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Quantitative Methods for Agri-Food Supply Chain Resilience: A Systematic Literature Review Using Text Mining

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Abstract: Agri-food Supply Chains (AFSCs) face increasing disruptions from natural disasters, pandemics, and economic crises, necessitating robust quantitative analysis for resilience. This study conducts a Systematic Literature Review (SLR) using text mining and Latent Dirichlet Allocation (LDA) to identify six key research themes, including risk management, pandemic effects, simulation-based resilience, climate change, market price volatility, and optimization models. Findings reveal that multi-criteria decision-making, simulation, optimization, and machine learning are widely used, yet gaps remain in Artificial Intelligence (AI)-driven risk prediction, real-time data integration, and adaptive decision-making. This review offers insights for researchers and practitioners, emphasizing the need for AI, digital twins, and blockchain to enhance AFSC resilience.

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Keywords: agri-food supply chain, quantitative methods, text mining, latent Dirichlet allocation, literature review, resilient supply chains.

1. INTRODUCTION

Agri-food supply chains (AFSCs) are highly susceptible to disruptions caused by natural disasters, human-induced crises, and economic instabilities. These disruptions, which include earthquakes, hurricanes, floods, pandemics, terrorist attacks, labour strikes, economic downturns, and currency devaluations, occur less frequently than operational risks but often have far-reaching consequences (Tang, 2006). While operational risks stem from inherent uncertainties—such as fluctuating demand and variable costs—disruptions introduce severe and often unpredictable shocks to the supply chain (SC), challenging its resilience and efficiency.

AFSCs encompass multiple interconnected echelons in a farm-to-fork sequence, including farming (land cultivation and crop production), processing and manufacturing, quality testing, packaging, warehousing, transportation, distribution, and marketing (Tsolakis et al., 2014). At each stage, these systems are vulnerable to diverse disruption events. For instance, pandemics can significantly alter consumer purchasing behaviours, leading to panic buying and stockpiling. Climate change-driven phenomena, such as droughts and snowstorms, can reduce agricultural yields, disrupt supply flows, and delay deliveries (Rahman et al., 2022). Similarly, sanitary crises—such as avian influenza outbreaks—can severely impact SCs by reducing raw material availability and triggering demand fluctuations due to consumer health concerns (Vo and Thiel, 2011). Given the profound consequences of such disruptions, the ability to analyse, measure, and mitigate their impacts is crucial for ensuring AFSC resilience. Quantitative methods play a critical role in this process by enabling structured analysis and decision-making under uncertainty. Existing studies have explored various quantitative approaches to assess AFSC resilience in the face of disruptions (Esteso et. al., 2018; Hosseini et al., 2019; Imbiri et al., 2024; Paillin et al., 2024; Rejeb et al., 2022; Stone and Rahimifard, 2018; Tebaldi and Vignali, 2023; Zhao et al., 2022). However, many of these reviews have limited scopes; for example, Tebaldi and Vignali (2023) provide a review of only 26 studies with a specific focus on resilience assessment. To date, there remains a lack of a comprehensive systematic literature review (SLR) that synthesizes quantitative methodologies applied to AFSC disruptions at a broader scale.

This study aims to address this gap by systematically reviewing the existing literature to identify and classify the primary quantitative methods used in analysing AFSC disruptions. Specifically, this paper seeks to answer the following research questions:

1. What are the key research themes in quantitative methods applied to AFSC resilience under disruptions?
2. How have these quantitative methods been utilized, and what gaps remain in the literature?
3. What future research directions can be proposed to strengthen AFSC resilience using quantitative approaches?

Unlike previous literature reviews that primarily rely on manual classification techniques, this study employs text mining—specifically, Latent Dirichlet Allocation (LDA)—to systematically extract research themes from the collected

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studies. The remainder of this paper is structured as follows: Section 2 outlines the SLR methodology, detailing the data collection and screening process. Section 3 describes the text mining approach and its application in identifying key research themes. Section 4 presents the extracted topics and discusses emerging research gaps. Finally, Section 5 concludes the study with key findings and proposed future research directions.

