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A Consumer-Centric Optimization Framework for Reverse Supply Chains Integrating FMEA and Deep Learning

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Abstract. This study develops a mathematically informed optimization framework for decision-making in reverse supply chain management, with an application to Apple's MacBook product line. The proposed framework integrates Failure Mode and Effects Analysis (FMEA) with deep learning, based sentiment analysis in a multi-stage structure designed to quantify risk factors and predict consumer-driven outcomes. The dataset consists of 91 days of Twitter user feedback on Apple notebooks, processed using supervised learning algorithms to extract sentiment scores and thematic indicators of product performance. The analysis identifies "power and battery" and "storage" as the most critical components contributing to user dissatisfaction and elevated risk severity. These data-driven insights are incorporated into an optimization model that supports decisions on product recycling, refurbishment, and reuse. The hybrid framework enhances decision stability and accuracy compared with conventional reverse logistics models, while improving operational efficiency and environmental performance. The results demonstrate the model's suitability as a scalable, machine-learning-supported optimization tool for reverse supply chain systems.

Keywords. Reverse supply chain, Deep learning, Sentiment analysis, Mathematical modelling, Social media analytics.

MSC. 34H05; 68T07; 49L12.

1 Introduction

Over recent decades, increasing global competition and rapid fluctuations in market demand have compelled organizations to adopt integrated management strategies across the entire supply chain, from raw material procurement to product delivery and post-sale services, to maintain and enhance their competitive position [14, 29, 32]. As a network of suppliers, manufacturers, distributors, intermediaries, and customers, the supply chain plays a central role in value creation. Effective coordination within this network is widely recognized as a key mechanism for cost minimization, efficiency enhancement, and service quality improvement [38].

In contrast to forward logistics, Reverse Supply Chain (RSC) management governs the movement of products in the opposite direction, beginning with the consumer and extending back to the manufacturer. Its primary objectives include recycling, repairing, remanufacturing, and managing returned or end-of-life products [9]. The importance of RSC activities has increased substantially, particularly in industrialized countries such as the United States, where approximately 20% of purchased goods are returned to retailers in some form [15]. This high return rate, combined with tightening environmental regulations obligating companies to reclaim their own waste, has transformed RSC optimization into a strategic imperative. Efficient reverse logistics can significantly reduce operational costs, prevent regulatory penalties, enhance resource recovery, and improve profit margins [11, 15, 47]. Nevertheless, firms continue to struggle with substantial challenges, including escalating costs associated with returned products, the need for flexible return policies to sustain customer loyalty, and the operational complexity of managing diverse product recovery pathways.

Although integrated supply chain management has received substantial attention as a means to deliver fast, reliable, and cost-effective services, a persistent gap remains in understanding consumer-driven factors that lead to product returns. Conventional approaches, such as in-store feedback, questionnaires, or interviews, remain limited in scope and often fail to provide actionable insights into the underlying causes of customer dissatisfaction or the systemic weaknesses that drive returns [14, 29, 32]. Consequently, manufacturers frequently lack a comprehensive and systematic mechanism for diagnosing failure modes, identifying critical defects, and prioritizing corrective actions.

An emerging and highly informative data source for improving RSC decisions is user-generated content in digital environments. Social media platforms, online reviews, and other forms of consumer-generated data contain rich information on user experiences, perceived product failures, and behavioral responses. When properly analyzed, these sources can reveal hidden patterns that are otherwise inaccessible through traditional data collection methods [22]. However, such data are typically high-volume, unstructured, and linguistically complex, necessitating advanced analytical techniques for extracting meaningful insights. Advances in data mining, natural language processing, and machine learning have made it possible to process these large-scale textual datasets and uncover latent consumer perceptions, emerging trends, and fault indicators [30].

Traditional reverse logistics methodologies often address only isolated components of the recovery process and are not designed to integrate consumer sentiment with risk assessment. Similarly, conventional uncertainty analysis tools, such as probabilistic models or basic fuzzy methods, face limitations when applied to large, unstructured text data or when required to combine risk evaluation with qualitative consumer insights. These methods typically fail to capture the intensity, polarity, or underlying tone of user feedback, leading to incomplete or suboptimal decisions. Therefore, there is a need for hybrid analytical frameworks that integrate deep learning–based sentiment analysis with structured reliability assessment tools.

To address these challenges, this study develops an analytical framework for reverse supply chain optimization grounded in consumer feedback, employing Failure Mode and Effects Analysis (FMEA) in combination with deep learning techniques. The proposed model incorporates Recurrent Neural Networks (RNNs) for sentiment analysis to quantify user satisfaction and identify critical product weaknesses. These sentiment-based indicators are subsequently fused with the risk prioritization metrics of FMEA to construct a data-driven decision-support mechanism for selecting optimal recovery actions, repair, remanufacturing, resale, recycling, or safe disposal. This integration enables the formulation of a consumer-oriented optimization model aimed at minimizing costs and waste while improving customer satisfaction and overall supply chain performance. The principal novelty of this study lies in unifying data-driven consumer analytics with systematic reliability assessment to create a comprehensive decision-optimization framework for reverse logistics.

The remainder of this paper is organized as follows. Section 2 reviews the theoretical background and the relevant literature on reverse supply chain optimization, deep learning methods, and the FMEA approach. Section 3 presents the proposed hybrid methodology, including data collection, sentiment analysis procedures, and the integration of deep learning outputs with FMEA. Section 4 provides an empirical case study and discusses the results of implementing the model. Finally, Section 5 summarizes the key findings, implications, limitations, and directions for future research.

2 Literature Review and Theoretical Background

2.1 Supply Chain Management (SCM)

Supply Chain Management (SCM) is a systematic and integrated approach for planning, coordinating, and controlling the flow of materials, information, and financial resources across all entities within a supply network, from upstream suppliers to end customers. Beyond internal operational management, SCM emphasizes inter-organizational coordination to achieve operational efficiency, rapid market responsiveness, and enhanced customer satisfaction [34]-[41].

A supply chain encompasses all activities and actors involved in transforming raw materials into finished goods and delivering them to consumers. Effective SCM seeks to minimize costs while maximizing value creation and service quality, thereby ensuring competitive advantage.

Driven by globalization, technological advances, and increasing market competition, SCM has evolved into a critical discipline in both industrial and business management. Modern SCM extends beyond the physical flow of goods to the management of information and capital, leveraging technologies such as Enterprise Resource Planning (ERP) systems, the Internet of Things (IoT), and big data analytics to optimize performance and responsiveness [41].

While the configuration of a supply chain varies across industries and operational models, it generally includes five fundamental stages [24]:

1. *Sourcing*: Selection and procurement of raw materials or components.
2. *Production*: Transformation of raw materials into intermediate or finished products.
3. *Assembly*: Integration of manufactured components into a final product.
4. *Sales and Distribution*: Placement of products into markets through appropriate channels.
5. *Delivery and After-Sales Service*: Final handover to customers and provision of post-purchase support.

These stages form an interconnected network, where the coordination of material, information, and financial flows is essential. Mathematical modeling of these flows underpins performance optimization and supports data-driven decision-making.

Cost management is a key dimension of SCM, focusing on identifying, analyzing, and controlling costs associated with procurement, production, warehousing, transportation, and distribution. The total supply chain cost (SCC) is typically represented as the sum of operational and logistical expenditures [4, 5, 46, 27]:

$$\text{SCC} = PC + TC + IC + DC, \tag{1}$$

where PC denotes production cost, TC is transportation cost, IC is inventory holding cost, and DC indicates distribution and delivery cost.

For performance evaluation, the overall efficiency of a supply chain (SC^E) is commonly modeled as the ratio of cumulative value added (V^{Added}) to total chain cost SC^E [4, 46]:

$$SC^E = \frac{V^{Added}}{\text{SCC}}. \tag{2}$$

These formulations provide a theoretical and mathematical foundation for modeling supply chain operations. They also serve as a basis for RSC optimization, allowing integration of consumer feedback, risk assessment, and recovery decision-making into a structured analytical framework [9, 15, 29, 32, 35, 47].

2.2 Reverse Supply Chain Management (RSCM)

Reverse Supply Chain Management (RSCM) refers to the process of planning, implementing, and controlling the efficient flow of materials, information, and related resources from the point of consumption back to the point of origin, with the objective of recapturing value or ensuring environmentally compliant disposal [9].

Unlike forward logistics, which governs the movement of raw materials to end consumers, reverse logistics involves product returns, remanufacturing, recycling, reuse, and repair. In an era of heightened environmental awareness and intensified market competition, RSCM has emerged as an essential component of modern operations strategy [10].

Formally, the reverse flow in a supply chain can be represented as:

$$\text{RSC} = \{(X_i, Y_i, Z_i) \mid X_i \in C, Y_i \in M, Z_i \in D\}, \tag{3}$$

where X_i denotes the source of returned products (customers), Y_i represents intermediate processing or remanufacturing nodes, and Z_i indicates the final destination, such as suppliers or recycling and disposal facilities. This structured representation supports a closed-loop system, promoting material recovery and regulatory compliance.

The primary objectives of RSCM include maximizing value recovery from returned products through repair, remanufacturing, or resale; minimizing waste generation and environmental impact; enhancing customer satisfaction through efficient return and service policies; and ensuring compliance with environmental and safety regulations [11]-[15].

Empirical evidence indicates that approximately 20% of products sold in the United States are returned via reverse channels, with variation across industries and product categories [15]. If not strategically managed, these returns can impose significant financial and operational burdens. Conversely, an efficient RSCM system can reduce total operational costs, improve profitability, and support sustainability initiatives [11, 13, 47]. The total profit function of reverse logistics can be expressed as:

$$\Pi^{RSC} = RR - (CC + TC + PC + DC), \tag{4}$$

where RR denotes revenue generated from recovered or resold products, CC represents collection costs, TC transportation costs, PC processing or remanufacturing costs, and DCdisposal costs. Maximizing Π^{RSC} sunder environmental and service-level constraints constitutes a central challenge in reverse supply chain optimization.

A major difficulty in RSCM is the uncertainty inherent in the return stream. The quantity, timing, quality, and type of returned products are often unpredictable, complicating capacity planning for refurbishment and repair centers [35]. A classic approach to managing such uncertainty is the Newsvendor Model, which determines the optimal recovery capacity Q^* by balancing the expected cost of underage (insufficient capacity) against the cost of overage (excess capacity). The optimal service level is given by the critical fractile:

$$P(D \leq Q^*) = \frac{C_u}{C_u + C_o}, \tag{5}$$

where $P(D \leq Q^*)$ denotes the probability that return demand does not exceed the selected capacity Q^*, C_u represents the marginal cost of underage (e.g., lost profit from a scrapped return), and C_0 denotes the marginal cost of overage (e.g., idle refurbishing capacity).

This model provides a quantitative framework for strategic capacity planning under volatile return flows typical of RSC [17]. Furthermore, companies face increasing financial pressure to offer flexible return policies to maintain customer loyalty, which can lead to significant costs. Properly designed RSCM frameworks that balance cost minimization with responsive service provide a critical competitive advantage in modern supply chain management.

