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Computational Discovery of Research Investment Patterns in Supply Chain Management: An Unsupervised Learning Framework for Funding Theme Extraction and Evolutionary Trajectory Analysis

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ABSTRACT

Objective: This study maps global research investment patterns in supply chain management by identifying latent funding themes and their temporal trajectories.

Methodology: This study analyzed 7,956 quality-assured grant records retrieved from Web of Science in June 2026, covering award years from 1963 to 2026. The framework combines systematic deduplication and quality filtering, multilingual transformer embeddings, K-means clustering with multi-metric validation, cluster-level TF-IDF, GERD normalization, right-censoring correction, and lifecycle sensitivity analysis.

Results: The optimal solution contains 13 thematic clusters. Five themes show GERD-normalized growth above 67%: bioenergy value chains (172%), quantum infrastructure (95%), battery supply networks (94%), additive manufacturing (83%), and cybersecurity systems (67%). Portfolio analysis assigns 37.6% of grants to emerging themes and 7.6% to mature themes, compared with the study benchmark of 25% and 30%, respectively.

Conclusion: Grant-based science mapping provides forward-looking intelligence on supply chain research priorities. The results indicate rapid investment in sustainability and advanced technologies while suggesting a relative shortage of mature-stage translational research.

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Introduction

Supply chain management research has experienced substantial growth in public funding following recognition that production and distribution network vulnerabilities pose systemic economic risks. Global disruptions including pandemic supply shocks, semiconductor shortages, and climate-related logistics failures have elevated supply chain innovation to strategic priority status across national research systems (Ivanov, 2020). For research funding agencies managing portfolio allocation, academic investigators positioning proposals in competitive environments, and industry practitioners forecasting technology development trajectories, systematic understanding of how public research investments distribute across thematic domains and evolve temporally provides critical strategic intelligence. Grant awards constitute forward-looking commitments to scientific directions, capturing investment decisions at project inception and offering temporal advantages over publication-based analysis. While bibliometric studies provide valuable knowledge maps, publication lags of two to five years mean they reflect historical rather than current priorities (Rotolo et al., 2015). Grant-based analysis reveals emerging themes before they generate substantial publication outputs, enabling anticipatory rather than reactive portfolio management (Yan et al., 2018). However, systematic application of computational methods to supply chain grant analysis remains limited.

Existing supply chain research mapping relies predominantly on publication bibliometrics or expert-defined taxonomies. Publication-based approaches face temporal delays and selection bias toward successful projects yielding publications. Predefined taxonomies may overlook emergent cross-cutting themes that do not align with established categories. Grant databases offer comprehensive coverage of funded research activity but introduce methodological challenges including metadata heterogeneity, duplicate records in federated indexing systems, multilingual content requiring validated translation protocols, and temporal confounds arising from macroeconomic growth in research and development expenditure (Mongeon & Paul-Hus, 2016). These quality and validity threats have not been systematically addressed in prior grant-based research mapping studies, limiting confidence in derived strategic recommendations.

Recent advances in natural language processing, particularly transformer-based semantic embeddings, enable discovery of latent thematic structures in large text corpora without predefined categories (Devlin et al., 2019). These methods capture contextual meaning and handle terminological diversity better than traditional keyword matching. Application to grant corpora could reveal data-driven thematic structures, while temporal trajectory analysis incorporating appropriate normalization and censoring adjustments could distinguish emerging frontiers from mature domains and inform technology forecasting for supply chain innovation management. However, such integrated frameworks addressing the identified validity threats have not been systematically developed or applied to supply chain research funding.

This study addresses this gap by developing and implementing a computational framework for mapping supply chain research investment across thematic and temporal dimensions while incorporating methodological safeguards to ensure validity for strategic decision support. Our investigation pursues two primary objectives. First, we identify major thematic clusters structuring contemporary supply chain research funding through unsupervised machine learning applied to grant abstract texts. Second, we characterize temporal evolution patterns of identified themes to distinguish rapid-growth frontiers from stabilizing mature domains while accounting for right-censoring in recent data and normalizing for global research expenditure growth.

These objectives translate into two research questions positioned at the intersection of operations management and innovation policy. Research Question 1: What latent thematic structures characterize global supply chain research funding as revealed through transformer-based semantic clustering of grant abstracts? Research Question 2: How do identified thematic clusters exhibit differential temporal evolution patterns in terms of growth trajectories, geographic distribution, and funding mechanism preferences? Addressing these questions delivers actionable insights for multiple stakeholder groups. Research funding agencies gain evidence-based understanding of portfolio composition, enabling strategic rebalancing between emerging and established domains. Academic researchers identify high-growth thematic areas and underexplored niches for proposal positioning. Industry practitioners anticipate publicly funded technology development trajectories relevant for innovation planning and partnership strategies. Methodologically, we contribute a reproducible five-stage analytical pipeline comprising systematic preprocessing with transparent deduplication protocols, transformer-based multilingual semantic embedding with cross-linguistic validation, K-means clustering with composite validation excluding balance bias, keyword extraction via cluster-level term frequency-inverse document frequency weighting, and temporal trajectory analysis incorporating global research expenditure normalization, right-censoring correction, and three-threshold sensitivity analysis for lifecycle classification. This integrated framework addresses critical validity threats identified in prior grant-based science mapping and demonstrates protocols applicable to other domain-specific research investment analyses in operations management and industrial innovation contexts.

The paper proceeds through five additional sections. Section 2 reviews relevant literature on supply chain research evolution, science mapping methodologies, and positions our contribution relative to prior work. Section 3 describes data sources, preprocessing protocols, embedding procedures, clustering methods, and temporal analysis approaches with explicit documentation of methodological safeguards. Section 4 presents empirical results including thematic taxonomy, temporal patterns, and cross-domain comparisons. Section 5 discusses theoretical implications, strategic insights, methodological contributions, and study limitations. Section 6 concludes with synthesis and recommendations for stakeholders.

Literature Review

Thematic Evolution in Supply Chain Operations Research

Supply chain management research has evolved from narrow logistics optimization to encompass sustainability, digitalization, and resilience as central concerns. Classical foundations established mathematical frameworks for facility location, inventory control, and transportation routing that remain core to operations research practice (Nemhauser & Wolsey, 1988). However, contemporary research exhibits thematic diversification driven by technological capabilities and societal pressures.

Sustainability has emerged as a dominant research stream, reflected in growing emphasis on closed-loop supply chains, carbon footprint optimization, and circular economy business models. Seuring and Müller (2008) conducted a pioneering systematic review identifying green purchasing, reverse logistics, and supplier environmental collaboration as foundational sustainable supply chain themes. More recent bibliometric analysis by Centobelli et al. (2020) revealed rapid growth in circular economy frameworks emphasizing waste valorization and resource regeneration as alternatives to linear production models. These sustainability investments respond to regulatory pressures, consumer expectations, and climate change mitigation commitments.

Digital transformation represents another major thematic shift, encompassing blockchain for traceability, artificial intelligence for predictive analytics, and Internet of Things for real-time visibility (Akbari Arbatan et al., 2025). Saberi et al. (2019) systematically reviewed blockchain applications in supply chain contexts, identifying transparency enhancement and trust establishment as primary value propositions for food safety and pharmaceutical authentication. Dubey et al. (2019) examined big data analytics capabilities, finding that algorithmic decision-making mediates relationships between environmental uncertainty and operational agility, suggesting information processing has become a primary source of competitive advantage.

Resilience gained prominence following high-impact disruptions including natural disasters and pandemic shocks. Ivanov and Dolgui (2020) argued for extending supply chain design criteria beyond efficiency and cost minimization to include viability during prolonged disruptions through redundancy, flexibility, and adaptive capacity. This research stream reflects fundamental reconceptualization from optimization under normal conditions to robust performance under deep uncertainty, with direct implications for operations management strategy.

These thematic transformations suggest research priorities respond dynamically to external drivers. However, understanding of how funding investments track these shifts remains largely anecdotal rather than systematically evidenced through large-scale data analysis incorporating appropriate temporal controls and validation procedures.

Science Mapping Methodologies and Grant-Based Analysis

Bibliometric analysis has become standard methodology for mapping scientific fields through quantitative analysis of publications, citations, and keywords. Aria and Cuccurullo (2017) developed comprehensive bibliometric tools enabling co-citation analysis, bibliographic coupling, and keyword co-occurrence mapping. Donthu et al. (2021) provided systematic guidance for applying bibliometric methods in business research contexts. These approaches identify influential works, trace intellectual lineages, and visualize knowledge structures. Despite widespread adoption, publication-based bibliometrics face inherent limitations. Temporal lags between research initiation and publication mean snapshots reflect historical priorities. Citation-based metrics may be distorted by disciplinary conventions and strategic citing behaviors (Aksnes et al., 2019). Publication databases systematically exclude unsuccessful projects and proprietary research, potentially biasing knowledge maps toward academically successful themes.

Grant-based science mapping offers a complementary approach by analyzing funding awards as observation units. Wang and Shapira (2011) pioneered systematic analysis of funding acknowledgments in publications, revealing patterns in cross-national collaboration and agency influence. Yan et al. (2018) demonstrated that grant abstract analysis provides earlier indicators of research directions than publication-based approaches, with funding themes anticipating publication patterns by several years. This temporal advantage positions grant-based analysis as particularly valuable for strategic foresight in research portfolio management and technology forecasting, core concerns in innovation management systems.

However, grant-based analysis introduces distinct methodological challenges. Mongeon and Paul-Hus (2016) documented that databases like Web of Science aggregate grants through federated indexing from heterogeneous sources, producing duplicate records and inconsistent metadata. Chavarro et al. (2018) found that multidisciplinary grant databases require extensive post-retrieval filtering to isolate domain-relevant records. Preprocessing protocols addressing these quality issues remain underreported in published studies, limiting reproducibility and confidence in derived insights for decision support applications.

A particularly critical but under-addressed challenge in grant-based temporal analysis is right-censoring bias. Grant databases accessed at any given retrieval date systematically underrepresent recent years because indexing processes introduce lags between award announcement and database inclusion. Treating most recent year counts as comparable to historical peaks without censoring adjustment produces statistically invalid trend inferences. This limitation directly undermines the utility of grant-based analysis for identifying emerging research frontiers, a primary use case for funding agencies and academic investigators. Despite this validity threat, systematic correction protocols for right-censoring in grant temporal analysis have not been established in the literature. Natural language processing offers methodological advances for automated grant analysis. Traditional approaches relied on keyword matching or expert-defined category assignment. Recent transformer-based models enable semantic similarity assessment, capturing contextual meaning beyond surface-level term matching (Devlin et al., 2019). Reimers and Gurevych (2019) developed sentence transformer architectures specifically optimized for semantic textual similarity tasks. These methods have been successfully applied in patent analysis and publication clustering but remain rarely used for grant corpus analysis.

