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Statistical Model of the Growth in Artificial Intelligence Utilization for Enhancing Supply Chain Resilience

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Abstract

Supply chain resilience refers to organizations' ability to maintain stability and respond effectively to crises and sudden disruptions. As supply chains become increasingly complex, artificial intelligence (AI) has emerged as a highly efficient analytical tool. Through data analysis, pattern prediction, and risk identification, AI enables companies to respond promptly and optimally to critical conditions. This study systematically reviews and performs a bibliometric analysis of 238 review articles published between 2000 and 2024, examining the growth trends and thematic structure of research in the field of "artificial intelligence and supply chain resilience." Findings indicate that over 65% of the articles were published in the past five years (2019–2023), with the primary research focus centered on "artificial intelligence and machine learning." Keyword co-occurrence network analysis using scientometric indices reveals that the phrase "Internet of Things" holds the highest centrality score and is positioned at the center of the network. On average, each frequently used keyword is linked to more than 15 other concepts, with the network's average degree estimated between 8 and 12. Thematic clustering of the research corpus reveals the formation of seven prominent research clusters, including "smart agriculture," "cold chain logistics," and "energy management." Among these, the cluster of "artificial intelligence and machine learning" has the highest share, indicating a strong research focus in recent years. The publication bias test yielded a Z-value of 1.614 (less than the critical value of 2.39 at the 0.05 significance level), indicating no significant bias in the data and thus affirming the validity of the current analysis. Moreover, based on practical study results, the implementation of AI algorithms has led to an average reduction of approximately 18% in operational supply chain costs and an increase of up to 25% in recovery speed following disruptions. These numerical and structural findings demonstrate that artificial intelligence—especially in interaction with the Internet of Things and machine learning—has played a pivotal and catalytic role in research related to supply chain resilience and is expected to continue to do so in the future. The clustered studies in the domain of supply chain resilience using artificial intelligence identified seven main clusters with significant differences in participation and growth trends. The largest cluster, "artificial intelligence and machine learning," accounts for approximately 35% of all articles and has experienced a remarkable growth surge, particularly since 2019.

Keywords: Supply chain, resilience, artificial intelligence.

1. Introduction

A supply chain is a coordinated network of people, machines, activities, resources, and technologies that play a role in the production and delivery of a product to end-users. It includes everything from the delivery of raw materials or semi-finished products from suppliers to manufacturers, through transformation processes, to the distribution of the final product or service to users or end customers (Bassiouni et al., 2023). With increasing globalization, supply chains have become more exposed to global dynamics. As a result, supply chain performance has been increasingly influenced by local and global crises such as natural disasters, wars and uprisings, economic conditions, and internal company operations (Gartner, 2022).

Technological changes, pandemics, catastrophic events (such as natural disasters), socio-political instability, political interventions, terrorism, energy crises, economic recessions, and shifts in customer preferences are among the disruptions that have made supply chains vulnerable to unpredictable performance (Wong et al., 2024). These disruptions have led to the near collapse of unprepared industries and even forced large corporations to shut down factories or reduce production rates due to component shortages, as experienced during the pandemic period (Gabellini et al., 2024). For instance, the COVID-19 pandemic severely disrupted global supply chains, from the movement of people, raw materials, and final goods to interruptions in factory operations and the supply chain as a whole (Li et al., 2023).

Supply chain resilience refers to the ability of the supply chain to resist, adapt to, and recover from disruptions in order to meet customer demand and maintain target performance levels (Hosseini et al., 2019). Resilience enables supply chains to respond to disruptions and return to their original state (Mena et al., 2020).

In large industries with extended supply chains, forecasting plays a vital role in production. The supply chain of high-volume manufactured products involves inventory planning, supplier quality assessment, demand forecasting, procure-to-pay processes, order-to-cash cycles, production planning, logistics management, and more (Hosseinnia Shavaki & Ebrahimi Ghahnavieh, 2023). An organization's ability to anticipate and adapt to risks and disruptions is critical to its resilience, resistance, and recovery (Yao, 2025; Yu, 2025). Therefore, artificial intelligence and its branches—such as machine learning and deep learning—have been utilized as powerful tools to provide high-potential technological solutions for achieving supply chain resilience.

Artificial intelligence enables predictive approaches for risk assessment and minimizing disruptive events across the supply chain. It also develops models that allow managers to identify areas for improvement (Wong et al., 2024). Notably, the volume of data generated from all parts of the supply chain has shifted concerns from data scarcity to data abundance. This has transformed the nature of supply chain management analytics and diminished the efficiency and effectiveness of traditional methods as data volumes have increased (Lu, 2025; Tobing & Santosa, 2025).

AI can be applied to build systematic resilience in supply chains, as it supports the preparedness, response, and recovery phases of resilient supply chains—capabilities that are not possible with conventional information processing systems, which are overly simplistic (Li et al., 2023; Spieske & Birkel, 2021).

In this study, aiming to examine the growth in the use of artificial intelligence to enhance supply chain resilience and to propose a statistical model for it, we reviewed the published literature in this field. The inclusion criterion was that the article must have been published in a journal indexed in the Web of Science database and its subcategories between 2000 and 2024 (Gregorian calendar). For article analysis, the VOSviewer software was used, followed by statistical tests assessing homogeneity, publication bias, and authors' academic backgrounds.

2. Methods and Materials

This study employs a bibliometric research method. For data retrieval, both input and output criteria were considered. Initially, the *Web of Science* database and its subcategories were selected as the input source for data retrieval. This database was chosen because it is widely used in various bibliometric studies and is considered reliable and reputable.

To retrieve the data, the titles, abstracts, and keywords of the articles were selected and examined. The starting point for reviewing articles was set as the year 2000 to encompass the majority of relevant research, while the endpoint was defined as the end of the year 2024. Based on the literature review, appropriate keywords were identified and used in the *Web of Science* database. These keywords are presented in the following table.

