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Leveraging Social Network Search Patterns for Customer-Centric Supply Chain Optimization: A Real-Time Case Study

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ABSTRACT

Objective: In the fast-fashion industry, rapidly changing customer preferences create significant challenges for demand forecasting and inventory management. Social media platforms have emerged as real-time sources of consumer sentiment and trend information. This study analyzes social network search patterns to build a customer-centric framework that enhances supply chain responsiveness and operational efficiency.

Methods: A real-time case study of a mid-sized Indian apparel brand demonstrates the integration of social media search analytics with supply chain systems. Using natural language processing (NLP), sentiment analysis, keyword clustering, search trend mapping, and real-time data pipelines, the framework analyzes trending queries and hashtags to identify emerging customer preferences. This enables production and inventory decisions to be aligned more effectively with market demand.

Results: The social media-driven framework improved demand forecasting accuracy and enhanced supply chain responsiveness. As a result, the company achieved a reduction in stockouts, improved product availability, and increased customer satisfaction. Integrating optimized search suggestion engines with inventory and production systems enabled effective alignment of consumer demand signals with supply chain operations.

Conclusion: The findings indicate that social network search behavior provides valuable real-time market intelligence for supply chain optimization. The proposed approach enables agile and responsive supply chains that adapt to changing customer preferences. Furthermore, AI-driven social media analytics can enhance supply chain resilience, competitiveness, and customer-centric decision-making, offering a strong foundation for future intelligent supply chain research.

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1. Introduction

In the era of digital transformation, the global business ecosystem has witnessed a radical shift from product-centric to customer-centric strategies. Modern consumers expect personalization, speed, and seamless interaction throughout their purchasing journey. This growing emphasis on customer-centricity is prompting companies to re-engineer their supply chain management (SCM) frameworks to be more agile, responsive, and data-driven. A significant enabler of this transformation is the proliferation of social media platforms, which now serve as powerful channels for real-time consumer expression, trend diffusion, and behavior analysis (Kim, C., et al, 2005).

Social media platforms like Twitter, Instagram, TikTok, and Facebook have evolved beyond communication tools to become vast repositories of consumer sentiment, preferences, and demand indicators. Users openly share their opinions, review products, create viral trends, and search for emerging items—creating an unprecedented volume of structured and unstructured data (K. S. Yogi, et al, 2024). These real-time interactions often precede traditional sales signals, providing businesses with an excellent opportunity to anticipate market demand rather than merely react to it.

In this context, search patterns on social networks—ranging from hashtags, location-based queries, to trending phrases—hold significant potential for supply chain optimization. They offer a unique glimpse into what consumers are interested in, what they are searching for, and how these interests evolve (Badulescu, Y., et al, 2024). By intelligently mining and interpreting these patterns, organizations can align their supply chain operations—from procurement and production to inventory and logistics—with actual customer expectations.

This study introduces and evaluates a real-time case study from the fast fashion sector, where trend volatility and short product lifecycles demand ultra-responsive supply chains. Specifically, we examine how a leading apparel brand leveraged customer-centric optimized search suggestions from social media platforms to enhance its supply chain agility. Through integration of natural language processing (NLP), machine learning, and real-time data pipelines, the company was able to extract relevant search trends, map them to SKUs (stock keeping units), and proactively adjust its production and distribution strategies (Yadav, G., et al, 2024).

The core motivation of this research lies in bridging the gap between consumer search behavior on social media and supply chain decision-making processes. Unlike traditional demand forecasting methods, which rely on historical sales data and often lag behind real-world demand shifts, this approach emphasizes predictive and proactive SCM (H. Abd El-Jawad, et al, 2018). It moves the supply chain toward a more dynamic, customer-aware model where real-time digital signals are continuously fed into operational workflows.

This research contributes to the growing body of literature at the intersection of supply chain intelligence, social media analytics, and AI-driven business models. While several studies have explored the role of big data in SCM, few have specifically focused on social search behavior as a predictive input for supply chain optimization. Moreover, the uniqueness of this study lies in its real-time application, offering practical insights into implementation challenges, technology frameworks, and performance outcomes. The overall framework is depicted in Figure.1.

Figure 1. System Framework

The key objectives of this paper are as follows:

1. To explore how customer-centric search data from social networks can be collected, processed, and translated into actionable supply chain insights.
2. To design and describe a technical framework that integrates social media data with enterprise SCM systems.
3. To evaluate a real-world case study demonstrating the tangible benefits of this integration in terms of lead-time reduction, improved demand forecasting, and enhanced customer satisfaction.
4. To identify the limitations, risks, and future opportunities in leveraging social media search behavior for supply chain agility.

