documented, allowing replication and extension by future studies (Donthu et al., 2021).

Validity is addressed through multiple mechanisms. Construct validity is enhanced by grounding keyword selection and harmonization in established theoretical concepts. Internal validity is supported through triangulation across complementary bibliometric techniques, including co-occurrence, co-citation, bibliographic coupling, and co-authorship analyses. Interpretive validity is further strengthened by integrating qualitative synthesis frameworks such as the 5W + 1H approach.

Methodological rigor is reinforced by separating data collection, preparation, and analysis stages, thereby minimizing cross-stage bias. At the same time, the study acknowledges the inherent limitations of bibliometric methods, including reliance on publication metadata, sensitivity to parameter choices, and partial representation of scholarly discourse. These limitations are considered in the interpretation of results rather than treated as methodological flaws.

An additional point relevant to methodological rigor concerns the use of single-reviewer metadata screening during the study selection stage. Although this approach is common and generally defensible in bibliometric studies that rely on structured bibliographic records rather than full-text qualitative evidence synthesis, it may nonetheless introduce a degree of subjective judgment, particularly in borderline cases where the relevance of a publication is not fully transparent from titles, abstracts, and keywords alone. This issue is especially pertinent in interdisciplinary fields such as disaster supply chain risk and resilience, where conceptually related studies may employ divergent terminologies drawn from operations research, humanitarian logistics, risk analysis, and artificial intelligence.

In the present study, this potential limitation was mitigated through several design features. First, the search strategy and screening logic were conceptually anchored in clearly articulated thematic dimensions. Second, inclusion and exclusion criteria were defined

explicitly and applied consistently across the dataset. Third, reasons for exclusion at the eligibility stage were reported transparently, thereby enhancing traceability. Fourth, the subsequent preprocessing and validation stages included manual checks and trial-network inspection, which helped identify possible inconsistencies, unexpected fragmentation, or anomalous inclusions that might reflect earlier screening errors. Nevertheless, the possibility of limited selection bias cannot be fully excluded and should be considered when interpreting the scope and boundaries of the final dataset. Acknowledging this trade-off strengthens the transparency of the study and provides a more balanced account of its methodological choices.

The review was not registered in a protocol database, as bibliometric reviews are not typically subject to formal registration. Risk of bias assessment at the study level was not conducted, as the analysis is based on aggregated bibliometric metadata rather than individual study outcomes.

2.8. Ethical Considerations

This study relies exclusively on publicly available bibliographic data obtained from peer-reviewed academic publications. No primary data were collected, and no human participants were involved in the research process. As a result, the study does not raise ethical concerns related to informed consent, privacy, or data protection.

The use of bibliographic data adheres to standard ethical practices in bibliometric research, including accurate representation of authorship, transparent reporting of methods, and proper citation of sources. By focusing on aggregated patterns rather than individual-level evaluation, the analysis avoids reputational or evaluative judgments about specific authors or institutions.

This study follows the PRISMA 2020 guidelines for systematic reviews, adapted to the requirements of bibliometric and knowledge-mapping research.

3. Results

3.1. Conceptual Structure of the Field: Keyword Co-Occurrence Analysis (Author Keywords)

The keyword co-occurrence analysis based on author-provided keywords was conducted to identify the core conceptual structure of research on AI-enabled risk and resilience management in disaster supply chains. Applying a minimum occurrence threshold of five keywords, the resulting network visualization (Figure 3) reveals a dense and highly interconnected knowledge structure, indicating a field that has moved beyond fragmentation toward conceptual consolidation.

At the center of the network, artificial intelligence clearly emerges as the dominant hub, exhibiting strong and numerous connections with machine learning, resilience, supply chain, and risk management. This central positioning suggests that AI is not merely treated as a supporting analytical tool but functions as a unifying paradigm that links methodological innovation with applied resilience challenges. In practical terms, this reflects a shift from isolated optimization or forecasting studies toward integrated decision-support frameworks embedded within disaster-prone supply chains.

Closer inspection of Figure 3 reveals several coherent thematic groupings. One prominent cluster revolves around resilience, risk, uncertainty, disruptions, and climate change, capturing the growing recognition of supply chains as vulnerable socio-technical systems exposed to cascading and compound hazards. This cluster reflects research efforts aimed at understanding how systems absorb shocks, adapt under stress, and recover following disruptive events.

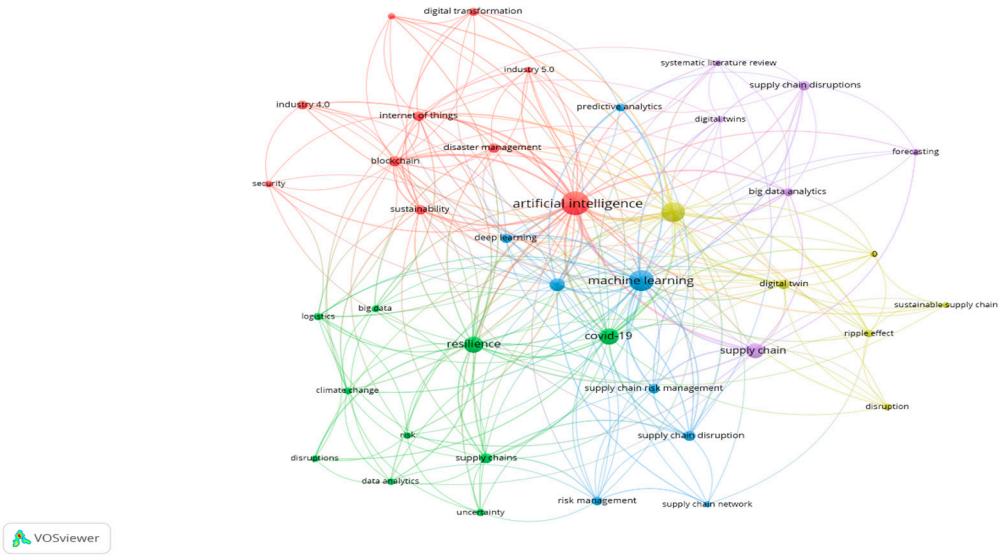


Figure 3. Keyword co-occurrence network based on author keywords (minimum occurrence = 5).

A second major cluster is primarily methodological and data-driven, dominated by keywords such as machine learning, deep learning, big data, and predictive analytics. The density of connections within this cluster indicates increasing methodological sophistication, with researchers leveraging advanced algorithms to enhance forecasting accuracy, scenario analysis, and real-time decision-making.

A third, more outward-looking cluster links digital transformation, Internet of Things, blockchain, Industry 4.0, and Industry 5.0 with disaster management and sustainability. This cluster points to an expanding research stream that situates AI-enabled supply chain resilience within broader digital and societal transitions, emphasizing connectivity, transparency, and human-centric system design.

Taken together, the keyword co-occurrence network illustrates a field characterized by conceptual convergence, where technological, operational, and resilience-oriented perspectives increasingly overlap rather than evolving in isolation. Results are summarized in Table 1.

Table 1. Compact summary of the main thematic clusters identified in the keyword co-occurrence network and their interpretive meaning.

Cluster	Representative Concepts Visible in the Network and Manuscript	Interpretive Summary
Resilience, risk, and disruption management	resilience, risk management, uncertainty, disruptions, climate change	This cluster captures the literature that conceptualizes disaster-prone supply chains as vulnerable socio-technical systems exposed to cascading and compound disruptions, with emphasis on preparedness, absorption, adaptation, and recovery.
AI-driven analytics and predictive decision support	artificial intelligence, machine learning, deep learning, big data, predictive analytics	This cluster reflects the methodological core of the field, where AI-based tools are used for forecasting, classification, scenario analysis, monitoring, and decision support under uncertainty.
Digital transformation, connectivity, sustainability	blockchain, internet of things, Industry 4.0, Industry 5.0, sustainability, disaster management	This cluster links supply chain resilience with broader digital and socio-technical transformation, emphasizing transparency, traceability, connectivity, human-centric design, and sustainability-oriented system redesign.