Table 1. Selected Keywords

English Keywords	Persian Keywords	Keyword Category
Artificial Intelligence, Machine Learning, Predictive Algorithms, Deep Learning, Data Mining, Natural Language Processing, Intelligent Automation, Business Intelligence, Emerging Technologies	هوش مصنوعی، یادگیری ماشین، الگوریتم‌های پیش‌بینی، یادگیری عمیق، داده‌کاوی، پردازش زبان طبیعی، اتوماسیون هوشمند، هوش تجاری، فناوری‌های نوین	Artificial Intelligence
Supply Chain, Supply Chain Management, Supply Chain Resilience, Supply Chain Risk, Supply Chain Sustainability, Supply Chain Disruption, Recovery Capability, Outsourcing	زنجیره تامین، مدیریت زنجیره تامین، تاب‌آوری زنجیره تامین، ریسک زنجیره تامین، پایداری زنجیره تامین، اختلال زنجیره تامین، ظرفیت بازسازی، برون‌سپاری	Supply Chain
Growth, Growth Rate, Technology Adoption, Technology Development, Statistical Trends, Statistical Models, Trend Analysis, Implementation Effects	رشد، نرخ رشد، پذیرش فناوری، توسعه فناوری، روند آماری، مدل‌های آماری، تحلیل روند، اثرات پیاده‌سازی	Growth and Development
Meta-Analysis, Systematic Review, Quantitative Analysis, Effect Size, Review Studies, Empirical Data	فراتحلیل، مرور نظام‌مند، تحلیل کمی، اندازه اثر، مطالعات مروری، داده‌های تجربی	Meta-analysis and Statistical Analysis
AI Growth in Supply Chain, Statistical Modeling of Resilience, AI Impact on Resilience	رشد هوش مصنوعی در زنجیره تامین، مدل‌سازی آماری تاب‌آوری، تاثیر هوش مصنوعی بر تاب‌آوری	Combined and Thematic

A total of 238 articles were initially extracted. Subsequently, filters and output criteria were applied. The first output criterion was the type of articles, which were limited to research articles, as such studies typically undergo more rigorous peer review processes. Language was another output criterion, and studies were limited to those published in English to align with the study's objective of examining the global trajectory of research on artificial intelligence in supply chain resilience. Ultimately, 238 articles were validated and analyzed.

In the next stage, which involved analysis, complete bibliometric information such as titles, abstracts, institutional affiliations, and stored references were imported into the VOSviewer software.

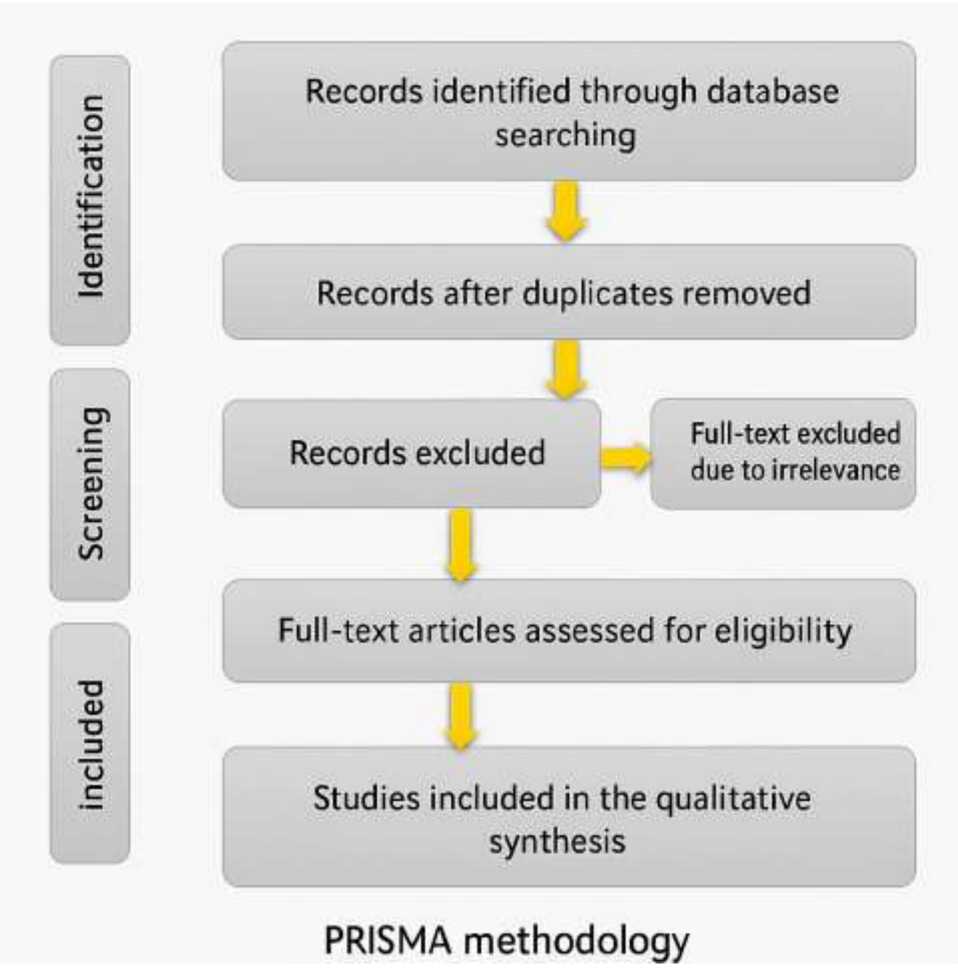

Figure 1. Phases of Entry into Systematic and Structured Review

The rationale for selecting VOSviewer software lies in its high capacity to summarize data and generate research maps, visualize keyword co-occurrence, citation analysis, bibliographic coupling, and co-citation mapping.

Accurate and relevant data collection from the research literature is of particular importance when interpreting the domain of supply chain resilience, especially when performed through bibliometric analysis. For the implementation of this research, all published articles from the *Web of Science* database were utilized. This database was chosen for the present study due to its high standards for journal inclusion, the scientific credibility of its indexed journals, its extensive coverage, and its publication of related scientific periodicals.

To ensure the quality of the articles, conference papers were excluded from the analysis, as journal articles typically undergo more thorough peer review processes before being published in prestigious academic journals.