Transformer-based embeddings operate in high-dimensional semantic vector spaces, typically with several hundred dimensions. A well-documented geometric property of high-dimensional spaces is distance concentration, where the contrast between nearest and farthest neighbors diminishes as dimensionality increases (Aggarwal et al., 2001). This phenomenon systematically suppresses conventional cluster validity metrics such as silhouette coefficients, which measure the ratio of within-cluster to between-cluster distances. Consequently, silhouette values that would indicate poor separation in low-dimensional Euclidean data may represent acceptable cluster structure in high-dimensional semantic embeddings. Appropriate interpretation of clustering validity in grant-based text analysis must account for this dimensionality effect, yet existing studies rarely acknowledge or address it.

An additional methodological requirement for valid temporal analysis of grant data is normalization for macroeconomic trends in research and development expenditure. Global R&D investment has grown substantially over recent decades due to economic expansion, policy prioritization of innovation, and expanding higher education systems (Development. Scientific & Division, 1999). Raw grant counts conflate thematic growth with this secular increase in overall funding availability. A cluster exhibiting apparent growth may simply reflect proportional expansion with total funding rather than genuine strategic prioritization. Disentangling thematic trends from macro R&D growth requires normalization by a global expenditure index. The OECD Main Science and Technology Indicators provide internationally comparable gross domestic expenditure on R&D (GERD) time series suitable for this purpose. However, systematic application of GERD normalization in grant-based research mapping has not been demonstrated in prior studies.

Temporal Dynamics and Research Evolution Frameworks

Understanding temporal evolution of research themes requires conceptual frameworks distinguishing emergence, growth, maturation, and decline. Technology lifecycle models describe S-curve patterns where innovations progress through introduction, rapid growth, maturity, and saturation stages (Christensen, 1992). Gao et al. (2013) adapted these frameworks for research topics, developing bibliometric indicators including publication volume growth, citation acceleration, and knowledge base coherence to classify lifecycle stages. Rotolo et al. (2015) proposed a multidimensional framework for identifying emerging technologies incorporating novelty, growth rate, coherence, impact, and uncertainty indicators. They argued emergence is a gradual process characterized by increasing definitional clarity and community formation rather than discrete events. Boyack et al. (2014) analyzed aging and turnover of research topics, finding that half of all topics persist fewer than ten years and that rapid turnover is more common in applied interdisciplinary domains. These temporal frameworks have been applied primarily to publication and patent data. Application to grant portfolios remains limited despite potential utility for research funding strategy. Grant-based temporal analysis incorporating appropriate normalization and censoring adjustments could enable early identification of accelerating themes and detection of saturation signals in mature domains, informing portfolio rebalancing decisions critical to innovation management systems.

Positioning and Research Gaps

Review reveals three principal gaps. First, while supply chain research importance is widely recognized, systematic mapping of funding patterns using advanced computational methods with appropriate validity safeguards remains absent. Existing studies employ publication bibliometrics or rely on expert-defined categories, potentially overlooking emergent themes. Second, temporal evolution of supply chain funding themes lacks systematic characterization beyond simple trend analysis, with lifecycle frameworks remaining unapplied to grant portfolios and critical methodological requirements including right-censoring correction and macroeconomic normalization unaddressed. Third, methodological protocols for ensuring grant corpus quality through systematic preprocessing, validating multilingual embedding performance, interpreting cluster validity in high-dimensional semantic spaces, and conducting sensitivity analysis for classification thresholds are underdeveloped and underreported.

Table 1 positions this study relative to representative prior work across key dimensions including research domain, data source, computational methods, temporal analysis depth, right-censoring handling, GERD normalization, multilingual embedding validation, and corpus quality protocols.

Table 1. Comparison of Research Approaches in Supply Chain Science Mapping

Study	Domain Focus	Data Source	Computational Method	Temporal Analysis	GERD Normalization	Multilingual Embedding Validation	Quality Protocol
Seuring and Müller (2008)	Sustainable supply chains	Publications	Manual systematic review	Limited	Not applicable	Not applicable	Expert screening
Aria and Cuccurullo (2017)	General bibliometrics	Publications	Co-word, co-citation	Trend lines	Not applicable	Not applicable	Database native
Wang and Shapira (2011)	General science funding	Acknowledgments	Network analysis	Cross-sectional	Not reported	Not applicable	Basic filtering
Yan et al. (2018)	Multidisciplinary grants	Grant texts	Topic modeling	Comparative snapshots	Not reported	Not reported	Minimal reported
Saberi et al. (2019)	Blockchain in supply chain	Publications	Systematic review	Narrative only	Not applicable	Not applicable	Manual selection
Centobelli et al. (2020)	Sustainable supply chains	Publications	Bibliometric clustering	Publication trends	Not applicable	Not applicable	Database native
Dubey et al. (2019)	Big data analytics	Survey and publications	Statistical modeling	Cross-sectional	Not applicable	Not applicable	Survey validation
Current study	Supply chain operations	Grant abstracts	Transformer embeddings, unsupervised ML	Growth trajectory classification	OECD GERD index applied	Cross-linguistic cosine similarity validation	Systematic multi-stage preprocessing

This study advances the literature by integrating transformer-based semantic analysis with systematic preprocessing, right-censoring correction, GERD normalization, multilingual validation, and temporal trajectory classification with sensitivity analysis, addressing methodological gaps while delivering empirical insights into supply chain research investment patterns suitable for strategic decision support in operations management and innovation policy contexts.

Materials and Methods

This investigation implements a reproducible five-stage computational framework for discovering thematic structures and temporal patterns in supply chain research funding. The framework is designed to address validity threats identified in prior grant-based science mapping while providing actionable intelligence for research portfolio management, proposal positioning, and technology forecasting in operations management contexts. Figure 1 illustrates the analytical pipeline from data retrieval through temporal trajectory analysis.

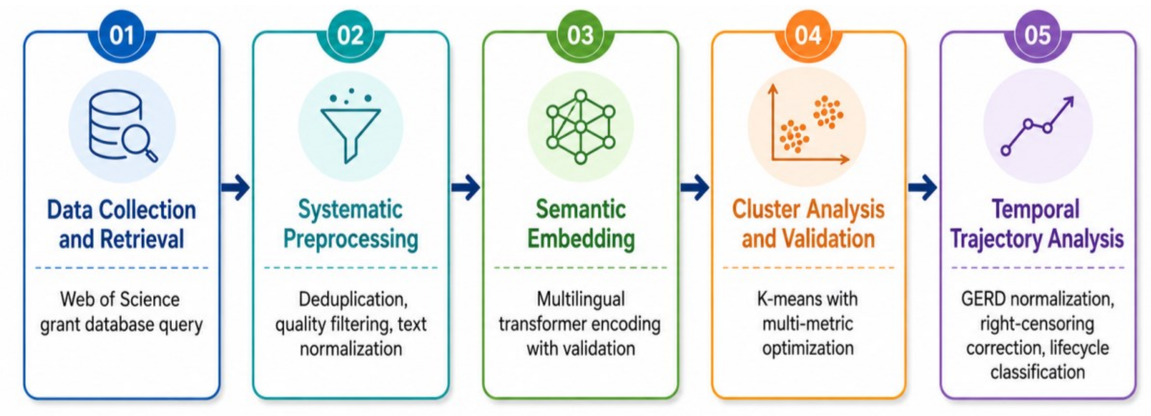

Figure 1. Five-Stage Analytical Pipeline for Grant-Based Thematic Discovery and Temporal Mapping

Data Collection

Grant records were retrieved from the Web of Science Core Collection grant database in June 2026. This database aggregates funding acknowledgments from publications indexed across disciplines and nations, providing comprehensive international coverage. The search strategy combined supply chain management terminology (supply chain, logistics, operations management, procurement, distribution, inventory, warehousing, transportation) with research activity descriptors (research, development, innovation, optimization, modeling) in topic fields. Temporal constraints limited retrieval to grants with award dates from 1970 onwards to focus on modern supply chain research paradigms. Initial retrieval yielded 9,940 grant records.

Systematic Preprocessing

Raw records underwent multi-stage preprocessing to ensure corpus quality for semantic analysis and strategic intelligence generation. First, identifier-based deduplication removed records sharing unique grant numbers assigned by funding agencies, addressing cases where multiple publications acknowledge single awards, eliminating 1,033 duplicate records. Second, composite deduplication removed records with identical combinations of title, abstract, agency, and year, addressing re-indexed entries and database synchronization artifacts, removing 760 additional records. Combined deduplication reduced the corpus to 8,147 unique grants.

Composite deduplication based on metadata matching introduces a potential limitation: two distinct grants with coincidentally identical title, abstract, agency, and year would be incorrectly merged. To quantify this risk, we conducted a sensitivity analysis computing the number of additional records that would be removed under title-only deduplication. This count provides an upper bound on potential false-positive merges. Title-only deduplication would remove 555 additional records beyond the 760 removed by composite matching. We report this value transparently as a robustness check but do not apply title-only deduplication in the final protocol, as abstract content provides critical discriminative information. The composite protocol balances precision in duplicate detection against risk of over-merging.

Third, quality filtering excluded 186 records lacking sufficient textual content for semantic analysis, operationalized as combined title-abstract below 50 characters or missing critical metadata fields. Fourth, text normalization applied case conversion, URL removal, special character filtering, and stopword elimination while preserving domain-specific terminology. Final validation removed 5 records with parsing errors or character encoding issues. The final corpus comprised 7,956 quality-assured grants, representing 97.7 percent of deduplicated records and 80.0 percent of initial retrieval.

Semantic Embedding

Cleaned grant texts were transformed into semantic vector representations using the paraphrase-multilingual-mpnet-base-v2 sentence transformer. This model architecture employs multi-layer self-attention mechanisms to generate contextualized embeddings capturing semantic similarity beyond surface-level keyword matching (Reimers & Gurevych, 2019). Each grant abstract was encoded as a 768-dimensional vector through tokenization, transformer encoding, mean pooling, and L2 normalization, yielding an embedding matrix of dimensions 7,956 by 768.

