Journal of Theoretical and Applied Information Technology
30th June 2025. Vol.103. No.12

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

CONSUMER PERCEPTION LINKED NOVEL SUPPLY-CHAIN MANAGEMENT (NCP-NSCM) ALGORITHM

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ABSTRACT

Consumer sentiment has emerged as a central driver of supply chain management (SCM) in the modern competitive and dynamic market conditions. Conventional SCM systems hardly incorporate real-time consumer sentiment, resulting in inefficiencies, misplaced production, and lower customer satisfaction. While big data analytics (BDA) has been increasingly used to improve SCM operations, the majority of current models do not account for direct incorporation of consumer sentiment. Filling this gap, the present study introduces the Novel Consumer Perception-linked Supply-Chain Management (NCP-NSCM) algorithm. This algorithm formally integrates consumer perception information into supply chain decision-making to improve responsiveness, flexibility, and consumer focus. In contrast to earlier approaches, the NCP-NSCM framework produces improved demand forecasting, risk detection, and operational responsiveness by means of integrated sentiment analysis and SCM modeling. The effectiveness of the strategy is proven through performance measures like accuracy, precision, recall, and major operational gains such as lower lead time, cost reductions, and better order accuracy. The research presents new frontiers for supply chain design that dynamically synchronizes with changing customer expectations.

Keywords: *Big Data Analytics (Bda), Supply Chain Management (Scm), Procurement Planning, Demand Forecasting, Real-Time Monitoring*.

1. INTRODUCTION

Big Data Analytics (BDA) and related technologies such as artificial intelligence (AI) and the Internet of Things (IoT) have transformed many industries by converting large quantities of raw data into meaningful insights. Within supply chain management (SCM), these technologies facilitate dynamic decision-making, operation optimization, and customer satisfaction enhancement. Nonetheless, in spite of extensive use of BDA to optimize inventory and improve process efficiency, little research has examined integrating real-time consumer perception data into supply chain models systematically.

Big data analytics (BDA) is increasingly applied across industries as a result of improvements in mobile technology and data-mining techniques. BDA enables business decision-makers to convert raw data into valuable information. Organizations can reduce costs, enhance decision-making, and enhance products and services through the BDA application [1]. Different primary company operations have been enhanced through the use of BDA, such as finance, marketing, supply chain management, and operations. One industry that has begun to use BDA and data mining is insurance. By combining different types of big data from different sources, they can price policies more accurately [2]. The supply chain has evolved into the primary organizational unit in the economy that is becoming more international [3]. Businesses are challenged with the need of efficiently managing supply chain operations that are progressively spreading outside their limits in the present business climate, which is characterized by rivalry among supply chain networks [4]. The use of business process automation (BPA) in supply chains has grown in recent years. This is because cloud computing has made it possible for supply chain partners to efficiently gather, transfer, store, and analyse massive amounts of data while also facilitating real-time data collaboration. Even more promising for supply chain management (SCM) decision-making, process optimization, and cost reduction is BDA for the supply chains [5]. The flow diagram for supply chain management is shown in Figure 1. Starting with planning and ending with the delivery of materials to the ultimate consumer, it illustrates the many processes involved in producing a product or service [6].

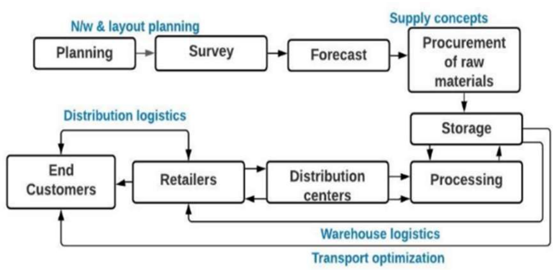

Figure 1: Supply Chain Management Process [7].

There is always pressure on retail firms to boost revenue, lower costs, and improve consumer satisfaction in the current competitive business landscape. Improving SCM is one of the strategies that traders who wish to be unique from the competitors will adopt. There are more opportunities for retailers to acquire useful information about their supply chain activities with the increasing volumes of digital information provided by sources such as e-commerce sites, customer loyalty schemes, and point-of-sale systems [8-10]. Supply

chain visibility is having an open view of the flow of goods from suppliers to consumers. This gives the retailers a better foundation for decision-making concerning inventory control, demand planning, product placement, and operational efficiency. With greater visibility, retailers can lower excess inventory, forecast and avoid stock-outs, ensure availability of products across the network, and enhance the overall customer experience [11-13].