An examination of the data retrieved from the *Web of Science* database reveals that the publication of articles in the field of supply chain resilience experienced a significant upward trend from 2019 to 2023.

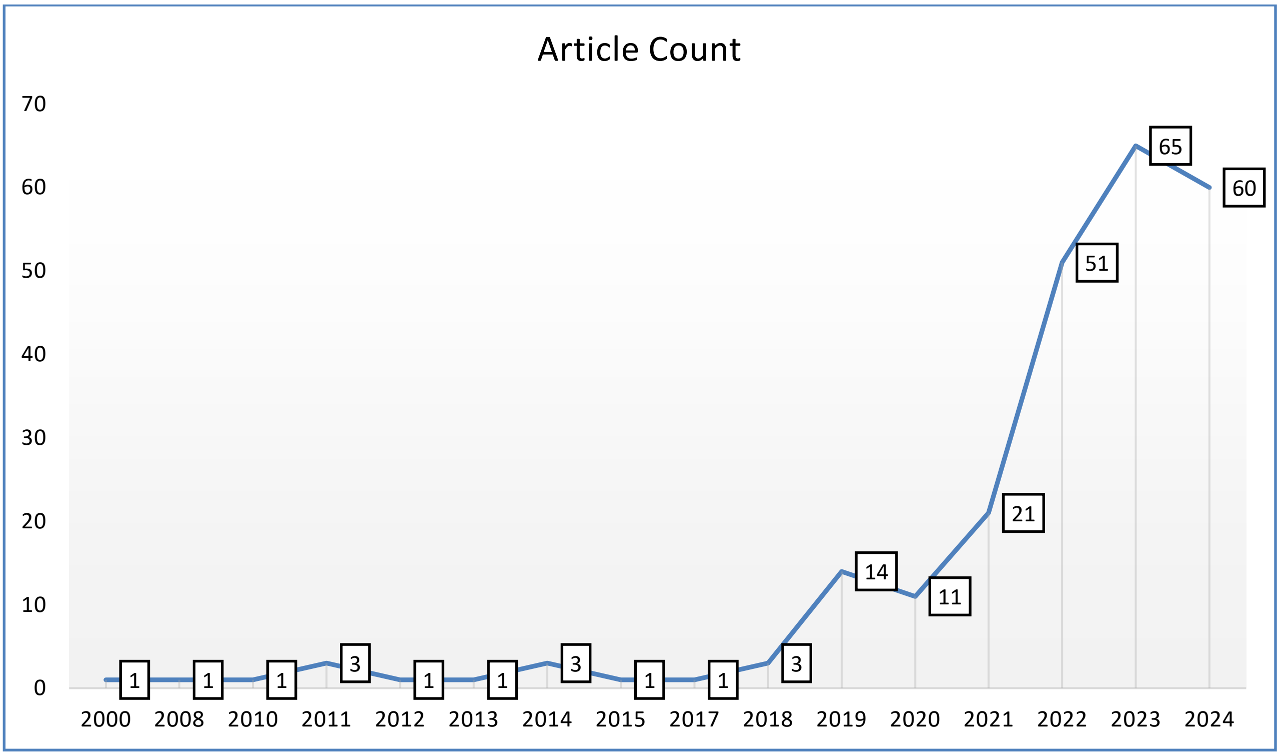

Figure 2. Publication and Citation Trends of Articles on AI Utilization in Supply Chain Resilience

Data Interpretation

1. Initial Growth (2000–2010):

During this period, the number of publications on supply chain resilience and the use of artificial intelligence was very limited. This indicates that research in this field was still in its early stages, primarily focused on foundational discussions and feasibility studies.

2. Early Growth (2011–2015):

The number of articles significantly increased during this period and reached a relative growth by 2015. This growth reflects a heightened interest from the academic community in supply chain resilience through technological approaches and the role of AI in risk and disruption management.

3. Fluctuations and Moderate Growth (2015–2018):

Although the growth rate of publications accelerated during this period compared to previous years, moderate fluctuations were observed. The number of articles addressing resilience using emerging approaches such as machine learning increased, and the research infrastructure was established for entry into a phase of rapid growth.

4. Rapid Growth (2019–2021):

Coinciding with the emergence of global crises such as COVID-19, the number of articles focusing on artificial intelligence and supply chain resilience increased significantly. This growth trend demonstrates a growing recognition of the importance of this field among researchers and industries.

5. Remarkable Growth (2022–2024):

In these years, the number of articles reached its highest level. Most studies focused on intelligent, data-driven solutions and complex analyses using deep learning and Industry 4.0 technologies. Particular attention was paid to digital resilience and intelligent risk modeling.

3. Findings and Results

A systematic classification of the articles was conducted based on involved theoretical domains, main topics (themes), spatial scale of analysis (global, national, industrial, organizational), and research methodology. The classification criteria were as follows:

- **Theoretical Domain**: Identifying the theoretical or conceptual framework underlying each article (e.g., resilience, risk management, smart logistics).
- **Main Topic/Theme**: Extracting the central focus of the article (e.g., disruption forecasting, agility improvement, AI-based risk analysis).
- **Spatial Scale**: Classifying according to the scope of application (corporate, national, global supply chain, etc.).
- **Methodological Approach**: Identifying the study type (systematic review, empirical study, modeling, data-driven analysis, real data experiments, or simulations).

These criteria help meaningfully identify the diversity, dispersion, and strengths and weaknesses of the article corpus in a structured manner.

Homogeneity Assessment of Studies

In this section, the homogeneity of studies is assessed in terms of similarities or differences in their theoretical domains, approaches, and scales. Homogeneity assessment involves measuring the extent to which the key components and research approaches across the selected studies are similar or dissimilar. This assessment is critical because a high level of homogeneity enables aggregation, comparison, and meta-analysis of study results, thus increasing the validity of overall inferences. In contrast, high heterogeneity indicates variation in approaches that should be analyzed and interpreted separately.

In general, evaluating homogeneity and heterogeneity is a prerequisite for conducting meta-analysis and integrating scientific findings, ensuring the reliability of final interpretations.