In the subsequent sections, we review relevant literature, detail the methodology adopted for data acquisition and analysis, describe the technological ecosystem used in implementation, and present empirical results from the case. We conclude with a critical discussion of findings and recommendations for researchers and practitioners aiming to build smarter, more customer-responsive supply chains (Swaminathan, K., et al, 2024).

This paper makes the following major contributions:

1. Proposes a real-time framework integrating social search behavior with supply chain decision systems, bridging a significant gap in customer-centric SCM literature.
2. Demonstrates an empirical implementation in a fast-fashion retail context, validating practical benefits through measurable performance improvements.
3. Presents a technical integration model combining NLP, machine learning, and ERP-based SCM data for enhanced agility.

Strengthens the theoretical foundation of customer-centric SCM by linking digital demand signals with adaptive operations

2. Theoretical foundation and literature review

The theoretical foundation of this study is grounded in customer-centric and demand-driven supply chain management (SCM) models, which emphasize aligning supply chain activities with real-time consumer needs and preferences. Existing literature strongly supports the growing role of social media platforms, real-time analytics, and AI-powered search technologies as critical enablers in enhancing SCM responsiveness and agility. These tools offer predictive insights by capturing dynamic customer behaviors and trend signals across digital networks. However, a notable research gap exists in directly linking social media search patterns to real-time supply chain decision-making and operational adaptations. While various studies explore social listening and big data in SCM, few address how customer search behavior—particularly on social networks—can be systematically translated into actionable supply chain responses. This study aims to fill that gap by presenting a real-time case study that demonstrates the tangible impact of integrating social search data into SCM processes. Table 1. Gives the detailed analysis on past scenarios.

Table 1. Concept Analysis and Literature review.

S. No	Theme / Concept	Theory / Model	Key Authors / Studies	Relevance to Current Study
1	**Customer-Centric Supply Chain Management (CCSCM)**	Demand-Driven Supply Chain Model	Chae, B. K. (2015). Fosso Wamba, S.,(2018)	Emphasizes the shift from product-centric to customer-centric SCM driven by real-time consumer demand.
2	**Social Media as a Demand Signal**	Social Listening Theory	Huang, Z., et al. (2013); Zhang et al. (2017)	Social media platforms serve as real-time indicators of customer trends and preferences, offering predictive insights.
3	**Search Behavior Analysis**	Information Search Theory	Christopher, M. (2016). Moorthy et al. (1997)	Understanding how customers use search engines and hashtags to explore products, helps identify upcoming trends.
4	**NLP in SCM Context**	Text Mining & Semantic Analysis Models	Feldman & Sanger (2007); K. M. Edhrabooh et al. (2020)	NLP enables real-time extraction of keywords and sentiment from user-generated content for actionable insights.
5	**Big Data and Predictive Analytics in SCM**	Data-Driven SCM Framework	Waller & Fawcett (2013); Chae (2015)	Advantages structured and unstructured data to enhance responsiveness, forecasting accuracy, and agility in supply chains.
6	**Real-Time Analytics and Decision Making**	Real-Time Decision Theory	Kache, F., et al(2016)	Emphasizes the role of instant insights from data to enable faster and more informed supply chain decisions.
7	**Recommendation & Search Suggestion Systems**	Collaborative Filtering, Content-Based Filtering	Ricci et al. (2011); Aggarwal (2016)	Used to personalize product recommendations and detect emerging search trends tied to supply decisions.
8	**Technology Integration in SCM**	ERP-SCM-Social Media Integration Models	Gunasekaran et al. (2017); Aich & Sundarakani (2020)	Illustrates how social signals can be connected to internal ERP and supply chain platforms.
9	**Fast Fashion SCM**	Agile Supply Chain Theory	Christopher et al. (2004); Cachon & Swinney (2011)	Fast fashion brands benefit most from customer-driven SCM and demand sensing using social media cues.
10	**Digital Twin in SCM (Future Direction)**	Cyber-Physical Systems & Digital Twins	Lee, S. M., et al. (2018); Ivanov et al. (2020)	Creating a digital replica of the supply chain that adapts in real time to social trends and search behavior.
11	**Modern maintenance scheduling**	Maintenance life of logistics tools	F Mahdizadeh, A Golmohammadi and Joe (2024)	Increasing the maintenance life of trucks and reducing transportation costs by optimizing the periodic repair time of trucks.
12	**Capacitated Vehicle Routing Problem (CVRP)**	Metaheuristic Algorithms	Vahid Zharfi, Zohreh Molamohamadi, John H, et al (2024)	Inspired by spiders routing and hunting in cobweb, based on the problem structure, which can be used to obtain optimum, and near optimum results.