3.2. Temporal Dynamics of Research Themes: Keyword Overlay Visualization

To explore how the focus of the literature has evolved over time, an overlay visualization was applied to the keyword co-occurrence network using all keywords (Figure 4). This visualization assigns colors to keywords based on their average publication year, allowing temporal patterns to be observed directly within the conceptual structure of the field.

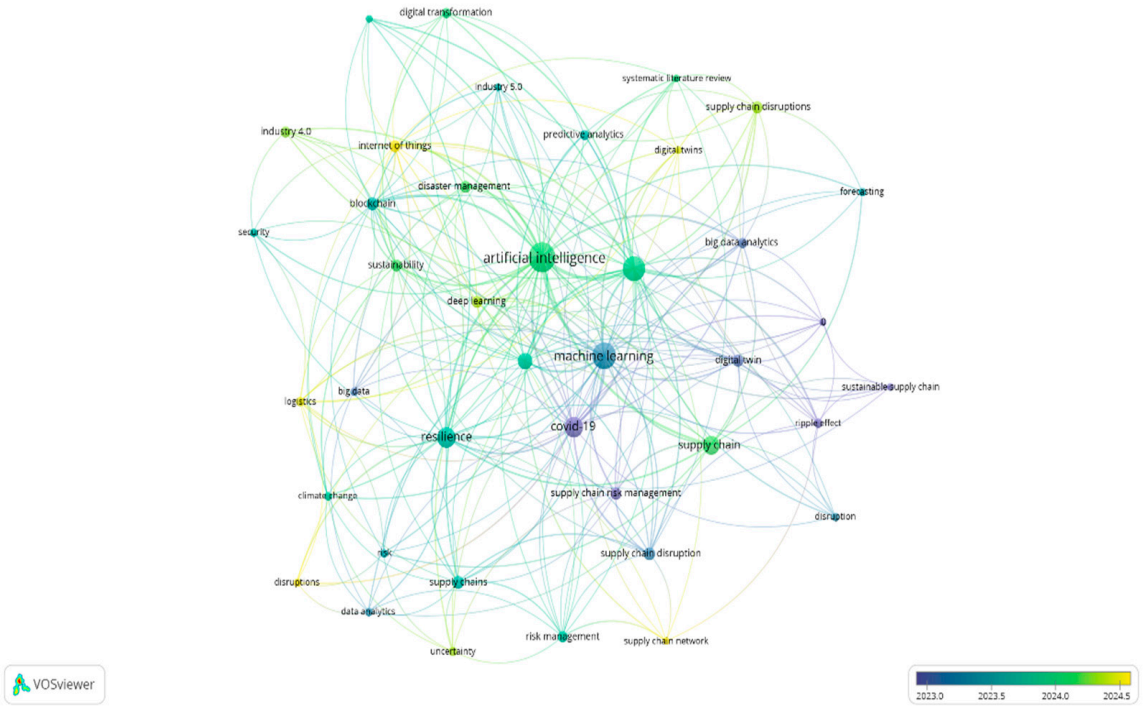


Figure 4. Overlay visualization of keyword co-occurrence network showing the temporal evolution of research themes.

As shown in Figure 4, earlier research activity is largely associated with foundational concepts such as risk management, supply chain disruption, and resilience, which appear in cooler color tones. These themes reflect the initial efforts of scholars to conceptualize vulnerability, disruption propagation, and recovery mechanisms within complex supply networks.

Moving toward more recent years, the color gradient shifts toward warmer tones, highlighting an increased emphasis on machine learning, predictive analytics, big data analytics, and digital twins. This temporal transition suggests a methodological evolution from predominantly descriptive and reactive approaches toward anticipatory and data-driven resilience strategies capable of supporting real-time decision-making.

Notably, emerging keywords such as Industry 5.0, sustainable supply chain, and ripple effect appear among the most recent nodes in the network. Their position signals growing interest in human-centric, sustainability-oriented, and system-wide perspectives that go beyond operational efficiency to address long-term resilience and societal impact.

Overall, the overlay visualization confirms that the field has undergone a clear transformation, accelerating significantly in recent years and increasingly aligning AI-enabled supply chain resilience research with contemporary global risk dynamics. Results are summarized in Table 2.

Table 2. Compact summary of major research themes emerging from the keyword and overlay analyses.

Research Theme	Main Content	Temporal Interpretation
AI as a central analytical enabler	AI is positioned as the main methodological hub connecting resilience, risk, and supply chain management.	Represents the field's conceptual center and unifying paradigm.
Shift from reactive to predictive resilience	Increasing use of machine learning, predictive analytics, and real-time monitoring.	More characteristic of the recent literature.
Expansion toward digital ecosystems	Growing links between resilience and blockchain, IoT, Industry 4.0, and Industry 5.0.	Indicates broadening of the field beyond traditional risk management.
Sustainability and socio-technical system thinking	Greater attention to sustainability, governance, visibility, and human-centric adaptation.	Reflects the newer, more integrative phase of the literature.

3.3. Global Research Collaboration: Co-Authorship Analysis by Countries

The co-authorship analysis at the country level provides insight into the geographical distribution of research activity and international collaboration patterns. Using a minimum threshold of three publications per country, the resulting collaboration network is presented in Figure 5.

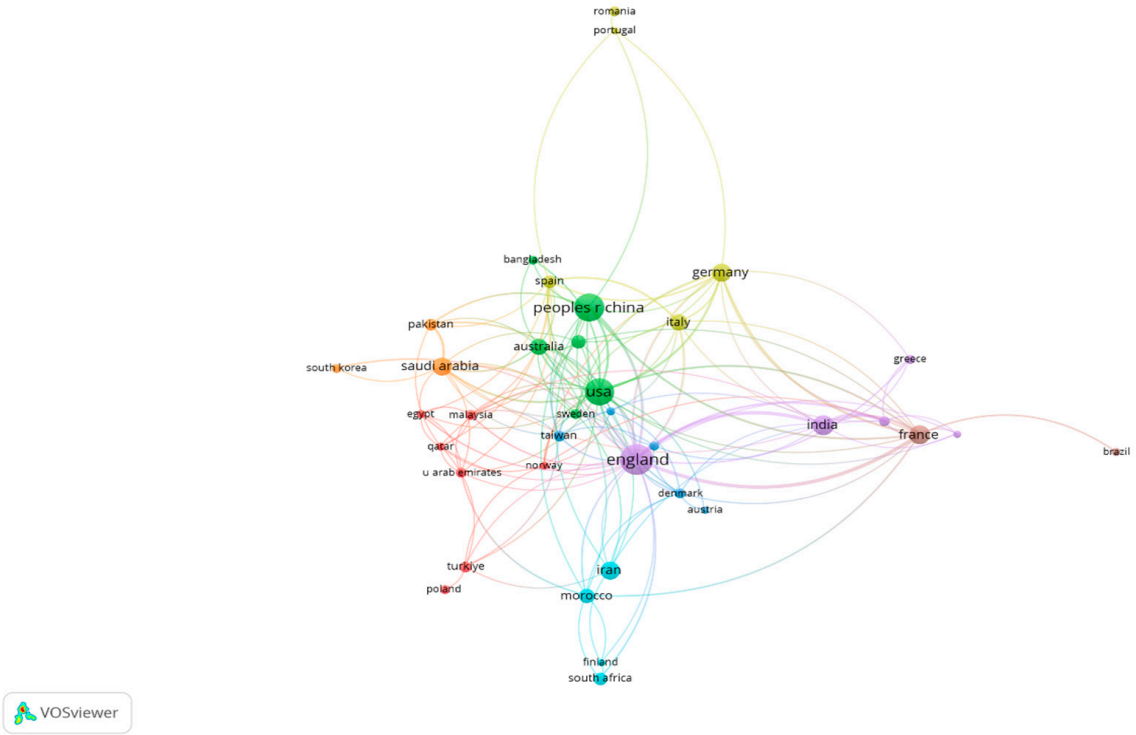


Figure 5. Country-level co-authorship network (minimum documents per country = 3).