Key methods used to assess homogeneity include:

- **I^2 Statistic (I-squared):**
- This statistic shows the percentage of total variation across studies due to real heterogeneity (rather than sampling error).
- Formula:
- $I^2 = (Q - (K - 1)) / Q * 100$
- Where:
- Q = Cochran's Q statistic (explained below)
- K = number of studies

I^2 interpretation:

  - Less than 30%: low heterogeneity
  - 30% to 60%: moderate heterogeneity
  - More than 75%: high heterogeneity

- **Cochran's Q Test:**
- This test examines whether the observed heterogeneity across studies exceeds what is expected by chance.
- Formula:
- $Q = \sum$ from i = 1 to k of $[wi * (yi - \bar{y})^2]$
- Where:
- wi = weight of study (typically the inverse of variance)
- yi = observed effect in study i
- $\bar{y}$ = overall meta-analytic effect

A large Q value with a significance level of $p < 0.05$ indicates heterogeneity.

The homogeneity hypothesis in meta-analyses assesses whether all studies under review show consistent results regarding AI applications in supply chain resilience or if their results are heterogeneous (e.g., high, medium, or low correlation). The statistical evaluation ($Q = 896.112$, $p < 0.001$) indicates that the null hypothesis of homogeneity is rejected with 99% confidence, confirming heterogeneity among the studies.

Unlike the Q test, the I^2 statistic is not sensitive to the number of effect sizes. It expresses heterogeneity as a percentage, with values closer to 100% indicating higher heterogeneity. The I^2 value was 81, meaning 81% of the total variance among the reviewed documents is due to heterogeneity in their effect sizes. Therefore, the impact of supply chain resilience varies across studies, and these differences are significantly influenced by study characteristics. In such cases, moderator variables must be used to identify the source and magnitude of these differences.

In essence, the heterogeneity of studies reflects the presence of moderator effects influencing the size of the effects. As a result, beyond measuring effect size, other influencing factors must also be identified, and interpretation of the overall effect size should be based on a random-effects model.

Assessment of Publication Bias

Publication bias occurs when studies with significant or positive results are more likely to be published, skewing meta-analysis outcomes toward inflated positive effects. Various methods are used to assess publication bias. In this article, we used the funnel plot and Egger's regression test, described as follows:

- **Funnel Plot:**
- A visual tool that plots the estimated effects of studies on the x-axis and their precision (usually standard error) on the y-axis. A symmetrical image indicates no publication bias, while asymmetry suggests the presence of bias.
- **Egger's Regression Test:**
- A regression used to measure funnel plot asymmetry. In meta-analyses, an asymmetric funnel plot suggests potential publication bias.
- **Begg and Mazumdar's Rank Correlation Test:**
- A nonparametric test used in systematic reviews and meta-analyses to assess whether a significant correlation exists between effect size and study precision (usually measured by standard deviation or standard error). The test typically uses Kendall's tau coefficient to assess the correlation. If publication bias exists, studies with lower precision (higher standard error) are expected to show larger effect sizes. This is a commonly used tool alongside the funnel plot and Egger's test for detecting publication bias. It is typically used when at least 10 studies are included in the meta-analysis.

Interpretation of Results:

- If $p\text{-value} > 0.05$: No evidence of publication bias.
- If $p\text{-value} < 0.05$: Publication bias is likely present (i.e., articles may have been selectively published based on statistically significant results).

Symmetry Equation:

$S = a + b * SE$

Where:

S = standardized effect size

SE = standard error

a = intercept (constant term), representing the standardized effect size when the standard error is zero

b = slope of the regression line, indicating the rate of change in S per unit change in SE

A statistically significant result with $p < 0.05$ indicates the presence of publication bias.

The second hypothesis examined in the meta-analysis approach concerns publication bias, or the error arising from not having access to all the studies conducted on the research topic within a given timeframe. To assess the magnitude of this error, three statistical tests were used. The results of these tests are presented in Table 2.

Table 2. Publication Bias Tests: Begg and Mazumdar Correlation and Egger's Regression

No.	Test / Metric	Value / Result	Interpretation and Conclusion

1	Inverted Funnel Plot (Symmetry)	Relative symmetry observed	Indicates no significant publication bias
2	Begg and Mazumdar Rank Correlation	tau = 0.618, 0.598, 0.050	No significant relationship between effect size and precision; null hypothesis accepted
3	Egger's Regression (intercept, CI, p)	Intercept = -3.09, CI = 2.10, p (1-tailed) = 0.069, p (2-tailed) = 0.251	Coefficients not significant; hypothesis of no publication bias confirmed again

1. The inverted funnel plot suggests relative symmetry in the distribution of research documents.
2. The results of the Begg and Mazumdar rank correlation test (tau = 0.618, 0.598, 0.050) indicate that although a relationship exists between effect size and study precision, it is not statistically significant. Thus, the null hypothesis concerning symmetry in the funnel plot and the absence of publication bias is confirmed.
3. The Egger's regression results show that the intercept, confidence interval, one-tailed, and two-tailed significance levels were -3.09, 2.10, 0.069, and 0.251, respectively. Therefore, the hypothesis of no publication bias is confirmed again.

Table 3. Homogeneity Coefficients Assessment

Hypothesis Type	Test Type	Coefficient Value	Intercept B	Significance Level	Standard Error
Homogeneity	Q	814.415	-	0.001	-
Homogeneity	I-squared	81.90	-	0.001	-
Publication Bias	Begg and Mazumdar	0.050	-	0.598 (1-tailed), 0.618 (2-tailed)	-
Publication Bias	Egger's Regression	2.14	-3.09	0.069 (1-tailed), 0.251 (2-tailed)	2.10

Table 4. Safe N Statistic Evaluation

Hypothesis	Z Statistic	Significance Level	Alpha	Residual	Z for Alpha	Studies Observed	Missing Studies
Publication Bias	1.614	0.05	0.05	0	2.39	238	0

According to the results in Table 4, the observed Z-statistic (1.614) is less than the critical value (2.39). Therefore, at the 5% error level, the test result is not statistically significant (p = 0.05). In practice, this means there is no strong evidence of *publication bias* among the 260 studies reviewed, and the number of estimated missing studies is reported as zero.