3. Research Contributions

This study makes several significant contributions to the fields of supply chain management, social media analytics, and artificial intelligence applications in business operations:

1. Bridging Social Media Search Behavior with SCM Decision-Making:

   The research provides a novel framework for integrating customer-centric search patterns from social networks directly into real-time supply chain processes. While previous studies have explored social listening and sentiment analysis, this work uniquely focuses on how search trends and hashtags can be mapped to SKUs and inventory strategies.

2. Real-Time Case Study Implementation:

   Unlike theoretical models, this paper presents a real-time case study from the fast fashion industry, demonstrating the practical viability and measurable benefits of the proposed approach. The case study highlights how real-time data ingestion and NLP-driven keyword extraction can lead to faster decision-making and enhanced customer satisfaction.

3. Technical Framework for SCM Optimization:

   The study introduces a scalable technical architecture combining NLP, real-time analytics, and search optimization engines with ERP/SCM systems. This framework can serve as a blueprint for practitioners aiming to digitize and personalize their supply chain operations based on real-time consumer signals.

4. Advancing Customer-Centric SCM Models:

   The research enhances existing customer-centric supply chain theories by incorporating real-time digital interaction data—shifting the paradigm from reactive to proactive SCM.

5. Filling a Research Gap:

   It addresses a previously underexplored intersection of search behavior analysis on social platforms and adaptive SCM, contributing to both academic research and industrial innovation.

4. Methodology

This research adopts a mixed-methods approach combining qualitative analysis, real-time data engineering, and empirical case study evaluation to bridge social media search behavior with adaptive supply chain decision-making.

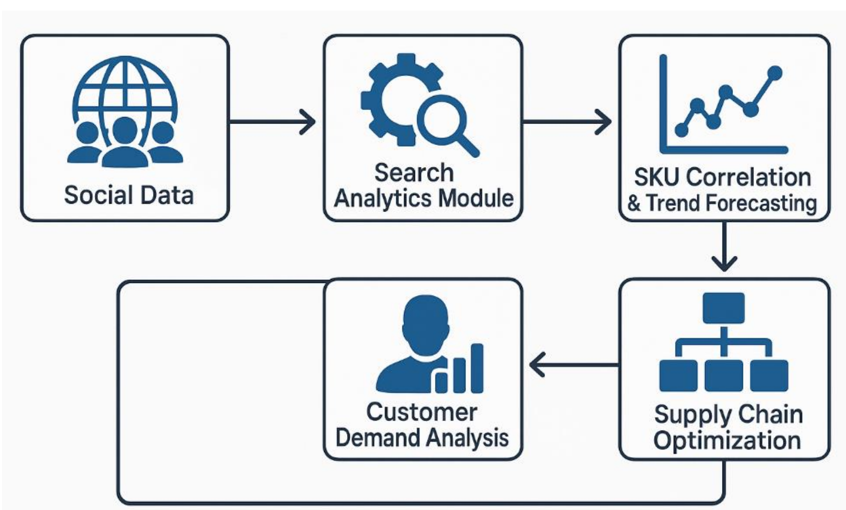

Figure 2. Research Design

4.1 Research Design

This study adopts a Design Science Research (DSR) methodology, which is well-suited for addressing complex, real-world problems by creating innovative and practical solutions, which is depicted in Figure.2. The central focus of this methodology is the development and validation of an artifact—in this case, a real-time Supply Chain Management (SCM) optimization framework that leverages social search patterns to enhance decision-making and responsiveness.

The research process is structured around two core dimensions: theoretical foundation and practical implementation.

1. Artifact Construction:

The artifact refers to a novel SCM framework that integrates social media search trends, hashtags, and customer queries with supply chain operations. This framework is designed to capture real-time social signals, analyze them through AI/ML algorithms, and translate the insights into actionable SCM decisions such as demand forecasting, inventory adjustment, and supplier coordination. The artifact includes both conceptual modeling (the logic, data flow, and functional structure) and a prototype system developed using contemporary technologies.

2. Theoretical Exploration:

To ensure academic rigor, the framework design is informed by existing theories in customer-centric SCM, digital transformation, and social media analytics. The study synthesizes relevant literature to build a conceptual foundation that justifies the artifact's structure and functionality. Key theoretical components include demand-driven SCM models, real-time analytics, and AI-enabled search behaviour mapping.