Procurement planning and accurate order forecasting have become more difficult for enterprises due to the growing complexity of global supply networks. Inefficiencies, delayed shipments, stockouts, or overstocking may result from the failure of traditional systems to provide real-time visibility into supply chain processes. For this purpose, BDA provides a game-changing solution through enabling businesses to sift through mounds of data, both structured and unstructured, gathered from sources like suppliers, logistics, and market trends. This research is centered on analyzing the effect of BDA in improving visibility throughout the supply chain, with specific reference to procurement planning and management of future orders. Through the use of predictive analytics, demand forecasting, and data-driven insights, organizations can optimize inventory levels, minimize lead times, and align procurement strategies with market demand. The findings of the current research work will develop the entire perspective as to how BDA can facilitate decision-makers with readiness to combat disruptions, leverage operational performance, and gain competitiveness in fluid business landscapes. This research paper has the purpose to develop and use a Consumer Perception linked Novel Supply-Chain Management (CP-NSCM) algorithm integrating the voice of customers and reviews along with key functions of supply chain management. The key purpose is to increase supply chains' operation efficiency and responsiveness via dynamic coordination with evolving consumer behavior, demand patterns, and satisfaction levels. Based on the use of consumer perception information, an optimization of key supply chain operations like inventory, demand planning, logistics, and supplier coordination is the focus of the study. Lastly, this strategy will attempt to create a more responsive and customer-focused supply chain mechanism that increases product availability, reduces operation expenses, and maximizes customer satisfaction. The following are the research objectives are as follows:

- To study and analyze the big data prediction model for Low-in-stock items at the warehouse/retail level.
- To define the framework for improving the operational agility like improved visibility of procurement planning and threshold orders.
- To design an algorithm or techniques for predicting and improving the customer satisfaction level.

2. REVIEW OF LITERATURE

This section provides a thorough evaluation of the research published in Consumer Perception linked Novel SCM. Also considered are the relevant works of many writers.

Ikevuje A. et al., (2024) [14] discussed into the revolutionary effects of data analytics and the IoT on operations throughout the supply chain, highlighting how these technologies may improve performance, save costs, and increase efficiency. Concerns including operating delays, ineffective inventory management, and a lack of real-time visibility are addressed. All four steps of data gathering, processing, analysis, and decision-making are part of the integration structure. Notable for their potential to further transform supply chains are emerging technologies such as digital twins, edge computing, blockchain, artificial intelligence, 5G, and artificial intelligence. Some strategic suggestions include funding IoT infrastructure, protecting data, encouraging skill development, bringing stakeholders together, and starting trial initiatives. In order to build supply chains that are robust, flexible, and sustainable, the results highlight the importance of data analytics and the IoT.

Jain P. et al., (2024) [15] discussed the problem of incorporating BDA into SSCM by determining the important elements and creating a framework for this objective. The PESTEL framework, which takes into account governmental, economic, social, technical, environmental, and legal aspects, is used to identify the most important ones after a thorough literature analysis and expert opinion. The findings from the MICMAC analysis and the total interpretive structural modelling (TISM) technique provide the basis of the structural model. Most of the other elements are influenced by data security and privacy legislation, the culture of data-based decision-making, the right selection of BDA technology, and legislative support for IT.

Ekren B. et al., (2024) [16] described consumer and e-grocery data to determine regulations for the fulfillment of online grocery orders. Allocation techniques are used to enhance performance parameters including fill rate, carbon emissions, and cost per order by analyzing historical purchase data, product popularity trends, and delivery patterns. Key determinants impacting these performance indicators will be identified via a sensitivity analysis, which is the goal of the research. Optimization of fulfillment policies using the aforementioned data metrics outperforms policies that are not data-informed, according to the findings. It is necessary to apply data-driven models in e-grocery order fulfilment, as these studies demonstrate. According to the outcomes several performance measures can be improved simultaneously with the help of a grocery allocation strategy that takes product availability and location into account.