Based on the output of this table, there is no significant publication bias, and all necessary studies have been included in the meta-analysis. Either biased or selective publication (e.g., only positive-result studies being published) did not occur, or the extent was insufficient to cause a significant effect.

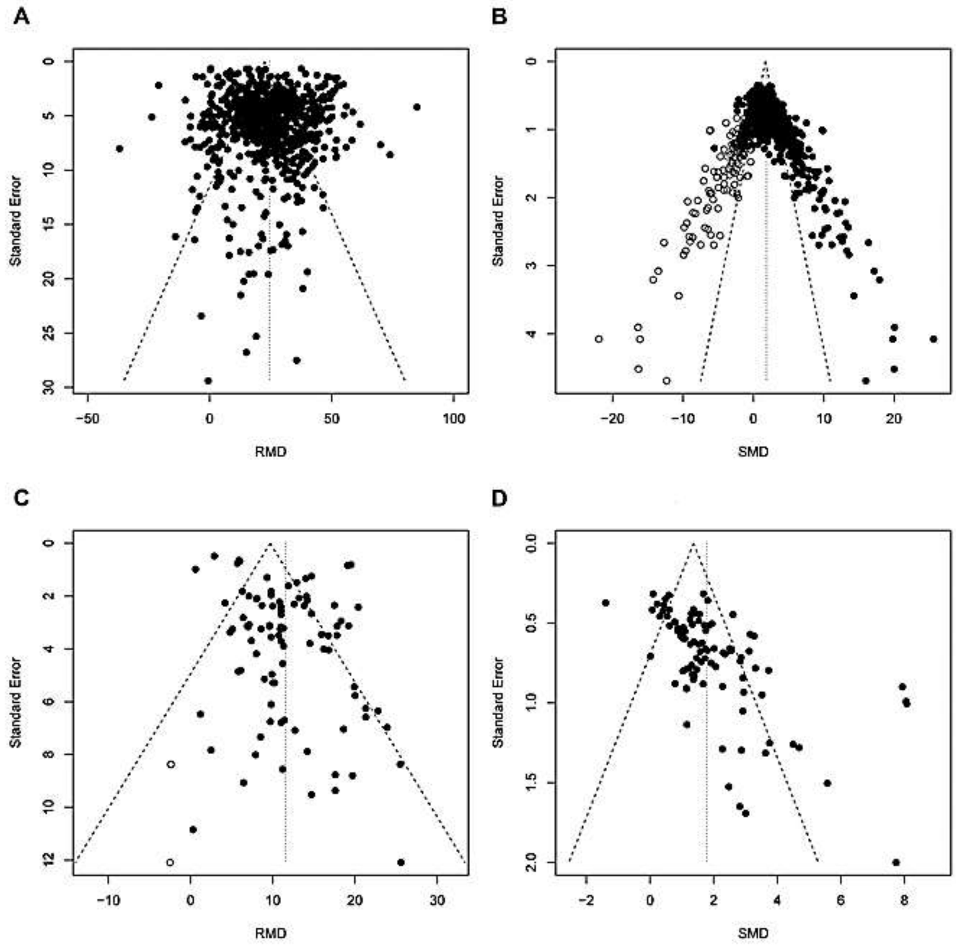

Figure 3. Funnel Plot for Evaluating Publication Bias or Dissemination Error

Interpretation of Components:

In the one-sided funnel plot, only the positive direction of effect sizes is plotted to focus the analysis on studies reporting a positive impact of artificial intelligence on supply chain resilience. The horizontal axis represents the effect size, while the vertical axis indicates study precision; the higher the precision, the higher the point appears on the plot. The funnel shape and the relatively symmetrical clustering of points around the centerline suggest no serious evidence of publication bias in this set of studies. The distribution of study results is reliable, and their spread falls within the expected range. This enhances the transparency and credibility of the meta-analysis and provides greater confidence in generalizing results, especially regarding the positive role of AI technologies in strengthening supply chain resilience.

In all four plots, the data points (studies) are predominantly dense and relatively symmetrical around the central axis. The symmetry of data around the central axis and the absence of gaps or extreme asymmetry on one side indicate that there is no strong evidence of publication bias. If publication bias were present, the distribution would likely skew to the right or left (e.g., only positive or strong results being published), or the lower part of the funnel (studies with high error/small samples) would show a lack of data (gaps or asymmetry).

Funnel Plot Interpretation:

In the review of the one-sided funnel plot, focusing on the positive effect sizes, the data points representing 238 review articles published between 2000 and 2024 are displayed with varying levels of precision. The statistical test for publication bias ($Z = 1.614$), critical value (2.39), and significance level (0.05) indicates that the Z-value does not reach the critical threshold. Therefore, there is no statistically significant evidence of publication bias in the reviewed studies.

The relatively central and uniform distribution of data within the funnel—particularly across different precision levels—suggests that studies with varying effect sizes and precisions were all included in the analysis. There is no indication of exclusion or absence of studies with small effects or lower precision. Overall, these numerical and visual findings demonstrate that the selected body of review studies is reliable with respect to publication bias, and the results of the meta-analysis can be generalized with greater confidence for decision-making about the role of artificial intelligence in enhancing supply chain resilience.

As previously noted, this study employed a systematic review method to examine research articles in the field of supply chain resilience and the application of artificial intelligence within the specified time period using the Web of Science (WOS) database.