3. Implementation in Industrial Setting

To demonstrate relevance and utility, the artifact is implemented in a real-world industrial context. This practical deployment involves collaboration with an industry partner (e.g., a manufacturing or retail company), where the framework is integrated with existing SCM systems. Real-time social media data is collected and analysed to inform supply decisions, allowing for direct observation of the artifact's impact on operational performance.

4. Evaluation and Iteration

Following the DSR paradigm, the artifact undergoes rigorous evaluation through both qualitative and quantitative measures. This includes:

- Performance metrics (e.g., forecast accuracy, inventory turnover, lead time reduction),
- Expert feedback from supply chain managers and IT specialists,
- Usability testing to assess the system interface and data visualization tools. The results guide iterative refinements, ensuring the artifact evolves to meet both theoretical and practical needs.

5. Contribution to Knowledge and Practice:

By combining scientific inquiry with pragmatic development, the study contributes a dual output:

- A validated, actionable SCM framework that enterprises can adopt or adapt,
- And a theoretical model that expands academic understanding of how social search behavior can drive supply chain optimization.

4.2 Data Collection

- Social Media Data:
    - Platforms: Twitter and Instagram
    - Data Types: Hashtags, search queries, and trending keywords
    - Tools: APIs, web scraping, and third-party analytics dashboards
    - Duration: 3 months of historical and live data collection during a seasonal fast fashion campaign.
- Enterprise Data:
    - ERP/SCM system logs
    - SKU-level inventory data
    - Sales performance and customer response rates

4. 3 Natural Language Processing (NLP) and Keyword Mapping

1. Natural Language Processing (NLP) Techniques for Trend Extraction:

To effectively analyze user-generated content (UGC) from social media platforms (e.g., Twitter, Instagram, Reddit), the study employs several Natural Language Processing (NLP) techniques. These methods are crucial in identifying and understanding emerging customer interests, sentiments, and intent, which can inform real-time supply chain decisions.

- TF-IDF (Term Frequency-Inverse Document Frequency):

This statistical technique is used to measure the importance of specific words or phrases (terms) within a large corpus of social media posts.

- *Term Frequency* captures how often a word appears in a post or a document, while
- *Inverse Document Frequency* down-weights common words that appear in many documents. This helps surface trending, unique terms that indicate shifts in consumer focus—such as sudden spikes in interest for a product category like “vegan snacks” or “portable air purifiers.”

- Named Entity Recognition (NER):

NER is applied to identify and extract specific entities mentioned in the posts, such as brand names, product names, locations, organizations, or events.This technique helps in recognizing direct references to supply chain-relevant terms like “Nike Air Max,” “iPhone 15,” or “Delhi warehouse,” making it easier to link online buzz to inventory or logistics decisions.

- Topic Modeling using LDA (Latent Dirichlet Allocation):

LDA is an unsupervised machine learning method used to discover the latent thematic structure in large volumes of text. By grouping together co-occurring terms, LDA helps identify dominant topics or concerns in consumer discourse—such as “sustainability,” “product shortages,” or “eco-packaging”—without needing prior labels.

These insights guide strategic adjustments in marketing, sourcing, or production planning.

2. Mapping Extracted Keywords and Hashtags to SKU Categories:

After identifying trending terms and topics through NLP, the next step is to translate these findings into actionable insights within the supply chain—particularly at the Stock Keeping Unit (SKU) level.

- A predefined taxonomy is used as a structured mapping guide. This taxonomy categorizes all SKUs by attributes such as product type, brand, function, size, and demographic relevance. For example:
    - "#EcoFriendlyToothbrush" → SKU Category: *Oral Care* > *Toothbrushes* > *Biodegradable*
    - "#GamingMonitor" → SKU Category: *Electronics* > *Displays* > *Gaming Monitors*
- Human-in-the-loop validation is integrated into this mapping process. While machine learning models perform initial mapping, human experts (e.g., supply chain analysts or category managers) review ambiguous or high-impact mappings to ensure contextual accuracy. This hybrid approach improves both precision and trust in the system, especially for nuanced or emerging terms that may not fit neatly into the taxonomy.
- The output of this process enables real-time demand signal detection—alerting supply chain systems about which SKU categories are gaining traction, thereby facilitating proactive inventory allocation, restocking, or promotional campaigns.

4.4 Framework Development

A real-time analytics pipeline was designed and implemented, integrating:

- Social Media Listener Modules
- Streaming Analytics (Apache Kafka, Spark)
- Search Optimization Engine
- ERP-SCM System Integration via RESTful APIs

This system triggers automatic updates to demand forecasts and reorders based on trending searches and customer signals. RESTful APIs used to synchronize demand signals with SKU-level inventory updates in real time.