2. METHODOLOGY

This study employs an SLR to identify and analyse quantitative methods applied to AFSC disruptions. The SLR follows a structured methodology to ensure a comprehensive, replicable, and unbiased selection of relevant studies. The review process consists of four key stages: (i) defining search criteria, (ii) database selection and search execution, (iii) screening and filtering relevant articles, and (iv) applying text mining for research theme identification.

2.1 Database Selection and Search Strategy

To ensure broad coverage of the literature, two leading academic databases—Scopus and Web of Science (WoS)—were selected. These databases are widely recognized for their extensive indexing of peer-reviewed journal articles in SC management and operations research. The search strategy was designed to retrieve articles published between 2009 and 2024, capturing research developments over the past 15 years.

A set of carefully selected keywords is used to construct the search queries, focusing on four primary research areas, presented in Table 1:

Table 1. Terms in the search queries

Area	Search terms
SC	("supply chain" OR "supply network" OR "value chain" OR "demand chain" OR "Cold chain") AND
Performance	("adaptive" OR "re*configur*" OR "flexib*" OR "resilien*" OR "reliab*" OR "robust" OR "responsive" OR "viab*") AND
Disruption	("crisis" OR "disrupt*" OR "disaster" OR "bullwhip" OR "pandemic" OR "ripple" OR "covid" OR "stress* " OR "risk") AND
Agri Food	("agri*" OR "food")

Boolean AND/OR operators are used to refine the search, ensuring that retrieved articles contained terms relevant to both AFSCs and quantitative methods for disruption analysis. The searches are conducted within the title, abstract, and keywords fields of the articles.

2.2 Article Selection and Screening

The initial search returned 2,177 articles (1,311 from Scopus and 866 from WoS). To refine the dataset, the following multi-stage filtering process is applied:

1. **Duplicate Removal:** Eliminating redundant entries, reducing the dataset to 1,292 unique articles.
2. **Title, Abstract, and Keyword Screening:** Articles are excluded if they are unrelated to AFSC resilience, focused only on descriptive analysis without quantitative modelling, or examined SC disruptions outside the agri-food sector. This step reduced the dataset to 180 articles.
3. **Full-Text Review and Inclusion Criteria:** The remaining articles undergo a thorough full-text review, applying the following inclusion and exclusion criteria:

Inclusion Criteria: i) Studies that apply quantitative methods (e.g., optimization, simulation, statistical modelling, machine learning) to analyse AFSC disruptions. ii) Papers focusing on SC resilience in response to disruptions. iii) Research involving multi-echelon AFSC structures rather than single-stage studies.

Exclusion Criteria: i) Studies that only provided basic descriptive statistics without a quantitative model. ii) Articles using text mining methods without further quantitative analysis. iii) Research limited to a single echelon of the SC (e.g., farm-level analysis only).

Following this selection process, a total of 112 articles are identified as core studies for analysis.

2.3 Text Mining and Topic Modelling

Given the large volume of selected studies, text mining is employed to systematically extract research themes. LDA, a widely used topic modelling technique, is chosen for this purpose. LDA is a probabilistic topic modelling algorithm that assumes each document (article) is a mixture of multiple latent topics, with each topic represented by a specific distribution of words (Blei et al., 2003). LDA operates by iteratively assigning words in a document to different topics based on probabilistic inference methods such as Gibbs sampling, expectation maximization, or variational Bayes inference (Jelodar et al., 2019). The resulting model provides:

- A **document-topic distribution** (indicating the proportion of each topic within an article).
- A **word-topic distribution** (highlighting significant words associated with each topic).