2.3 Reverse Logistics (RL)

Reverse Logistics (RL) constitutes a strategic component of supply chain management, addressing the flow of products, information, and resources from the point of consumption back to the point of origin to recover value or ensure proper disposal [9, 19, 45]. The RL encompasses returns management, remanufacturing, and recycling, aiming to minimize waste and maximize asset utilization. Optimization of RL systems often targets maximizing the Net Recovery Value (NRV), defined as the total revenue from recovered products minus the associated operational costs:

$$Max \quad NRV = \sum_{i=1}^{n} \left(R_i - C_{c,i} - C_{t,i} - C_{p,i} - C_{d,i}\right), \tag{6}$$

where R_i denotes the revenue generated from product i, and $C_{c,i}$, $C_{t,i}$, $C_{p,i}$, and $C_{d,i}$ represent the collection, transportation, processing, and disposal costs, respectively. Key decision variables in RL models include the routing of returned products, the location and capacity of recovery facilities, and the allocation of products among re-manufacturing, recycling, and disposal options.

Historically, RL originated during World War II when military logistics emphasized reusing spare parts and packaging due to supply limitations [19]. In the commercial sector, RL gained importance in the late 1980s in response to environmental regulations and cost pressures. Today, sectors such as electronics and automotive integrate RL into core operations, often within a Closed-Loop Supply Chain (CLSC) framework that simultaneously optimizes forward and reverse flows. A typical CLSC objective can be formulated as a bi-objective problem:

$$Min \quad Z = w_1 \sum_{i=1}^{n} (C_{f,i} + C_{r,i}) - w_2 \sum_{i=1}^{n} E_i, \tag{7}$$

where $C_{f,i}$ and $C_{r,i}$ denote forward and reverse logistics costs, respectively, E_i represents environmental benefits associated with recovery activities, and $w_1, w_2 > 0$are weighting coefficients reflecting managerial preferences.

The RL process typically involves collection, inspection, sorting, reprocessing, and redistribution. Operational uncertainties, including variable product quality and return timing, are often modeled probabilistically. A common optimization objective is minimizing expected total cost:

$$Min \quad \mathbb{E}\left[G_{\text{total}}\right] = \sum_{i=1}^{n} \left(p_i C_{r,i} + (1 - p_i) C_{d,i}\right), \tag{8}$$

where p_i denotes the probability that product i is reusable, $C_{r,i}$ is the recovery cost, and $C_{d,i}$ represents the disposal cost. Solving these complex, often non-linear optimization problems typically involves metaheuristic algorithms such as Genetic Algorithms or Particle Swarm Optimization [45].

2.4 Data Mining in Supply Chain Management

With digital transformation, SCM has become increasingly data-driven, requiring advanced analytics to improve efficiency, reduce costs, and enhance decision-making in complex networks [18, 22]. Data Mining (DM) provides systematic tools for extracting actionable insights from large and unstructured datasets.

Formally, DM can be cast as an optimization problem to maximize Information Gain (IG), which measures the reduction in uncertainty achieved by a predictive attribute [48]:

$$Max \quad IG = \sum_{i=1}^{n} P(C_i) \sum_{j=1}^{m} P(A_j \mid C_i) \log_2 \frac{P(A_j \mid C_i)}{P(A_j)}, \tag{9}$$

where $P(C_i)$ denotes the prior probability of class C_i, and $P(A_j \mid C_i)$ represents the conditional probability of attribute A_j given class C_i. Maximization of IG reduces classification entropy and improves predictive performance.

Clustering is a common DM technique in SCM for grouping similar entities, such as suppliers, customers, or shipments, based on defined similarity metrics, facilitating segmentation and targeted decision-making [40, 48]:

$$Min \quad J = \sum_{i=1}^{K} \sum_{x_j \in C_i} \| x_j - \mu_i \|^2, \tag{10}$$

where J is the total within-cluster variance, x_j denotes a data point, and μ_i is the centroid of cluster C_i. Centroids are updated iteratively according to:

$$\mu_i^{(i+1)} = \frac{1}{|C_i|} \sum_{x_j \in C_i} x_j \tag{11}$$

where $|C_i|$ denotes the number of observations assigned to cluster C_i at iteration t.

Although computationally efficient, K-Means assumes spherical clusters and is sensitive to initialization. Density-based approaches, such as DBSCAN, are preferred for non-linear or irregular supply network structures.

Integrating DM outputs into SCM models supports predictive and prescriptive analytics. Predictive models, including linear regression and neural networks, forecast key performance indicators such as demand, lead times, or return rates [20].

$$\hat{y} = f(X) = \beta_0 + \sum_{i=1}^{P} \beta_i x_i + \epsilon, \tag{12}$$

where $\hat{y}$ is the predicted outcome (e.g., defect rate or delivery time), x_i are explanatory variables, β_i are coefficients, and ϵ is the error term. Incorporating DM-derived features, including supplier reliability measures and customer sentiment profiles, enables the model to function as a hybrid analytical layer that links predictive data exploration with optimization-based decision processes.

2.5 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are computational frameworks modeled after the structure and functioning of biological neural systems. They consist of interconnected processing units, or neurons, that transmit signals through weighted connections. Each neuron aggregates its inputs, applies corresponding weights and a bias term, and transforms the result through an activation function to generate an output. A typical ANN architecture includes an input layer, one or more hidden layers, responsible for capturing nonlinear patterns, and an output layer [21].

The general structure of an artificial neural network is illustrated in Figure 1.

For a single neuron, the output can be expressed as:

$$y = f(\sum_{i=1}^{P} w_i x_i + b), \tag{13}$$

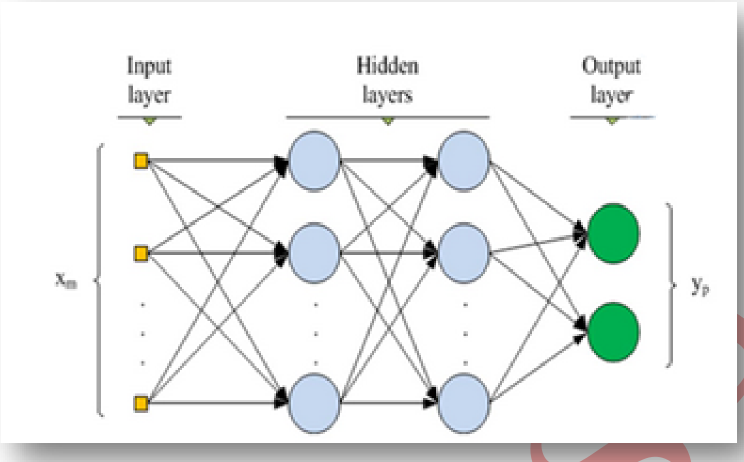

Figure 1: General structure of artificial neural networks

where x_i denotes the input features, w_i represents the synaptic weights, bis the bias term, and $f(\cdot)$ is the activation function, such as the sigmoid or Rectified Linear Unit (ReLU) function [20].

Training an ANN involves adjusting the network weights to minimize a predefined loss function over a training dataset. For regression problems, a commonly used loss function is the mean squared error (MSE), defined as:

$$E = \frac{1}{2N} \sum_{k=1}^{N} (y_k - \hat{y}_k)^2, \tag{14}$$

where y_k denotes the true target value for observation k, $\hat{y}_k$ is the corresponding network prediction, and N is the number of training samples [16]. Minimization of E is typically performed using gradient-based optimization methods through backpropagation.

For sequential or temporal data, Recurrent Neural Networks (RNNs) extend the standard ANN architecture by incorporating feedback connections that enable information persistence across time steps. In a simple recurrent cell, the hidden state update is given by:

$$h_t = \phi(W_h h_{t-1} + W_x x_t + b), \tag{15}$$

where h_t represents the hidden state at time t, x_t is the input vector, W_h and W_x are weight matrices associated with the recurrent and input connections, respectively, bdenotes the bias vector, and $\phi(\cdot)$ is an activation function such as the hyperbolic tangent [28]. This formulation enables RNNs to capture temporal dependencies and sequential patterns, making them well-suited for applications involving time-series data and natural language processing.

2.6 Deep Learning

Deep learning, an advanced subfield of machine learning, utilizes multilayer neural architectures to achieve superior performance in complex pattern-recognition tasks. It plays a central role in applications such as text mining, image analysis, multimedia retrieval, and speech recognition [3, 39]. By leveraging hierarchical feature extraction, deep learning models automatically learn discriminative representations from raw data, reducing the need for manual feature engineering. Progress in computing hardware and the availability of large-scale datasets have accelerated the development of deep and distributed learning systems [1, 6]. Deep learning models are commonly classified into four major categories, as illustrated in Figure 2.

Deep learning models are generally categorized into four major groups:

1. **Supervised Deep Models**: These models are trained using labeled datasets and aim to minimize a predefined loss function. The general training objective is formulated as:

$$\min_{\theta} L(\theta) = \frac{1}{N} \sum_{i=1}^{N} \ell(f_\theta(x_i), y_i), \tag{16}$$

where f_θ denotes the neural network parameterized by θ, (x_i, y_i) are the input–output training pairs, and $\ell(\cdot)$ represents a sample-wise loss function. For classification tasks with softmax outputs, the cross-entropy loss is commonly applied:

$$\ell_{CE}(p, y) = -\sum_{c} y_c \log p_c, \tag{17}$$

where p_c is the predicted probability of class cand y_c is the corresponding ground-truth label. Training is typically performed using gradient-based optimization algorithms such as stochastic gradient descent (SGD) or Adam [23, 43].

2. **Unsupervised Deep Models:**
Unsupervised deep models aim to discover latent structures and hidden patterns from unlabeled data. Representative examples include Autoencoders (AEs) and Restricted Boltzmann Machines (RBMs), which are widely used for dimensionality reduction and feature learning [33, 36, 42]. An autoencoder minimizes the reconstruction error between inputs and outputs:

$$\min_{\theta,\phi} \quad L_{AE} = \frac{1}{N} \sum_{i=1}^{N} \| x_i - \hat{x}_i \|^2, \tag{18}$$

where $h_\theta(\cdot)$ denotes the encoder, $g_\phi(\cdot)$ the decoder, and $\hat{x}_i = g_\phi(h_\theta(x_i))$. Alternative loss functions may be employed depending on data characteristics and modeling objectives.

3. **Deep Reinforcement Learning (DRL):** Deep Reinforcement Learning combines reinforcement learning with deep neural networks to enable agents to learn optimal decision policies in environments modeled as Markov Decision Processes (MDPs) [31]. The optimal state-value function satisfies the Bellman optimality equation:

$$V^*(s) = \max_a \mathbb{E}\left[r_t + \gamma V^*(s_{t+1}) \mid s_t = s, a_t = a\right], \tag{19}$$

where r_t denotes the immediate reward and $\gamma \in (0, 1)$ is the discount factor. In DRL, deep neural networks are used to approximate value functions or action–value (Q) functions, and training proceeds by minimizing temporal-difference errors derived from this formulation.