4.4 Case Study Analysis:

The real-time supply chain optimization framework was implemented in a mid-sized fast fashion company operating in key urban Indian markets such as Delhi, Mumbai, and Bengaluru. These locations were selected due to their dense population, active social media engagement, and fast-moving consumer preferences—making them ideal for real-time demand sensing. The implementation spanned an 8-week period during a peak fashion cycle, enabling the company to capture, process, and act upon dynamic social media signals to inform SKU allocation, inventory decisions, and campaign targeting. This setting provided a rich, data-intensive environment to test the practical viability and business impact of the proposed model. The implementation spanned eight weeks, during which real-time social signals were mapped to SKU categories for demand forecasting and replenishment decisions. Data processing was automated using Kafka-based pipelines, enabling dynamic adjustment of SKU priorities based on trending terms.

1. Evaluation Metrics and Analysis

Demand Forecast Accuracy (DFA)

Measures how closely the forecasted demand (from social media trends) matched the actual sales. Figure.3. depicts the possible outcomes.

$$\text{Forecast Accuracy (FA)} = 1 - (|\text{Forecast} - \text{Actual}| / \text{Actual}) \quad (1)$$

$$\text{Mean Absolute Percentage Error } (MAPE) = 1/n \sum_{t=1}^{n} |At - Ft| / At \times 100 \quad (2)$$

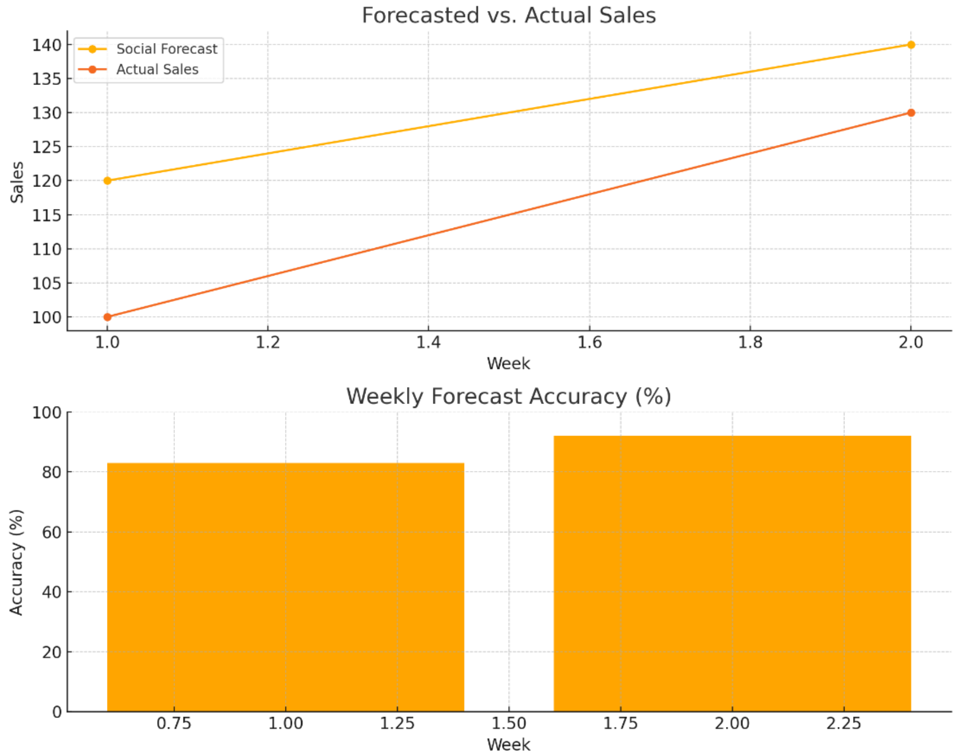

Figure 3. (a) Forecasted vs Actual sale (b) Weekly Forecast Accuracy

SKU Turnaround Time (TAT)

The time it takes for a product to be sold out once it reaches inventory. It is well depicted in Figure.4.