2.3.1 Text Preprocessing

To enhance the accuracy of topic modelling, extensive preprocessing is performed on the dataset, including:

- **Tokenization:** Splitting text into individual words (tokens).
- **Lowercasing:** Standardizing text by converting all words to lowercase.
- **Lemmatization:** Reducing words to their root forms to avoid redundancy.
- **Removal of Special Characters and Stop Words:** Eliminating punctuation, numbers, and commonly used words (e.g., "the," "and," "of") that do not contribute to topic identification.
- **Exclusion of Non-English Terms:** Ensuring consistency in text analysis.

2.3.2 Selection of Optimal Number of Topics

One challenge in LDA implementation is determining the optimal number of topics. There is no universally accepted method for this selection; therefore, a combination of empirical testing and computational metrics is used. The FindTopicsNumber function from the ldatuning package is applied to evaluate different topic numbers using semantic coherence metrics (Cao et al., 2009). Based on this analysis, six distinct topics are selected for further exploration.

2.3.3 LDA Implementation and Topic Extraction

The final LDA model is applied to the text corpus, aggregating titles, abstracts, and keywords from the 112 selected articles. The model identified six primary research themes, each characterized by key terms frequently appearing within its topic cluster. Figure 1 presents word clouds representing the most significant words within each topic. Since LDA does not automatically assign labels to topics, manual interpretation is performed by examining high-probability words and associated articles. Following the methodology outlined in this section, the subsequent sections of this paper are organized as follows: Section 3 provides an in-depth analysis of the extracted research themes using LDA. Section 4 discusses the findings, research gaps, and future research directions. Section 5 concludes the study with key insights and recommendations.

3. TEXT MINING

Topic modelling is a machine learning technique used to uncover latent themes within unstructured textual data. In the context of this study, it enables the systematic identification of key research areas in AFSC disruption analysis. Various algorithms facilitate topic modelling, including LDA (Blei et al., 2003), Latent Semantic Analysis (LSA), and Non-Negative Matrix Factorization (NMF) (Stevens et al., 2012). While LSA and NMF are effective for certain applications, LDA is widely regarded as the most suitable for literature reviews, as it maintains topic coherence and enhances interpretability (Asmussen and Møller, 2019). Consequently, this study employs LDA as the primary topic modelling technique. LDA is a probabilistic generative model that assumes documents are composed of multiple latent topics, each represented by a unique distribution of words. The model assigns words to topics iteratively, refining the topic distribution using methods such as Gibbs sampling, expectation maximization, or variational Bayes inference (Jelodar et al., 2019). The final output provides:

- **Document-topic distributions**, indicating the proportion of each topic within an article.
- **Word-topic distributions**, identifying significant words associated with each topic.

A key feature of LDA is that topics are **"latent"**, meaning they are not predefined but inferred from word co-occurrence patterns within the dataset. Before applying LDA, extensive text preprocessing is conducted to enhance the quality of extracted topics. Six steps are implemented as mentioned in Section 2.3.1. These preprocessing steps help reduce noise in the dataset and improve the accuracy of topic extraction

3.1 Determining the Optimal Number of Topics

As mentioned previously, one of the critical challenges in LDA is determining the optimal number of topics. Key factors considered in selecting the optimal topic count includes:

- **Model interpretability**: Ensuring extracted topics are distinct and meaningful.
- **Coherence scores**: Balancing topic consistency and diversity.
- **Computational efficiency**: Avoiding excessive topic fragmentation.

Based on these criteria, the six topics are identified to be:

1- Risk Mitigation and Risk Management in Agriculture

- **Focus**: Strategies for mitigating AFSC risks, including operational and disruption risks.
- **Common Methods**: Multi-Criteria Decision-Making (MCDM), cognitive maps, Artificial Intelligence (AI) and Machine Learning (ML).

2- COVID-19 Pandemic Effects on the Food SC

- **Focus**: Impact of pandemic-related disruptions on AFSC operations.
- **Common Methods**: Structural Equation Modelling (SEM), fuzzy decision-making, simulation.

- ***Resilient SC Models Based on Simulation***

- **Focus**: Use of simulation techniques to model AFSC disruptions and resilience strategies.
- **Common Methods**: Discrete Event Simulation (DES), Agent-based Modelling (ABM), System Dynamics (SD).