Figure 5 highlights China, the United States, England, Germany, and India as the most prominent contributors, both in terms of publication output and collaborative reach. These countries occupy central positions within the network, functioning as key hubs that connect multiple regional research communities.

China and the United States, in particular, exhibit extensive international linkages, bridging collaborations across Asia, Europe, and the Middle East. European countries form a dense sub-network, with strong connections among England, Germany, Italy, France, and Greece, reflecting sustained cross-border cooperation in areas such as operations research, resilience modeling, and sustainability-focused supply chain studies.

At the same time, the presence of peripheral nodes indicates that research capacity and collaboration intensity remain unevenly distributed. Several countries appear weakly connected, suggesting that despite the global relevance of disaster-related supply chain risks, participation in AI-driven resilience research is still concentrated within a limited set of research hubs.

To complement the co-authorship map, Table 3 summarizes the principal collaborating countries and reports their descriptive representation in the retained dataset, including publication presence, internationally co-authored papers, and the number of distinct partner countries.

Table 3. Compact summary of the main country-level collaboration patterns identified in the co-authorship network, with descriptive collaboration counts derived from the retained Web of Science dataset.

Country	Papers in Retained Dataset (*n*)	Internationally Co-Authored Papers (*n*)	Distinct Partner Countries (*n*)
England	54	39	40
China	44	19	21
United States	43	26	27
India	24	16	16
France	22	21	18
Iran	20	7	9
Saudi Arabia	19	12	14
Germany	19	12	17
Italy	15	9	9
Greece	5	2	5

3.4. Intellectual Foundations of the Field: Citation Analysis of Sources

Citation analysis at the source level was conducted to identify the journals that exert the greatest influence on the development of the field. Applying a minimum citation threshold of ten, the resulting citation network is shown in Figure 6.

As illustrated in Figure 6, journals such as the *International Journal of Production Research*, *Annals of Operations Research*, *Sustainability*, and *IEEE Access* occupy central positions within the citation structure. Their prominence reflects the interdisciplinary nature of the field, which integrates analytical rigor from operations research and engineering with applied perspectives on sustainability and resilience.

The dense citation links among these journals indicate a high degree of intellectual exchange, suggesting that advances in AI-enabled disaster supply chain research are built upon a shared and cross-disciplinary knowledge base. Rather than evolving within isolated academic silos, the field draws simultaneously on methodological innovation and applied problem-solving traditions. To complement the source citation map, Table 4 summarizes the principal journals visible in the field and reports their frequency of occurrence in the retained dataset, thereby combining intellectual influence with descriptive publication presence.

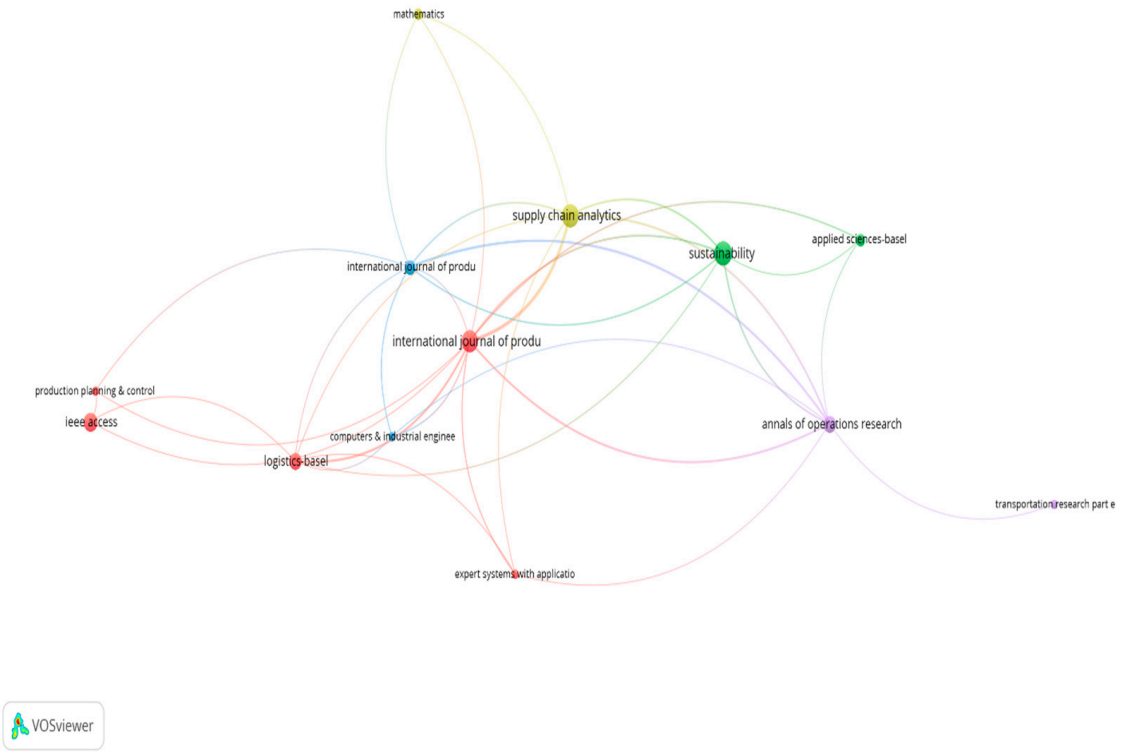


Figure 6. Citation network of sources (minimum citations = 10).

Table 4. Compact summary of the principal journals shaping the intellectual foundations of the field according to the source citation analysis, together with their representation in the retained Web of Science dataset.

Journal/Source	Publications in Retained Dataset (*n*)	Role in the Field
Sustainability	17	Connects resilience research with sustainability-, policy-, and transformation-oriented perspectives.
Supply Chain Analytics	16	Signals the growing importance of data-driven, AI-enabled, and application-focused supply chain research.
International Journal of Production Research	15	Provides a major platform for analytical, resilience, disruption, and modeling-oriented supply chain studies.
IEEE Access	11	Reflects the growing integration of AI, digital systems, and engineering-driven approaches into supply chain resilience research.
Annals of Operations Research	9	Contributes strong analytical, optimization, simulation, and decision-support foundations.

3.5. Current Research Front: Bibliographic Coupling Analysis (Documents)

Bibliographic coupling analysis at the document level was employed to capture the structure of the most recent and actively developing research streams. The resulting network and density visualizations are presented in Figures 7 and 8, respectively.

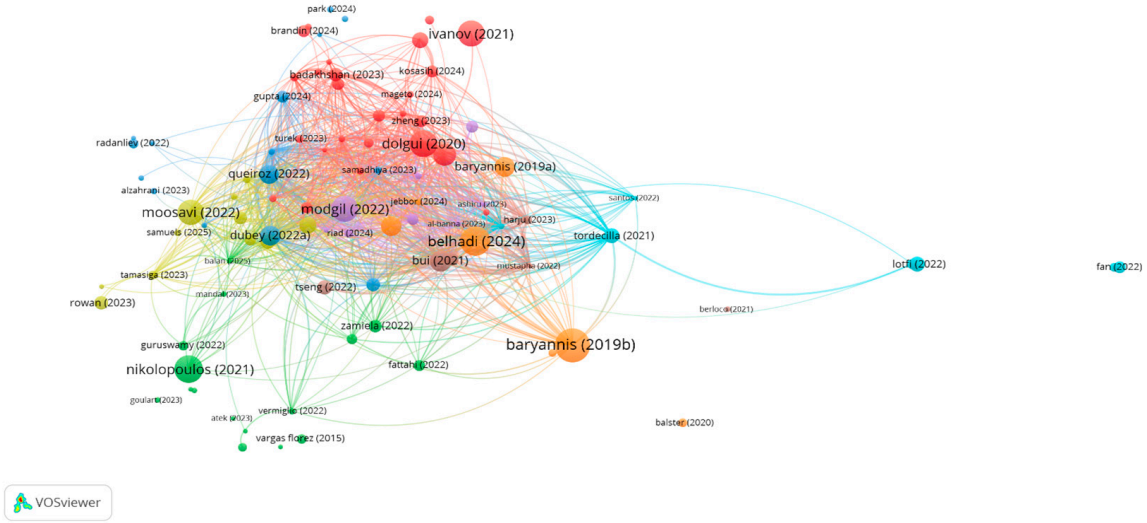


Figure 7. Bibliographic coupling network of documents.