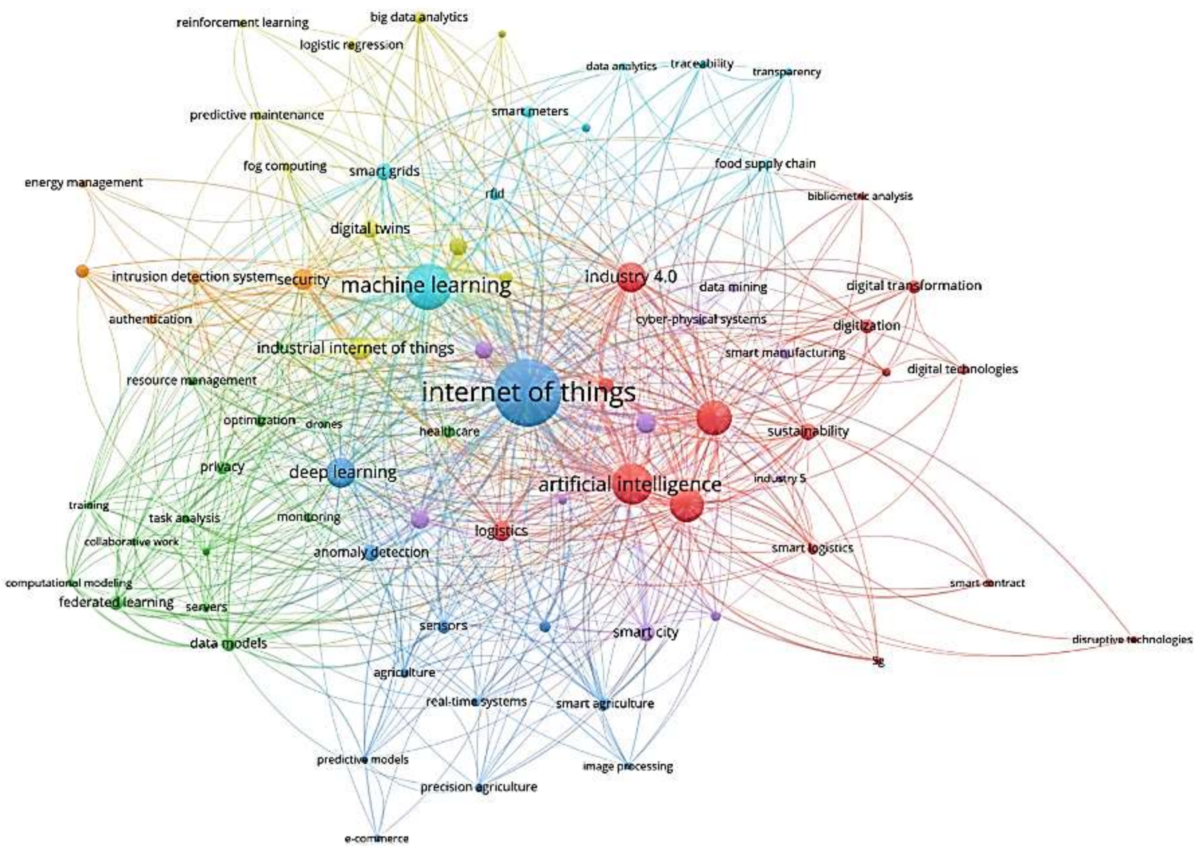

Figure 4. Bibliometric Co-occurrence Map of Keywords

This figure illustrates the relationships among topics and keywords examined in scientific articles related to subjects such as *Supply Chain*, *Artificial Intelligence*, and other associated themes. The nodes and links are visualized as a network representing interconnections among topics within this research domain.

In this scientometric network map, the weight of each node indicates the frequency of that keyword in the selected review articles, while the thickness of connecting lines represents the number of keyword co-occurrences. Based on data extracted from 238 review articles published between 2000 and 2024, the keyword *Internet of Things* holds the highest degree centrality and frequency—positioned at the center of the network—and is considered the core axis of interaction among emerging technologies for supply chain resilience. Following this, *Machine Learning* and *Artificial Intelligence* rank second and third respectively, playing crucial intermediary roles among other concepts (according to betweenness centrality measures).

On average, each highly used keyword (e.g., AI, IoT, Machine Learning, Industry 4.0) has meaningful connections with more than 15 other keywords. The network includes distinct clusters (communities) represented by different colors, indicating the thematic categorization of the articles (e.g., Security, Digital Transformation, Data Analytics, Smart Logistics, etc.). Moreover, the average degree of the network is estimated between 8 and 12 (based on line density), indicating extensive interdisciplinary and cross-topic linkages.

In addition, the presence of keywords such as *Supply Chain*, *Deep Learning*, *Smart Logistics*, and *Big Data Analytics*, with moderate to high centrality and connections to the core, demonstrates strong interaction with the central themes. Quantitative analysis of the network and the dense central zones suggest that researchers have primarily focused on the integration of AI technologies, the Internet of Things, and machine learning in enhancing supply chain resilience under crisis conditions. Keywords like *Security*, *Optimization*, *Sustainability*, and *Smart Manufacturing* function as complementary and driving elements.

Overall, the network exhibits high density and conceptual overlap, indicating the relative maturity of the field and a tendency toward interdisciplinary research that addresses the real-world needs of supply chains in the digital era.