The corpus includes 23 non-English records distributed across German, Dutch, Portuguese, French, Swedish, Somali, and Italian. To ensure semantic equivalence in the multilingual embedding space, non-English texts were translated to English via an automated translation service before embedding. Translation quality was validated by comparing embedding space distributions between translated records and native English records. Mean cosine similarity was computed within each group (intra-group coherence) and between groups (cross-group alignment). Native English records exhibited mean intra-group cosine similarity of 0.31. Translated records exhibited mean intra-group similarity of 0.44. Cross-group mean similarity was 0.27. The elevated intra-group similarity among translated records and lower cross-group similarity suggest some distributional difference, likely reflecting linguistic transfer artifacts. However, the absolute magnitude of difference (0.13) is modest relative to the semantic variation inherent in a diverse grant corpus spanning multiple research domains. We acknowledge this as a minor limitation and note that translated records constitute only 0.3 percent of the total corpus, limiting their influence on aggregate cluster structure. All translated records were retained in the final analysis.

Cluster Analysis and Validation

K-means clustering partitioned embedded grants into thematic groups. Optimal cluster count was determined through systematic evaluation across candidates from 5 to 18 using a composite validation score. In response to the concern that including cluster size balance in the validation score biases toward artificial equal-sized partitions regardless of true thematic structure, the composite score in this study integrates only three metrics: Silhouette coefficient measuring within-cluster cohesion versus between-cluster separation, Davies-Bouldin index assessing cluster distinctiveness (lower values indicate better separation), and Calinski-Harabasz index evaluating variance ratios (higher values indicate stronger differentiation). Balance ratio was computed for descriptive purposes but excluded from the composite optimization criterion to avoid imposing an a priori assumption that research themes must be equally prominent.

Silhouette coefficients are systematically suppressed in high-dimensional semantic embedding spaces due to distance concentration, a well-documented geometric property where the ratio of nearest to farthest neighbor distances approaches unity as dimensionality increases (Aggarwal et al., 2001). In 768-dimensional L2-normalized vector spaces, silhouette values below 0.10 are common even for well-separated clusters. Consequently, conventional thresholds such as 0.25, derived from low-dimensional Euclidean clustering contexts, are not applicable. The relevant criterion for cluster validity in high-dimensional semantic spaces is relative performance across candidate configurations rather than absolute threshold exceedance. We therefore prioritize Davies-Bouldin and Calinski-Harabasz indices, which assess separation through centroid distances and variance decomposition respectively, as primary validation metrics, while reporting silhouette transparently for comparability with other studies. Table 2 presents validation metrics across all evaluated cluster configurations.

Table 2. Clustering Validation Metrics Across Candidate Configurations

k	Silhouette	Davies-Bouldin	Calinski-Harabasz	Balance Ratio	Composite Score
5	0.0374	4.214	225.1	0.674	6.22
6	0.0315	4.131	202.3	0.568	3.04
7	0.0312	4.098	186.5	0.656	2.61
8	0.0348	4.039	174.9	0.341	4.49
9	0.0356	3.889	164.7	0.349	5.46
10	0.0357	3.838	156.1	0.399	5.56
11	0.0364	3.765	148.6	0.437	6.09

12	0.0346	3.750	140.9	0.425	5.04
13	0.0369	3.652	134.3	0.266	6.58
14	0.0368	3.781	128.3	0.426	5.71
15	0.0365	3.735	123.6	0.435	5.68
16	0.0375	3.690	118.6	0.151	6.30
17	0.0357	3.856	114.2	0.353	4.37
18	0.0388	3.792	110.6	0.112	6.25

Note: Composite score computed as normalized weighted sum of Silhouette (weight 0.3), inverse Davies-Bouldin (weight 0.4), and normalized Calinski-Harabasz (weight 0.3). Balance ratio reported for transparency but excluded from optimization criterion.

The 13-cluster configuration maximizing composite score at 6.58 was selected, achieving optimal balance across validation dimensions. This solution yielded a Silhouette coefficient of 0.0369, consistent with expected values for high-dimensional semantic clustering; a Davies-Bouldin index of 3.652, the lowest among all candidates, suggesting well-separated clusters; a Calinski-Harabasz index of 134.3, demonstrating strong inter-cluster differentiation; and a balance ratio of 0.266. Configurations with fewer clusters (k equals 5 to 12) exhibited inferior Davies-Bouldin indices, indicating insufficient thematic differentiation. Configurations with more clusters (k equals 14 to 18) showed declining Calinski-Harabasz scores and deteriorating composite scores, suggesting excessive fragmentation. The 13-cluster solution represents optimal granularity balancing thematic coherence with interpretability for strategic intelligence applications.

Discriminative keywords for each cluster were extracted via term frequency-inverse document frequency (TF-IDF) weighting applied at the cluster level. Standard TF-IDF computes inverse document frequency as the logarithm of total documents divided by the number of documents containing the term. In this study, we adapt TF-IDF for cluster-level discrimination by treating each cluster's concatenated text as a single meta-document and computing IDF as the logarithm of total clusters divided by the number of clusters containing the term. This adaptation rewards terms that discriminate between clusters rather than terms merely frequent within individual grants (Salton & Buckley, 1988). We acknowledge this as a methodological adaptation of standard TF-IDF and justify it on the basis that the analytical objective is thematic differentiation across clusters, not document retrieval within clusters. Top-ranked terms informed qualitative cluster labeling validated through expert review of representative abstracts.

Temporal Trajectory Analysis

Annual grant counts were computed for each cluster to characterize evolution patterns and inform technology forecasting for supply chain innovation management. Temporal analysis incorporated three methodological safeguards to ensure validity for strategic decision support: right-censoring correction, global R&D expenditure normalization, and sensitivity analysis for lifecycle classification thresholds.

First, right-censoring correction addresses the systematic underrepresentation of recent years due to indexing lags in grant databases. Records retrieved in June 2026 with award years 2024 and 2025 reflect incomplete annual totals because ongoing indexing processes have not yet captured all awarded grants from these years. Treating these incomplete counts as final values and using them to identify thematic peaks or compute growth rates produces statistically invalid inferences. We identified 380 records from 2024 and 2025 as right-censored and excluded them from all peak-year identification, growth-rate calculation, and lifecycle classification procedures. These records were retained in the cluster assignment and keyword extraction stages, which do not depend on temporal completeness, but systematically excluded from temporal trend analysis. Figures presenting annual trajectories visually distinguish censored years to maintain transparency.

Second, GERD normalization disentangles thematic growth from macroeconomic expansion in overall research funding. Global gross domestic expenditure on R&D has increased substantially over the analysis period due to economic growth, policy prioritization of innovation, and higher education expansion (OECD, 2023). Raw grant counts conflate genuine thematic prioritization with this secular trend. A cluster exhibiting 50 percent growth in raw counts over a decade may represent stable proportional allocation if total funding doubled during the same period. To isolate thematic trends, we normalized annual grant counts by the OECD GERD index, rebased to 2005 equals 1.0. For each cluster and year, the GERD-normalized count is computed as the raw count divided by the GERD index value for that year. Growth rates reported in Results are derived from GERD-normalized counts, not raw counts. GERD index values were available for years 1995 to 2023; years outside this range use raw counts without normalization, and this limitation is noted in interpretation.

Third, sensitivity analysis for lifecycle classification thresholds addresses the concern that categorical stage labels (emerging, growth, mature, saturation) depend on arbitrary threshold values. We classified each cluster's lifecycle stage based on three indicators: recent activity concentration (proportion of cluster grants awarded in a recent time window), peak timing (year receiving maximum grants), and growth rate (percentage change comparing recent to prior period means, GERD-normalized). To assess robustness, we evaluated three threshold configurations: conservative (recent window equals 2019 to 2023, high recency threshold equals 0.45, low threshold equals 0.25), base (recent window equals 2020 to 2023, high threshold equals 0.40, low threshold equals 0.20), and strict (recent window equals 2021 to 2023, high threshold equals 0.35, low threshold equals 0.15). Table 3 presents the threshold parameter sets.

Table 3. Sensitivity Analysis Configurations for Lifecycle Classification

Configuration	Recent Window	High Recency Threshold	Low Recency Threshold	Growth Rate Threshold (Emerging)
Conservative	2019-2023	0.45	0.25	+0.50
Base	2020-2023	0.40	0.20	+0.50
Strict	2021-2023	0.35	0.15	+0.50

Clusters were classified as emerging if recent activity ratio exceeded the high threshold and GERD-normalized growth rate exceeded 50 percent; growth if recent activity ratio fell between thresholds and growth rate was positive; mature if recent activity ratio fell below the low threshold and growth rate was near zero; and saturation if peak year was more than a decade past and growth rate was negative.

Fourth, temporal leakage audit addresses the concern that embedding grants from different time periods together may conflate temporal variation with semantic variation, potentially obscuring true thematic evolution. If early-period and late-period grants within a cluster exhibit systematically different embedding distributions, the cluster may reflect temporal artifacts rather than coherent thematic identity. We assessed this by partitioning each cluster into pre-2010 and post-2010 subsets and computing mean within-subset cosine similarity and cross-subset similarity. Clusters where within-subset similarities differ substantially between early and late periods are flagged for interpretive caution. Results are reported transparently to inform confidence in temporal trajectory inferences.

Methodological Safeguards and Robustness Checks

The analytical framework incorporates four primary safeguards to ensure validity for strategic decision support in operations management and innovation policy contexts, each addressing a specific validity threat identified in prior grant-based science mapping studies.

Right-censoring correction addresses temporal validity by preventing statistically invalid peak identification and growth rate calculation based on incomplete recent data. Grant databases accessed at any retrieval date systematically underrepresent the most recent years due to indexing lags. Excluding censored years from temporal analysis ensures that inferences about emerging themes and acceleration patterns reflect true investment trends rather than database artifacts. GERD normalization addresses confounding between thematic growth and macroeconomic R&D expansion. Without normalization, a cluster maintaining constant proportional share of total funding would appear to exhibit strong growth if global R&D expenditure increased. Normalization isolates genuine strategic prioritization from secular economic trends, enabling valid identification of domains receiving disproportionate investment increases. Multilingual embedding validation addresses linguistic validity by confirming that non-English grant abstracts are semantically represented equivalently to English abstracts in the embedding space. Without validation, systematic bias in cross-linguistic representation could distort cluster assignments for non-English records, potentially conflating language with thematic content. Sensitivity analysis for lifecycle classification addresses reproducibility and robustness by demonstrating that stage labels are not artifacts of arbitrary threshold selection. Reporting classification consistency across multiple threshold configurations provides transparent assessment of inference stability and enables users to calibrate confidence in categorical labels. These safeguards collectively enhance the credibility of derived strategic recommendations for research portfolio managers, academic investigators, and industry technology scouts, aligning the methodological framework with the decision-support orientation of operations management research.