Baqleh L. et al., (2024) [17] investigated BDA as a moderator in the effect of supply chain management practices (SCMPs) on competitive advantage (CA) among Jordanian manufacturing firms. The information was collected from 156 Jordanian manufacturing firms using the quantitative method. Hierarchical linear multiple regression was carried out using the SPSS technique in testing the hypotheses of the research, in order to analyze the influence of SCMPs on CA. The findings indicate that SCMPs positively have an effect on CA. Specifically, information quality (IQ) and information sharing (ISh) have a highly positive effect on CA. Interestingly, none of these relied on strategic supplier partnerships (SSPs) or customer relationship management (CRM). BDA was discovered not to reinforce the effect of SCMPs on CA.

Hallikas J. et al., (2021) [18] examined data analytics' function in the digitization of purchasing as well as digitalization's impact on supply chain performance. A company's data analytics skills are its capacity to use both internal and external data in its operations. A company's digital procurement capabilities may be defined as its capacity to implement and make use of different electronic procurement procedures to enhance the efficiency of its supply chain. As a result, digital procurement capabilities develop in tandem with external analytics capabilities that help businesses better understand their suppliers, markets, and operating environment. On the other hand, analytics capabilities that concentrate on improving internal operational efficiency have a smaller impact on digital procurement capabilities but do affect supply chain performance. Companies could improve their digital procurement skills by enhancing their competencies in external analytics, and their supply chain performance can be enhanced by investing in analytics capabilities.

Benzidia S. et al., (2021) [19] enhanced the idea of organizational information processing by including BDA-AI and establishing digital learning as a facilitator of the green supply chain procedure. We devised a theoretical framework to apply structural equation modeling based on partial least squares regression to data collected from 168 hospitals in France. The results shown that green supply chain cooperation and environmental process integration are significantly impacted by the adoption of BDA-AI innovations. Environmental process integration and green supply chain cooperation were both identified as having a major influence on environmental performance in the research. A key finding that has not been addressed in the existing literature, the findings emphasize the moderating influence of green digital learning in the interactions

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

between BDA-AI and green supply chain cooperation.

Bag S. et al., (2020) [20] evaluated the function of BDA capacity as a method for operational excellence in enhancing sustainable supply chain performance, using dynamic capability theory as a basis. The mining executives in South Africa's burgeoning economy were questioned, and we got 520 legitimate replies (47% reaction rate). Parametric Least Squares Structural Equation Modeling (PLS-SEM) was used for the data analysis. In this study, they found that the ability to handle big data analytics significantly affects the creation of novel environmentally friendly products and the success of supply chain sustainability initiatives. Staff growth and long-term supply chain results are somewhat impacted by big data analytics skill capacities, but they are still substantial.

Srinivasan R. et al., (2018) [21] relies on demand and supply awareness as core resources, and organizational flexibility is a supplementary skill. Our data research of 191 worldwide companies shows that improved analytics capacity is linked to more information about both supply and demand. Once supply chain businesses have the organizational flexibility to swiftly and effectively act upon insights provided by analytics, it is shown that analytics competence is more closely linked to operational performance. Even more so, compared to stable markets, organizations operating in volatile ones benefit more from analytical competence and organizational flexibility when used together as complementing characteristics. These results not only provide managers theoretically sound advice on how to build analytics capabilities within their companies, but they also further OIPT by improving our grasp of modern information processing technology applications.

3. METHODOLOGY

The Figure 2 illustrates a framework of CP-NSCM system model. This methodology integrates consumer perception with supply chain management to create a CP-NSCM algorithm that helps optimize supply chain operations and adapt to shifting consumer demands. The process includes capturing and analyzing customer feedback systematically, processing data, supply chain process modeling, training the system, and generating actionable recommendations for operational effectiveness.

The following are the steps of the proposed methodology are described in given below:

Step 1: Consumer Perception

Consumer sentiment is gathered from sources such as online reviews, surveys, social media, and feedback forms. Sentiment analysis techniques are used to derive sentiment scores, keywords, and detect consumer trends, gaining insights into customer opinions and future preferences.

Step 2: Supply Chain Management (SCM)

All this refers to the set of critical supply chain management (SCM) data, including inventory level, delivery time, supplier performance, and logistics cost. The data is utilized to analyze and enhance supply chain activities. Additionally, key SCM performance measures, such as lead time, order accuracy, and stock-out rate, are established to establish the efficiency and effectiveness of the supply chain processes. They are used as benchmarks for measuring performance as well as improvement areas.

Step 3: Input Dataset

Consumer sentiment data and supply chain management (SCM) data are combined into a single dataset that has both numerical features (i.e., sentiment scores) and categorical features (i.e., supplier type) for analysis.