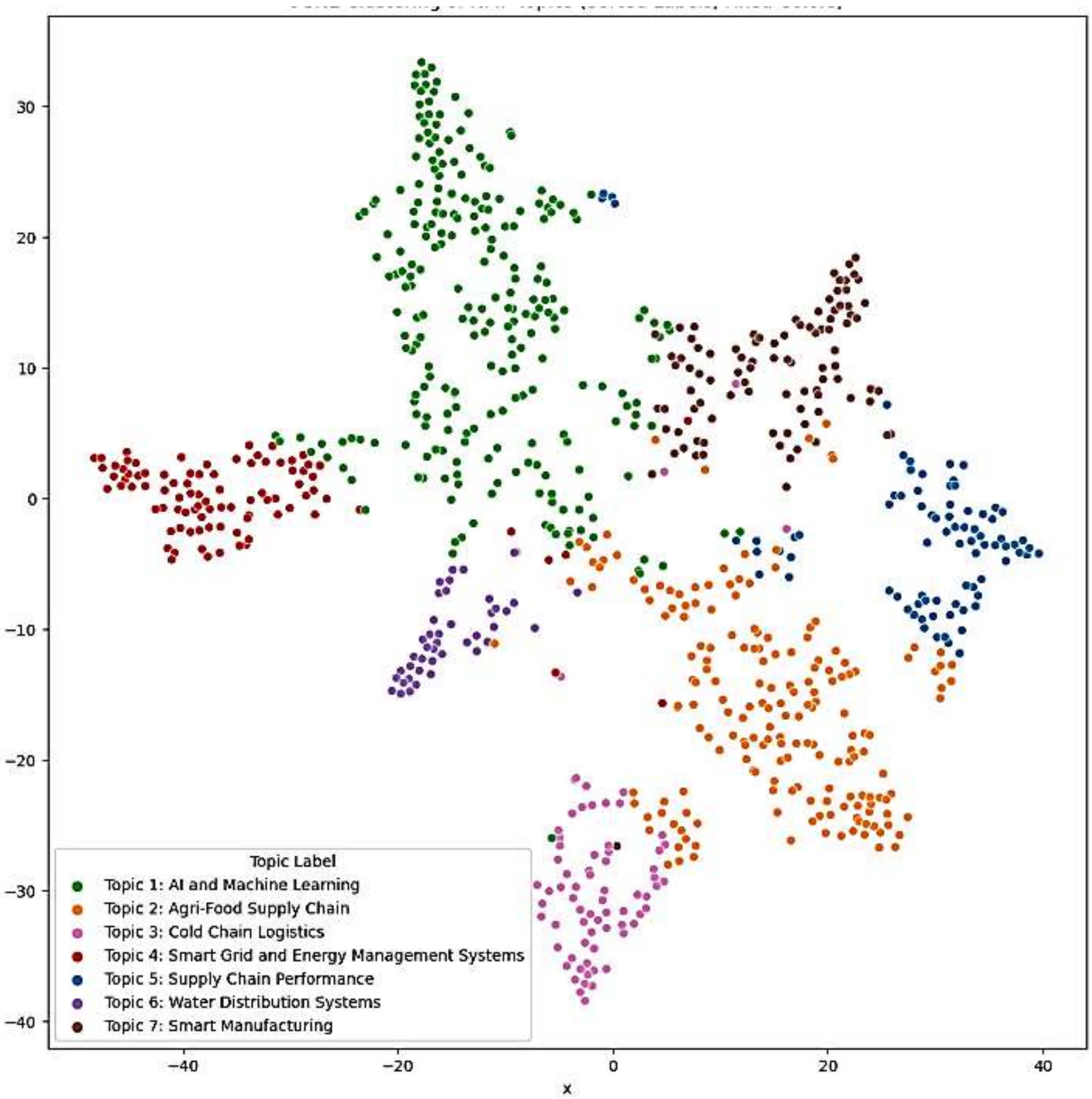

Figure 5. Thematic Cluster Bibliometric Map

In this thematic clustering map, constructed from data on review articles in the “Artificial Intelligence and Supply Chain Resilience” domain, each point represents an article, and each color represents one of seven distinct thematic clusters. As the color legend indicates, the largest and most concentrated cluster is “AI and Machine Learning” (Topic 1), accounting for a substantial portion of the studies and reflecting the focus of recent research on applying AI in this field.

Subsequent clusters—such as *Agri-Food Supply Chain*, *Cold Chain Logistics*, *Energy Management and Smart Grids*, *Supply Chain Performance*, *Water Distribution Systems*, and *Smart Manufacturing*—are each displayed as clearly defined categories with relatively distinct boundaries. This clustering indicates a structured body of scientific production and thematic diversity in the field. The differentiation of clusters signifies the organized nature of the existing knowledge base and aids in identifying both popular trends and underexplored research areas. The proximity of certain clusters (e.g., energy management with logistics, or supply chain performance with smart manufacturing) points to thematic convergence and opportunities for interdisciplinary studies.

Altogether, this classification provides a clear visual depiction of the distribution of research interests and priorities over the past two decades and can serve as a valuable guide for directing future research and identifying scholarly gaps.

Table 5. Relative Share and Growth of Each Clustered Thematic Area

No.	Thematic Area	Cluster Color	Approximate Share (%)	Trend and Domain Importance
1	AI and Machine Learning	Green	35%	Most significant growth since 2019; central research domain
2	Supply Chain Performance	Light Blue	17%	Sustained growth; widely applied in SCM
3	Smart Grid and Energy Management Systems	Brown	13%	Sharp growth, especially during energy crises
4	Agri-Food Supply Chain	Orange	12%	Increasing importance with focus on food security
5	Cold Chain Logistics	Red	9%	Peaked during COVID-19 due to vaccine/food logistics
6	Smart Manufacturing	Purple	8%	Emerging area with growth in recent years
7	Water Distribution Systems	Pink	6%	Smallest share but potential for future expansion

