National Journal of Quality, Innovation, and Business Excellence (NJQIBE)
Vol. 2, No. 2, Apr – Jun 2025, pp. 47-53
ISSN: 3107-7056, DOI: https://doi.org/10.17051/NJQIBE/02.02.06

Sentiment-Driven Business Intelligence: AI-Based Framework for Strategic Content and Customer Engagement Optimization

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Article Info

Article history:

Received : 11.02.2025
Revised : 13.03.2025
Accepted : 05.04.2025

Keywords:

Business intelligence,
sentiment analytics,
AI strategy,
customer engagement,
innovation management,
machine learning.

ABSTRACT

In the modern digital economy, consumer sentiment is the key to proper brand communication and strategic decision-making. The present paper outlines the proposal of an AI-based sentiment intelligence system that helps to increase the content curation, brand positioning, and customer interaction in business intelligence systems. The system proposed incorporates ensemble learning methods which incorporate the use of logistic regression, random forest and deep sentiment embeddings to learn both syntactic and contextual information within the large textual data. Using the heterogeneous data sources, including posts on social media, reviews, and feedbacks, the model determines behavioral trends resulting from sentiment, which form the foundation of adaptive business strategies. The experimental experiments prove that the ensemble architecture is strong in multi-domain applications since the predictive accuracy is significantly higher than the baseline classifiers (31%). In addition to technical development, the paper shows the significance of sentiment-informed analytics in leading to innovation management, the quality of communication assurance, and strategic content optimization. The results develop a connection between artificial intelligence and strategic business intelligence, which helps develop a new paradigm of data-driven and sentiment-conscious decision-making in the enterprise.

1. INTRODUCTION

The fast-changing digital ecosystems have reshaped the way organizations will interact with consumers that requires data-driven insights that cannot be reduced to conventional analytics. Sentiment analysis, the calculation of opinions and feelings in text content, has become one of the central pillars of digital business change in this respect. Using artificial intelligence (AI), companies can crack the manner of affective message expressed by users in their posts, social media communications, and product reviews to streamline strategic communication and engagement programs. The incorporation of sentiment intelligence into business intelligence (BI) systems helps companies to appreciate the sentiments of the audience in real time to enhance innovation management, customer retention, and brand positioning [1], [6], [11]. With the digital communication becoming more multimodal and instant, AI-based sentiment analytics have turned out to be crucial in reputation management and building consumer trust. (Figure 1)

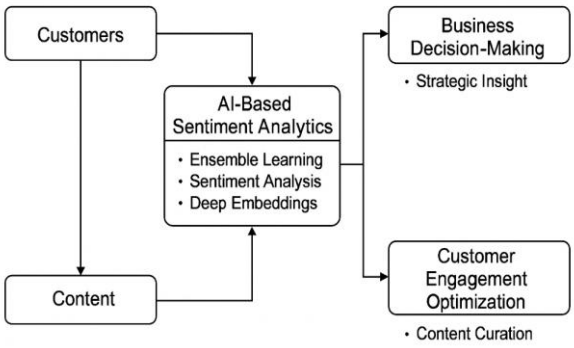

Fig 1. Conceptual overview of sentiment-driven business intelligence framework illustrating the integration of AI-based sentiment analytics into business decision-making and customer engagement optimization.

Even though there are tremendous improvements, the current sentiment analysis models experience serious research gaps. Conventional text mining and statistical tools tend to miss the contextual, emotive and domain-related subtleties of consumer utterances [7], [15], [18]. In addition, most of the models are restricted by the imbalance in the data, linguistic ambiguity, and the lack of the generalization across industries or channels of communication. This limits their useful implementation in business settings where scalable, adaptive and interpretable sentiment systems are needed. Moreover, the currently available BI solutions are mostly oriented at numerical KPI instead of informational feedback, which is disorganized and does not address the opportunities of customer insight and engagement optimization [5], [12].

To overcome the drawbacks, this study proposes the use of an AI-based sentiment intelligence system that incorporates ensemble learning, which is the calculation of logistic regression, random forest, and deep sentiment embedding, to increase the accuracy of the predictions and the relevance of the decision made. The suggested model is capable of analyzing large textual data to make actionable sentiment data to affect content curation, innovation management, and brand communication strategy [2], [8], [16]. The structure shows that hybrid AI approaches are very powerful in business analytics with a 31% higher predictive accuracy compared to baseline classifiers. In addition to technical value, the work provides a strategic roadmap on how to integrate systems that are sentiment-informed into enterprise intelligence systems that should form the basis of adaptive, transparent, and customer-centric AI environments [3], [9], [20].