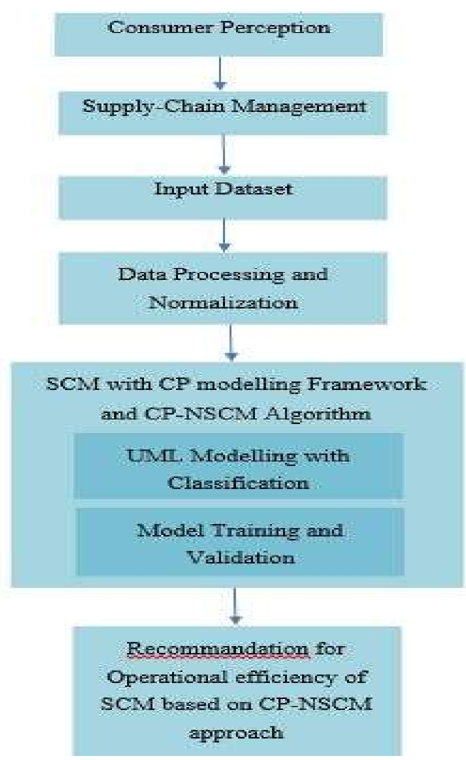

Figure 1: Proposed Methodology

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Step 4: Data Processing and Normalization

The dataset is pre-processed by eliminating duplicates and missing value handling and then normalized through scaling techniques. Features such as consumer sentiment-based demand forecasts are derived to enable easier analysis.

Step 5: SCM with CP Modeling Framework and CP-NSCM Algorithm

- **UML Modeling with Classification:**

  UML diagrams are used to graphically depict the workflow, and classification techniques are applied to classify products, orders, and consumers by sentiment and SCM aspects.

- **Model Training and Validation:**

  Data are divided into training and test sets, and prediction models are developed to forecast demand and identify supply chain risk. Model performance is evaluated on accuracy, precision, recall, and F1 score.

Step 6: Recommendations for Operational Efficiency of SCM Based on CP-NSCM Approach

Recommendations stem from delivery schedule optimization, supplier optimization, and inventory management. Performance of such activities is assessed in terms of key metrics such as cost saving, order accuracy, and reduction in lead time.

Calculating Consumer Sentiment Score Based on SCM Indicators

In order to derive a sentiment score based on consumer sentiment towards supply chain management (SCM) performance, this approach utilizes consumer ratings of essential SCM-related issues like delivery time, product quality, price, sustainability, and service quality. The approach uses a formula to quantify and normalize the sentiment in comparison to the relative significance of the issues.

1. Sentiment Score Formula

The sentiment score (SS) is computed using the following weighted formula:

$$SS = \frac{\sum_{i=1}^{n} (W_i \times SCM\ Indicator\ Sentiment\ (i)}{\sum_{i=1}^{n} W_i}$$

Where:

- n: Total number of SCM indicators.
- $SCM\ Indicator\ Sentiment\ (i)$: Sentiment score for SCM indicator ii, reflecting consumer feedback (positive, neutral, or negative).
- W_i: Weight for SCM indicator i, representing its relative importance in consumer perception.
- The denominator $\sum_{i=1}^{n} W_i$ normalizes the score by the total weight.

2. SCM Indicators in the Formula

The analysis of SCM indicators is done through sentiment analysis methods including machine learning algorithms and lexicon-based processes:

- **Delivery Time**: Feedback on speed and accuracy of product delivery.
- **Product Quality**: Satisfaction with durability, functionality, or appearance.
- **Price Fairness**: Perception of value relative to cost.
- **Sustainability**: Sentiment toward sustainable practices in packaging and production.
- **Customer Service**: Evaluation of communication, return policies, and support.

All the SCM metrics are analysed using sentiment analysis techniques, i.e., either lexicon-based techniques or machine learning algorithms, and combined in the ultimate measure.

3. Weights (W_i)

Weighting of SCM indicators depends on their priority to consumer sentiment in a specific situation. In situations where clients value speed in delivery, they will place high priority on the delivery time compared to the environment sustainability drivers. Customer opinion through surveys and study of behavior patterns and trends, and specialist opinion, provide the basis for setting weights.

4. Customization Options

- **Dynamic Weights**: Adjust weights according to customer preferences, product categories, or market trends-like assigning more weight to sustainability for environmentally friendly customers.
- **Indicator Flexibility**: Add or subtract signs like return policies, packaging quality

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

based on the needs of a particular market or consumers.