Figure 8. Density visualization of bibliographic coupling.

The coupling network (Figure 7) reveals several tightly connected clusters of recent publications that share common reference foundations. These clusters are primarily centered on machine learning-based modeling, predictive analytics, and digital twin applications, indicating a rapidly consolidating research front focused on real-time monitoring, simulation, and anticipatory decision support.

The density visualization (Figure 8) further highlights areas of high concentration within the literature, where multiple recent studies converge around similar conceptual and methodological approaches. In contrast, more sparsely populated regions of the map correspond to emerging or specialized topics, such as context-specific disaster applications or hybrid analytical frameworks that have yet to fully coalesce into dominant research streams.

Together, these findings suggest that the field is not only theoretically grounded but also actively evolving, with recent contributions increasingly building upon shared intellectual foundations while exploring new application domains.

3.6. Key Insights from Bibliometric Results

Synthesizing the findings of the bibliometric and network-based analyses, several key insights emerge regarding the structure, evolution, and current state of research on AI-enabled risk and resilience management in disaster supply chains.

First, the field is characterized by a high degree of conceptual integration. The keyword co-occurrence analysis suggests that artificial intelligence functions as a central unifying concept rather than a peripheral methodological add-on. Its strong connections with resilience, risk management, and supply chain disruption suggest that AI is increasingly being positioned within the core logic of resilience-oriented supply chain research, rather than being applied in isolation or as a purely technical enhancement.

Second, the temporal evolution of keywords suggests a clear methodological transition. Earlier research focused primarily on understanding disruption mechanisms and resilience concepts, while more recent studies increasingly emphasize predictive, data-driven, and real-time approaches. The emergence of themes such as machine learning, digital twins, and predictive analytics suggests a shift from reactive and descriptive models toward anticipatory and adaptive decision-support systems capable of operating under deep uncertainty.

Third, the bibliometric results point to the growing prominence of digital and socio-technical paradigms. Keywords associated with digital transformation, Industry 4.0, and Industry 5.0 are increasingly linked with disaster management and sustainability concerns, indicating that resilience is no longer framed solely as an operational problem but as a broader system-level challenge involving technology, governance, and human-centric design.

Fourth, the country-level co-authorship analysis reveals a partially globalized yet uneven research landscape. While a small number of countries act as central hubs of knowledge production and international collaboration, significant portions of the global research community remain weakly connected. This suggests that, despite the global nature of disaster-related supply chain risks, research capacity and collaborative integration are still concentrated within specific regions.

Fifth, citation and bibliographic coupling analyses suggest a field that is both intellectually grounded and rapidly evolving. Influential journals from operations research, supply chain management, and sustainability provide a stable theoretical foundation, while bibliographic coupling reveals an active and converging research front focused on advanced analytics, simulation, and intelligent decision support. This combination reflects a balance between methodological rigor and responsiveness to emerging global risk dynamics.

Collectively, these insights suggest a research field that appears to be moving toward conceptual maturity, while simultaneously undergoing rapid methodological and thematic expansion. The bibliometric evidence suggests that future advances are likely to depend not only on further algorithmic innovation but also on deeper integration across disciplines, regions, and real-world disaster contexts—an issue explored in the following discussion section.

3.7. AI-Assisted Synthesis and Emerging Trend Detection

To extend the interpretive depth of the bibliometric results, an AI-assisted analytical layer was applied as a complementary post-bibliometric synthesis. This analysis did not replace or re-cluster the VOSviewer outputs; instead, it operated on the already identified bibliometric structures to refine thematic interpretation and to detect emerging and weakly established research directions. Human validation was applied throughout the process to ensure conceptual coherence and to avoid black-box inference.

3.7.1. AI-Assisted Thematic Refinement of Bibliometric Clusters

The first AI-based analysis focused on the semantic refinement of the thematic clusters identified through keyword co-occurrence analysis. Cluster-level keyword sets derived from VOSviewer were analyzed using AI-assisted semantic interpretation to identify latent sub-themes, clarify conceptual boundaries, and assign interpretable thematic labels.

This process revealed that several bibliometric clusters encompass multiple conceptual layers that are not immediately visible through network visualization alone. For example, clusters broadly centered on artificial intelligence and machine learning were found to include distinct sub-themes related to (i) predictive risk assessment, (ii) adaptive decision support under uncertainty, and (iii) real-time monitoring and control of disrupted supply chains. Similarly, clusters associated with resilience and risk management were internally differentiated between strategic resilience planning, operational robustness, and post-disruption recovery analytics.

The AI-assisted refinement, therefore, enhanced interpretability by transforming visually coherent but semantically broad clusters into conceptually nuanced thematic groupings. Importantly, this process did not introduce new themes but clarified how existing ones are internally structured, supporting a more precise understanding of how AI is positioned across different resilience functions.

To enhance transparency and verifiability, Table A4 (Appendix D) provides a comparative presentation of the original VOSviewer cluster structure, the subsequent AI-assisted semantic refinement, and the final author-validated thematic interpretations retained in the study. This Table clarifies that the bibliometric clusters were generated exclusively through keyword co-occurrence analysis, while the AI-assisted layer functioned only as a complementary interpretive support mechanism used to identify latent sub-themes and clarify conceptual boundaries within the pre-existing clusters.

3.7.2. AI-Based Detection of Emerging Topics and Weak Signals

The second AI-based analysis was applied to identify emerging research topics and weak signals within the field. Using keyword occurrence patterns in combination with temporal attributes derived from overlay visualization, the AI-assisted analysis examined which themes exhibit increasing recency, low but growing frequency, and cross-cluster connectivity.

This analysis identified several research directions that appear to be transitioning from peripheral to integrative roles. Topics such as digital twins, predictive analytics, real-time decision support, and Industry 5.0 display relatively recent average publication years while simultaneously connecting to multiple established clusters, suggesting early-stage convergence rather than isolated novelty. Similarly, sustainability-oriented resilience concepts increasingly co-occur with AI-enabled analytics, indicating a shift toward more holistic and human-centric resilience paradigms.

At the same time, the AI-based analysis highlights areas where conceptual development remains fragmented. Certain AI applications are still primarily used for narrow predictive tasks, with limited integration into adaptive learning or system-level resilience mechanisms. These weak signals point to underexplored opportunities for extending AI beyond forecasting toward dynamic, feedback-driven decision support in disaster contexts.

3.7.3. Added Value of the AI-Assisted Analytical Layer

The integration of AI-assisted thematic refinement and trend detection provides a forward-looking complement to traditional bibliometric analysis. While bibliometric networks reveal how the literature is structured and how themes relate, the AI-based layer

helps explain how these structures are evolving and where future consolidation or divergence is likely to occur.

By operating strictly on bibliometric outputs and remaining subject to human validation, the AI-assisted analysis enhances interpretive depth without compromising transparency or methodological rigor. This approach supports a more nuanced synthesis of the field and informs the discussion of research gaps and future directions in the following section.

3.8. 5W + 1H Analytical Synthesis of the Field

Building upon the bibliometric, citation, and network-based results derived from the VOSviewer analyses, this section employs a structured 5W + 1H analytical framework to synthesize the intellectual landscape of research on risk and resilience management of disaster supply chains through artificial intelligence. The framework enables a higher-order interpretation of who contributes to the field, what is being studied, when and where knowledge is produced, and why and how AI-driven approaches are deployed.