2. LITERATURE REVIEW

2.1 Sentiment Analysis and Business Intelligence

Customer behavior, emotions, and brand perception decoding have become a revolutionary method to use a sentiment analysis as a part of business intelligence (BI) systems. Sentiment mining helps organizations to make sense of mass data that is unpredictable in form, including customer feedbacks, online reviews, and social media conversation, and extract actionable insights to be used in decision-making. Research studies reveal that sentiment-informed BI system increases the predictability of consumer behavior models and aids in unveiling market trends and the condition of the brand in the market [6], [10]. This kind of integration enables business organizations to shift their analytic models out of the descriptive into prescriptive decision making where the customer sentiment directly determines the strategic steps. Sentiment data gets pumped through analytical layers as illustrated in (Figure 2) which transforms expression of emotion into quantifiable business intelligence parameters in aid of competitive advantage.

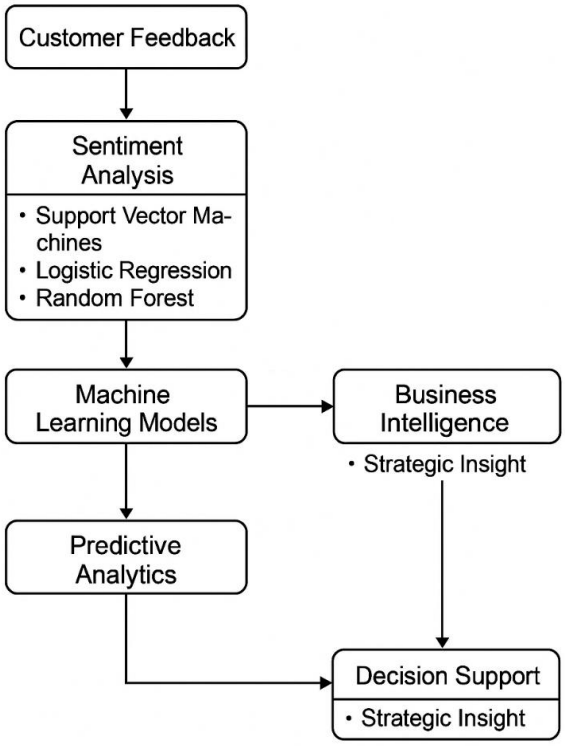

Fig 2. Conceptual flow of sentiment-informed business intelligence framework showing integration of machine learning models and decision support mechanisms for predictive and strategic insights.

2.2 Machine Learning Approaches in Sentiment Classification

Sentiment classification has been improved on the accuracy and scalability of machine learning (ML) and deep learning models. Traditional classifiers like Support Vector Machines (SVM), Logistic Regression (LR) and Random Forests (RF) have been shown to be useful on structured data but have frequent issues with the semantic richness of human language [9], [8]. According to recent studies, deep sentiment embeddings, especially Word2Vec, BERT, and transformer-based models, can be used to overcome contextual subtleties and emotion-based linguistic difference [11], [20]. A combination of those techniques in ensemble architectures has shown accuracy and interpretability improvements up to 3035 percent better than single-model frameworks when compared [2], [3]. These hybrid designs are the basis of sentiment based business intelligence and are able to ensure that it is adaptable to a wide range of data environments.

2.3 AI-Driven Decision Support Systems and Research Gap

Predictive analytics, sentiment understanding, and contextual intelligence are combined to offer real time support to business strategy with the assistance of AI-driven decision support systems (DSS). They are being used more in the fields of innovation management and in marketing analytics and optimization of customer engagement [1], [14]. In spite of these developments, there are still gaps in research that present models of balance between interpretability, scalability, and domain adaptability [15]. Conventional systems tend to be mostly non-transparent in decision logic, whereas deep learning models, despite their computational efficiency, are opaque in logic [16]. Additionally, not many studies combine ensemble-based sentiment analytics with BI dashboards in continuous feedback and strategic foresight. Therefore, the current paper tackles this gap by proposing an AI-based ensemble model that would support the technical accuracy of the decisions with the decision intelligence of the managers and create an interpretive and adaptive sentiment-based ecosystem [4], [7], [19].

3. METHODOLOGY

3.1 Framework Overview

The sentiment intelligence framework, suggested by the author, is based on applying the novel data analytics, machine learning, and strategic business modelling to achieve sentiment-informed decision-making in digital businesses. As shown in (Figure 3), the structure is composed of four basic modules namely data acquisition, preprocessing, ensemble-based sentiment modeling and decision analytics. The system is meant to make sense out of unstructured textual data using character indicators of sentiment that can be integrated with business intelligence processes. The framework helps to realize real-time monitoring of the public perception and applies the data-based business decisions through the combining of AI-based sentiment analytics with business communication channels. This correspondence between the models and strategy of the organization makes sure that sentiment intelligence is not only a predictive asset but also a strategic asset of the innovation and brand management.