4. **Hybrid Deep Models:** Hybrid deep learning models integrate supervised, unsupervised, and reinforcement-learning paradigms within a unified framework. Such models are particularly effective in complex decision-making problems involving heterogeneous, high-dimensional, or multimodal data, as they exploit the complementary strengths of different learning strategies.

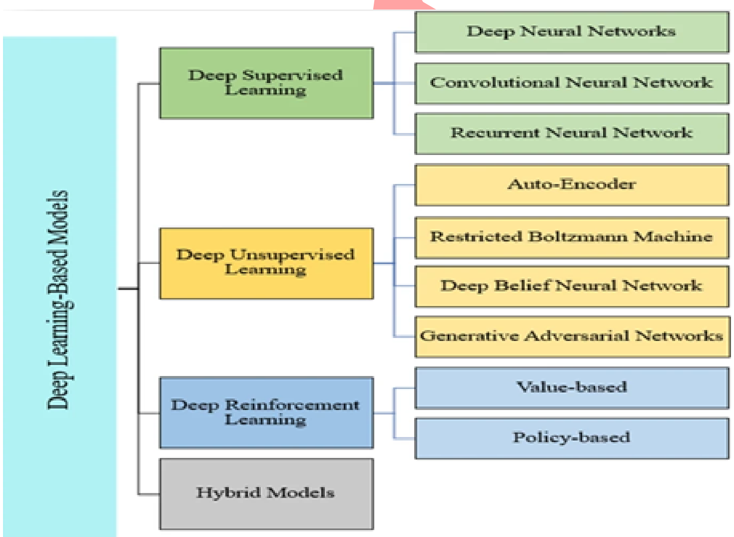

Figure 2: Types of models in deep learning

2.7 Failure Mode and Effects Analysis (FMEA)

Failure Mode and Effects Analysis (FMEA) is a structured and proactive risk-assessment methodology designed to identify potential failure modes within a system or process, evaluate their consequences, and prioritize associated risks. By systematically examining how components, subsystems, or operational activities may fail, FMEA enables organizations to prevent failures before they occur and to enhance system reliability, safety, and performance.

The standard FMEA procedure typically consists of the following stages:

- Formation of an expert team comprising managers, engineers, and technical specialists with detailed knowledge of the system under study;
- Identification of potential failure modes at the component, subsystem, or process level;
- Assessment of the effects, causes, and consequences associated with each failure mode;
- Prioritization of risks through the calculation of the Risk Priority Number (RPN) [2].

The RPN is the central quantitative indicator in FMEA. It is calculated based on three risk dimensions, Severity (S), Occurrence (O), and Detection (D), each rated on a scale from 1 to 10 according to expert evaluation and predefined criteria. The classical RPN is defined as [44]:

$$\text{RPN} = S \times O \times D, \tag{20}$$

where:

S: denotes the severity of the potential effect,

O: represents the likelihood of failure occurrence, and

D: reflects the probability that the failure will not be detected prior to its impact.

This formulation enables ranking failure modes according to their combined risk profile. However, in complex systems where the influence of each risk factor is not equal, traditional RPN scoring may not accurately reflect actual risk levels. To address this limitation, weighted FMEA models introduce coefficients w_i that represent the relative importance of each factor. The weighted RPN is expressed as [44]:

$$\text{RPN}_{weighted} = (w_S \cdot S) + (w_O \cdot O) + (w_D \cdot D), \tag{21}$$

where

$$w_S + w_O + w_D = 1.$$

Here, w_S, w_O, and w_D denote the relative importance weights assigned to severity, occurrence, and detection, respectively.

Incorporating weighting factors provides a more flexible and context-sensitive prioritization mechanism, especially in scenarios where expert judgment indicates that certain aspects, such as severity or detection capability, should be emphasized more heavily than occurrence probability. Overall, the FMEA remains a foundational tool in risk-informed decision-making, supporting preventive maintenance planning, process improvement and quality assurance across a wide range of industrial and engineering applications.

2.7.1 Sentiment-Weighted FMEA Integration

While conventional FMEA relies primarily on expert judgment, it does not explicitly incorporate large-scale consumer feedback that reflects real-world product usage and perceived failures. To address this gap, we extend the classical and weighted FMEA frameworks by integrating sentiment analysis outputs derived from social media data as quantitative modifiers of the FMEA risk parameters.

Let f denote a product feature or component. Two sentiment-based indicators are defined:

- $P_f \in [-1, 1]$: aggregated sentiment polarity associated with feature f, where negative values indicate dissatisfaction and positive values indicate satisfaction;

- $C_f \in [0, 1]$: sentiment confidence score reflecting the reliability of the polarity estimate.

These indicators are extracted from the deep learning–based sentiment analysis model described in Section 3 and represent consumer-perceived risk signals complementary to expert evaluations.

1. **Sentiment-Adjusted Risk Parameters**: To incorporate consumer sentiment into risk evaluation, the expert-assigned FMEA parameters are adjusted as follows.

   i. **Adjusted Severity**: Consumer dissatisfaction often reflects perceived functional degradation or performance loss. Accordingly, the severity score is modified as:

   $$S_f^* = S_f \times (1 + \alpha_s \, |P_f| \, C_f),$$

   where $\alpha_s \geq 0$ is a calibration coefficient controlling the influence of sentiment on perceived severity.

   ii. **Adjusted Occurrence**: Repeated negative feedback may indicate frequent or latent failures. The occurrence score is therefore adjusted as:

   $$O_f^* = O_f \times (1 + \alpha_0 |P_f| \, C_f),$$

   where $\alpha_o \geq 0$ regulates the contribution of sentiment intensity and confidence to failure likelihood.

   iii. **Adjusted Detection**: Failures that consumers report as unexpected or difficult to diagnose suggest reduced detectability. The detection score is adjusted as:

   $$D_f^* = D_f \times (1 + \alpha_d |P_f| \, C_f),$$

   wherconsumer sentiment is integrated intoe $\alpha_d \geq 0$ captures sentiment-derived uncertainty in detection capability.

The term $|P_f|C_f$ jointly represents the strength and reliability of consumer sentiment. Features associated with strong, high-confidence negative sentiment result in higher adjusted risk scores, while weak or uncertain sentiment produces marginal adjustments.

2. **Sentiment-Weighted Risk Priority Number**: The sentiment-adjusted parameters are integrated into a weighted FMEA formulation. The sentiment-weighted RPN for feature fis computed as:

$$\mathrm{RPN}_f^{\text{sent}} = (w_S \cdot S_f^*) + (w_O \cdot O_f^*) + (w_D \cdot D_f^*). \tag{22}$$

This formulation preserves the interpretability of classical FMEA while explicitly embedding consumer-derived risk signals into the prioritization process. As a result, the proposed sentiment-weighted FMEA provides a transparent and data-driven mechanism for aligning expert-based risk assessment with large-scale consumer perceptions, thereby improving the robustness and relevance of reverse supply chain decision-making.
The calibration coefficients α_s, α_0, and α_d are determined based on expert judgment and sensitivity analysis to ensure stability of the risk rankings.

3 Research Methodology

This applied research employs a mixed-methods design that integrates data-driven sentiment analysis with a structured risk assessment framework to support decision-making in reverse supply chain management. The methodological structure consists of two interconnected phases. In the first phase, consumer sentiment is extracted from large-scale social media data and modeled using deep learning techniques to generate quantitative polarity and confidence indicators. In the second phase, risk factors within the reverse supply chain are evaluated using the Failure Mode and Effects Analysis (FMEA) framework.

The outputs of the sentiment analysis phase are formally integrated into the FMEA-based risk assessment through sentiment-adjusted Severity, Occurrence, and Detection parameters, as explicitly modeled in Section 2.7.1. The resulting sentiment-weighted risk indicators are then incorporated into a unified optimization model designed to improve reverse logistics decision-making.

3.1 Population and Data Collection

Data collection was conducted using two complementary sources: structured customer surveys and unstructured social media data. A stratified sample of 100 respondents was selected from a population of 1,000 customers to ensure proportional representation across relevant consumer segments.

The primary dataset for the analytical framework was obtained from Twitter. Using the Twitter Streaming API and a curated set of product-specific keywords, data were collected continuously over a 91-day period. Twitter content was retrieved in standard JSON format in accordance with ISO/IEC 21778:2017. To reduce redundancy and noise, retweets, quoted tweets, and duplicate tweet objects were identified and consolidated during preprocessing. To quantify the relative influence of individual tweets, an engagement-based weighting index α was defined as:

$$\alpha = RT + Q + R + L, \tag{23}$$

where RT denotes the number of retweets, Q represents the number of quote tweets, R indicates the number of replies, and L corresponds to the number of likes. This index is used as a weighting factor during sentiment aggregation, allowing highly engaged content to exert greater influence on aggregated sentiment scores.

3.2 Proposed Framework

The proposed framework integrates social media analytics, text mining, and learning-based decision support to evaluate consumer feedback and guide reverse supply chain decisions. Multilingual tweets were standardized through a preprocessing pipeline that included tokenization, part-of-speech (POS) tagging, stop-word removal, and n-gram extraction.

Sentiment polarity was analyzed using a recurrent neural network (RNN) architecture capable of capturing contextual dependencies in sequential textual data. For each tweet, the model generated quantitative sentiment outputs that were subsequently aggregated at the product-feature level. These aggregated sentiment indicators were incorporated into an FMEA-based assessment module to identify dominant failure modes and compute weighted priority indices for reverse supply chain decisions.

Figure 3 illustrates the first stage of the proposed framework, including keyword extraction from social media data, text preprocessing, and sentiment analysis using deep learning techniques. Figure 4 presents the second stage of the proposed framework, demonstrating the integration of sentiment analysis outputs into the FMEA-based risk assessment process and their incorporation into reverse supply chain decision-making.

3.3 Content Analysis

Given the unstructured and heterogeneous nature of social media data, content analysis was performed using text mining and Natural Language Processing (NLP) techniques. To improve

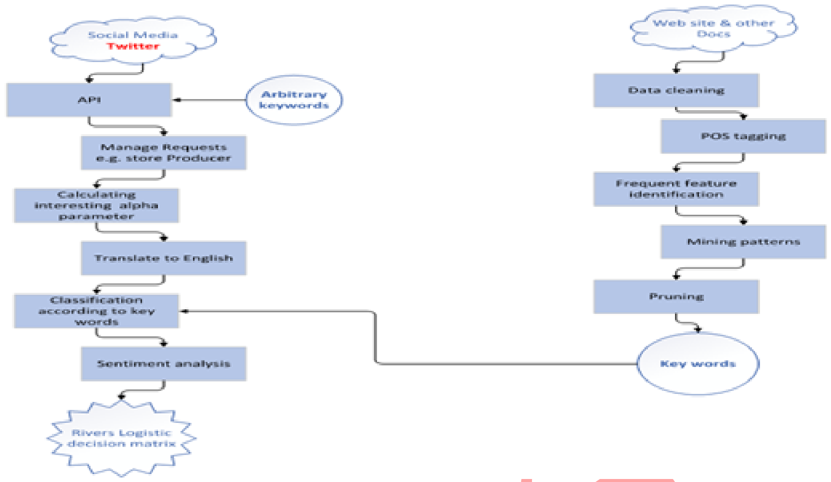

Figure 3: First stage of proposed framework

classification robustness and reduce model-specific bias, a weighted ensemble approach was adopted instead of relying on a single sentiment classifier. The ensemble integrates three independent sentiment analysis algorithms, and their outputs are combined through a weighted voting mechanism to enhance overall accuracy.