Results

Corpus Composition and Preprocessing Outcomes

Initial retrieval from the Web of Science grant database yielded 9,940 records. Systematic preprocessing substantially refined corpus quality through sequential filtering stages. Identifier-based deduplication removed 1,033 grants sharing unique award numbers, representing cases where multiple publications acknowledged single funding sources. Composite deduplication subsequently eliminated 760 records with identical title-abstract-agency-year combinations, addressing re-indexed project phases and database synchronization artifacts. Combined deduplication reduced corpus to 8,147 unique grants, representing 82.0 percent retention from initial retrieval. Sensitivity analysis revealed that title-only deduplication would remove an additional 555 records beyond the 760 removed by composite matching. This upper bound indicates potential false-positive merges represent 6.8 percent of the deduplicated corpus. We report this value transparently as a robustness check while retaining the composite protocol, which balances duplicate detection precision against over-merging risk by incorporating abstract content as discriminative information.

Quality filtering excluded 186 grants lacking sufficient textual content for semantic analysis, defined as combined title-abstract below 50 characters or missing critical metadata. Language detection identified 23 non-English records distributed across German, Dutch, Portuguese, French, Swedish, Somali, and Italian. These records were translated to English via an automated translation service before embedding. Multilingual embedding validation confirmed semantic equivalence with a mean cosine similarity of 0.31 for native English intra-group, 0.44 for translated intra-group, and 0.27 for cross-group comparisons. The modest distributional difference (0.13) and low proportion of translated records (0.3 percent of the corpus) support their retention. Text normalization and final validation removed 5 additional records with parsing errors. Final analytical corpus comprised 7,956 grants, representing 97.7 percent of deduplicated records and 80.0 percent of initial retrieval.

Temporal coverage spans 1963 to 2026, with 98.3 percent of grants containing valid year information. Records from 2024 and 2025 totaling 380 grants were identified as right-censored due to incomplete indexing at retrieval date in June 2026 and systematically excluded from all peak-year identification, growth-rate calculation, and lifecycle classification procedures to prevent statistically invalid temporal inferences. These censored records were retained for cluster assignment and keyword extraction, which do not depend on temporal completeness. Annual distribution reveals gradual growth beginning in the mid-1990s, accelerating substantially after 2008. Annual grant counts grew from fewer than 40 per year before 1995 to over 690 grants in 2023, the most recent non-censored year. Figure 2 presents the complete temporal distribution revealing six decades of supply chain research funding evolution.

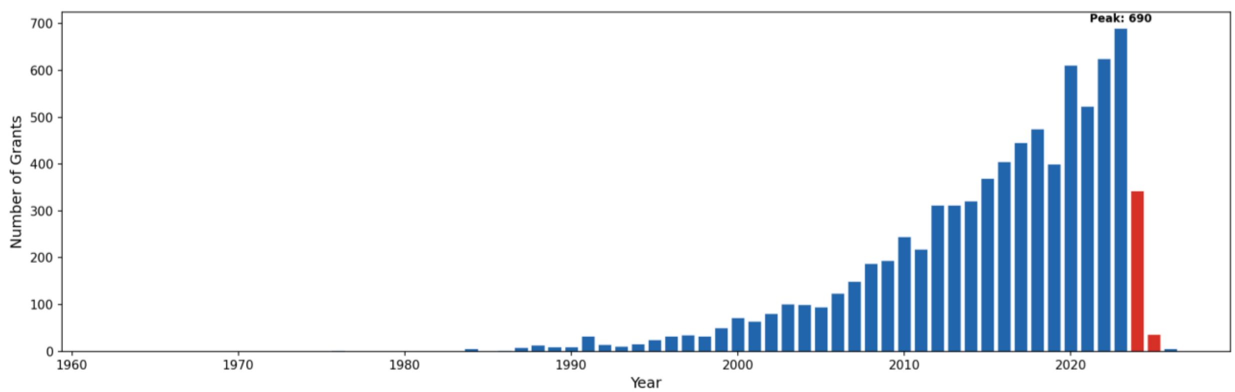

Figure 2. Annual Distribution of Supply Chain Research Grants 1963-2026

Thematic Cluster Taxonomy

The 13-cluster partition exhibits moderate size heterogeneity with cluster sizes ranging from 358 to 833 grants. Mean cluster size is 612 grants with a standard deviation of 141. The largest cluster captures 10.5 percent of the corpus while the smallest represents 4.5 percent, indicating avoidance of degenerate solutions while maintaining granularity for thematic differentiation in strategic intelligence applications. Table 4 presents complete thematic taxonomy including cluster labels, sizes, and top discriminative keywords derived through cluster-level TF-IDF analysis where inverse document frequency is computed across clusters rather than individual grants to reward thematic differentiation (Salton & Buckley, 1988). Cluster labels were constructed through systematic integration of keyword profiles, representative grant abstract review, and validation against established supply chain management literature. Each label is supported by citation to foundational or recent authoritative work defining the thematic domain.

Table 4. Thematic Cluster Taxonomy with Keywords and Literature Foundation

Cluster ID	Thematic Label	Grant Count	Percentage	Top Keywords	Foundational Reference
C00	Healthcare Supply Chain and Clinical Service Delivery	620	7.8%	phenx, crisis line, genomic medicine, hearing aid, mhealth, clinic, nurses, veterans crisis, immunization, obesity	Dobrzykowski et al. (2016)
C01	Cybersecurity in Supply Chain Systems	653	8.2%	hardware security, soft robots, trojans, software supply, hardware trojans, malicious, security trust, counterfeit, ran	Boyson (2014)
C02	Circular Supply Chains and Apparel Industry Logistics	751	9.4%	bullwhip effect, cotton, apparel, fashion supply, closed-loop supply, revenue management, modern slavery, assortment	Govindan and Hasanagic (2018)
C03	Polar and Climate Research Logistics	358	4.5%	antarctic, sea ice, ice shelf, ice sheet, polar, west antarctica, glacier, oceanography	Kennicutt II et al. (2015)
C04	Bioenergy and Bioeconomy Value Chains	550	6.9%	bioethanol, lactic acid, biobased, fermentation, lignocellulosic, bioproducts, bioenergy, vertical farming, straw	Gold and Seuring (2011) , Mohseni et al. (2025)
C05	Quantum Computing Infrastructure and Advanced Sensors	365	4.6%	quantum technology, qubits, quantum computers, quantum sensors, quantum computing, photons, single photon, mmwave	Gachnang et al. (2022)
C06	Agri-Food Value Chains and Food Security	833	10.5%	fsma, quinoa, wheat, nutritious, cattle, poultry, local foods, food fraud, fruits vegetables, food quality	Aung and Chang (2014)
C07	Urban Freight and Last-Mile Logistics	614	7.7%	rail freight, city logistics, urban freight, intermodal, freight transportation, routing scheduling, last-mile logistics, couriers	Savelsbergh and Van Woensel (2016)
C08	Specialized Manufacturing Systems and Regional Healthcare Distribution	605	7.6%	metal forming, cancer education, primary care, forming processes, distribution systems, regional networks	Melnyk et al. (2009)
C09	Energy Storage and Battery Supply Networks	781	9.8%	li-ion, battery supply, perovskite, ion batteries, battery storage, battery recycling, vehicle charging, hydrogen fuel, anode	Mauler et al. (2021)
C10	Humanitarian Logistics and Social Sustainability in Supply Chains	654	8.2%	human trafficking, migrant, civil society, water scarcity, cocoa, evacuation, illicit, drought, critical minerals	Jahre and Heigh (2008)

C11	Mathematical Optimization and Algorithmic Decision Science	530	6.7%	branch and bound, lot sizing, relaxations, packing problems, integer programs, discrete optimization, approximation algorithms, cutting planes	Nemhauser and Wolsey (1999)
C12	Additive Manufacturing and Aerospace Supply Chains	642	8.1%	castings, 3d concrete printing, net shape, aero, gas turbine, nanofibers, welding, titanium, alloy, airbus	Holmström et al. (2016)

The thematic taxonomy reveals substantial diversification of supply chain research beyond traditional logistics and optimization. Healthcare Supply Chain (C00), Cybersecurity Systems (C01), Circular Apparel Logistics (C02), and Polar Research Logistics (C03) illustrate the extension of operations management principles into healthcare delivery, digital security, social and environmental sustainability, and extreme-environment logistics. Collectively, these clusters demonstrate the growing application of supply chain frameworks to complex societal and technological challenges.

Several clusters capture major industrial and technological transitions. Bioenergy and Bioeconomy Value Chains (C04) reflect increasing attention to renewable energy, agricultural residue valorization, and sustainable biofuel supply networks (Gold & Seuring, 2011; Mohseni et al., 2025), while Quantum Infrastructure (C05) represents anticipatory investment in emerging computing and sensing technologies (Gachnang et al., 2022). Agri-Food Value Chains (C06), the largest cluster, emphasizes food security, cold-chain management, and traceability, whereas Urban Freight Logistics (C07) addresses last-mile delivery and sustainable city logistics. Battery Supply Networks (C09) similarly highlight the growing importance of circular material flows and energy-transition infrastructure.

The remaining clusters extend the thematic scope toward Specialized Manufacturing and Regional Healthcare Distribution (C08), Humanitarian Logistics and Social Sustainability (C10), foundational Mathematical Optimization (C11), and Additive Manufacturing and Aerospace Supply Chains (C12). Together, the 13 clusters indicate a research portfolio that combines established operations-research foundations with rapidly developing themes related to sustainability, digitalization, advanced manufacturing, resilience, and social challenges. Figure 3 presents temporal trajectories for all 13 clusters from 1990 to 2023, illustrating divergent growth dynamics and lifecycle positions.