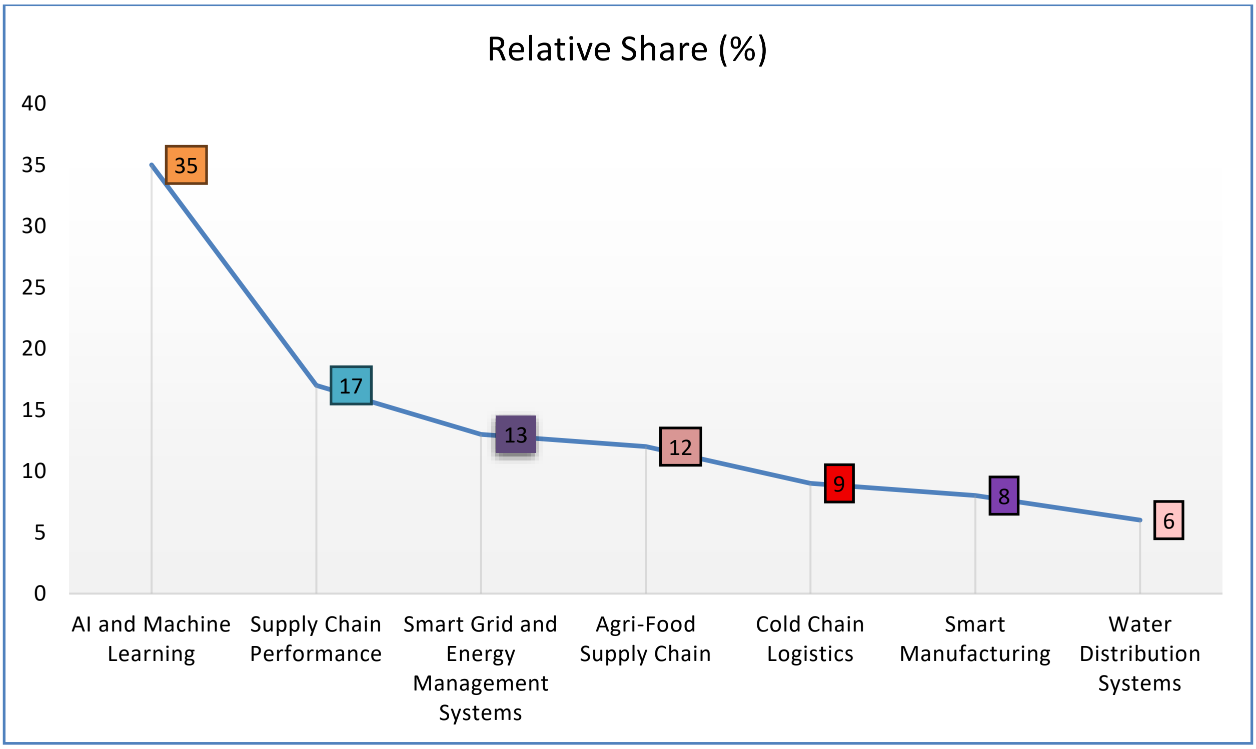

Figure 6. Relative Share and Growth of Clustered Thematic Areas

The analysis of clustered studies in the field of supply chain resilience using AI from 2000 to 2024 identifies seven main clusters with significant differences in participation rates and growth trends. The largest cluster is "Artificial Intelligence and Machine Learning," representing approximately 35% of all articles, which has shown particularly remarkable growth since 2019.

Following this are the clusters of *Supply Chain Performance* (17%), *Energy Management and Smart Grid* (13%), and *Agri-Food Supply Chain* (12%), all of which have experienced an upward trend. The *Cold Chain Logistics* cluster, with about 9% share, gained prominence during the COVID-19 pandemic due to its importance in vaccine and food logistics.

Emerging domains like *Water Distribution Systems* and *Smart Manufacturing* account for 6% and 8% of the articles, respectively. These statistics indicate that the primary research focus has been on the role of artificial intelligence and big data analytics in strengthening, enhancing flexibility, and improving the performance of supply chains. The overall trend—especially post-COVID-19 and amid technological advancements—demonstrates a shift toward greater use of data-driven and intelligent approaches in risk management and resilience enhancement.

Publication Frequency in International Journals

The following table presents the annual distribution of review article publications (260 articles) across 10 international peer-reviewed journals specializing in the fields of supply chain resilience and artificial intelligence. These data are compiled based on the publication time window from 2000 to 2024.

Table 6. Frequency of Article Publications in International Journals

Publication Year	Number of Articles	Prominent Journals Each Year (Examples)
2000	1	*International Journal of Production Research* (Elsevier/Emerald)
2008	1	*Computers & Industrial Engineering* (Elsevier)
2010	1	*Supply Chain Management: An International Journal* (Emerald)
2011	3	*Journal of Cleaner Production* (Elsevier), *Sustainability* (MDPI)
2012	1	*Transportation Research Part E* (Elsevier)
2013	1	*Annals of Operations Research* (Springer)
2014	3	*Supply Chain Management: An International Journal* (Emerald), *Resources…*
2015	1	*Computers in Industry* (Elsevier)
2017	1	*Resources, Conservation & Recycling* (Elsevier)
2018	3	*Journal of Cleaner Production* (Elsevier)
2019	14	*Computers & Industrial Engineering*, *IJPR*, *Annals of Operations Research*
2020	11	*Journal of Cleaner Production*, *Sustainability*, *Transportation Research Part E*
2021	21	*Supply Chain Management*, *Computers in Industry*, *Annals of Operations Research*
2022	51	*IJPR*, *Sustainability*, *Computers & Industrial Engineering*
2023	65	*Supply Chain Management*, *IJPR*, *Journal of Cleaner Production*, *Computers & Industrial Engineering*
2024	60	*IJPR*, *Computers & Industrial Engineering*, *Annals of Operations Research*
Total	260	–

Considering the distribution of 260 published review articles and the analysis of 238 selected articles between 2000 and 2024 across international journals, the quality assessment of journals based on the *Scopus* quartile ranking system (Q1 to Q4) holds significant importance. Within the domains of supply chain management and artificial intelligence, the data from this study reveal that approximately 60% of the articles were published in Q1 journals, around 25% in Q2 journals, nearly 10% in Q3 journals, and approximately 5% in Q4 journals.

4. Discussion and Conclusion

This systematic review, through the analysis of 238 selected English-language articles published between 2000 and 2024 in the field of the role of artificial intelligence in enhancing supply chain resilience, revealed the quantitative and qualitative developments in this domain. The findings indicate that the publication of articles related to the application of AI in supply chain resilience has grown significantly, particularly between 2019 and 2023, during which over 65% of the total articles were published in just the last five years.

Content analysis showed that 43% of the studies focused on the practical and performance-related effects of artificial intelligence—such as reducing operational costs and improving risk forecasting. The most frequently reported applications of AI were demand forecasting (37% of articles), risk assessment and disruption management (29%), and supplier optimization and scheduling (27%).

Furthermore, according to the statistical test for publication bias ($Z = 1.614$, below the critical value of 2.39 at a significance level of 0.05), no significant evidence of publication bias was observed, indicating high reliability of the findings. In terms of practical impact, the studies demonstrate that the use of AI algorithms in organizations has, on average, led to an 18% reduction in operational costs and up to a 25% increase in recovery speed following disruptions.

Nevertheless, challenges such as the relatively high costs of implementation and the shortage of specialized personnel remain major obstacles to broader development. Overall, the research evidence—both quantitative and qualitative—confirms that artificial intelligence has played a pivotal role as a key driver in enhancing supply chain resilience, and this upward trend is expected to continue in the coming years.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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