For each tweet, two numerical indicators were computed:

- *Polarity (P)*: the orientation and intensity of sentiment, defined over the interval $[-1, +1]$;
- *Confidence (C)*: the reliability of the sentiment classification, defined over the interval $[0, 1]$.

Tweets associated with higher absolute polarity values and higher confidence levels were interpreted as strong indicators of consumer sentiment. This dual-indicator structure enables consistent sentiment evaluation across multiple classifiers and provides stable, quantitative inputs for subsequent integration with the FMEA-based risk assessment framework.

3.4 Algorithmic Structure and Reverse Logistics Network Modeling

The reverse logistics network designed in this study integrates two NP-hard optimization components:

1. Capacitated facility location, and
2. Bidirectional flow optimization.

The model incorporates all major nodes within a closed-loop supply chain, including suppliers, manufacturers, collection and recovery centers, recycling units, distribution hubs, and

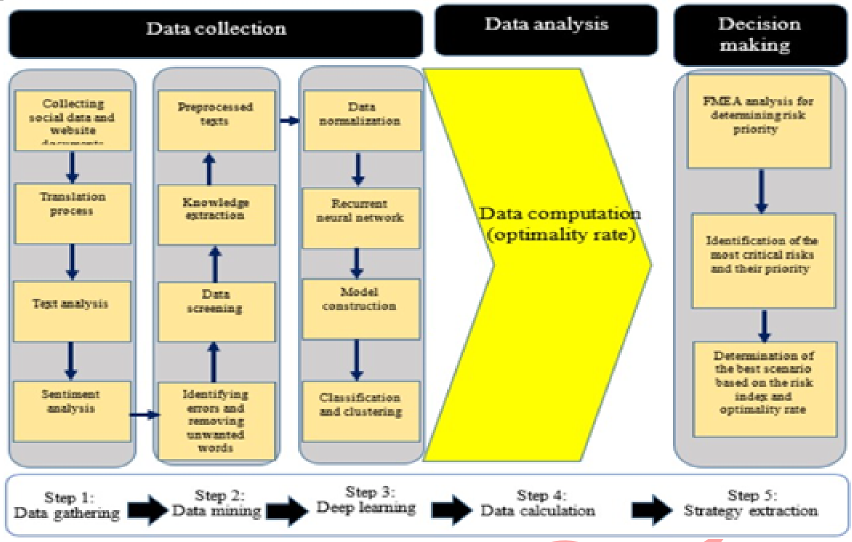

Figure 4: Second stage of proposed framework

disposal facilities. It accommodates multiple product categories and assigns tunable parameters that represent the proportion of items that are repairable, remanufacturable, recyclable, or destined for disposal.

The reverse logistics network is modeled as a multi-echelon, capacitated, closed-loop flow optimization problem, integrating facility location, routing, and multi-product recovery decisions. The model includes the following node sets:

I: Customer zones (return sources),

J: Collection centers,

K: Repair and re-manufacturing centers,

L: Recycling facilities,

M: Disposal units.

Let x_{ij}, y_{jk}, z_{kl}, and w_{lm} denote flow variables between consecutive nodes.

Objective Function

The general objective is to minimize the total reverse logistics cost:

$$\min Z = \sum_{i\in I}\sum_{j\in J} C_{ij}x_{ij} + \sum_{j\in J}\sum_{k\in K} C_{jk}y_{jk} + \sum_{k\in K}\sum_{l\in L} C_{kl}z_{kl} + \sum_{l\in L}\sum_{m\in M} C_{lm}w_{lm} - \sum_{k\in K} R_k(\cdot), \tag{24}$$

where C_{ab} denotes the unit transportation or processing cost between nodes a and b, and $R_k(\cdot)$ represents the revenue generated from recovered products at center k. The revenue function is assumed to be concave to reflect diminishing returns in recovery operations.

Flow Constraints

Demand satisfaction at customer zones is enforced as:

$$\sum_{j \in J} x_{ij} = d_i, \quad i \in I, \tag{25}$$

and capacity limitations at collection centers are given by:

$$\sum_{i \in I} x_{ij} \leq \text{Cap}_j, \quad j \in J. \tag{26}$$

Multi-product flows are defined as non-negative variables:

$$x_{ij}^{(p)}, y_{jk}^{(p)}, z_{kl}^{(p)}, w_{lm}^{(p)} \geq 0. \tag{27}$$

Return-Type Probability Model

Each returned product belongs to one of four recovery classes:

- repairable with probability p_r,
- remanufacturable with probability p_m,
- recyclable with probability p_c,
- disposable with probability p_d,

subject to:

$$p_r + p_m + p_c + p_d = 1. \tag{28}$$

These parameters are estimated using sentiment-derived indicators from Section 3.3.

To solve this complex multi-product and multi-node optimization problem, a Genetic Algorithm (GA) was applied (Algorithm 1). GA performance depends critically on its control parameters, particularly crossover and mutation rates. Therefore, an extensive parameter-tuning experiment was conducted using MINITAB to determine the optimal combination of GA parameters.

This enhanced pseudo-code emphasizes constraint repair and elitism, both essential for hard combinatorial logistics problems.

Algorithm 1 GA-ReverseLogistics

Input: Cost matrices, recovery probabilities, capacity constraints.

Output: Optimal or near-optimal solution Z^*.

1. Initialize a population P with size N.
2. Evaluate the fitness of each chromosome using the objective function [23].
3. Repeat until the termination condition is satisfied:
   - 3.1 Select parent chromosomes using tournament selection.
   - 3.2 Apply crossover operator with probability P_c.
   - 3.3 Apply mutation operator with probability P_m.
   - 3.4 Repair infeasible solutions to satisfy capacity and flow constraints.
   - 3.5 Evaluate the fitness of the offspring.
   - 3.6 Form the new population using an elitism strategy.
4. Return the best chromosome Z^*.

Enhanced RNN Module (Pseudo-Code)

The RNN architecture (See Algorithm 2) maps text sequences into sentiment polarity scores P and confidence scores C.

3.5 Statistical and Analytical Techniques

The analytical workflow proceeded in two stages. First, descriptive statistics were used to explore the distributional characteristics of the collected tweet corpus and survey responses. In the second phase, the outputs of the sentiment analysis model, specifically polarity and confidence, were mapped onto the FMEA risk matrix, enabling a systematic linkage between consumer perception and failure mode prioritization.

All machine learning, sentiment analysis, and optimization procedures were implemented using MATLAB, while statistical validation and parameter tuning were supported by MINITAB.

Table 1, presents the main symbols, parameters, and variables used throughout the proposed sentiment-driven FMEA and reverse supply chain optimization framework. This nomenclature is provided to enhance clarity, consistency, and reproducibility of the mathematical formulations and analytical procedures employed in this study.

Algorithm 2 RNN_SentimentAnalysis

Input: Preprocessed tweet sequence X_t.

Output: Polarity P, Confidence C.

1. Initialize network parameters W_x, W_h, W_o, b_h, and b_o.
2. For each time step t, compute the hidden state:
$$h_t = \tanh\left(W_h h_{t-1} + W_x X_t + b_h\right).$$
3. Compute the output layer using the softmax function:
$$y_t = \text{softmax}\left(W_o h_t + b_o\right).$$
4. Determine the sentiment polarity:
$$P = f(y_t).$$
5. Compute the confidence score:
$$C = \max(y_t).$$
6. Return polarity P and confidence C.

4 Results and Findings

This section presents the numerical and empirical results derived from the proposed mixed-integer fuzzy optimization model for the integrated forward–reverse logistics network. The evaluation encompasses three analytical layers:

i. A data-driven sentiment analytics pipeline, Twitter data $\rightarrow$ sentiment analysis $\rightarrow$ Recurrent Neural Network (RNN) classifier.

ii. the subsequent FMEA-based risk quantification, and

iii. the influence of consumer-driven signals on reverse logistics decisions via an RL-inspired decision mechanism.

Model performance was assessed using classifier accuracy, multi-objective optimization indicators, and computational efficiency measures.

Table 1: Nomenclature of Main Symbols and Parameters

Symbol	Description
f	Index representing a product feature or component
P_f	Aggregated sentiment polarity associated with feature f, where $P_f \in [-1, 1]$
C_f	Sentiment confidence score for feature f, where $C_f \in [0, 1]$
S_f	Expert-assigned Severity score for feature fin classical FMEA
O_f	Expert-assigned Occurrence score for feature fin classical FMEA
D_f	Expert-assigned Detection score for feature fin classical FMEA
S_f^*	Sentiment-adjusted Severity score for feature f
O_f^*	Sentiment-adjusted Occurrence score for feature f
D_f^*	Sentiment-adjusted Detection score for feature f
α_s	Calibration coefficient controlling sentiment influence on Severity
α_o	Calibration coefficient controlling sentiment influence on Occurrence
α_d	Calibration coefficient controlling sentiment influence on Detection
w_S	Weight associated with Severity in weighted FMEA
w_O	Weight associated with Occurrence in weighted FMEA
w_D	Weight associated with Detection in weighted FMEA
RPN	Classical Risk Priority Number
$\text{RPN}_f^{\text{sent}}$	Sentiment-weighted Risk Priority Number for feature f
$L(\theta)$	Loss function used for training the deep learning sentiment analysis model
θ	Vector of trainable parameters in the deep learning model
OR	Optimization Rate, representing the proportion of decisions redirected from reuse to recycling

4.1 Data Collection and Sentiment Analysis

The empirical analysis commenced with large-scale data acquisition from Twitter over a continuous 91-day observation period, in accordance with the methodological framework described in Section 3. Using the Twitter Streaming API and a curated set of product-related keywords associated with Apple MacBook Pro models, a substantial volume of user-generated content was collected. The dataset comprised original tweets, retweets, quoted tweets, and quotes derived from retweets, thereby capturing both direct consumer opinions and amplified engagement-driven reactions.

Following data acquisition, a comprehensive preprocessing pipeline was applied to improve data quality and analytical reliability. This pipeline included the removal of URLs, user mentions, duplicated content, and tweets that were either excessively short or semantically uninformative. Language identification revealed that English, Japanese, and Portuguese were the dominant languages in the corpus; these languages were retained for subsequent analysis to ensure sufficient data density and linguistic consistency.

Table 2 summarizes the composition of the collected dataset and the subset of tweets filtered using the keyword "*MacBookPro*".