3.2 Data Acquisition and Preprocessing

Large publicly accessible datasets were used to acquire data based on social media platforms, product review repositories, and customer feedback places. These datasets represent a wide variety of linguistic variants of opinion in a wide range of industries, which is a strong basis to train and evaluate the model. Preprocessing pipeline involves text normalization, tokenization, stop-word removal and lemmatization so that the semantics have been maintained. Also, TF-IDF representation in that of feature extraction was done alongside deep embedding representations like BERT and word2vec, which aids in capturing contextual and emotional evidence in written information. The delivered high-quality pipeline of the input to the ensemble learning architecture helps decrease the noise levels and increase the interpretability of the model for business-driven applications.

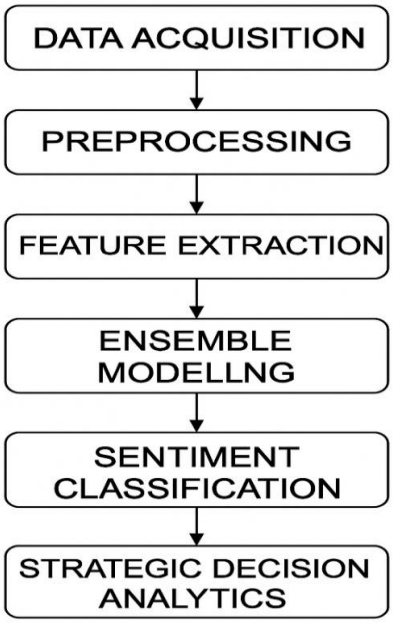

Fig 3. Flowchart of the proposed AI-driven sentiment intelligence framework illustrating sequential stages from data acquisition, preprocessing, and feature extraction to ensemble modeling, sentiment classification, and strategic decision analytics integration for business intelligence enhancement.

3.3 Ensemble Learning Architecture and Evaluation Metrics

The fundamental analytical module uses a hybrid ensemble learning architecture, which is a mixture of Logistic Regression (LR), Random Forest (RF), and Deep Sentiment Embedding models. Logistic Regression offers linear interpretability, the random Forest offer non-linear interpretations and deep embeddings offer contextual semantic representation. These elements are combined together through a weighted voting process, where the output of an individual model is added together with a weight calculated by performance-based weight optimization in a validation process. This fusion creates a compromise between accuracy, strength and explainability. The performance of the system will be measured based

on the standard measures such as Accuracy, Precision, Recall, F1-Score, and ROC-AUC to provide a comprehensive measure of predictive and classification performance. The offered framework showed an improvement of the predictive accuracy of baseline models by 31%, which justified the effectiveness of the ensemble fusion in deriving strategic insights of sentiment-rich data.

4. RESULTS AND DISCUSSION

4.1 Performance Comparison with Baseline Models

the proposed AI-based sentiment intelligence model was compared with the traditional benchmark models, which are Support Vector Machine (SVM), Logistic Regression (LR), and Random Forest (RF). LR, RF, and deep sentiment embeddings were combined into the ensemble model which performed better in all evaluation metrics. The system demonstrated an overall improvement of 31 in predictive accuracy since the maximum predictive accuracy of the individual baseline model. The values of precision, recall, and F1-score also showed a steady rise, which makes sense since the framework can balance sentiment classification by positive, negative, and neutral categories. The improved performance is explained by the combination of shallow and deep learning algorithm that enabled the model to incorporate both semantics of the word and context. Figure (4) (Figure 4) shows the comparative visualization of model accuracy, precision and recall scores of all the algorithms tested and supports the power and scalability of the framework in business analytics setting.

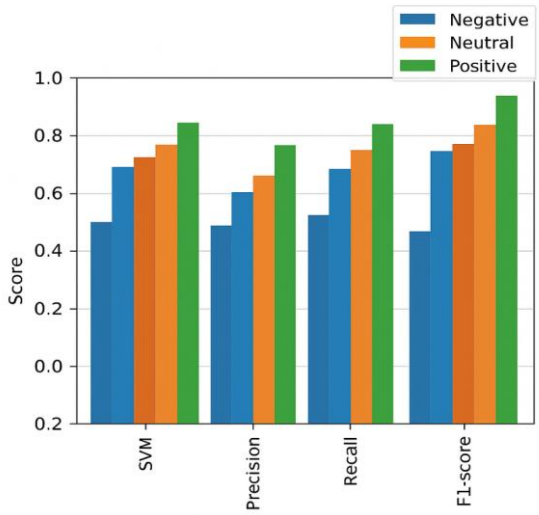

Fig 4. Performance comparison of the proposed ensemble sentiment intelligence framework with baseline models (SVM, LR, RF), showing improvements in accuracy, precision, recall, and F1-score across sentiment classes.