3.8.1. Who: Key Knowledge Producers and Research Communities

The analysis reveals that the field is shaped by a relatively concentrated yet expanding community of authors and institutions, with strong representation from Asia (notably China, Taiwan, India, and South Korea), followed by Europe and, to a lesser extent, North America. Highly productive and influential authors tend to operate at the intersection of operations research, supply chain management, and intelligent systems, often publishing across multidisciplinary journals.

Institutional collaboration patterns indicate that technical universities and applied research centers dominate the knowledge production process, reflecting the methodological complexity of AI-enabled disaster supply chain research. Co-authorship networks suggest the emergence of regional research clusters, while intercontinental collaboration remains comparatively limited, indicating fragmentation across geographic and disciplinary boundaries.

3.8.2. What: Dominant Research Themes and Conceptual Focus

The thematic structure of the field is anchored around four core research streams.

AI-driven optimization and decision support are used for disaster and emergency logistics, including multi-objective optimization, fuzzy systems, and intelligent decision-support architectures. Supply chain resilience and robustness, emphasizing adaptability, continuity, and recovery under extreme disruption scenarios. Digital and emerging technologies, such as blockchain, real-time event detection, drones, and smart contracts, are used to enhance visibility, coordination, and trust during crises. Risk assessment and performance evaluation, integrating resilience metrics, simulation models, and data-driven analytics.

These themes collectively reflect a shift from traditional, efficiency-focused supply chain models toward resilience-oriented, adaptive, and intelligence-augmented systems capable of operating under deep uncertainty.

3.8.3. When: Temporal Evolution of the Research Field

Temporal overlay analysis highlights a clear acceleration of scholarly output after 2020, coinciding with the COVID-19 pandemic and the resulting global supply chain disruptions. Earlier studies predominantly focused on conceptual resilience frameworks and classical optimization models. In contrast, more recent research emphasizes real-time analytics, AI-enabled learning mechanisms, and autonomous decision-making, indicating a maturation of the field toward operationally deployable solutions.

Emerging topics—including Industry 5.0 alignment, human–AI collaboration, and ethical or governance aspects of intelligent supply chains—suggest that the field is entering a consolidation and diversification phase.

3.8.4. Where: Geographic and Institutional Distribution

Research output is geographically uneven. Asia-based institutions contribute a substantial share of publications, particularly in technically intensive domains such as fuzzy optimization, blockchain-enabled logistics, and algorithmic decision support. European contributions are more prominent in resilience theory, sustainability, and systemic risk, while North American research tends to focus on strategic supply chain risk management and analytics. This spatial distribution reflects differing regional priorities: operational optimization and technological deployment in Asia, conceptual and policy-oriented resilience in Europe, and strategic risk governance in North America.

3.8.5. Why: Drivers Behind AI Adoption in Disaster Supply Chains

The mapped literature suggests that the primary drivers associated with the integration of AI into disaster supply chain management include the inadequacy of traditional planning models under cascading and compound crises, as well as the need for rapid, data-driven decision-making in time-critical disaster environments. Also, increasing exposure to systemic risks, such as pandemics, climate-induced disasters, and geopolitical disruptions, along with demand for transparency, traceability, and coordination across fragmented humanitarian and commercial supply networks, are presented as strong drivers for integrating AI approaches. Taken together, these patterns suggest that AI is increasingly positioned in the literature not merely as an auxiliary tool, but as a broader enabler of resilience, addressing both operational complexity and epistemic uncertainty.

3.8.6. How: Methodological and Technological Approaches

Methodologically, the field is characterized by a strong reliance on:

i. Hybrid AI models, combining machine learning with fuzzy logic, neutrosophic sets, and multi-criteria decision-making.
ii. Simulation and optimization techniques, including agent-based models and network-based routing algorithms.
iii. Digital infrastructures, such as blockchain platforms and real-time monitoring systems, to support trustworthy and adaptive logistics operations.

These approaches demonstrate a clear trend toward integrated, multi-layered decision architectures, where AI supports sensing, reasoning, and acting across the disaster supply chain lifecycle.

3.8.7. Synthesis

Overall, the 5W + 1H analysis suggests a rapidly evolving, technically sophisticated, yet geographically and thematically fragmented research field. While significant progress has been made in developing AI-enabled tools for disaster supply chain resilience, the results point to the need for greater cross-regional collaboration, methodological standardization, and translation of models into operational practice. This synthesis provides a structured bridge between bibliometric evidence and the critical discussion presented in the following section.

4. Discussion: Implications for Supply Chain Resilience and Financial Risk Management

Beyond operational resilience, the findings also highlight important financial implications, as disruptions in supply chains frequently propagate liquidity constraints, payment delays, and financial exposure across interconnected firms.

4.1. Interpretation of Bibliometric Findings and Research Trends

The findings of this study suggest that research on disaster supply chain risk and resilience is entering a phase of conceptual consolidation, driven largely by the increasing integration of artificial intelligence into both analytical and decision-support frameworks. To improve clarity, the main findings are summarized as follows:

- The literature shows a clear shift from static risk management toward dynamic resilience thinking. Earlier research often treated disasters primarily as exogenous shocks requiring post-event recovery, redundancy, and robustness measures. In contrast, the current body of work increasingly conceptualizes resilience as a dynamic and adaptive capability grounded in continuous sensing, anticipation, response, and learning. This interpretation is consistent with foundational contributions in supply chain resilience research, which define resilience not as a fixed property but as an evolving organizational and system-level capability (Christopher & Peck, 2004; Sheffi & Rice, 2005).
- Artificial intelligence now occupies a central rather than peripheral role in resilience-oriented supply chain research. The bibliometric centrality of AI-related concepts observed in this study suggests that intelligent analytics are no longer used only for isolated optimization or forecasting tasks but are increasingly embedded within the core logic of resilience-oriented supply chain management. This finding aligns with recent scholarship emphasizing the role of AI in disruption management, predictive assessment, and adaptive decision support under uncertainty (Choi et al., 2018; Ivanov & Dolgui, 2020).
- The mapped literature also suggests important secondary interpretive implications for financial exposure and supply chain finance in disrupted networks. Supply chain disruptions frequently propagate financial stress through delayed payments, liquidity constraints, supplier distress, and broader solvency risks across interconnected firms. From this interpretive perspective, AI-enabled monitoring and predictive analytics discussed in the mapped literature may have relevance for supply chain finance risk management by improving earlier detection of repayment risk and disruption-related cash-flow instability. This interpretation is consistent with prior supply chain finance research showing that operational disruptions can transmit financial stress across supply networks (Gelsomino et al., 2016; Wuttke et al., 2013).
- Certain AI-enabled tools identified in the broader mapped literature appear potentially relevant for financially exposed supply chain environments. Predictive analytics may support reverse factoring arrangements by helping focal firms and financial institutions identify supplier distress earlier, detect abnormal payment patterns, and make more informed decisions regarding the extension, repricing, or adjustment of financing mechanisms under heightened uncertainty. In parallel, digital twin technology may improve collateral monitoring in inventory financing by enabling dynamic and near real-time visibility over inventory condition, location, and disruption exposure. Through the integration of sensor data, logistics information, and event tracking, such systems may reduce information asymmetry, improve collateral valuation, and support more responsive risk assessment. Taken together, these mechanisms suggest that AI may influence supply chain finance not only through better operational forecasting

but also through stronger monitoring, valuation, and protection of financially relevant supply chain assets.