Table 2: Number of Tweets Collected and Filtered

Type	ID	Tweet Count	Ratio	Tweets Filtered by Keyword "MacBookPro"
Original Tweet	TO	$43,261,451$	46.6%	$19,089,139$
Retweet	TO-RSO	$10,241,784$	11.0%	$4,885,205$
Quote	TO-QSO	$31,131,579$	33.5%	$13,490,872$
Quote from Retweet	TO-RSO-QSO	$8,246,194$	8.9%	$3,390,762$
Total	—	$\mathbf{92,881,008}$	**100%**	$\mathbf{40,855,979}$

Feature Ontology Construction

To construct a structured and interpretable representation of consumer feedback, a standardized product feature ontology was developed using official Apple technical documentation and manufacturer repositories. This ontology serves as a conceptual abstraction layer that links unstructured textual content to analytically meaningful product attributes.

Based on this ontology, n-grams $(n = 1, \ldots, 5)$ were generated from the cleaned tweet corpus. Part-of-speech tagging was applied to extract semantically meaningful unigrams and multiword expressions. High-frequency n-grams were mapped to predefined product features and subsequently validated by domain experts to ensure semantic accuracy, domain relevance, and consistency across product generations.

The validated feature–keyword associations formed the basis for constructing a *consumer opinion matrix*, which quantitatively captures the relationship between product features and user sentiment. This matrix constitutes a core analytical input to both the sentiment classification module and the subsequent FMEA-based risk assessment, enabling a consistent and data-driven linkage between consumer perceptions and reverse logistics decision variables.

Table 3 represents a standardized and expert-validated feature ontology, serving as a conceptual abstraction rather than raw empirical frequency counts. This design enhances interpretability, reduces semantic noise in social media data, and facilitates a reliable mapping between consumer sentiment indicators and the subsequent FMEA-based risk evaluation framework.

Table 3: Standardized Product Features and Representative Keywords for MacBookPro Sentiment Analysis

No.	Main Feature	Representative Keywords (Illustrative and Standardized)
1	Price	price, cost, value, expensive, affordable
2	Storage	storage, SSD, capacity, disk space
3	Memory	RAM, memory, multitasking, performance lag
4	Processor (Chip)	M1, M2, M3, processor, chipset, performance
5	Graphics	GPU, graphics, rendering, visual performance
6	Display	display, screen, Retina, brightness, resolution
7	Design & Build	design, weight, thickness, aluminum, portability
8	Keyboard & Trackpad	keyboard, trackpad, touchpad, typing
9	Battery & Power	battery life, charging, power adapter, fast charge
10	Thermal Performance	overheating, fan noise, temperature
11	Connectivity	Wi-Fi, Bluetooth, wireless, signal
12	Ports & Connectors	USB-C, Thunderbolt, HDMI, ports
13	Audio	speakers, sound quality, microphone
14	Camera	webcam, FaceTime camera, video quality
15	Software Compatibility	macOS, updates, compatibility, bugs
16	Reliability & Durability	reliability, lifespan, failure, durability
17	Warranty & Repair	warranty, repair, service, AppleCare
18	Sustainability & Recycling	recycling, trade-in, refurbished, environment

Sentiment Classification and Aggregation

Following feature categorization, a sentiment analysis matrix was constructed to quantify consumer attitudes toward each product feature. Tweets were classified into two discrete sentiment categories—Happy (H) and Unhappy (U)—based on polarity and confidence scores generated by the sentiment classification model. For each product model mand feature n, an aggregated sentiment score x_{mn} was computed by combining polarity intensity and classification confidence across all associated tweets. To ensure robustness and minimize classification noise, only high-confidence observations were retained, defined as those satisfying:

$$| \text{ confidence } | \geq 0.8.$$

Sentiment class assignment followed strict thresholds:

$$\text{mean polarity} \geq +0.8 \Rightarrow H, \quad \text{mean polarity} \leq -0.8 \Rightarrow U.$$

These thresholds ensure that only strongly expressed and reliably classified consumer opinions influence downstream risk evaluation and reverse logistics decisions.

The resulting sentiment analysis matrix serves as a key input to both the reinforcement-learning decision rule and the FMEA-based risk evaluation framework. This integrated sentiment-analytics pipeline achieved an overall accuracy of 89.9%, offering competitive performance with significantly reduced computational complexity compared with deep learning alternatives.

Table 4: Aggregated Sentiment Analysis Matrix and Classifier Evaluation

Classifier	Support	F1-Score	Coverage	Accuracy (%)
SVM	160	0.97	0.94	81.3
MaxEnt	160	0.97	0.97	79.2
NB	157	0.86	0.89	79.6
Voting Classifier	159	0.88	0.85	91.7
Accuracy Criterion	636	0.92	–	–
Macro Average	636	0.92	0.92	0.92
Weighted Average	636	0.92	0.92	0.92

To further evaluate classification reliability, Figure 5 presents the confusion matrix of the final ensemble sentiment classification model, demonstrating balanced predictive performance across sentiment classes and confirming the stability and robustness of the proposed sentiment analytics pipeline.

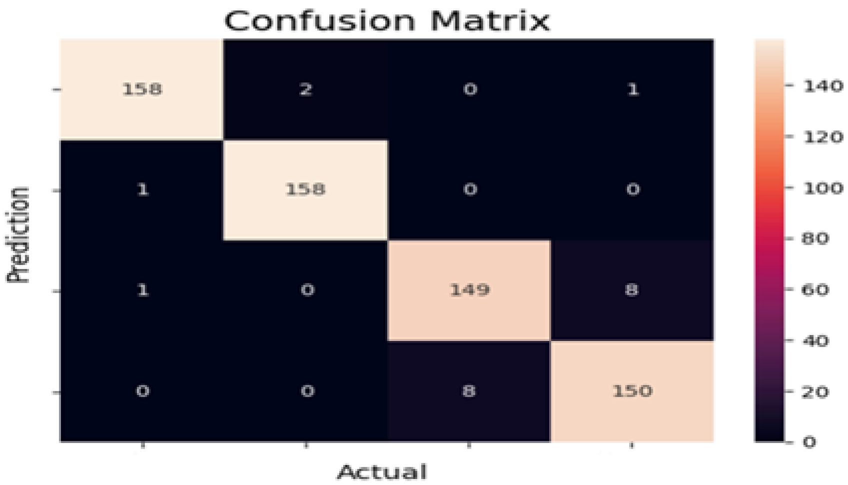

Figure 5: Confusion Matrix of the Sentiment Classification Model

4.2 Consumer-Oriented Reverse Logistics Decisions

The core contribution of this study lies in the explicit integration of consumer sentiment signals into reverse logistics decision-making within the reverse supply chain. Unlike traditional reverse logistics models, which predominantly rely on cost, condition, or expert-based assessments, the proposed framework incorporates aggregated consumer perceptions as an additional, data-driven decision criterion.

Within the proposed decision-support system, consumer sentiment functions as an operational indicator of perceived product and component quality. Specifically, aggregated negative sentiment is interpreted as a signal of diminished perceived value or functional dissatisfaction, thereby favoring recycling-oriented recovery strategies. Conversely, aggregated positive sentiment indicates acceptable or desirable product performance from the consumer perspective, supporting reuse-oriented recovery strategies, including refurbishment and secondary market redistribution.

To operationalize this logic, sentiment classifications were organized into a structured decision matrix in which each MacBook Pro model was evaluated across its major product features (e.g., storage, memory, design, display, processor, power and battery, and graphics). Each matrix entry represents the dominant sentiment class—Happy (H) or Unhappy (U)—derived from high-confidence sentiment observations for a specific model–feature combination. Dominance was determined based on the aggregated sentiment score x_{mn} introduced in Section 4.1.

Table 5 presents the aggregated sentiment outcomes for MacBook Pro models from 2015 to 2024. A clear temporal pattern emerges from the results. As shown, earlier-generation models such as MacBookPro11.4 and MacBookPro12.1 exhibit widespread dissatisfaction, especially with regard to Wireless and Design. Based on the RL decision rule, these items should predominantly be directed to recycling. In contrast, user feedback for more recent models, such as MacBookPro15.2 and MacBookPro16.3, indicates satisfaction with several features (e.g., Power & Battery), supporting reuse strategies for these components.

Importantly, the proposed framework does not rely on sentiment signals in isolation. Rather, consumer sentiment acts as an initial screening and prioritization mechanism that informs the subsequent FMEA-based risk evaluation and learning-informed optimization processes. In this manner, sentiment-driven insights enhance the responsiveness and consumer alignment of reverse logistics decisions while maintaining methodological rigor and operational feasibility.

4.3 Quantifying the Impact: Optimization Rate

To assess how consumer sentiment influences reverse-logistics decisions relative to the company's baseline strategy (typically "reuse"), an *Optimization Rate* (OR) metric was developed.

Table 5: Aggregated Consumer Sentiment by Product Model and Feature (Happy/Unhappy)

Year	Model	Storage	Memory	Design	Display	Chip	Camera	Wireless	Power & Battery	Graphics	Sensors	Interface	Accessories	Total
2015	MacBookPro11.4	U	U	U	U	U	U	U	U	U	U	H	U	U
2015	MacBookPro12.1	U	U	U	U	U	U	U	U	H	U	U	U	U
2016	MacBookPro13.1/2	U	U	U	U	U	U	H	U	H	U	U	H	U
2016	MacBookPro13.3	U	U	U	U	H	H	H	U	H	U	H	H	U
2017	MacBookPro14.1	H	U	U	U	U	H	H	U	H	U	U	H	U
2017	MacBookPro14.2	U	H	H	H	U	U	H	U	H	H	U	H	H
2017	MacBookPro14.3	U	U	U	U	U	H	H	U	H	H	U	H	U
2018	MacBookPro15.1	U	U	U	U	H	U	H	U	H	U	U	H	U
2018	MacBookPro15.2	H	H	H	U	U	U	H	U	U	H	H	H	H
2019	MacBookPro15.3	U	H	H	U	U	U	H	U	U	H	H	H	U
2019	MacBookPro15.4	H	U	H	H	U	U	H	H	H	H	H	H	H
2019	MacBookPro16.1	U	H	H	H	H	H	H	H	H	H	H	H	H
2019	MacBookPro16.4	H	H	H	U	H	H	H	U	H	H	U	H	H
2020	MacBookPro16.2	U	H	H	H	H	H	H	H	H	H	U	H	H
2020	MacBookPro16.3	H	H	H	U	H	H	H	U	H	H	U	H	H
2020	MacBookPro17.1	H	H	H	U	H	H	H	H	H	H	H	H	H
2021	MacBookPro17.2	H	H	H	U	H	H	H	U	H	H	H	H	H
2021	MacBookPro17.3	H	H	H	H	H	H	H	H	H	H	H	H	H
2021	MacBookPro17.4	H	H	H	H	H	H	H	H	H	H	H	H	H
2021	MacBookPro	U	H	H	U	H	H	H	U	H	H	U	H	H
2022	M3 Pro/Max 13	H	H	H	H	H	H	H	H	H	H	H	H	H
2023	M3 Pro/Max 14	H	H	H	H	H	H	H	H	H	H	H	H	H
2024	M3 Pro/Max 16	H	H	H	H	H	H	H	H	H	H	H	H	H

In the baseline scenario, all returned products are assumed to follow a reuse-oriented recovery policy, which reflects common industry practice aimed at maximizing residual value. The OR captures the proportion of these baseline reuse decisions that are modified to recycling-oriented actions after incorporating consumer sentiment information. The OR is formally defined as:

$$\text{OR} = \frac{\text{Number of decisions changed from reuse to recycle}}{\text{Total number of baseline reuse decisions}}.$$

This metric provides an interpretable and scale-independent measure of how strongly sentiment-driven insights influence operational decision-making within the reverse logistics system. To capture decision impacts at different levels of granularity, the OR was computed at three hierarchical levels:

1. **Feature level**, reflecting sentiment-driven adjustments associated with specific product attributes;

2. **Model level**, capturing overall decision changes for each notebook generation; and

3. **Combined (two-dimensional) level**, jointly accounting for interactions between product models and features.