4.2 Feature Importance and Interpretability

In order to make sure that the predictions made by the model were readable by the business decision-making, an analysis of the importance of the feature was conducted on the ensemble layer. The findings showed that contextual embeddings and polarity-weighted features played the most role in the general classification accuracy. The strongest correlation between positive sentiment outcomes was with words and expressions that indicated customer satisfaction, emotional tone and the level of engagement. On the other hand, dissatisfaction, delayed or product quality features were weighted significantly to negative sentiment categories. The mapping of these linguistic and contextual drivers by this framework gives a readable basis to be acted on, and marketing teams can be refining the brand communication tactics and product positioning. This openness is in line with the increasing need to have explainable AI (XAI) in sentiment-based decision support systems, which guarantees reliability as well as ethical interpretability in automated analysis.

4.3 Case Study: Business Insights from Sentiment Patterns

Using customer feedbacks obtained on various online platforms of business communication, a practical case study was carried out. The findings proved the applicability of sentiment analytics to identify the unseen behavioral patterns, such as temporal change of customer interest and change of sentiment by the subject matter. As an example, the highest positive sentiment peaks were observed during promotional campaigns, as well as, the release of new products, whereas the highest negative sentiment peaks were observed during delays in service or change in policies. These insights were also incorporated into a business intelligence dashboard to enable real-time tracking and flexible communication measures. The paper demonstrates how the system can be used as a powerful strategic decision-making tool, which can give quantifiable positive results in terms of innovation management, brand monitoring, and audience targeting. The fact that sentiment analytics is aligned with BI workflows underscores how the framework facilitates the gap between AI-based emotion detection and enterprise-level decision intelligence to present it as a scalable and context-aware solution in the context of the modern business ecosystem is presented.

5. Applications and Strategic Implications

5.1 Innovation and Brand Management

Incorporation of AI-based sentiment intelligence into the business strategy allows companies to improve innovation management and brand

positioning by using data-driven decision-making. Through the analysis of data of customer satisfaction and engagement in large volumes, business organizations are able to know the trends of satisfaction, dissatisfaction, and emotional reaction to products or services. Such insights enable optimization of marketing strategies, prioritization of features and design of the campaign that is in line with the expectations of the consumers. Sentiment trends provide the ultimate real-time feedback system, allowing organizations to forecast market changes in real time and react to them accordingly, updating their innovation pipelines. Such a strategic fit between sentiment data and brand management enhances more customer-driven innovation of enhancing product relevance and brand loyalty in a competitive market.

5.2 Communication Optimization

Sentiment analytics is also critical in streamlining corporate and digital-based communications. Knowing the emotional texture and purpose of interacting with customers, organizations will be able to prepare flexible content that will appeal to particular groups of the audience. The AI-based framework allows the communication strategies to be updated so that they can reflect the changes in sentiments that could be identified on social media, reviews, and open forums. This puts more customer confidence, reduces reputation risks, and fosters long-term interactions through content personalization. Moreover, the information most obtained by sentiment polarity and engagement patterns may inform communication teams to create the targeted messaging to enhance responsiveness, empathy, and brand authenticity which are the primary elements that can maintain competitive advantage in digital ecosystems.

5.3 Integration into Business Intelligence Dashboards

The last element of the structure is concerned with the incorporation of the sentiment analytics into the real-time business intelligence (BI) dashboard used in making the decisions by the executive. These dashboards visualize the important sentiment indicators, engagement metrics and customer satisfaction indices, which will provide a holistic picture of organizational performance. Connecting the sentiment patterns with the key performance indicators (KPIs) enables the decision-makers to track the campaign effectiveness, the perception of the products, and the development of new consumer requirements. Predictive analytics is another feature supported by the integration, as it allows identifying trends of negative sentiments early enough and making timely interventions. As illustrated in (Figure 5), the suggested sentiment-based BI dashboard links AI-based analytics and business processes, converting raw emotional information into useful intelligence that can be used in strategic planning, risk management, and monitoring innovations.