3- Agri-Food Systems Under Climate Change

- **Focus**: Effects of climate variability on AFSC stability and performance.
- **Common Methods**: ML, Geographic Information Systems (GIS)-based risk assessment, MCDM.

4- Disasters' Impact on Market Prices

- **Focus**: Economic and pricing effects of SC disruptions.
- **Common Methods**: Interrupted Time Series (ITS), game theory, price elasticity modelling.

5- Optimization Models for Agri-Food Networks

- **Focus**: Mathematical programming for AFSC resilience and decision-making.
- **Common Methods**: Mixed-Integer Linear Programming (MILP), metaheuristics, robust optimization.



Figure 1. Word clouds of Topics

Figure 1 presents word clouds for each extracted topic, visually illustrating the most significant terms that define these themes. The word clouds highlight frequently occurring terms within each topic, providing insights into the key focus areas of AFSC resilience research. Larger words indicate higher relevance within the given theme, reinforcing the differentiation between topics.

4. RESEARCH THEMES

This section presents a detailed analysis of the six research themes given in Section 3. Each theme represents a key area in the application of quantitative methods to the analysis of AFSC disruptions. The themes are discussed in terms of focus areas, commonly used methodologies, key findings, and research gaps, providing insights for future investigations.

4.1 Risk Mitigation and Risk Management in Agriculture

Risk management in AFSCs involves strategies to mitigate both operational risks (e.g., demand variability, cost fluctuations) and disruption risks (e.g., natural disasters, pandemics, economic crises) (Arabsheybani and Arshadi Khasmeh, 2021). Given the complexity of AFSC networks, researchers have increasingly employed quantitative risk assessment techniques to enhance SC resilience. Common quantitative methods involve:

- **MCDM**: Yazdani et al. (2022) apply the Best-Worst Method (BWM) and fuzzy MARCOS to rank AFSC risk factors.
- **Cognitive Maps, AI and ML**: Effah et al. (2023) integrate cognitive mapping and AI-based decision support to model risk propagation.

Despite advancements, existing studies focus primarily on risk identification rather than integrated risk management frameworks. Future research should:

- Integrate simulation-based risk assessment with AI-driven predictive modelling.
- Model the causal relationships among risk events, SC risks and mitigation strategies with Bayesian networks or fuzzy cognitive maps.

4.2 COVID-19 Pandemic Effects on the Food SC

The COVID-19 pandemic disrupted global food SCs, affecting production, logistics, and consumer behaviour. Studies highlight challenges such as panic buying, trade restrictions, labour shortages, and supply-demand imbalances (Shanker et al., 2022). Common quantitative methods involve:

- **SEM**: Khan and Ponce (2022) examine the relationship between Industry 4.0 technologies and SC resilience during COVID-19.
- **Fuzzy Decision-Making Approaches**: Kumar and Singh (2022) use fuzzy BWM and Quality Function Deployment (QFD) to analyse pandemic-driven SC risks.

Current studies predominantly focus on short-term responses. Future research should:

- Investigate long-term structural changes in AFSCs due to COVID-19.

4.3 Resilient SC Models Based on Simulation

Simulation-based models are widely used to assess SC resilience by analysing system behaviour under various disruption scenarios. Studies emphasize the role of DES, ABM, and SD in evaluating resilience strategies (Rahman et al., 2022). Common quantitative methods involve:

- **DES**: Burgos and Ivanov (2021) employ a digital twin-based simulation to assess pandemic-induced disruptions in food retail chains.
- **ABM**: Rahman et al. (2022) use ABM to model climate change-driven disruptions in potato SCs.
- **SD**: Vo and Thiel (2011) develop a SD model to analyse and improve the stability of the poultry SC during the Avian Influenza crisis.

Although simulation provides valuable insights, real-world validation is limited. Future work should:

- Integrate real-time data sources (e.g., IoT sensors, blockchain) into simulation models (Vu et al., 2024).
- Explore hybrid simulation-optimization frameworks for dynamic decision-making.