4.3.1 Feature-Level Optimization Analysis

At the feature level, the OR quantifies the extent to which reuse-oriented recovery decisions are redirected toward recycling after incorporating sentiment-weighted risk information. Specifically, feature-level redirection is driven by the sentiment-adjusted Risk Priority Numbers (RPN_f^{sent}), computed using the modified Severity, Occurrence, and Detection parameters defined in Section 2.7.1.

The results indicate that durability-related features—most notably Power and Battery and Storage—exhibit the highest ORs. These features are associated with elevated sentiment-adjusted RPN values, reflecting strong and high-confidence negative consumer sentiment that amplifies expert-assessed risk levels. From an operational perspective, this pattern suggests increased degradation, higher failure likelihood, and reduced residual value in secondary use contexts, thereby justifying a shift from reuse-oriented strategies toward recycling-based recovery. In contrast, the connector category demonstrates the lowest OR and consistently low sentiment-adjusted RPN values. This outcome indicates stable perceived functionality and high consumer satisfaction, implying limited additional risk beyond expert assessments. Consequently, connector-related components remain strong candidates for reuse-oriented recovery strategies, such as refurbishment or remanufacturing.

These feature-level results are illustrated in Figure 6, which presents ORs aggregated by product attribute and clearly distinguishes high-risk, sentiment-sensitive features from those that remain reuse-favorable under the proposed sentiment-weighted FMEA framework.

4.3.2 Model-Level Optimization Analysis

At the model level, substantial heterogeneity is observed across product generations. As illustrated in Figure 7, recent MacBook Pro models equipped with M3 Pro/Max processors (14-inch and 16-inch variants) exhibit the most favorable performance, with minimal deviations from the baseline reuse strategy. This outcome indicates strong consumer satisfaction and high perceived residual value for newer models. Conversely, early-generation models such as *MacBookPro11.4* and *MacBookPro12.1* display the lowest optimization scores, implying frequent

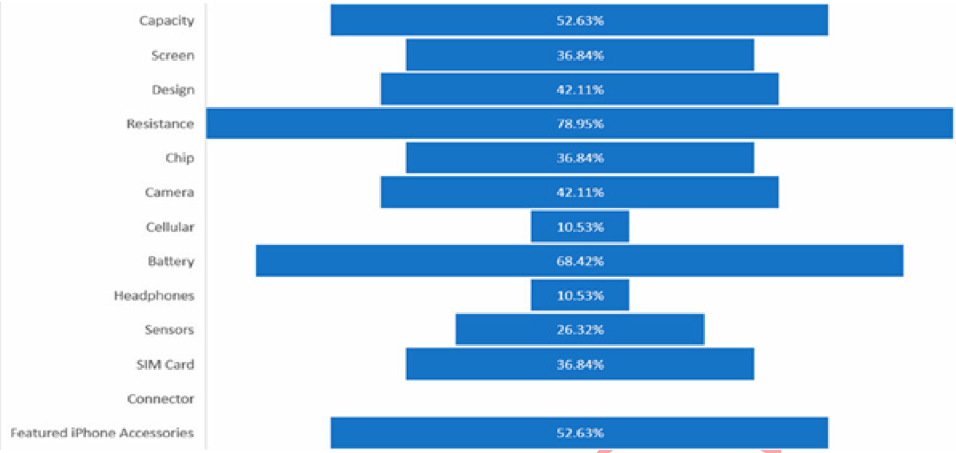

Figure 6: The OR of RL Decisions by Feature

sentiment-driven redirection toward recycling. These findings are consistent with the aggregated sentiment patterns reported in Section 4.2 and reflect the cumulative effects of aging hardware, outdated design, and declining functional performance.

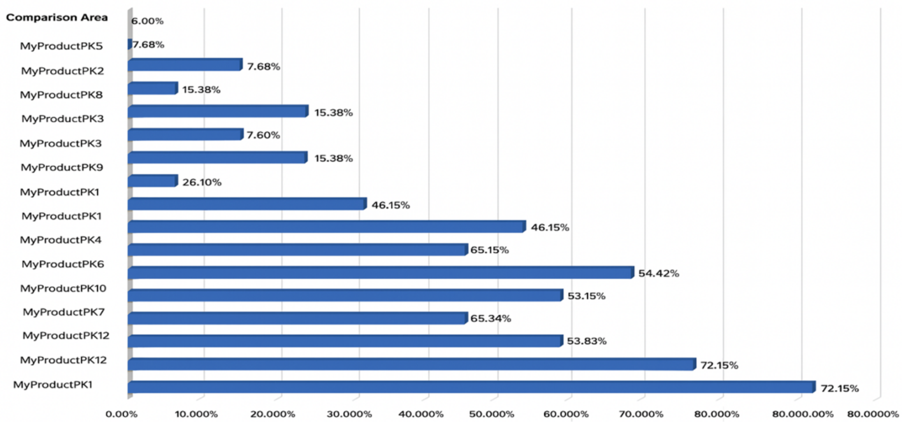

Figure 7: The OR for the RL Decisions Separated by MacBook Pro Models

4.3.3 Joint Model–Feature Optimization Surface

To examine the interaction between product model maturity and feature-specific satisfaction, a three-dimensional optimization surface was constructed. For model iand feature j, the joint optimization score O_{ij} was defined as:

$$O_{ij} = \sqrt{R_i \times F_j},$$

where R_i denotes the aggregated satisfaction score for model i, and F_j represents the aggregated satisfaction score for feature j. This formulation balances model-level and feature-level effects while preserving interpretability.

The resulting 3D surface, depicted in Figure 8, reveals distinct clusters of high and low reusability potential. Regions with high O_{ij} values correspond to feature–model combinations that are well suited for reuse, whereas low-value regions identify candidates for recycling prioritization.

Notably, newer product generations, particularly those released in 2024, consistently occupy the high-O_{ij} region of the surface. This pattern indicates substantially increased reusability potential and suggests a lower environmental footprint for reverse logistics operations involving these models.

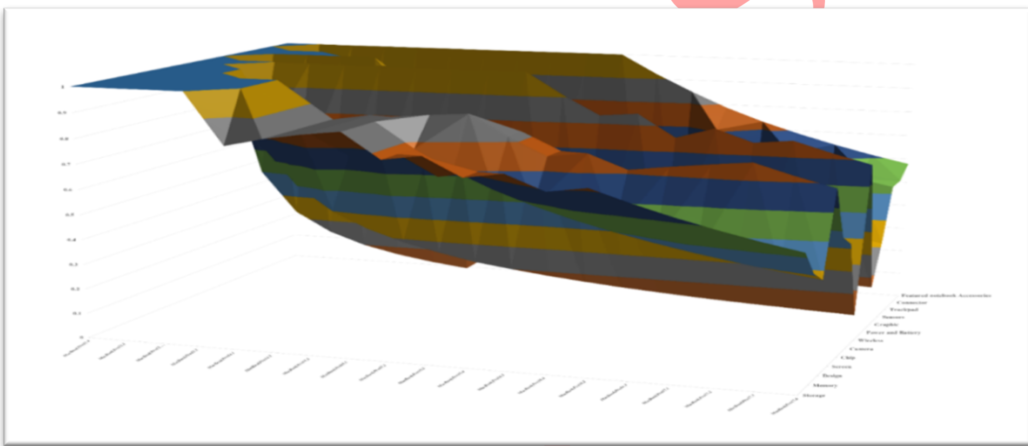

Figure 8: 3D Plot of Notebook Models and Features

4.3.4 Reliability Verification and Classification Robustness

To further validate the robustness of feature-level decision outcomes, classification reliability for notebook features in 2024 was evaluated using a Logistic Regression (LR) classifier. The resulting confusion matrix, presented in Figure 9, demonstrates balanced classification performance and confirms the stability of sentiment-based feature categorization for the most recent product generation.

4.3.5 FMEA-Based Risk Evaluation

To complement the sentiment-driven optimization analysis and identify critical components within the reverse supply chain, the Failure Mode and Effects Analysis (FMEA) methodology

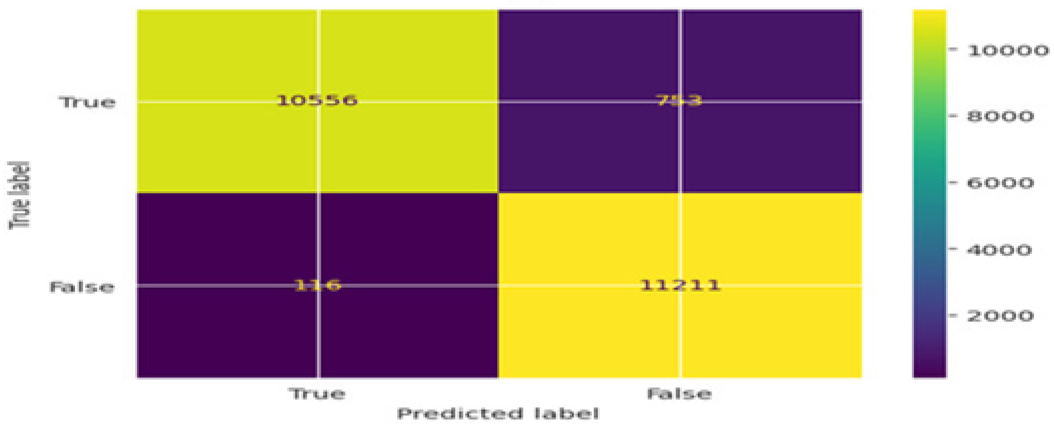

Figure 9: Confusion Matrix for LR Classifier for Notebook Features in 2024

was applied. FMEA enables systematic decomposition of system complexity into manageable components, thereby enhancing the precision and interpretability of risk assessments.
Table 6 summarizes the evaluation scales used for Severity (S), Occurrence (O), and Detection (D), which together determine the Risk Priority Number (RPN) for each component.