- Despite this apparent maturity, the field continues to display a persistent imbalance between methodological advancement and theoretical integration. Machine learning, predictive analytics, and simulation-based approaches are now widely used, yet many studies apply these tools in narrowly scoped contexts such as demand forecasting or disruption prediction without fully connecting them to resilience theory, socio-technical systems thinking, or adaptive organizational capabilities. This concern has also been raised in prior reviews, which caution that analytical sophistication does not automatically translate into stronger adaptive capacity or systemic resilience (L. V. Snyder et al., 2016; Tang, 2006).
- The field is undergoing a gradual transition from reactive to anticipatory resilience paradigms. Temporal analysis indicates that recent studies increasingly focus on early warning, predictive risk assessment, continuous monitoring, and real-time decision support, reflecting growing awareness of cascading and compound risks in global supply networks. This trend is consistent with research emphasizing the need to move beyond static contingency planning toward adaptive and forward-looking resilience models (Ivanov, 2020). At the same time, the literature suggests that anticipatory resilience remains unevenly operationalized. Although prediction capabilities have advanced substantially, fewer studies examine how predictive insights are translated into adaptive action, organizational learning, and structural change. Similar limitations have been identified in earlier resilience assessments (Pettit et al., 2013).
- The global knowledge base remains unevenly distributed. Although disaster supply chain risks are inherently transnational, knowledge production remains concentrated in a limited number of countries and institutions, while regions facing disproportionate disaster exposure remain underrepresented. This raises concerns about contextual bias and the external validity of dominant analytical models. Such an imbalance echoes long-standing critiques in humanitarian logistics and disaster operations research, which have highlighted the gap between analytically elegant models and the realities of crisis response environments (Altay & Green, 2006; Kovács & Spens, 2007). It also reflects the continued fragmentation between operations research-driven studies and context-sensitive work rooted in sustainability and humanitarian perspectives, despite increasing calls for stronger integration (Dubey et al., 2021).
- The field appears to be characterized by a productive but fragile coexistence of intellectual stability and methodological innovation. Citation and bibliographic coupling analyses suggest that the literature remains anchored in a relatively stable intellectual core shaped primarily by operations research and supply chain management journals, while simultaneously supporting a dynamic and converging research front. Although this coexistence is productive, it may also become constraining if methodological novelty is not accompanied by theoretical renewal. In this respect, the findings suggest that future advances are more likely to emerge from integrative approaches that combine AI with system dynamics, governance perspectives, and human-centered design rather than from isolated algorithmic improvements alone. This interpretation is consistent with recent arguments that resilience research must increasingly address learning, institutional capacity, and socio-technical adaptation rather than focusing exclusively on efficiency and optimization (Ivanov & Dolgui, 2020; Wieland & Durach, 2021).
- Finally, the AI-assisted interpretive layer used in this study points to broader methodological implications. When used as a decision-support mechanism rather than as an autonomous analytical engine, AI can enhance scholarly sensemaking by helping identify latent structures, emerging themes, and weak signals across complex studies.

At the same time, the analysis reinforces the importance of transparency, reflexivity, and human validation. AI-assisted interpretations remain sensitive to prompt framing and underlying data structures, and therefore should be treated as complementary rather than authoritative. This position is consistent with recent methodological guidance in bibliometric and knowledge-mapping research (Donthu et al., 2021; Zupic & Čater, 2015).

Taken together, these findings suggest that disaster supply chain research is at a critical inflection point. The field now possesses a stronger conceptual core and increasingly powerful analytical tools, yet its future contribution will depend on deeper theoretical integration, broader geographic and disciplinary inclusion, and greater attention to how AI-enabled insights are embedded in real-world decision processes. From this perspective, the central question is no longer simply what artificial intelligence can do for disaster supply chains, but how artificial and human intelligence can be combined to support resilience under conditions of extreme uncertainty.

4.2. Financial Risk Implications of AI-Enabled Disaster Supply Chains

This section interprets the bibliometric findings through a conceptually differentiated lens: disruptions are treated as operational disturbances, resilience as the adaptive capability to manage such disturbances, financial risk as the resulting exposure transmitted across firms, and supply chain finance as the set of financing arrangements through which that exposure may be absorbed, amplified, or mitigated.

Beyond operational disruptions, disasters frequently generate significant financial stress across interconnected supply networks (Gelsomino et al., 2016; Ivanov et al., 2019). Interruptions in production, transportation, and inventory flows may trigger cascading financial effects such as delayed payments, liquidity shortages, and increased supplier default risk. These dynamics illustrate that supply chain disruptions are not purely operational phenomena but are also financially consequential shocks that propagate across firms and industries. This view is consistent with the supply chain finance literature, which conceptualizes supply chain finance as the coordinated management of financial flows, working capital, and inter-organizational financial arrangements across supply chain partners (Gelsomino et al., 2016; Wuttke et al., 2013).

The financial significance of disruption propagation becomes clearer when considered through the ripple effect perspective. Ripple effect research emphasizes that a disruption at one node may spread through the supply network and affect performance across multiple tiers and dimensions rather than remaining confined to a single location or process (Dolgui & Ivanov, 2021; Ivanov, 2018). In this sense, disruption propagation alters not only product flows and service levels but also the stability of underlying payment cycles, financing needs, and supplier viability. Particularly in disruption-prone environments, operational instability can therefore intensify financial vulnerability by weakening firms' ability to convert inventory into cash, maintain predictable receivables, and meet short-term obligations. The epidemic and pandemic literature reinforces this point by showing how severe disruptions expose structural fragilities in globally dispersed and tightly coupled supply chains, thereby increasing both operational and financial pressures simultaneously (Queiroz et al., 2022).

Against this background, the bibliometric findings of this study suggest that artificial intelligence is increasingly positioned as a key analytical capability for managing these complex risk dynamics. The mapped literature indicates a growing emphasis on machine learning, predictive analytics, and real-time monitoring as tools for anticipating disruptions, improving situational awareness, and supporting resilience-oriented decision-making. When such tools are linked to financially relevant indicators, they may also

support earlier detection of supplier distress, cash-flow instability, and disruption-related financial exposure. In that respect, AI-enabled analytics can strengthen not only operational resilience but also the analytical foundations of supply chain finance risk management by improving visibility into the evolving interaction between material disruption and financial vulnerability.

These broader bibliometric and interpretive patterns may also carry secondary implications for specific supply chain finance mechanisms. Financial arrangements such as reverse factoring, dynamic discounting, and other risk-sharing structures are designed to stabilize financial flows across supply networks, especially where smaller suppliers are exposed to liquidity pressure. Predictive analytics may enhance reverse factoring risk management by supporting earlier recognition of supplier instability, abnormal payment patterns, or disruption-related deterioration in operating conditions. By combining operational, transactional, and contextual data, AI-based models may help focal firms and financing institutions assess whether supplier risk is increasing before stress becomes fully visible in conventional financial statements. In this way, predictive analytics can improve the timing and quality of financing decisions, helping preserve financing continuity while reducing exposure to disruption-driven defaults (Gelsomino et al., 2016; Wuttke et al., 2013).

A related implication concerns digital twin technology and collateral monitoring in inventory financing. Recent ripple effect and digital supply chain research increasingly associate digital twins with end-to-end visibility, disruption tracking, and more responsive decision support in volatile environments (Ivanov et al., 2019). Within inventory financing settings, this capability may improve collateral monitoring by providing a dynamic representation of inventory location, condition, movement, and disruption exposure. Such visibility can reduce information asymmetry between firms and financiers, support more accurate collateral valuation, and improve the early identification of inventory deterioration, immobilization, or disruption-related losses. Although this remains an emerging implication rather than a mature financial subfield in the literature, it suggests that AI-related technologies may strengthen supply chain finance not only through forecasting but also through more robust monitoring of financially relevant assets embedded in disrupted supply networks.

Overall, the convergence of artificial intelligence, resilience analytics, and supply chain finance should be interpreted cautiously and strictly as an interpretive extension of the broader mapped literature. The present study does not identify or operationalize a dedicated finance bibliometric sub-analysis, nor does it claim to detect a fully developed financial-risk cluster in its own right. Rather, the bibliometric findings suggest that financial risk and supply chain finance emerge as secondary but meaningful implications of the broader AI-enabled disaster supply chain research stream. From this perspective, AI appears increasingly relevant not only for disruption prediction and resilience planning, but also, by implication, for anticipating and monitoring the financial stress that disruptions may transmit across interconnected firms and supply chain finance arrangements (Gelsomino et al., 2016; Queiroz et al., 2022).