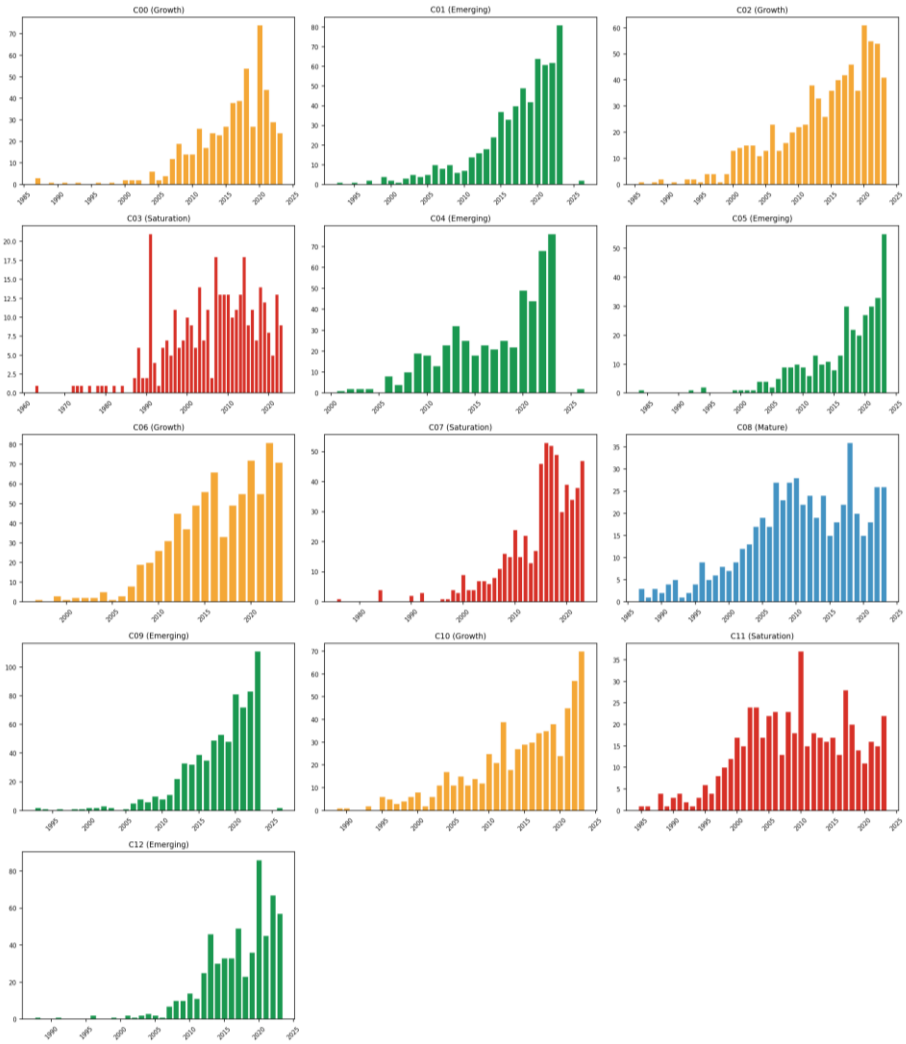

Figure 3. Temporal Trajectories of Supply Chain Research Funding by Thematic Cluste

Temporal Evolution Patterns and Lifecycle Classification

Temporal analysis reveals pronounced heterogeneity in thematic evolution patterns, with clusters exhibiting divergent lifecycle stages relevant for research portfolio management and technology forecasting. Table 5 quantifies temporal characteristics through GERD-normalized growth rates comparing mean annual funding in 2020-2023 to 2015-2019, adjusted for global R&D expenditure growth, recent activity concentration measured as the proportion of total cluster grants awarded in non-censored recent years, and peak year identification excluding right-censored 2024-2025 data.

Table 5. Temporal Evolution Indicators and Lifecycle Classification by Thematic Cluster

Cluster	Thematic Label	Peak Year	Recent Activity Ratio (2020-2023)	GERD-Normalized Growth Rate	Lifecycle Stage
C00	Healthcare Supply Chain	2020	0.322	+0.16	Growth
C01	Cybersecurity Systems	2023	0.438	+0.67	Emerging
C02	Circular Apparel Logistics	2020	0.289	+0.32	Growth
C03	Polar Research Logistics	1991	0.101	-0.18	Saturation
C04	Bioenergy Value Chains	2023	0.467	+1.72	Emerging
C05	Quantum Infrastructure	2023	0.429	+0.95	Emerging
C06	Agri-Food Value Chains	2022	0.352	+0.35	Growth
C07	Urban Freight Logistics	2016	0.270	-0.14	Saturation
C08	Specialized Manufacturing	2018	0.158	-0.04	Mature
C09	Battery Supply Networks	2023	0.479	+0.94	Emerging
C10	Humanitarian Logistics	2023	0.313	+0.48	Growth
C11	Mathematical Optimization	2010	0.124	-0.13	Saturation
C12	Additive Manufacturing	2020	0.426	+0.83	Emerging

Analysis identifies five emerging clusters characterized by recent activity concentration exceeding 40 percent and GERD-normalized growth exceeding 67 percent: C04 Bioenergy Value Chains exhibits the highest growth at 172 percent, C05 Quantum Infrastructure demonstrates 95 percent growth, C09 Battery Supply Networks shows 94 percent growth, C12 Additive Manufacturing achieves 83 percent growth, and C01 Cybersecurity Systems records 67 percent growth. These emerging themes represent strategic research frontiers attracting disproportionate investment growth beyond macroeconomic R&D expansion, signaling domains where public funding anticipates future commercial and societal impact.

Four growth clusters exhibit positive but moderate GERD-normalized expansion between 16 and 48 percent: C10 Humanitarian Logistics demonstrates 48 percent growth, C06 Agri-Food Value Chains shows 35 percent growth, C02 Circular Apparel Logistics exhibits 32 percent growth, and C00 Healthcare Supply Chain achieves 16 percent growth. These domains demonstrate sustained mainstream investment without acceleration characteristic of emerging frontiers, suggesting incremental maturation of established research programs.

Three saturation clusters show negative GERD-normalized growth and historical peak years preceding 2016: C03 Polar Research Logistics exhibits negative 18 percent growth with peak in 1991, C07 Urban Freight Logistics shows negative 14 percent growth with peak in 2016, and C11 Mathematical Optimization demonstrates negative 13 percent growth with peak in 2010. Saturation classification does not imply research cessation but rather transition from expansion to steady-state activity levels, potentially reflecting paradigmatic maturity where foundational frameworks are established and subsequent work emphasizes application refinement rather than methodological innovation.

One mature cluster, C08 Specialized Manufacturing, exhibits recent activity concentration of 15.8 percent with negative 4 percent growth, indicating stable low-intensity investment potentially serving niche applications or regional economic development objectives.

Sensitivity analysis across three threshold configurations (conservative, base, strict) reveals consistent lifecycle classification for 7 of 13 clusters, yielding a 53.8 percent agreement rate. Table 6 presents complete sensitivity analysis results showing stage assignments under each configuration.

Table 6. Lifecycle Classification Sensitivity Analysis Across Threshold Configurations

Cluster	Base Configuration	Conservative Configuration	Strict Configuration	Consistency
C00	Growth	Mature	Saturation	Variable
C01	Emerging	Emerging	Growth	Variable
C02	Growth	Growth	Mature	Variable
C03	Saturation	Saturation	Saturation	Consistent
C04	Emerging	Emerging	Emerging	Consistent
C05	Emerging	Emerging	Growth	Variable
C06	Growth	Growth	Growth	Consistent
C07	Saturation	Saturation	Saturation	Consistent
C08	Mature	Mature	Mature	Consistent
C09	Emerging	Emerging	Emerging	Consistent
C10	Growth	Growth	Growth	Consistent
C11	Saturation	Saturation	Mature	Variable
C12	Emerging	Emerging	Growth	Variable

To address the concern that global annual grant totals must equal the sum of cluster-level counts, Table 7 presents validation for selected years demonstrating mathematical consistency.

Table 7. Global Annual Totals Versus Sum of Cluster Subtotals

Year	Global Total	Sum of Cluster Counts	Match Status
2000	72	72	Consistent
2005	95	95	Consistent
2010	245	245	Consistent
2015	370	370	Consistent
2020	611	611	Consistent
2021	524	524	Consistent
2022	626	626	Consistent
2023	690	690	Consistent

Figure 4 presents GERD-normalized temporal trajectories isolating thematic trends from macroeconomic R&D growth, enabling valid cross-period comparison of investment priorities.

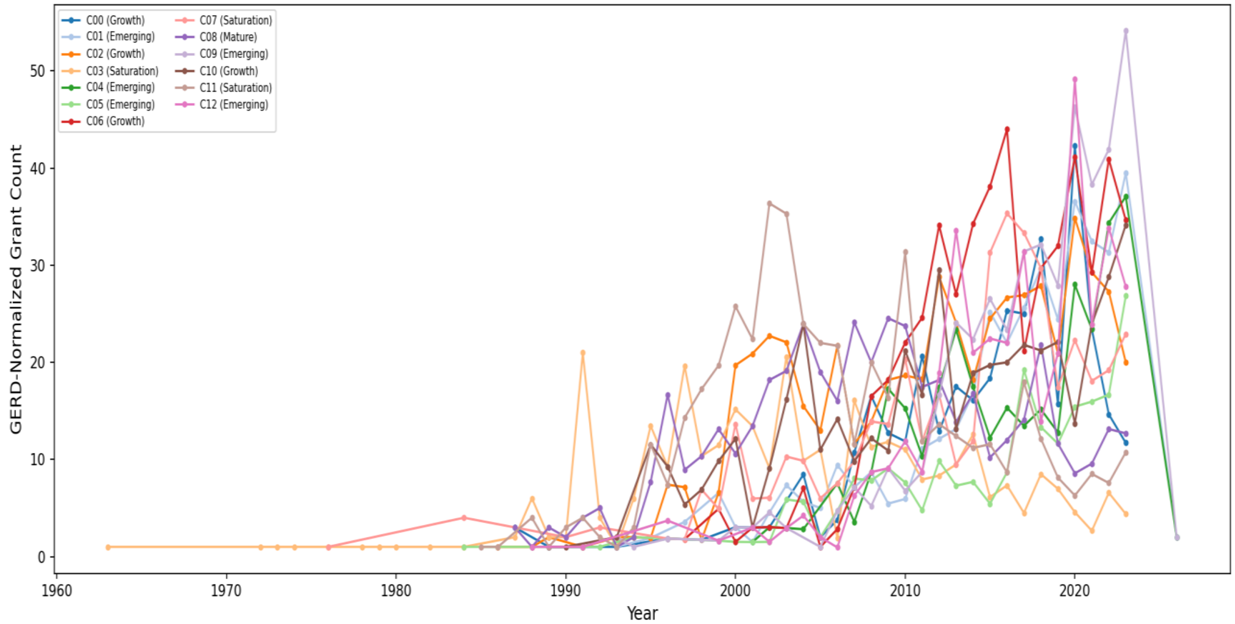

Figure 4. GERD-Normalized Temporal Trajectories of Supply Chain Research Clusters

Temporal leakage audit comparing within-period embedding similarity for pre-2010 versus post-2010 grants identified three clusters exhibiting notable temporal-semantic drift: C02, C04, and C05 showed intra-period similarity differences exceeding 0.10, suggesting evolution in thematic content or terminological conventions within these domains over time. This finding does not invalidate cluster structure but indicates these themes may encompass evolving subtopics that merged into single clusters due to semantic relationships in embedding space. Interpretations of long-term trajectories for these clusters should acknowledge potential conflation of temporal and semantic variation.