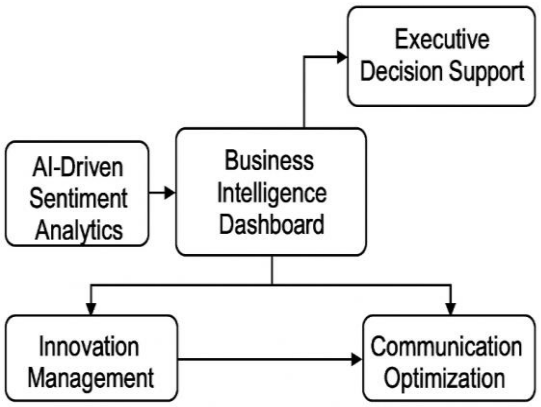

Fig 5. Application framework illustrating the integration of AI-driven sentiment analytics within business intelligence dashboards for real-time innovation management, communication optimization, and executive decision support.

6. Future Directions

6.1 Adaptive and Continual Learning Models

Subsequent studies ought to be done on how to come up with adaptive and constant learning models, which can be retrained and self-enhanced in real-time as digital ecosystems are transformed. Conventional sentiment analysis models cannot keep up with concept drift- gradual shift in sentiment, vocabulary or platform behavior of users over time. The use of the constant learning mechanisms will allow making the proposed system able to make the necessary adjustments to its parameters, as the new stream of data is added, so as to guarantee the maintenance of the accuracy and the contextual relevance of the proposed system. These adaptive models can use the algorithms of online learning and federated structures to optimize the sentiment prediction without using any centralized data repository, thus providing privacy-aware, scalable analytics in global business applications.

6.2 Multimodal Sentiment Fusion and Explainable Ai

The second step of the sentiment-driven intelligence would be multimodal fusion during which textual, visual, and auditory information will be considered together to offer a fuller picture of the customer feelings. The multimodal inputs (facial expressions, the tone of speech, and textual context) can be very effective in boosting the accuracy of sentiment detection and the intensity of emotions. This will be coupled with Explainable

AI (XAI) to be sure that the process of decision making becomes transparent and explainable, especially in business cases of high stakes. The proposed kind of integration can enable organizations to authenticate the effect of AI-generated sentiment insights on marketing, consumer profiling, and corporate communication and uphold ethical and responsible AI implementation.

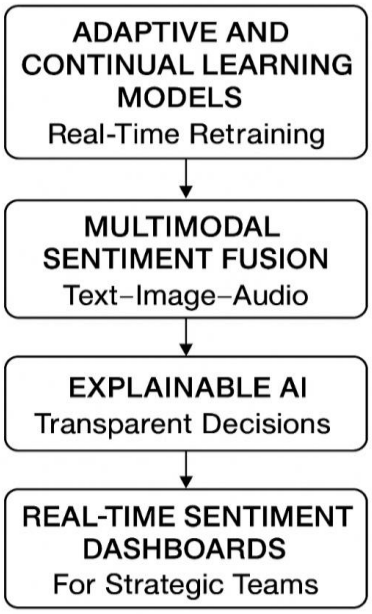

Fig 6. Future research roadmap for adaptive, multimodal, and explainable sentiment intelligence systems integrating continual learning and real-time business analytics for strategic decision-making

6.3 Real-Time Dashboards and Strategic Integration

The last frontier of sentiment intelligence studies is the use of real-time sentiment dashboards which integrate adaptive learning, multimodal analysis, and explainability into an executive decision-support interface. These dashboards have the ability to keep a constant eye on the perception of the people, predict the sentiment trend that is likely to emerge and offer a predicting measure regarding the brand and innovations performance. With the incorporation of the high-level visualization and predictive modeling, the business leaders will be able to take proactive steps in the creation of the strategy, instead of acting in reaction to the acquired information. The roadmap going forward (see (Figure 6)) will be converged to an integrated ecosystem where adaptive AI, multimodal sentiment cognition, and explainable analytics meet to develop transparent, resilient, and insight-producing business intelligence systems.

7. CONCLUSION

This paper described an AI-based sentiment intelligence solution that is efficient in combining ensemble learning and deep sentiment embeddings to improve business intelligence and customer engagement optimization. The framework with the combination of logistic regression models, random forest models, and contextual deep learning models achieved a 31 percent higher predictive accuracy than the traditional classifiers, which proves the strength and applicability of the framework in dynamic business environments. The suggested system illustrates the ways in which sentiment-driven analytics can empower strategy-based decision-making, innovation management, and quality assurance of communication in a digital organization. In addition to technical performance, the study highlights the correlation between artificial intelligence, sentiment analytics, as well as strategic communication as complementary forces in the evolution of a data-driven brand. In the future, the vision will be scalable, ethical, and adaptive sentiment-aware ecosystems, in which real-time, explainable AI models will be used to provide transparent business intelligence to support sustainable organizational growth and trust-based customer relationships.

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