5. Conclusions

5.1. Summary of Core Findings

This study provides a systematic and integrative examination of disaster supply chain risk and resilience research, with a specific focus on the role of artificial intelligence as an enabling analytical and decision-support capability. Through bibliometric mapping, complementary qualitative synthesis, and AI-assisted interpretation, the analysis reveals a field that has transitioned from fragmented and reactive perspectives toward a more coherent and forward-looking understanding of resilience.

The bibliometric results indicate that artificial intelligence occupies an increasingly central position in the indexed literature on disaster supply chain risk and resilience. The mapped literature suggests that AI-related concepts are increasingly associated not only with optimization and forecasting, but also with themes of anticipation, sensing, and adaptive decision support under uncertainty. At the same time, the bibliometric patterns point to persistent imbalances in thematic emphasis, theoretical integration, and geographic representation within the field. Any implications for financial risk and supply chain finance should therefore be understood as secondary interpretive extensions of this broader mapped literature, rather than as evidence of a separately operationalized finance-specific bibliometric domain.

5.2. Theoretical Contributions

This study contributes to resilience theory by reinforcing and extending the conceptualization of resilience as a dynamic, adaptive capability rather than a static property or a post-disruption recovery mechanism. Consistent with foundational perspectives in supply chain resilience research (Sheffi & Rice, 2005; Christopher & Peck, 2004), the findings indicate that contemporary research increasingly frames resilience as a continuous process involving anticipation, learning, and reconfiguration.

Importantly, the bibliometric evidence suggests that the literature increasingly positions artificial intelligence within broader resilience-oriented analytical framings. Rather than appearing only as an external analytical add-on, AI is increasingly linked in the literature with predictive awareness, real-time assessment, and resilience-oriented decision support. However, the study also highlights that this integration remains conceptually incomplete. While methodological sophistication has advanced rapidly, theoretical engagement with socio-technical systems, organizational learning, and governance dynamics remains uneven.

By identifying this gap, the study advances resilience theory by emphasizing the need to align AI-enabled analytical power with broader conceptual understandings of adaptation, coordination, and systemic transformation (Ivanov & Dolgui, 2020; Wieland & Durach, 2021).

5.3. Methodological Contributions

From a methodological perspective, this study demonstrates the value of combining bibliometric mapping, structured qualitative synthesis, and AI-assisted interpretive analysis within a single, transparent research design. Bibliometric techniques provide scalability and structural clarity, while qualitative frameworks enable conceptual depth and contextual interpretation.

The integration of the 5W + 1H framework illustrates how quantitative network outputs can be translated into interpretable research narratives, bridging the gap between structural patterns and substantive meaning. Furthermore, the use of artificial intelligence as a post hoc interpretive support tool, rather than as an autonomous analytical engine, highlights a responsible and methodologically rigorous pathway for incorporating AI into literature-based research.

By maintaining human oversight and validation, the study aligns with best practices in bibliometric methodology and demonstrates how AI can augment, rather than replace, scholarly judgment (Zupic & Čater, 2015; Donthu et al., 2021).

5.4. Practical and Policy Implications

The findings of this study carry important implications for practitioners and policymakers involved in disaster risk management and supply chain governance. The growing emphasis on anticipatory and data-driven resilience suggests that organizations should

move beyond static contingency planning toward continuous monitoring, learning, and adaptive response mechanisms. For practitioners, this implies investing not only in analytical tools but also in organizational capabilities that translate predictive insights into timely and coordinated action. For policymakers and public-sector actors, the results underscore the importance of institutional frameworks that support data sharing, cross-sector collaboration, and the ethical deployment of AI in disaster-prone environments.

Crucially, the study highlights that technological sophistication alone is insufficient. Resilience emerges from the interaction between intelligent systems, human decision-makers, and institutional contexts, particularly under conditions of extreme uncertainty. In addition, the integration of AI-enabled analytics with supply chain finance mechanisms may improve financial resilience by supporting early detection of liquidity risks and disruption-related financial contagion within supply networks. From a financial perspective, AI-enabled resilience analytics may support more robust supply chain finance mechanisms by improving early detection of disruption-related liquidity risks and supplier vulnerability.

5.5. Limitations and Directions for Future Research

While this study provides a comprehensive overview of the academic discourse on AI-enabled disaster supply chain resilience, several limitations should be acknowledged. First, the analysis is based exclusively on peer-reviewed journal publications indexed in the Web of Science Core Collection and is limited to English-language sources. Although this database provides high-quality and standardized citation metadata suitable for bibliometric analysis, relevant publications indexed in other databases or practitioner-oriented outlets may not be fully captured. Consequently, practitioner knowledge, gray literature, and region-specific insights—particularly from disaster-prone areas in the Global South—remain underrepresented. Also, the reliance on a single bibliographic database and English-language publications may limit coverage and introduce selection bias.

Future research could address these limitations by expanding geographic and contextual coverage and by integrating empirical case studies with bibliometric and computational approaches. In addition, further research is needed to explore how AI-enabled insights are operationalized within organizations, translated into adaptive action, and embedded within organizational learning and governance processes. Finally, future studies may investigate these financial risks and supply chain finance implications more explicitly as a dedicated line of inquiry, examining how AI-driven analytics can support risk monitoring, liquidity management, and decision-making within supply chain finance ecosystems exposed to extreme disruptions.

5.6. Final Remarks

Taken together, this study suggests that disaster supply chain research stands at a critical inflection point. The field possesses powerful analytical tools and an increasingly shared conceptual vocabulary, yet its long-term impact will depend on deeper theoretical integration, broader contextual sensitivity, and more meaningful engagement with real-world decision-making processes.

Rather than asking what artificial intelligence can achieve in isolation, future research should increasingly ask how intelligent systems—both artificial and human—can co-evolve to support resilient, adaptive, and ethically grounded supply chains in an era of escalating uncertainty and systemic disruption.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
AR6	Sixth Assessment Report (IPCC)
COVID-19	Coronavirus Disease 2019
DSS	Decision support systems
IoT	Internet of Things
IPCC	Intergovernmental Panel on Climate Change
ML	Machine learning
OR/MS	Operations research/management science
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
WoS	Web of Science

Appendix A. Database Search Strategy Parameters

The database search string and parameters are described in detail below and were not modified during data collection to ensure reproducibility:

Search string

(disaster* OR crisis OR emergency* OR “extreme event*”)
AND
(“supply chain*” OR logistics OR “humanitarian supply chain*” OR “emergency logistics”)
AND
(“risk management” OR “risk assessment” OR resilien* OR robustness OR adaptab*)
AND
(“artificial intelligence” OR “machine learning” OR algorithm* OR “data-driven” OR simulation OR “agent-based model*”)

Filters applied:
Document types: Article, Review.
Language: English.
Time span: 2000–2025.

Appendix B. VOSviewer Settings and Mapping Parameters

Table A1. Detailed parameter matrix for the keyword co-occurrence, overlay, bibliographic coupling, source citation, and country co-authorship analyses.