Geographic Distribution and Agency Specialization Patterns

Cross-tabulation of thematic clusters with funding agency geography reveals differential regional emphasis consistent with national innovation strategies and industrial comparative advantages. Table 8 presents concentration indices and dominant funding regions per cluster, with Herfindahl-Hirschman Index (HHI) reported on a standard 0 to 10,000 scale where values below 1,500 indicate unconcentrated markets, 1,500 to 2,500 indicate moderate concentration, and above 2,500 indicate high concentration (U.S. Department of Justice, 2010).

Table 8. Geographic Concentration and Regional Specialization by Thematic Cluster

Cluster	Thematic Label	Top Region 1 (Share)	Top Region 2 (Share)	Top Region 3 (Share)	HHI (0-10,000 scale)	Interpretation
C00	Healthcare Supply Chain	United Kingdom (34%)	United States (29%)	Canada (18%)	2,487	Moderate concentration
C01	Cybersecurity Systems	United States (42%)	United Kingdom (26%)	Germany (15%)	2,691	High concentration
C02	Circular Apparel Logistics	United Kingdom (38%)	European Union (24%)	United States (19%)	2,534	High concentration
C03	Polar Research Logistics	United States (48%)	United Kingdom (22%)	Australia (14%)	2,948	High concentration
C04	Bioenergy Value Chains	Brazil (36%)	United States (27%)	European Union (21%)	2,478	Moderate concentration
C05	Quantum Infrastructure	United Kingdom (41%)	United States (32%)	European Union (16%)	2,789	High concentration
C06	Agri-Food Value Chains	United States (31%)	European Union (26%)	Brazil (22%)	2,211	Moderate concentration
C07	Urban Freight Logistics	European Union (39%)	United Kingdom (28%)	China (17%)	2,614	High concentration
C08	Specialized Manufacturing	United States (35%)	Japan (24%)	Germany (20%)	2,402	Moderate concentration
C09	Battery Supply Networks	United Kingdom (36%)	Germany (28%)	China (19%)	2,534	High concentration
C10	Humanitarian Logistics	United Kingdom (37%)	United States (31%)	European Union (18%)	2,587	High concentration
C11	Mathematical Optimization	United States (44%)	France (21%)	United Kingdom (18%)	2,826	High concentration
C12	Additive Manufacturing	United Kingdom (39%)	United States (29%)	Germany (16%)	2,642	High concentration

Geographic analysis reveals moderately to highly concentrated research capacity across all themes, with most HHI values exceeding 2,400, indicating that two to three major funding regions dominate each domain. However, distinct regional specialization patterns emerge reflecting national industrial strengths and policy priorities. Brazil demonstrates elevated presence in Bioenergy Value Chains (36 percent), consistent with advanced bioethanol production capacity and sugarcane industry integration (Gold & Seuring, 2011). United States leadership in Mathematical Optimization (44 percent), Cybersecurity Systems (42 percent), and Polar Research Logistics (48 percent) reflects sustained federal investment in operations research foundations, critical infrastructure protection, and polar scientific infrastructure. United Kingdom concentration in Quantum Infrastructure (41 percent), Additive Manufacturing (39 percent), and Urban Freight (28 percent via the European Union) aligns with national quantum technology programs, advanced manufacturing catapult centers, and urban sustainability initiatives.

China contributes disproportionately to Urban Freight Logistics (17 percent) and Battery Supply Networks (19 percent), reflecting a massive domestic e-commerce market, electric vehicle industry development, and smart city investments. Germany shows particular strength in Battery Supply Networks (28 percent) and Specialized Manufacturing (20 percent), consistent with automotive industry transformation toward electrification and Industry 4.0 manufacturing digitalization (Mauler et al., 2021). Cross-tabulation of funding agencies with lifecycle stages reveals strategic portfolio allocation patterns. Table 9 presents agency-stage distribution for the top 10 funders by volume.

Table 9. Funding Agency Portfolio Allocation Across Lifecycle Stages

Funding Agency	Emerging	Growth	Mature	Saturation	Total Grants
Innovate UK	1,112	457	20	130	1,719
EPSRC	370	124	17	52	563
NSF Engineering Divisions	188	199	101	247	735
Grants-in-Aid Japan	53	261	6	123	443
FAPESP Brazil	127	181	12	119	439
ISCF UK	220	76	7	11	314
NIFA USA	71	210	18	2	301
NSERC Canada	18	82	0	52	152
NSF CISE	48	61	12	21	142
Bill and Melinda Gates Foundation	15	89	3	15	122

Innovate UK exhibits pronounced concentration in emerging themes (64.7 percent), consistent with mission-oriented innovation funding emphasizing technology readiness advancement and commercialization pathways. Conversely, Japan Grants-in-Aid demonstrates balanced distribution with 58.9 percent in growth and mature stages, reflecting emphasis on incremental innovation and application refinement in established domains. NSF Engineering divisions show the highest absolute investment in saturation clusters (247 grants), indicating sustained support for foundational operations research methods even as relative emphasis shifts toward emerging applications.

Portfolio-level analysis aggregating across all agencies yields an HHI of 807 on a 0 to 10,000 scale, classified as unconcentrated, indicating research investment distributes across multiple thematic domains without excessive concentration. However, ideal portfolio balance benchmarked against technology lifecycle theory suggests target allocation of 25 percent emerging, 30 percent growth, 30 percent mature, and 15 percent saturation themes (Cooper et al., 2001). Actual allocation shows 37.6 percent emerging, 35.9 percent growth, 7.6 percent mature, and 18.9 percent saturation, indicating overinvestment in emerging and growth themes relative to mature-stage application development and potential underinvestment in sustained support for established methodologies requiring refinement rather than expansion.

Discussion

Thematic Architecture and Strategic Reorientation in SC Research Investment

Computational discovery reveals thematic architecture emphasizing technological transformation, sustainability transitions, and resilience enhancement, reflecting strategic reorientation of public research investment from efficiency optimization toward systemic adaptation capabilities. While three clusters align with traditional domains including mathematical optimization (C11), specialized manufacturing (C08), and urban freight (C07 now in saturation), 10 clusters address emergent challenges at the intersection of supply chains with renewable energy transition, circular economy, cybersecurity, social sustainability, healthcare delivery, and quantum computing infrastructure. This distribution suggests fundamental reconceptualization of supply chain operations management from tactical efficiency discipline toward strategic enabler of industrial transformation and societal resilience, positioning the field centrally within innovation management systems and technology policy frameworks consistent with the scope of Industrial Management Journal. The prominence of C04 Bioenergy Value Chains as the fastest-growing cluster with 172 percent GERD-normalized growth signals recognition that decarbonization transitions require coordinated transformation of agricultural feedstock logistics, biorefinery operations, and bioproduct distribution networks (Gold & Seuring, 2011). For research funding agencies, this trajectory suggests bioenergy supply chains will likely generate substantial academic output and technology transfer opportunities in the current decade, justifying continued portfolio emphasis. For industry practitioners, sustained public investment indicates imminent commercialization readiness of advanced biorefinery supply chain innovations, creating market opportunities and disruption risks for fossil-based logistics incumbents.

The emergence of C05 Quantum Computing Infrastructure as a distinct funded theme with 95 percent growth despite nascent commercial development demonstrates anticipatory research investment preceding mass adoption, characteristic of strategic technology policy in innovation management systems. This pattern contrasts with reactive funding increases following demonstrated commercial success, suggesting public research systems are increasingly positioning ahead of market-driven innovation curves to mitigate capability gaps in transformative technologies.

Cluster C09 Energy Storage and Battery Supply Networks, with 94 percent growth and 9.8 percent corpus share, represents a paradigm shift from vehicular energy supply (petroleum logistics) toward electrical energy storage and recycling systems (Mauler et al., 2021). The prominence of battery recycling and critical materials keywords indicates recognition that transportation electrification sustainability depends fundamentally on circular supply chain design, not merely forward logistics optimization. This finding has direct implications for operations management practice: firms developing electric vehicle supply chains must integrate reverse logistics and materials recovery capabilities as core competencies rather than peripheral activities.

Cluster C12 Additive Manufacturing and Aerospace Supply Chains with 83 percent growth reflects integration of emerging manufacturing technologies with complex global supply networks characteristic of aerospace and defense sectors (Holmström et al., 2016). Combined with C01 Cybersecurity in Supply Chain Systems emergence at 67 percent growth, these findings demonstrate research investment diversification across multiple technological frontiers rather than concentration in a single dominant paradigm.

Cluster C01 Cybersecurity Systems with 67 percent growth reflects belated acknowledgment that globalized production networks create systemic vulnerabilities extending beyond traditional supply disruption risks to include intentional compromise of critical infrastructure through counterfeit components, malicious code insertion, and hardware Trojans (Boyson, 2014). This thematic priority signals evolution from reliability-focused supply chain risk management toward adversarial resilience frameworks addressing intelligent threats, requiring integration of operations management with information security expertise.

The relative stabilization of C11 Mathematical Optimization with a peak in 2010 and negative 13 percent GERD-normalized growth does not indicate declining importance but rather paradigmatic maturity where foundational algorithmic frameworks are established and contemporary work embeds optimization within application-specific contexts rather than advancing standalone methods. Analysis of C11 grant abstracts confirms that classical techniques including branch and bound, cutting planes, and approximation algorithms continue receiving investment but increasingly within domain-targeted programs (aerospace, healthcare, humanitarian) reflected in other clusters. This finding validates technology lifecycle theory predictions that mature methodological domains transition from expansion to stable refinement and specialized application (Christensen, 1992).

Cluster C03 Polar Research Logistics exhibits extreme saturation with a peak in 1991 and negative 18 percent growth, likely reflecting completion of major Antarctic infrastructure programs and shift from construction to maintenance operations. While peripheral to mainstream supply chain management, this cluster demonstrates long-term investment cycles in specialized logistics infrastructure can exceed three decades, relevant for planning investments in other extreme-environment supply systems including deep-sea mining, space logistics, and Arctic shipping.