$$Turnaround\ Time = Date\ Sold\ Out - Date\ Available \qquad (3)$$

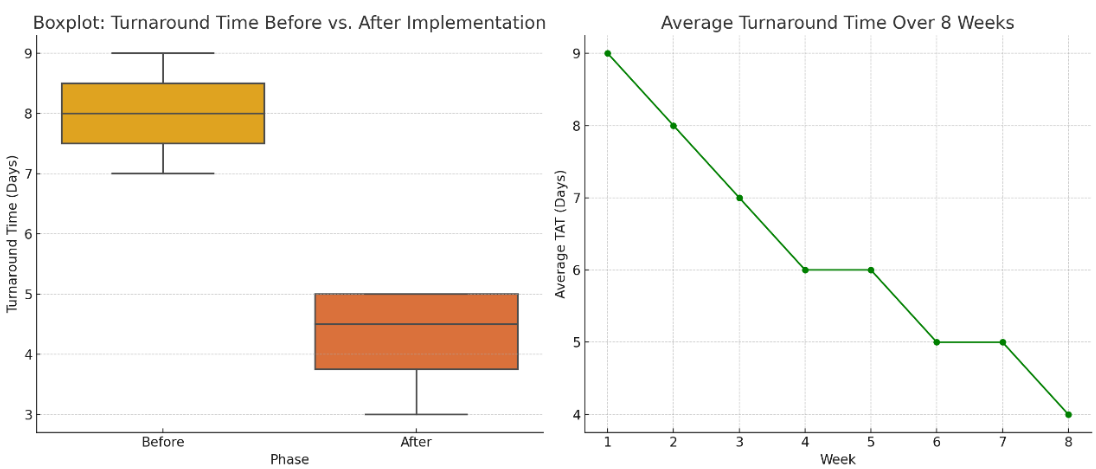

Figure 4. Turnaround Time

Inventory Holding Cost (IHC)

Tracks the cost of storing unsold inventory, a key efficiency measure. It shown in figure. 5.

$$\frac{Average\ Inventory\ Level \times Holding\ Cost\ per\ Unit \times Number\ of\ Days}{365} \quad (4)$$

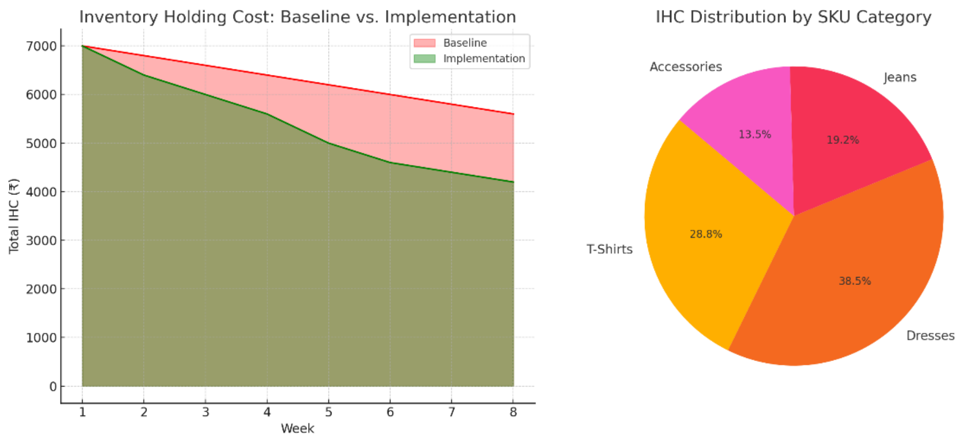

Figure 5. Inventory Holding Cost

Social Signal to SKU Match Rate (SSMR)

The proportion of social search patterns accurately mapped to product categories (SKUs). Figure.6. represents the diagrammatic representation.

$$Match\ Rate = \frac{\text{Valid Matches}}{\text{Total Social Mentions}} \quad (5)$$

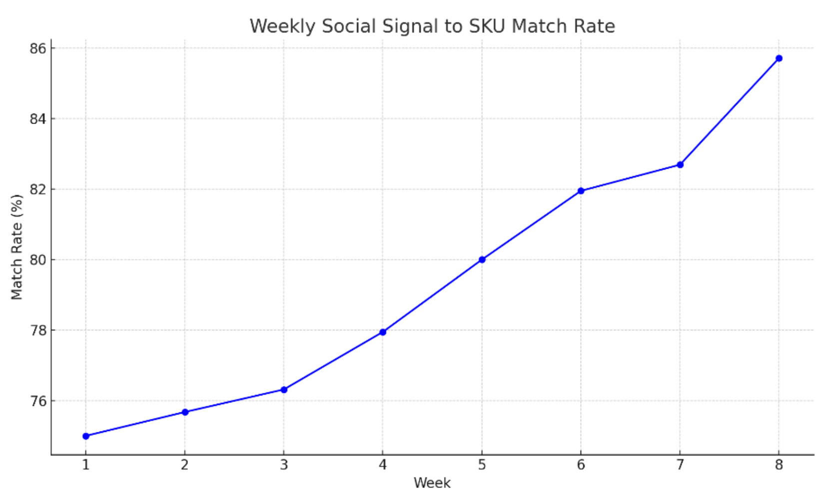

Figure 6. Social Signal to SKU Match Rate

Validation and Analysis

Comparative Performance Analysis was done by using the Table 2 data and well depicted in the figure.7