Based on expert evaluations, aggregated FMEA results are reported in Table 7. The findings indicate that *Power* and *Battery* represents the most critical risk category, followed by *Storage*. Together, these components account for nearly one-third of the total risk exposure within the reverse supply chain.

Conversely, attributes such as *Design* and *Memory* exhibit minimal risk contributions, suggesting lower strategic priority for mitigation efforts. These results are visually reinforced in Figure 10, which illustrates the comparative dominance of battery- and storage-related risks within the FMEA framework.

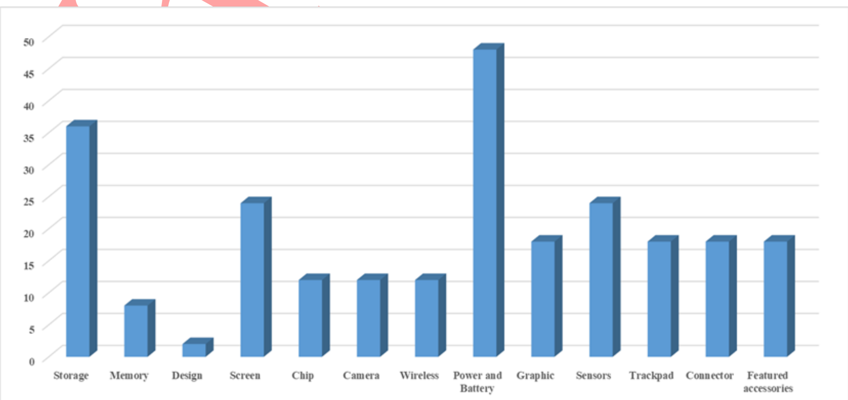

Figure 10: Graphical Representation of Risk Priority Index

Table 6: Main Evaluation Criteria

Rating	Probability (Occurrence Rating)
1	Very unlikely (almost impossible; no known failures in comparable products or high-hour operations).
2	Remote (few documented failures).
3	Occasional (failures occur intermittently).
4	Reasonably possible (failures observed frequently).
5	Repeated (failure is almost unavoidable).
Severity of Impact	
1	No meaningful impact on reliability or safety.
2	Very minor (no damage or injury; simple maintenance may be required; noticeable only to highly discerning users).
3	Minor (light damage affecting typical users; limited impact on system performance).
4	Critical (loss of functional performance or safety margins; severe damage or injury; possible single fatality).
5	Catastrophic (product becomes inoperable; unsafe operation; potential for multiple fatalities).
Detectability	
1	Certain (failure is reliably identified through routine testing).
2	Almost certain.
3	High detectability.
4	Moderate detectability.
5	Low detectability (failure is unlikely to be detected before it occurs).

4.3.6 Optimization Engine Validation

Finally, the robustness of the optimization engine was assessed through systematic parameter tuning of the Genetic Algorithm (GA). As shown in Figure 11, the optimal parameter configuration was identified as a crossover rate of 0.8 and a mutation rate of 0.1. This configuration ensured rapid convergence and stable performance across multiple experimental runs.

Table 7: Risk Priority Index and Relative Risk Weights

Property	Probability	Severity	Diagnosis	Risk Priority Index	Rank	Relative Risk Weight
Storage	4	3	3	36	2	0.144
Memory	2	2	2	8	6	0.032
Design	1	2	1	2	7	0.008
Screen	3	4	2	24	3	0.096
Chip	2	2	3	12	5	0.048
Camera	2	3	2	12	5	0.048
Wireless	2	3	2	12	5	0.048
Power and Battery	4	4	3	48	1	0.192
Graphics	2	3	3	18	4	0.072
Sensors	2	3	4	24	3	0.096
Display	3	2	3	18	4	0.072
Interface	2	3	3	18	4	0.072
Featured Accessories	3	2	3	18	4	0.072

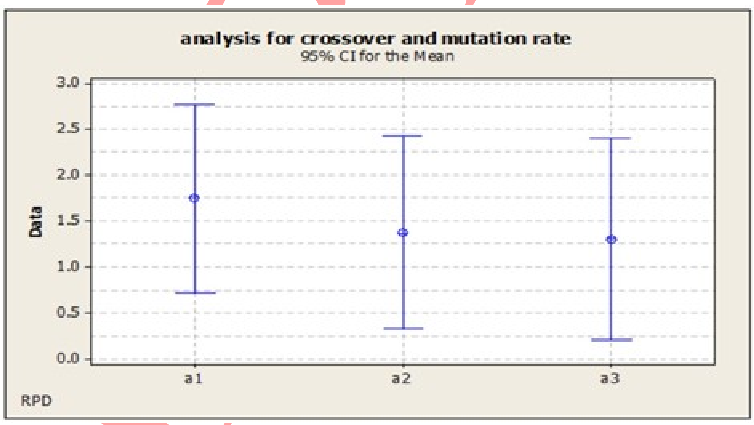

Figure 11: MINITAB Output for Tuning Crossover and Mutation Rates

4.3.7 Integrated Interpretation

The results of the optimization and risk analyses reinforce the earlier sentiment classification findings. For instance, consumer dissatisfaction with battery performance—frequently observed in sentiment data—is independently corroborated by its high RPN score in the FMEA assessment. This convergence of consumer-derived and technical risk indicators demonstrates the analytical strength of the proposed framework.

Overall, the integration of sentiment analytics, optimization modeling, and FMEA-based risk evaluation provides a holistic and robust foundation for reverse logistics decision-making. The proposed approach supports more reliable, consumer-oriented, and environmentally responsible recovery strategies, thereby enhancing both operational efficiency and sustainability outcomes.

5 Discussion

This study has established a coherent and effective link between the qualitative expectations of consumers and the quantitative, strategic requirements of the reverse supply chain by developing and validating an integrated analytical framework. The findings clearly demonstrate the strength and practical relevance of this approach.

A central contribution of this work is the convergence of insights obtained from two independent analytical sources: sentiment analysis, representing the consumer viewpoint, and FMEA, reflecting the technical risk perspective. For example, sentiment analysis highlighted widespread dissatisfaction regarding Power and Battery performance, while the FMEA results independently identified this same component as a high-priority strategic risk, responsible for nearly one-third of total supply chain risk. This alignment offers a strong basis for managerial decision-making, assuring stakeholders that resulting actions are simultaneously responsive to customer feedback and supported by technical evidence.

In addition, the OR metric introduced in this research offers a valuable managerial tool. It enables decision-makers to quantitatively assess the benefits of shifting from a default reuse policy to a more dynamic, data-driven strategy guided by user sentiment. These outcomes correspond closely with the strategic–tactical–operational decision-making hierarchy proposed by De Brito and Dekker [7], illustrating how real-time consumer-derived data can meaningfully inform high-level decisions within reverse logistics.

Despite its demonstrated utility, the interpretation of these findings must consider several limitations. First, the 91-day data collection period may not fully represent long-term sentiment fluctuations. Second, the reliance on publicly available online data limits the framework's effectiveness in sectors with low digital participation. Third, although translation methods were applied, the predominance of English-language content may introduce linguistic bias and obscure culturally specific emotional patterns. These limitations delineate the current scope of applicability while simultaneously providing clear directions for future research.

6 Conclusion and Future Work

This study introduced a data-driven hybrid framework that integrates Failure Mode and Effects Analysis (FMEA) with deep learning–based sentiment analysis to strengthen decision-making within reverse logistics systems. The framework demonstrates how large-scale consumer feedback, particularly from high-traffic platforms such as Twitter, can substantially improve risk prioritization and support the development of more sustainable product recovery strategies. The findings confirm that incorporating consumer perspectives into reverse logistics can enhance both environmental and operational performance by extending product lifecycles, reducing waste, and increasing overall profitability. Additionally, the incorporation of the α parameter as a measure of user engagement provided meaningful insight into the dynamic influence of consumer sentiment and its temporal evolution. Despite the significant contributions of this research, several constraints were identified. Real-time data acquisition remains challenging due to platform limitations, and the computational demands of large-scale sentiment analysis restrict the scalability of current methods. Addressing these issues will require more advanced optimization techniques, improved system architectures, and the creation of open-access datasets to support reproducibility. Future investigations could expand on this work through the following directions:

1. *Keyword Refinement and Topic Modeling*: Employing more sophisticated topic modeling techniques—such as LDA, NMF, or transformer-based models—may enhance the accuracy of keyword extraction and improve contextual interpretation of social media content.

2. *Extended Data Horizons and Multi-Platform Integration*: Incorporating longer data collection periods and expanding analysis to platforms such as Reddit, YouTube, and product review forums would improve robustness and capture broader sentiment dynamics.

3. *API and Algorithmic Enhancements*: Leveraging advanced data retrieval APIs and integrating additional sentiment analysis models (e.g., Multinomial Naïve Bayes, Random Forest, or transformer-based networks) could increase predictive strength and analytical depth.

4. *Integration of Multi-Criteria Decision-Making (MCDM) Approaches*: Combining FMEA with fuzzy logic, AHP, or hybrid MCDM methods would enrich interpretability and enhance managerial confidence in risk prioritization outcomes.

5. *Algorithmic and Computational Optimization*: Incorporating metaheuristic algorithms, such as Genetic Algorithms, Particle Swarm Optimization, or Tabu Search, could reduce computational overhead and improve convergence efficiency in complex datasets.

6. *Temporal Weighting of the Alpha Parameter*: Because the α parameter reflects time-sensitive user engagement, future models should implement temporal weighting to more accurately capture evolving sentiment patterns.

In summary, the proposed framework provides a scalable, intelligent decision-support system that integrates machine learning methods, risk analysis techniques, and behavioral data within a unified structure. It offers a practical pathway toward developing greener, more consumer-responsive and data-optimized supply chain systems. Future research should focus on improving algorithmic generalization, facilitating cross-industry implementation, and ensuring the ethical management of consumer-generated data to support the development of more sustainable and resilient industrial ecosystems.

Declarations

Availability of Supporting Data

All data generated or analyzed during this study are included in this published paper.

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Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Author Contributions

Niousha Zeidyahyaee: Conceptualization; Methodology; Data curation; Formal analysis; Investigation; Software; Writing – original draft; Visualization. **Sajjad Shokouhyar:** Conceptualization; Methodology; Validation; Writing – review & editing; Supervision; Theoretical development; Project administration; Corresponding author. **Alireza Motameni:** Methodology; Resources; Data generation; Formal analysis; Model implementation; Writing – review & editing.

Artificial Intelligence Statement

The authors used AI-based tools solely as part of their writing and editing workflow. Specifically, AI-assisted capabilities were employed to improve language quality, clarity, grammar, and stylistic consistency. The authors did not rely on AI to generate original scientific content, data, analyses, or interpretations.

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References

[1] Adeel, A., Gogate, M., Hussain, A. (2020). "Contextual deep learning-based audio-visual switching for speech enhancement in real-world environments". *Information Fusion*, 59, 163–170. DOI: https://doi.org/10.1016/j.inffus.2019.08.008

[2] AIAG (2008). "Potential failure mode and effect analysis (FMEA)", 4th Edition. *Automotive Industry Action Group*. https://www.aiag.org/training-and-resources/manuals/details/FMEA-4.