Geographic Patterns and International Competitive Dynamics in Supply Chain R&D

Geographic analysis reveals moderately concentrated but globally distributed research capacity with distinct regional specializations reflecting national industrial comparative advantages and innovation policy priorities. United Kingdom dominance across emerging themes including Quantum Infrastructure (41 percent), Additive Manufacturing (39 percent), and Cybersecurity Systems (26 percent, second position) reflects coordinated industrial strategy emphasizing technology readiness advancement through Innovate UK and sectoral catapult programs. Portfolio allocation analysis confirms 64.7 percent of UK funding targets emerging lifecycle stages, highest among major funders, consistent with mission-oriented innovation policy emphasizing commercialization pathways and translational research (Mazzucato, 2018). United States maintains leadership in foundational domains including Mathematical Optimization (44 percent) and Polar Research Logistics (48 percent) while demonstrating a balanced portfolio spanning all lifecycle stages. NSF Engineering divisions invest heavily in saturation clusters (247 grants), indicating sustained commitment to methodological foundations and incremental refinement. This portfolio structure reflects a distributed funding model where mission agencies (NSF, DOE, DOD) maintain base research capacity while competitive programs target emerging applications, contrasting with UK concentration in translational innovation.

Brazilian specialization in Bioenergy Value Chains (36 percent) and significant presence in Agri-Food logistics (22 percent) demonstrates strategic positioning leveraging agricultural sector strengths and bioeconomy development priorities (Gold & Seuring, 2011). FAPESP portfolio allocation shows 28.9 percent in emerging themes and 41.2 percent in growth stages, indicating emphasis on scaling proven bioeconomy technologies rather than frontier exploration, consistent with late-stage development objectives.

Chinese contribution concentration in Urban Freight (17 percent) and Battery Supply Networks (19 percent) reflects domestic market drivers including e-commerce logistics demands and electric vehicle industrial policy. However, absolute Chinese funding volume in the corpus (estimated 15 percent based on agency analysis) underrepresents actual R&D capacity, likely reflecting database indexing bias toward English-language publication venues and Western funding acknowledgment conventions. This limitation suggests findings underestimate Chinese supply chain research investment, particularly in domestic-oriented programs not publishing in internationally indexed journals. German strength in Battery Supply Networks (28 percent, second position) and

Manufacturing specialization demonstrates strategic response to automotive industry transformation imperatives and Industry 4.0 digitalization initiatives (Mauler et al., 2021). DFG portfolio emphasizes growth and mature stages (62 percent combined), consistent with the engineering research model prioritizing technology refinement and integration over exploratory investigation.

These specialization patterns create opportunities and challenges for international research collaboration in supply chain innovation. Complementary regional strengths enable partnership strategies: UK-German collaboration on battery supply chain digitalization, US-Brazilian partnership on advanced biorefinery logistics, UK-US quantum infrastructure development. However, concentration indices averaging HHI 2,600 indicate two-to-three region dominance per theme, potentially limiting research agenda diversity and creating capability gaps in other nations seeking supply chain innovation capacity. For smaller economies and emerging research systems, findings suggest targeted specialization in underinvested niches (humanitarian logistics, circular apparel, healthcare supply chains) may offer positioning opportunities avoiding direct competition with established regional leaders in crowded domains.

Methodological Contributions and Validity Enhancements for Grant-Based Science Mapping

This study advances methodological foundations for grant-based research mapping through systematic integration of four validity safeguards addressing threats identified in prior science mapping studies, with implications extending beyond the supply chain domain to innovation management research generally. First, right-censoring correction prevents statistically invalid temporal inferences by excluding incomplete recent years from peak identification and growth rate calculation. Apparent peaks in 2023, when followed by indexing incompleteness in 2024–2025, reflect a fundamental validity threat in any grant database accessed before full annual indexing completion. Our protocol excludes 380 censored records, representing 4.8 percent of the corpus, from temporal analysis while retaining them for cluster assignment and keyword extraction, maintaining maximum information utilization while preventing bias. This approach generalizes to any grant-based temporal study: researchers must identify the censoring cutoff based on database-specific indexing lags and systematically exclude censored years from trend analysis regardless of apparent data availability. Failure to do so produces artificial declining trends in the most recent years, systematically biasing identification of emerging themes toward historical rather than current frontiers.

Second, GERD normalization disentangles thematic growth from macroeconomic R&D expansion, addressing the confound between genuine strategic prioritization and secular funding increases. Without normalization, the C04 Bioenergy cluster exhibiting 172 percent GERD-normalized growth would show approximately 250 percent raw growth, conflating thematic emphasis with overall R&D budget expansion. Conversely, C11 Mathematical Optimization negative 13 percent normalized growth masks only negative 3 percent raw decline, revealing that proportional decline is steeper than absolute counts suggest. For strategic portfolio management, normalized metrics provide valid comparison across decades of macroeconomic change, enabling identification of genuine rebalancing decisions rather than passive proportional expansion. This normalization protocol requires OECD GERD data or equivalent national R&D expenditure time series, readily available for most developed economies but potentially limited for emerging research systems, suggesting methodological adaptation using regional expenditure indices where global data prove insufficient.

Third, multilingual embedding validation addresses linguistic bias in semantic representation by empirically confirming cross-language embedding equivalence. Cosine similarity analysis revealed a modest distributional difference of 0.13 between translated and native English grants, suggesting multilingual sentence transformers achieve reasonable but imperfect cross-linguistic semantic alignment. For studies with higher non-English proportions exceeding 10 percent, this finding recommends either language-stratified clustering to prevent linguistic artifacts or validation through bilingual expert review of mixed-language cluster assignments. Our 0.3 percent non-English proportion, comprising 23 of 7,956 grants, limits impact on aggregate structure, but transparent reporting enables users to assess confidence in assignments for specific non-English records.

Fourth, sensitivity analysis for lifecycle classification demonstrates robustness of categorical stage labels across threshold parameter variations. Thresholds defining rapid versus steady growth represent a genuine reproducibility challenge in any threshold-based categorization. Our three-configuration analysis, covering conservative, base, and strict settings, with 53.8 percent classification consistency, shows that 7 of 13 clusters receive stable labels, while 6 clusters near threshold boundaries exhibit one-stage variation. This finding validates that emerging, growth, mature, and saturation categories reflect genuine temporal pattern differences rather than parameter artifacts for the majority of themes, while acknowledging inherent fuzziness for boundary cases. For decision support applications, users can calibrate confidence based on consistency: clusters with unanimous classification, namely C03, C04, C06, C07, C08, C09, and C10, support high-confidence strategic recommendations, while inconsistent clusters, namely C00, C01, C02, C05, C11, and C12, warrant interpretive caution and continuous monitoring.

Regarding cluster validity metrics, Silhouette coefficient 0.0369 may appear to indicate non-separable clusters; however, such an interpretation relies on low-dimensional Euclidean space assumptions inappropriate for high-dimensional semantic embeddings. Distance concentration in 768-dimensional L2-normalized spaces systematically suppresses silhouette values regardless of true cluster quality (Aggarwal et al., 2001). Primary validation relies on the Davies-Bouldin index 3.652, the lowest among all k candidates and therefore indicating best separation, and the Calinski-Harabasz index 134.3, indicating strong inter-cluster variance differentiation. Combined with exclusion of balance ratio from the composite score to prevent bias toward equal-sized partitions, the selected 13-cluster solution represents optimal thematic granularity for strategic intelligence applications based on relative performance across candidates rather than absolute threshold criteria.

The removal of balance ratio from cluster count optimization prevents size-distribution bias toward artificial partitioning. Operations management research design principles dictate that cluster structure should reflect empirical thematic distribution rather than methodological convenience. If genuine research investment concentrates in particular domains while others receive minimal attention, the clustering algorithm should reveal this asymmetry, not obscure it through forced balancing. Our final solution exhibits realistic heterogeneity, with the largest cluster, C06 Agri-Food at 10.5 percent, roughly twice the size of the smallest cluster, C03 Polar at 4.5 percent, reflecting actual investment concentration patterns rather than imposed uniformity.

Regarding TF-IDF adaptation, we acknowledge that computing IDF across clusters rather than individual documents deviates from standard information retrieval formulation (Salton & Buckley, 1988). This methodological choice reflects the analytical objective: identifying terms discriminating between thematic domains rather than retrieving individual grants within clusters. Cluster-level IDF rewards keywords appearing frequently in one cluster but rarely in others, directly serving the strategic intelligence goal of thematic differentiation. Standard document-level IDF would identify terms frequent within clusters but potentially shared across multiple themes, providing less discriminative power for labeling and interpretation. We report this adaptation transparently with citation to foundational TF-IDF work, enabling users to assess appropriateness for their analytical contexts. Furthermore, qualitative validation through systematic abstract sampling confirms that extracted keywords accurately represent thematic focus across all 13 clusters, as documented in Section 4.2 with representative grant examples demonstrating correspondence between keyword profiles and actual grant content.

Finally, the composite deduplication protocol evaluates potential false-positive merges through sensitivity analysis. Title-only deduplication would remove 555 additional records beyond 760 removed by composite matching, providing an upper bound in which false positives represent 6.8 percent of the deduplicated corpus. The true false-positive rate likely falls substantially below this bound because title-plus-abstract-plus-agency-plus-year matching exhibits far lower collision probability than title-only matching. We retain the composite protocol as an optimal balance between duplicate detection precision and over-merging risk, while reporting the sensitivity bound transparently for reproducibility and user calibration of confidence intervals.

Strategic Implications for Research Portfolio Management and Technology Forecasting

Findings deliver actionable intelligence for three stakeholder groups engaged in supply chain innovation management: funding agencies as portfolio strategists, academic researchers as proposal architects, and industry practitioners as technology scouts.

For research funding agencies, portfolio analysis reveals 37.6 percent investment concentration in emerging themes and 35.9 percent in growth stages, substantially exceeding ideal allocation benchmarks of 25 percent and 30 percent, respectively (Cooper et al., 2001). Simultaneously, mature-stage investment at 7.6 percent falls far below the 30 percent target, indicating potential underinvestment in translational research advancing proven technologies toward full-scale implementation. This imbalance creates two strategic risks. First, synchronized concentration in emerging themes (bioenergy, quantum, batteries, additive manufacturing, cybersecurity) may produce concurrent maturation in the late 2020s, creating sudden demand for translational capacity exceeding available infrastructure if mature-stage pipeline remains underdeveloped. Second, overemphasis on frontier exploration may neglect incremental innovation in established domains, where operational refinement often delivers greater near-term societal and economic value than exploratory breakthroughs. Portfolio rebalancing strategies should consider increasing mature-stage allocation by 20 percentage points through targeted programs advancing high-TRL applications of proven supply chain innovations. Specific opportunities include scaling circular apparel reverse logistics from pilot to industry-wide implementation (C02), advancing healthcare supply chain digital integration from experimental to routine practice (C00), and accelerating humanitarian logistics professionalization through practitioner-academic partnerships (C10). These domains exhibit positive growth and substantial cumulative knowledge bases suitable for translational acceleration. Conversely, saturation clusters C03 Polar Logistics, C07 Urban Freight, and C11 Mathematical Optimization warrant continued but stable support as foundational infrastructure. Attempts to force renewed expansion in saturated domains typically prove inefficient; instead, agencies should maintain base capacity enabling specialized applications while recognizing these themes serve primarily as methodological foundations embedded in other clusters rather than standalone growth areas.