Parameter	Keyword Co-Occurrence	Overlay Visualization	Bibliographic Coupling	Citation Analysis of Sources	Co-Authorship by Countries
Software	VOSviewer 1.6.20	VOSviewer 1.6.20	VOSviewer 1.6.20	VOSviewer 1.6.20	VOSviewer 1.6.20
Input database	Web of Science Core Collection	Same base map as keyword analysis	Web of Science Core Collection	Web of Science Core Collection	Web of Science Core Collection
Analysis type	Co-occurrence	Co-occurrence	Bibliographic coupling	Citation	Co-authorship
Unit of analysis	All keywords	All keywords	Documents	Sources	Countries
Counting method	Full counting	Full counting	Full counting	Full counting	Full counting
Normalization	Association strength	Association strength	Association strength	Association strength	Association strength
Threshold	Minimum occurrences = 5	Minimum occurrences = 5	Minimum citations per document = 10	Minimum citations = 10	Minimum documents = 3
Attribute displayed	Keyword links and thematic clusters	Average publication year	Shared reference structure among documents	Citation linkages among sources	International co-authorship relations
Thesaurus applied	Yes	Yes	No direct thesaurus application	No direct thesaurus application	No direct thesaurus application
Preprocessing dependency	Strong	Strong	Moderate	Moderate	Moderate
Layout settings	Default	Default	Default	Default	Default
Clustering settings	Default	Default	Default	Default	Default

Table A2. Common VOSviewer settings and analysis-specific parameters used across the bibliometric maps.

Analysis	Analysis Type in VOSviewer	Unit of Analysis	Visualization Type	Counting Method	Normalization Method	Threshold/ Selection Criterion
Keyword thematic structure	Co-occurrence	All keywords	Network visualization	Full counting	Association strength	Minimum keyword occurrences = 5
Keyword temporal evolution	Co-occurrence	All keywords	Overlay visualization	Full counting	Association strength	Minimum keyword occurrences = 5
Contemporary research front	Bibliographic coupling	Documents	Network visualization, Density visualization	Full counting	Association strength	Minimum citations per document = 10
Intellectual foundations	Citation	Sources	Network visualization	Full counting	Association strength	Minimum citations per source = 10
International collaboration	Co-authorship	Countries	Network visualization	Full counting	Association strength	Minimum documents per country = 3

Table A3. Illustrative entries from the VOSviewer thesaurus applied for keyword cleaning and semantic harmonization before map construction.

Category	Variant Term	Standardized Term
Artificial intelligence	AI	artificial intelligence
Artificial intelligence	Artificial intelligence	artificial intelligence
Artificial intelligence	Artificial Intelligence	artificial intelligence
Artificial intelligence	Artificial Intelligence (AI)	artificial intelligence
Artificial intelligence	artificial intelligence (AI)	artificial intelligence
Artificial intelligence	Artificial intelligence (AI)	artificial intelligence
Artificial intelligence	ARTIFICIAL-INTELLIGENCE	artificial intelligence
Big data	BIG DATA	big data
Big data	Big Data	big data
Big data analytics	BIG DATA ANALYTICS	big data analytics
Big data analytics	Big Data analytics	big data analytics
Big data analytics	Big Data Analytics	big data analytics
Blockchain	Blockchain	blockchain
COVID-19	coronavirus (COVID-19)	COVID-19
COVID-19	COVID-19	COVID-19
COVID-19	COVID-19	COVID-19
COVID-19	COVID-19 pandemic	COVID-19
COVID-19	Pandemic COVID-19	COVID-19
COVID-19	Post COVID-19	COVID-19
COVID-19	Post-COVID-19 pandemic	COVID-19
Decision support systems	Decision support systems	Decision support system
Internet of Things	Internet of things	internet of things
Internet of Things	Internet of Things	internet of things
Internet of Things	IoT	internet of things
Internet of Things	IOT	internet of things
Machine learning	Machine learning	machine learning
Machine learning	machine-learning	machine learning
Multi-criteria decision-making	MCDM	multi-criteria decision-making
Multi-criteria decision -making	multiple criteria decision making	multi-criteria decision-making
Supply chain management	Supply Chain Management	supply chain management
Supply chain management	SUPPLY CHAIN MANAGEMENT	supply chain management
Supply chain management	Supply chain management	supply chain management
Supply chain management	Supply Chain Management (SCM)	supply chain management
Supply chain management	supply chain management (SCM)	supply chain management
Supply chain resilience	Supply chain resilience	supply chain resilience
Sustainable supply chain management	Sustainable supply chain management	sustainable supply chain management
Humanitarian supply chain management	Humanitarian supply chain management	humanitarian supply chain management
Green supply chain management	green supply chain management (GSCM)	green supply chain management
Resilience	Resilience	resilience
Supply chain	Supply chain	supply chain

Appendix C. Artificial Intelligence Analysis Parameters

Prompt Used in the AI-Assisted Interpretive Layer:

"You are assisting with the post-bibliometric interpretation of a study on artificial intelligence in disaster supply chain risk and resilience management.

You will be provided with the following materials derived from the bibliometric analysis already completed in VOSviewer:

i. cluster-level keyword sets;

ii. temporal information, including average publication year and overlay visualization patterns where relevant;
iii. bibliographic coupling information where relevant; and
iv. representative article titles, abstracts, and author keywords associated with the identified cluster or thematic grouping.

Based only on the material provided, perform the following tasks:
Propose a concise thematic label for the cluster.

Identify up to three latent sub-themes, where these are clearly supported by the provided material.

Explain the conceptual logic connecting the keywords, documents, and thematic elements within the cluster.

Indicate whether the thematic pattern appears to reflect an established research theme, an emerging topic, or a weak signal.

Highlight any conceptual ambiguity, thematic overlap, or limited internal coherence evident in the cluster.

Apply the following constraints throughout your response:
Do not introduce external references, evidence, or concepts not contained in the provided bibliometric material.
Do not generate new clusters, alter the bibliometric structure, or reinterpret the underlying network relationships beyond the supplied outputs.
Do not treat the response as a final analytical result.
Maintain a neutral academic tone suitable for subsequent human review and validation."

The output should be understood as provisional interpretive support only and must remain strictly subordinate to the bibliometric findings and author-led validation process.

Note to Use and Validation: The output generated through this prompt was reviewed manually against the original bibliometric maps and representative source documents. Outputs judged overly broad, semantically unsupported, or insufficiently aligned with the bibliometric evidence were rejected or reformulated by the authors. Accordingly, the prompt functioned only as part of a controlled interpretive support process and did not replace author judgment or the primary bibliometric analysis.

Appendix D. Comparison of Original VOSviewer Clusters, AI-Assisted Semantic Refinement, and Final Author-Validated Thematic Interpretations

Table A4. Comparative presentation of the original VOSviewer cluster structure, the subsequent AI-assisted semantic refinement, and the final author-validated thematic interpretations retained in the study.

	Objective Bibliometric Basis	AI-Assisted Semantic Refinement	Final Author-Validated Interpretation
Cluster 1	High-frequency co-occurrence among keywords such as resilience, risk, uncertainty, disruptions, and climate change	Internal differentiation between strategic resilience planning, operational robustness, and post-disruption recovery analytics	Disaster supply chain resilience and risk management under uncertainty

Table A4. *Cont.*

	Objective Bibliometric Basis	AI-Assisted Semantic Refinement	Final Author-Validated Interpretation
Cluster 2	Strong co-occurrence links among artificial intelligence, machine learning, deep learning, big data, and predictive analytics	Internal differentiation between predictive risk assessment, adaptive decision support under uncertainty, and real-time monitoring and control of disrupted supply chains	AI-enabled predictive risk assessment and resilience-oriented decision support
Cluster 3	Co-occurrence among digital transformation, Internet of Things, blockchain, Industry 4.0, Industry 5.0, sustainability, and disaster management	Clarification of the cluster as linking digital connectivity, system transparency, and human-centric socio-technical resilience transitions	Digital and socio-technical transformation in resilient supply chains

Note: The clusters reported in this Table were generated exclusively through VOSviewer based on bibliometric network analysis. The AI-assisted semantic refinement did not generate new clusters or alter the original bibliometric structure. Its role was limited to clarifying latent sub-themes, conceptual boundaries, and provisional thematic descriptors within the pre-existing clusters. Final interpretations were retained only after manual review and validation by the authors against the original keyword co-occurrence maps, overlay visualizations, bibliographic coupling patterns, and representative source documents.

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