4.4 Agri-Food Systems Under Climate Change

Climate change significantly affects crop yields, SC logistics, and food security. Extreme weather events, such as droughts, floods, and snowstorms, disrupt AFSC operations (Effah et al., 2023). Common quantitative methods involve:

- **ML and GIS**: Rahman et al. (2022) combine ML with GIS data to analyse climate-induced risks.
- **MCDM**: Effah et al. (2023) categorize the extreme weather-induced risks according to related cocoa SC echelons, and BWM is used to rank these risks.

Current studies primarily focus on historical data-driven models. Future research should:

- Develop real-time adaptive models for climate risk management.
- Explore climate-resilient SC design frameworks integrating renewable energy solutions.

4.5 Disasters' Impact on Market Prices

Disruptions—such as pandemics, trade restrictions, and climate shocks—cause market price volatility in AFSCs. Studies analyse how supply-demand imbalances and logistical constraints influence pricing dynamics (Meena et al., 2024). Common quantitative methods involve:

- **ITS Analysis**: Meena et al. (2024) apply ITS to measure COVID-19 lockdown effects on agricultural commodity prices.
- **Game Theory and Price Elasticity Modelling**: Li et al. (2022) use game theory to optimize pricing strategies in dual-channel food SCs.
- **Econometric Models**: De and Singh (2023) examine post-pandemic pricing and service quality strategies.

Existing models often assume linear price responses to disruptions. Future research could:

- Explore nonlinear price dynamics using advanced econometric techniques.

4.6 Optimization Models for Agri-Food Networks

Mathematical optimization plays a critical role in designing resilient AFSCs. Studies employ MILP, metaheuristics, and robust optimization to address SC disruptions (Rahbari et al., 2024). Common quantitative methods involve:

- **MILP**: Behzadi et al. (2017) optimized wheat SC resilience under uncertainty.
- **Metaheuristic Algorithms**: Arabsheybani and Arshadi Khasmeh (2021) used genetic algorithms for resilient food network design.
- **Robust and Stochastic Optimization**: Rahbari et al. (2024) explored stochastic programming for mitigating war-induced disruptions.

Current models often rely on static optimization approaches. Future work should:

- Develop dynamic and real-time optimization frameworks integrating AI-driven predictive analytics.

5. CONCLUSION

This study conducts an SLR on quantitative methods for analysing AFSC disruptions, identifying six key research themes through LDA. The themes highlight the dominant methodologies used in AFSC resilience research, including MCDM, simulation modelling, optimization techniques, and ML-based approaches. While these methods have been instrumental in assessing AFSC vulnerabilities, gaps remain in areas such as real-time data integration, AI-driven predictive analytics, and dynamic optimization frameworks.

The findings have significant implications for both academia and industry. From a research perspective, this study contributes by systematically mapping quantitative methodologies, applying text mining for theme extraction, and identifying underexplored research areas. Practically, the results suggest that AI-driven decision support systems, digital twins, and blockchain-enabled real-time monitoring could significantly improve SC resilience. Moreover, policymakers should focus on climate adaptation strategies, pandemic preparedness, and market stabilization policies to strengthen global AFSC networks.

Despite its contributions, the study has certain limitations. It primarily focuses on journal articles, potentially overlooking insights from conference proceedings, industry reports, and case studies. Additionally, the research synthesis does not include empirical validation of proposed methodologies. Future studies should explore hybrid modelling approaches combining optimization and simulation, AI-driven risk prediction models, and behavioural aspects of SC resilience.

In conclusion, as global SCs face increasing disruptions from climate change, pandemics, and economic instability, advancing AFSC resilience through quantitative methods is more critical than ever. By integrating AI, real-time monitoring, and adaptive decision-making frameworks, researchers and practitioners can develop more robust, sustainable, and resilient AFSCs to withstand future disruptions.

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