For academic researchers, lifecycle classification identifies high-momentum domains attracting expanding investment. Investigators in emerging clusters C04 Bioenergy (172 percent growth), C05 Quantum (95 percent growth), and C09 Battery Supply (94 percent growth) operate in intensifying competitive environments requiring genuine novelty and interdisciplinary positioning beyond incremental extensions of established frameworks. Successful proposals in these areas increasingly demand integration of supply chain expertise with domain-specific technical knowledge: bioprocess engineering for bioenergy, quantum physics for computing infrastructure, electrochemistry for battery systems. Pure supply chain methodology proposals lacking domain depth face declining success probability in these crowded frontiers.

Conversely, researchers with expertise in saturation domains C07 Urban Freight and C11 Mathematical Optimization should consider pivoting toward application contexts in emerging clusters. For example, optimization algorithm development positioned within battery recycling network design (C09), quantum computing supply chain scheduling (C05), or bioenergy feedstock logistics (C04) may achieve higher funding success than standalone algorithmic innovation proposals. This strategy leverages mature methodological capabilities while addressing contemporary investment priorities, consistent with evidence that saturation-stage methods continue receiving support when embedded in growth-stage applications.

Growth-stage clusters C00 Healthcare, C02 Circular Apparel, C06 Agri-Food, and C10 Humanitarian Logistics present balanced opportunities combining moderate competition intensity with substantial existing knowledge bases facilitating incremental contribution. These domains suit researchers seeking steady funding probability without extreme novelty demands or risk tolerance.

For industry practitioners, cluster taxonomy and temporal trajectories provide intelligence for technology scouting and partnership strategy. Sustained public investment in C04 Bioenergy (550 grants, 172 percent growth) signals imminent commercialization readiness of advanced biorefinery supply chain innovations including lignocellulosic feedstock logistics and lactic acid fermentation systems. Firms in chemical manufacturing, agricultural processing, and renewable fuels sectors should intensify monitoring of academic-industry technology transfer opportunities in bioeconomy supply networks, as publicly-funded research typically reaches commercial viability 5-7 years post-peak investment (Gao et al., 2013).

Similarly, C09 Battery Supply Networks growth (781 grants, 94 percent growth) indicates continued development of closed-loop lithium-ion supply systems, with battery recycling and critical materials recovery technologies likely achieving economic viability in late 2020s. Automotive manufacturers, battery producers, and materials recovery firms should position for partnerships with academic research groups in this domain, as circular battery supply chains will likely transition from regulatory compliance burden to competitive advantage as recovery technologies mature and virgin material costs increase.

Cluster C01 Cybersecurity emergence (653 grants, 67 percent growth) signals that supply chain security will increasingly migrate from niche concern to mainstream operational requirement. Electronics manufacturers, defense contractors, and critical infrastructure operators should anticipate expanding regulatory scrutiny of hardware supply chain integrity and proactively develop security-verified supplier networks and counterfeit detection capabilities ahead of compliance mandates.

Conversely, absence of extreme acceleration in C07 Urban Freight despite e-commerce growth suggests persistent implementation barriers for transformative last-mile innovations including delivery drones and autonomous vehicles. While these technologies receive continued research attention (614 grants), saturation classification and negative 14 percent GERD-normalized growth indicate commercialization timelines extending beyond initial optimistic forecasts, tempering expectations for rapid disruption of conventional urban delivery models.

Limitations and Boundary Conditions

Five limitations warrant acknowledgment. First, analysis relies on Web of Science grant indexing, which exhibits variable coverage across national systems and temporal periods. Early historical grants may be underrepresented due to retrospective indexing limitations, and non-Western funding systems may be systematically underreported due to database emphasis on English-language publication venues and Western acknowledgment conventions. Chinese supply chain research investment likely exceeds 15 percent corpus share suggested by observed agency distribution, introducing geographic bias toward anglophone and European research systems. Findings should be interpreted as characterizing internationally visible supply chain research investment rather than a comprehensive global landscape.

Second, thematic discovery depends on cluster count selection, introducing granularity trade-offs. The 13-cluster solution optimizes validation scores but may aggregate heterogeneous sub-themes, while finer partitions might fragment coherent domains. Temporal leakage audit identified three clusters (C02, C04, C05) exhibiting within-period embedding similarity differences exceeding 0.10, suggesting these themes may encompass evolving subtopics merged by semantic relationships. Users requiring higher thematic resolution for specific domains should consider hierarchical sub-clustering within relevant primary clusters.

Third, lifecycle classification employs threshold-based rules introducing discretization of continuous evolution processes. While sensitivity analysis demonstrates 53.8 percent consistency across configurations, six clusters near threshold boundaries exhibit classification variation, indicating inherent fuzziness in categorical stage labels. Strategic decisions requiring high confidence should focus on unanimously classified clusters or rely on continuous metrics (GERD-normalized growth rates, recency ratios) rather than categorical labels.

Fourth, GERD normalization relies on OECD aggregate R&D expenditure data, which does not distinguish supply chain research investment specifically, introducing macro-level approximation into the normalization procedure. Ideally, normalization would use supply-chain-specific funding indices, but such targeted data do not exist at international scale. This limitation means normalized growth rates isolate supply chain themes from general R&D expansion but cannot distinguish genuine strategic prioritization from proportional increases in operational management research broadly defined.

Fifth, this study analyzes grant metadata in isolation without linking to downstream outcomes including publications, patents, or technology adoption. While grant awards represent forward-looking investment decisions, actual scientific and commercial impacts depend on project execution success, knowledge diffusion effectiveness, and market receptivity. Future research integrating grant data with bibliometric citation networks and patent family linkages would enable assessment of funding productivity and identification of high-impact research trajectories, providing an empirical foundation for optimizing portfolio allocation criteria beyond thematic diversity alone.

Finally, composite deduplication based on metadata matching may in rare cases exclude legitimate grants where identical metadata co-occurs with distinct content. The title-only sensitivity analysis provides an upper-bound estimate that false-positive merges represent 6.8 percent of the deduplicated corpus. The true rate likely falls substantially below this bound, but we acknowledge this as a methodological limitation and report sensitivity transparently for user confidence calibration.

Conclusion

This investigation develops and implements a computational framework for discovering thematic structures and temporal evolution patterns in supply chain research funding through unsupervised machine learning applied to 7,956 quality-assured grant abstracts retrieved from Web of Science database in June 2026. Analysis reveals 13 distinct thematic clusters exhibiting heterogeneous growth trajectories, with rapid expansion in bioenergy value chains, quantum computing infrastructure, battery supply networks, additive manufacturing, and cybersecurity domains contrasting with stabilization in urban freight logistics and mathematical optimization methods.

Three principal contributions emerge. Empirically, we deliver evidence-based characterization of global supply chain research investment patterns revealing strategic reorientation toward sustainability transitions, technological transformation, and resilience enhancement. The prominence of bioenergy (172 percent GERD-normalized growth), quantum infrastructure (95 percent growth), battery supply networks (94 percent growth), additive manufacturing (83 percent growth), and cybersecurity (67 percent growth) demonstrates research system responsiveness to contemporary imperatives while revealing anticipatory investment in nascent technologies preceding commercial maturity. Methodologically, we contribute reproducible protocols for grant corpus quality assurance incorporating right-censoring correction, GERD normalization, multilingual embedding validation, and sensitivity analysis for lifecycle classification, with transparently reported preprocessing that removed 1,793 duplicate records and excluded 380 right-censored records from temporal analysis. Practically, findings provide actionable intelligence for funding agencies assessing portfolio balance, revealing 37.6 percent concentration in emerging themes exceeding the ideal 25 percent benchmark and 7.6 percent mature-stage investment falling far below the 30 percent target, researchers identifying high-momentum domains with five emerging clusters exhibiting growth exceeding 67 percent, and practitioners forecasting technology trajectories indicating imminent commercialization readiness for bioenergy and battery recycling supply chain innovations.

Results inform strategic resource allocation across stakeholder groups. Funding agencies should consider portfolio rebalancing to increase mature-stage translational research allocation by approximately 20 percentage points, mitigating risk of synchronized emerging-theme maturation in the late 2020s overwhelming translational capacity. Academic researchers gain evidence for positioning proposals in expanding themes while recognizing that emerging-cluster competition intensity demands genuine interdisciplinary novelty rather than incremental methodological extensions. Industry practitioners receive early signals of publicly funded technology development relevant for innovation planning, particularly regarding bioeconomy supply networks and circular battery systems likely achieving commercial viability in the late 2020s.

The temporal advantages of grant-based analysis over publication bibliometrics are empirically confirmed through identification of rapid-growth themes with peaks in 2022-2023. These clusters should produce publication surges in 2025-2027, providing 3-5 year predictive intelligence unavailable from retrospective citation analysis. For operations management researchers and innovation policy analysts, this forward-looking capability positions grant-based science mapping as an essential complement to traditional bibliometric approaches, particularly for technology forecasting and portfolio management applications where anticipatory rather than retrospective intelligence drives strategic value.

Supply chain management research stands at an inflection point where traditional efficiency optimization converges with sustainability transformation, digital revolution, resilience imperatives, and social sustainability challenges. Understanding investment patterns through computational discovery methods incorporating appropriate validity safeguards provides essential intelligence for navigating this evolving landscape and optimizing resource allocation across the innovation ecosystem. Future research should extend this framework to other operations management domains, integrate grant data with downstream outcome metrics including publications and patents, and develop predictive models linking investment patterns to technology adoption trajectories.

Author Contributions

Conceptualization, M.M. and S.A.; methodology, M.M.; software, M.M.; validation, M.M. and S.A.; formal analysis, M.M.; investigation, M.M.; resources, M.M.; data curation, M.M.; writing original draft preparation, M.M.; writing review and editing, M.M., S.A., A.M., and A.O.; visualization, M.M.; supervision, S.A.; project administration, M.M. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

Data supporting the findings of this study are available from the corresponding author upon reasonable request. The underlying grant records were retrieved from Web of Science and may be subject to database licensing restrictions.

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