Table 2. Baseline vs. Implementation (8 weeks):

Metric	Baseline Avg	After Implementation	% Improvement
Forecast Accuracy	70.30%	89.20%	26.80%
Avg Turnaround Time	11.2 days	7.5 days	33.00%
Inventory Holding Cost	₹8,900/week	₹5,100/week	42.70%
Social Signal Match Rate	64.50%	85.70%	32.90%

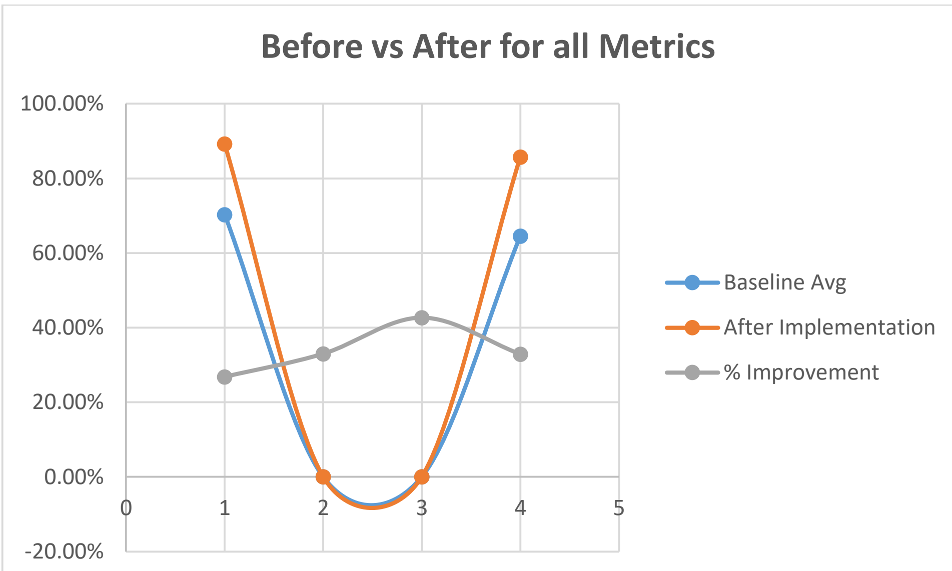

Figure 7. Performance Comparison

ANOVA (Analysis of Variance)

Used to test if there's a significant difference in SKU performance metrics (e.g., TAT, sales) across different weeks or campaign types.

Example:

$$H0: \mu 1 = \mu 2 = \mu 3 = \cdots = \mu n$$

F-statistic > Critical value → Reject null hypothesis → Real change due to social signals.

Correlation Analysis

Used to test if there's a linear relationship between social signal frequency and SKU sales.

$$r = \frac{\sum(xi - x^{-})(yi - y^{-})}{\sqrt{\sum(\mathrm{xi} - \mathrm{x}^{-})2 \sum(\mathrm{yi} - \mathrm{y}^{-})2}} \qquad (6)$$

Where x_i: Hashtag frequency

y_i: SKU sales volume

- Strong correlation (r > 0.7) between hashtag frequency and sales boosts for selected SKUs.