[3] Amrit, C., Paauw, T., Aly, R., Lavric, M. (2017). "Identifying child abuse through text mining and machine learning". *Expert Systems with Applications*. 88, 402–418. DOI: https://doi.org/10.1016/j.eswa.2017.06.035

[4] Ayers, J.B. (Ed.). (2000). "Handbook of supply chain management (1st ed.)". *CRC Press*. DOI: https://doi.org/10.1201/9781420025705

[5] Bowersox, D.J., Closs, D.J. (1996). "Logistical management: The integrated supply chain process". *McGraw-Hill Companies Inc.*, New York.

[6] Dalal, N., Triggs, B. (2005). "Histograms of oriented gradients for human detection". In: *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*, 1, 886–89. DOI: https://doi.org/10.1109/CVPR.2005.177

[7] De Brito, M.P., Dekker, R. (2003). "Modelling product returns in inventory control—exploring the validity of general assumptions". *International Journal of Production Economics*, 81, 225-241.

[8] Fattah, M., Haq, M.A. (2024). "Tweet prediction for social media using machine learning, engineering", *Technology & Applied Science Research*, 14(3), .14698-14703 DOI: https://doi.org/10.48084/etasr.7524

[9] Fazlollahtabar, H. (2018). "Operations and inspection cost minimization for a reverse supply chain". *Operational Research in Engineering Sciences: Theory and Applications*, 1(1), 91–107. DOI: https://doi.org/10.31181/oresta19012010191f

[10] Flygansvær, B., Dahlstrom, R., Nygaard, A. (2018). "Exploring the pursuit of sustainability in reverse supply chains for electronics". *Journal of Cleaner Production*, 189, 472–484. DOI: https://doi.org/10.1016/j.jclepro.2018.04.014

[11] Garg, C.P., Sharma, A. (2020). "Sustainable outsourcing partner selection and evaluation using an integrated BWM–VIKOR framework". *Environment, Development and Sustainability*, 22, 1529–1557. DOI: https://doi.org/10.1007/s10668-018-0261-5

[12] Gattorna, J. (1998). "Strategic supply chain alignment: Best practice in supply chain management (1st ed.)". *Routledge*. DOI: https://doi.org/10.4324/9781315242262

[13] Ghasemi, P., Goodarzian, F., Abraham, A., Khanchehzarrin, S. (2022). "A possibilistic-robust-fuzzy programming model for designing a game theory based blood supply chain network". *Applied Mathematical Modelling*, 112, 282–303. DOI: https://doi.org/10.1016/j.apm.2022.08.003

[14] Olugu, E.U., Wong, K.Y., Shaharoun, A.M. (2010). "A comprehensive approach in assessing the performance of an automobile closed-loop supply chain". *Sustainability*, 2(4), 871-889. DOI: https://doi.org/10.3390/su2040871

[15] Goodarzian, F., Navaei, A., Ehsani, B., Ghasemi, P., Muñuzuri, J., (2023). "Designing an integrated responsive-green-cold vaccine supply chain network using Internet-of-Things: Artificial intelligence-based solutions". *Annals of Operations Research*, 328, 531–575. DOI: https://doi.org/10.1007/s10479-022-04713-4

[16] Goodfellow, I., Bengio, Y., Courville, A., Bengio, Y. (2016). "Deep learning". *MIT Press, Cambridge, MA.*

[17] Han, J., Kamber, M., Pei, J. (2012). "Data mining: Concepts and techniques (3rd ed.)". *Waltham: Morgan Kaufmann Publishers.*

[18] Hand, D.J., Manila H., Smyth, P. (2001). "Principles of data mining". *A Bradford Book*, The MIT Press, Cambridge, Massachusetts, London, England.

[19] Abbasi, S., Damavandi, S., RadmanKian, A.H. Zeinolabedinzadeh, K., Kazancoglu, Y. (2025). "Designing a green forward and reverse logistics network with an IoT approach considering backup suppliers and special disposal for epidemics management". Results in Engineering, 26. DOI: https://doi.org/10.1016/j.rineng.2025.104770

[20] Haykin, S.S. (2009). "Neural networks and learning machines". Volume 10, *Prentice Hall*.

[21] Heaton, J. "Ian Goodfellow, Yoshua Bengio, and Aaron Courville: Deep learning". *Genetic Programming and Evolvable Machines*, 19, 305–307 (2018). DOI: https://doi.org/10.1007/s10710-017-9314-z

[22] Jiawei, H. Kamber, M., Pie, J. (2001). "Data mining: Concepts and techniques", *Morgan Kaufmann Publishers Inc., Elsevier*. DOI: https://dl.acm.org/doi/10.5555/1972541.

[23] Kattenborn, T., Leitloff, J., Schiefer, F., Hinz, S. (2021). "Review on convolutional neural networks (CNN) in vegetation remote sensing". *ISPRS Journal of Photogrammetry and Remote Sensing*, 173, 24–49. DOI: https://doi.org/10.1016/j.isprsjprs.2020.12.010

[24] Keith, R.(2021). "So Why Do We Call it a 'Supply Chain' Anyway?", Industry Week, emphasis added. https://www.industryweek.com/supply-chain/article/22007454/so-why-do-we-call-it-a-supply-chain-anyway.

[25] Kulkarni, A., Shivananda, A.(2019). "Natural language processing recipes: Unlocking text data with machine learning and deep learning using Python". *Apress Berkeley*, CA. https://doi.org/10.1007/978-1-4842-7351-7.

[26] Lambert, D.M., Enz, M. (2025). "Supply chain management: Processes, partnerships, performance". *Supply Chain Management Institute*-5th Edition.

[27] Lambert, D.M., Cooper, M.C., Pagh, J.D. (1998). "Supply chain management: implementation issues and research opportunities". *International Journal of Logistics Management*, 9(2), 1–20. DOI: https://doi.org/10.1108/09574099810805807

[28] LeCun, Y., Bengio, Y. Hinton, G. (2015). "Deep learning". *Nature*, 521(7553), 436–444. DOI: http://dx.doi.org/10.1038/nature14539

[29] Lee, J., Gen, M., Rhee, K. (2009). "Network model and optimization of reverse logistics by hybrid genetic algorithm". *Computers & Industrial Engineering*, 56(3), 951-964. DOI: https://doi.org/10.1016/j.cie.2008.09.021

[30] Lee, S.J. and Siau, K. (2001). "A review of data mining techniques". *Industrial Management and Data System*. 101(1), 41-46. DOI: https://doi.org/10.1108/02635570110365989

[31] Levine, S., Kumar, A., Tucker, G., Fu, J. (2020). "Offline reinforcement learning: Tutorial, review, and perspectives on open problems". *ArXiv preprint arXiv*:2005.01643. DOI: https://doi.org/10.48550/arXiv.2005.01643

[32] Lu, Z., Bostel, N. (2007). "A facility location model for logistics systems including reverse flows: The case of remanufacturing activities". *Computers & Operations Research*, 34(2), 299-323. DOI: https://doi.org/10.1016/j.cor.2005.03.002

[33] Luong, N.C., Hoang, D.T., Gong, S., Niyato, D., Wang, P., Liang, Y.C., Kim, D.I. (2019). "Applications of deep reinforcement learning in communications and networking: A survey". *IEEE communications surveys & tutorials*, 21(4), 3133-3174. DOI: https://doi.org/10.48550/arXiv.1810.07862

[34] Mentzer, J.T., DeWitt, W., Keebler, J.S., Min, S., Nix, N.W., Smith, C.D., Zacharia, Z.G. (2001). "Defining supply chain management". *Journal of Business Logistics*. 22(2), 1–25. DOI: https://doi.org/10.1002/j.2158-1592.2001.tb00001.x

[35] Minner, S. (2001). "Strategic safety stocks in reverse logistics supply chains". *International journal of production economics*, 71(1-3), 417-428. DOI: https://doi.org/10.1016/S0925-5273(00)00138-9

[36] Mousavi, S.M., Beroza, G.C. (2022). "Deep-learning seismology". *Science*, 377(6607): eabm4470. DOI: https://doi.org/10.1126/science.abm4470.

[37] Ngai, E.W.T., Hu, Y., Wong, Y.H., Chen, Y., Sun, X. (2011). "The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature". *Decision Support Systems*, 50(3), 559-569. DOI: https://doi.org/10.1016/j.dss.2010.08.006

[38] Pang, Sh., Chen, Mu.Ch. (2024). "Investigating the impact of consumer environmental consciousness on food supply chain: The case of plant-based meat alternatives". *Technological Forecasting and Social Change*. 201, 123190. DOI: https://doi.org/10.1016/j.techfore.2023.123190

[39] Potok, T.E, Schuman, C., Young, S., Patton, R., Spedalieri, F., Liu, J., Yao, KT., Rose, G., Chakma, G. (2018). "A study of complex deep learning networks on high-performance, neuromorphic, and quantum computers". *The ACM Journal on Emerging Technologies in Computing Systems*, 14(2), 1–21. DOI: https://doi.org/10.1145/3178454

[40] Rand, W.M. (1971). "Objective criteria for the evaluation of clustering methods". *Journal of the American Statistical Association*. 66(336), 846-850. DOI: https://doi.org/10.2307/2284239

[41] Ross, J.W., Weill, P., Robertson, D. (2006). "Enterprise architecture as strategy: Creating a foundation for business execution". *Harvard Business School Press*.

[42] Song, X., Li, J., Cai, T., Yang, S., Yang, T., Liu, C. (2022). "A survey on deep learning-based knowledge tracing". *Knowledge-based Systems*. 258, 110036. DOI: https://doi.org/10.1016/j.knosys.2022.110036

[43] Srinidhi, C.L., Ciga, O., Martel, A.L. (2021). "Deep neural network models for computational histopathology: A survey". *Medical Image Analysis*, 67, 101813. DOI: https://doi.org/10.1016/j.media.2020.101813

[44] Stamatis, D.H. (2003). "FMEA a general overview". In: *Failure Mode and Effect Analysis: FMEA from Theory to Execution, ASQ Quality Press*, Milwaukee, WI, 488.

[45] Stock, J.R. (1998). "Development and implementation of reverse logistics programs". (Oak Brook, IL: *Council of Logistics Management.*

[46] Terwiesch, C. and Cachon, G.P. (2018). "Matching supply with demand: An introduction to operations management". *McGraw-Hill Education*.

[47] Tibben-Lembke, R.S., Rogers, D.S. (2002). "Differences between forward and reverse logistics in a retail environment". *Supply Chain Management: An International Journal*, 7(5), 271–282. DOI: https://doi.org/10.1108/13598540210447719

[48] Witten, I.H., Frank, E., Hall, M.A. (2016). "Data mining: Practical machine learning tools and techniques (4th ed.). *Morgan Kaufmann*.