This methodology allows for a structured and flexible approach to calculating consumer sentiment, directly linking their perceptions to SCM optimization efforts.

Algorithm:

Step 1: Start

Step 2: Data Collection and Preparation

▪Collect Consumer Perception Data (CPD) from sources such as social media, surveys, and online reviews.

▪Gather Supply Chain Data (SCD) from supply chain systems, including data on inventory, delivery, and suppliers.

▪Clean and preprocess the datasets: handle missing values, remove duplicates, and ensure consistency.

Step 3: Data Integration and Feature Engineering

▪Merge CPD and SCD into a unified dataset to align consumer sentiment data with supply chain metrics.

▪Normalize all numerical features, such as sentiment scores and logistics costs, using Min-Max scaling.

▪Engineer features that combine consumer sentiment insights with supply chain operations, such as sentiment-driven demand forecasts.

Step 4: Framework Modeling Using UML

▪The implementation of UML designs must depict information movement and interconnections between principal supply chain entities which involve Consumers along with Products and Logistics.

▪Establish classification systems that organize orders and products and consumers through analysis of sentiment data from supply chain operations.

Step 5: Machine Learning Model Training

▪Divide the dataset into training and testing subsets.

▪Train predictive models (e.g., Random Forest, Gradient Boosting, or Neural Networks) to forecast demand and assess supply chain risks.

▪The reliability of predictions must be verified through accuracy tests combined with precision and recall measurements and calculation of F1 score metrics.

Step 6: Optimization Framework (CP-NSCM Algorithm)

▪Conduct a workflow for machine learning model prediction outputs to join the optimization structure. framework.

▪Linear Programming and Genetic Algorithms optimization methods should be applied to reach specified objectives:

- Minimize supply chain costs.

- Optimize inventory levels and supplier prioritization.

- Balance supply and demand based on consumer sentiment insights.

Step 7: Generate Recommendations

▪Create useful recommendations to adjust inventory amounts and modify supplier approaches and enhance delivery schedule performance.

▪The team should recommend operational changes for greater efficiency through shorter processes and superior customer experiences.

Step 8: Evaluation and Iteration

▪Test the algorithm for KPI achievement including lead time reduction together with cost efficiency improvements and better order accuracy results.

▪Repeated algorithm refinement will occur through evaluation results to enhance both performance and adaptation qualities.

Step 9: Stop

4. LIMITATION

Although the CP-NSCM algorithm provides significant improvements, several limitations must be recognized. First, the model's performance depends heavily on the availability and quality of consumer perception data, which might be noisy, biased, or incomplete. Second, sentiment analysis techniques may fail to perfectly interpret true customer intent due to sarcasm, cultural nuances, or vague expressions. Third, scalability across various industries and large-scale supply chains remains to be extensively validated. Lastly, integration issues may emerge in the process of integrating the CP-NSCM framework within legacy systems without drastic infrastructure overhaul.

5. CONCLUSION

Consumer perception integrated into the supply chain management process offers a revolutionary approach towards the enhancement of operational efficiency and customer satisfaction. The study introduces the CP-NSCM algorithm that combines consumer sentiment data with supply chain metrics to optimize processes such as demand forecasting, inventory management, supplier selection, and delivery scheduling. A weighted sentiment scoring framework and machine learning techniques, the algorithm aligns supply chain operations with consumer expectations effectively; hence, it improves key performance indicators such as reduced lead times, cost savings, and enhanced order accuracy. The results point out the importance of a consumer. A centric approach in developing responsive and resilient supply chains that lay the foundation for more advances in sentiment-driven strategies and their usage across various sectors and Global markets.

6. FUTURE RESEARCH DIRECTION

Future studies can attempt to extend the CP-NSCM model to other industries like healthcare, manufacturing, and agribusiness to test its performance and applicability in various contexts. More advanced sentiment analysis models, especially transformer-based deep learning methods like BERT, can be incorporated to enhance the accuracy of consumer perception extraction. The integration of CP-NSCM with blockchain technologies may also boost transparency and traceability of consumer feedback along the supply chain. Ultimately, longitudinal investigations monitoring the extended-running operational advantage of consumer-perceived supply chains would provide added testaments of sustainability and utility to the effectiveness of the model.

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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