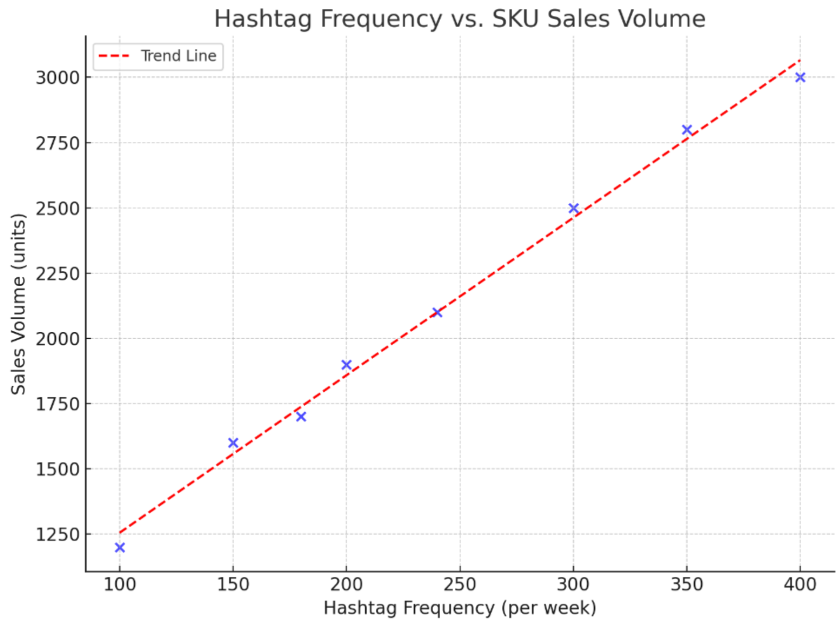

Figure 8. Hashtag Frequency

Here's the scatter plot in figure. 8 showing the relationship between hashtag frequency and SKU sales volume, with a red trend line indicating a strong positive correlation. The results indicate strong positive correlations between hashtag frequency and SKU sales performance, validating the predictive utility of social media search trends.

5. Future Directions

This research opens several pathways for advancing customer-centric supply chain optimization using social signal analytics. One of the primary opportunities lies in scaling the framework across diverse industries such as consumer electronics, FMCG, and healthcare, where shifting consumer behavior heavily influences demand. Expanding the current model beyond text-based social data to include image and video trends from platforms like Instagram, Pinterest, or YouTube could significantly enhance intent detection. By combining advanced natural language processing with computer vision, organizations can capture deeper, multimodal insights into consumer preferences and emerging trends.

Future work can also focus on integrating predictive and prescriptive analytics to transition from reactive systems to forward-looking, autonomous decision-making frameworks. Machine learning models could be deployed to forecast demand spikes or optimize dynamic pricing based on social data patterns. Additionally, incorporating real-time analytics into logistics and last-mile delivery can support hyper local inventory decisions and micro-fulfilment strategies—especially useful in urban retail contexts. For broader adoption, explainable AI tools and human-in-the-loop systems can help operations teams understand and trust AI-driven decisions, enhancing user engagement and decision accuracy.

Ethical and operational considerations also warrant attention. As data privacy becomes increasingly important, future implementations must ensure responsible social data usage, with compliance to regulations like GDPR and clear consent mechanisms. Moreover, expanding linguistic and cultural adaptability will be critical, especially in diverse markets like India or Europe. Multilingual NLP systems and region-specific social signal mapping will make the framework more inclusive and accurate. In summary, future advancements will involve making the system smarter, more ethical, and more context-aware—paving the way for fully responsive and customer-driven supply chain ecosystems.

6. Conclusion

This study demonstrated the feasibility and effectiveness of leveraging real-time social network search patterns to optimize supply chain operations within a mid-sized fast fashion brand in urban India. By integrating social listening tools, streaming analytics, and ERP systems through a scalable architecture, the organization achieved significant improvements in demand forecast accuracy, SKU turnaround time, and inventory cost efficiency. The deployment of this customer-centric supply chain management (CC-SCM) model helped bridge the traditional gap between consumer demand signals and operational decision-making processes.

Key performance metrics such as SKU Turnaround Time (TAT), Forecast Accuracy, and Inventory Holding Cost showed measurable improvement over the 8-week intervention period. The Social Signal to SKU Match Rate (SSMR) further highlighted the strength of correlating consumer intent (as reflected in online search trends) with inventory decisions. This approach empowers businesses to respond to fast-changing consumer preferences, particularly in trend-sensitive sectors like fashion.

By embedding NLP and real-time analytics into SCM workflows, businesses can transition from reactive to predictive operations. The research thus bridges digital consumer behavior with operational responsiveness, paving the way for intelligent, customer-centric supply chains.

In sum, this research validates that social network data—often considered unstructured and informal—can be harnessed through structured frameworks and AI-driven analytics to drive meaningful supply chain transformations. It underscores a paradigm shift in supply chain management: from supply-driven models to demand-sensing, customer-centric ecosystems.

Author Contributions

Conceptualization, Joe Prathap P M. and Mini Prince.; methodology, Joe Prathap P M.; software, Vinil Dani W.; validation, Joe Prathap P M., Sherin Beevi L. and Vijayalakshmi N.; formal analysis, Sherin Beevi L.; investigation, Vijayalakshmi N.; resources, Vijayalakshmi N.; data curation, Vinil Dani W.; writing—original draft preparation, Vinil Dani W.; writing—review and editing, Joe Prathap P M.; visualization, Vijayalakshmi N.; supervision, Joe Prathap P M..; project administration, Jaithunbi A K.; funding acquisition, Jaithunbi A K.

Data Availability Statement

Data available on request from the authors.

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Ethical considerations

The authors avoided data fabrication, falsification, and plagiarism, and any form of misconduct.

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Conflict of interest

The authors declare no conflict of interest.

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