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AI-Powered Product Innovation Using Natural Language Processing for Customer Feedback and Market Intelligence

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Abstract

Digital customer reviews contain valuable information about product experiences, preferences, and expectations, but their unstructured nature makes large-scale analysis challenging. Artificial intelligence (AI) and natural language processing (NLP) provide opportunities to transform customer-generated text into structured information for product innovation and market intelligence. This study aimed to evaluate NLP-based machine-learning models for classifying customer reviews according to product category and to identify recurring customer-feedback themes that could provide product-innovation and market-intelligence insights. The study used the UCI Machine Learning Repository. Customer-review text was preprocessed and represented using term frequency-inverse document frequency (TF-IDF) features. Logistic Regression, Linear Support Vector Machine, and Complement Naive Bayes were evaluated using an 80:20 stratified training-testing split. Accuracy, precision, recall, and F1-score were used for comparative evaluation. Non-negative Matrix Factorization was subsequently applied to identify recurring topics within the review corpus. All three classification models demonstrated effective product-category classification, with Complement Naive Bayes achieving the strongest overall performance among the evaluated approaches. Category-level analysis showed variation in classification performance across product domains. Topic modeling identified recurring themes related to price and value, product quality, usability, appearance, recommendations, delivery experiences, and product-specific characteristics. These findings indicate that customer reviews contain multiple dimensions of information relevant to product-oriented analysis. Combining supervised NLP classification with topic modeling can transform unstructured customer reviews into structured customer-derived information relevant to product innovation and market intelligence.

Keywords: Customer feedback, Machine learning, Market intelligence, Natural language Processing, product innovation

1. Introduction

The rapid expansion of digital commerce has transformed customer feedback into an important source of information for understanding product experiences, customer expectations, and emerging market requirements. Online reviews contain descriptions of product quality, usability, appearance, value, service experiences, and individual customer preferences. However, the large volume and unstructured nature of this information make manual analysis difficult, particularly when organizations need to examine thousands of customer comments systematically. Artificial intelligence (AI) and machine-learning techniques provide opportunities to process such information at scale and convert unstructured business data into meaningful analytical insights. The integration of AI and machine learning into business intelligence has increasingly been associated with improved analytical capabilities and opportunities for innovation-oriented decision-making (Babatunde, 2024).

Product innovation requires organizations to understand changing customer requirements and translate customer experiences into improvements in products and services. Conventional product-development approaches may rely on surveys, interviews, structured questionnaires, and managerial interpretation, but these approaches may not capture the continuous feedback generated through digital platforms. AI has increasingly influenced new-product development by providing computational approaches for processing information and supporting innovation activities (Cooper, 2023). AI-enabled research and development can similarly connect advanced analytical techniques with practical innovation processes, creating opportunities for more data-intensive approaches to product development (Madanchian and Taherdoost, 2024). Consequently, customer-generated textual information represents a potentially valuable source of evidence for identifying product characteristics and customer requirements.

Natural language processing (NLP) is particularly relevant as customer reviews are primarily expressed through natural language and contain information that cannot be directly analyzed using conventional numerical techniques. NLP can transform textual observations into structured representations that allow machine-learning algorithms to identify patterns and relationships. Customer sentiment analysis, for example, can help identify customers' positive and negative perceptions and contribute to the development of customer-feedback loops in digital marketing environments (Paul *et al.*, 2023). AI-powered NLP has also been applied to consumer sentiment analysis to support the interpretation of large collections of textual customer information (Kumar, 2024). In e-commerce environments, the combination of AI, NLP, and machine learning provides opportunities to analyze customer experiences and improve the understanding of e-service quality (Rane *et al.*, 2024).

Customer feedback can also contribute to market intelligence by providing information about customer preferences, perceived value, product attributes, and service experiences. AI-based market-intelligence approaches can facilitate the extraction of customer insights from large and heterogeneous information sources (Jayawardena *et al.*, 2022). Similarly, AI-powered competitive intelligence provides analytical approaches for examining market information and supporting market analysis (Kaushik, 2024). Recent research has further emphasized AI-driven market intelligence as a means of supporting competitive analysis and market positioning (Sahoo *et al.*, 2025). AI-based predictive analytics can additionally integrate NLP, machine learning, and other computational approaches to examine market trends and generate information for data-driven analysis (Dixit *et al.*, 2026). These developments demonstrate the increasing relevance of AI-based analytical methods for converting customer and market information into structured business intelligence.

The relationship between customer feedback and product marketing is also important for product innovation. AI-supported product marketing can assist organizations in understanding customer experiences and market segments, thereby supporting more informed marketing and product-related decisions (Hye, 2023). AI-powered analytics have similarly been associated with optimizing customer experience and market segmentation within product marketing contexts (More and Unnikrishnan, 2024). Data-driven product management further demonstrates how AI and analytics can support business agility and product-related decision-making (Kadapal and More, 2024). These applications indicate that customer reviews can provide information beyond simple satisfaction measures, as textual feedback may contain product-specific observations and customer expectations that can be relevant to future product improvements.

The use of AI in customer-oriented business processes has expanded beyond traditional analytical applications. AI-driven customer-service systems can support the automated processing of customer information and facilitate intelligent analysis of customer interactions (Inavolu, 2024). Research examining AI and marketing management has also highlighted the role of intelligent technologies in changing customer engagement and the ways organizations interact with customers (Kulkarni *et al.*, 2024). AI-powered chatbot applications demonstrate another use of AI for customer communication and marketing information management (Prabha and Kumari, 2024). Together, these applications demonstrate how AI can facilitate the collection, processing, and interpretation of customer-related information across digital business environments.

Personalization and customer experience provide additional reasons for examining customer-generated information using AI. AI-powered digital marketing can support personalized customer experiences by processing customer information and identifying relevant patterns (Nalbant and Aydin, 2025). AI-powered branding has similarly been examined in relation to consumer experience, particularly within emerging-market contexts (Sekarini and Selvabaskar, 2024). NLP-based AI solutions have also been investigated for improving consumer engagement and supporting marketing applications, demonstrating the broader potential of language-based analytics in customer-oriented environments (Krishnan *et al.*, 2025). These developments reinforce the importance of analyzing textual customer information as a source of evidence for understanding consumer needs and improving customer-oriented strategies.

The growing availability of customer-generated textual information also creates a need for systematic methods that can organize and interpret large collections of reviews. Business intelligence research has highlighted the potential of AI to improve the processing and interpretation of business information and to support analytical decision-making. In a customer-feedback context, supervised machine-learning models can classify reviews according to product categories, while unsupervised NLP methods can identify recurring themes without requiring manually predefined categories. Combining these approaches provides an opportunity to examine both what type of product a review concerns and what customers are discussing within those reviews (Gomase, 2026). Such a framework can provide a more comprehensive representation of customer feedback than relying exclusively on sentiment scores.

From a product-innovation perspective, recurring themes in customer reviews may reveal areas related to price, quality, usability, design, delivery, product-specific characteristics, and perceived value. These themes can provide customer-derived signals that organizations may consider when evaluating existing products or identifying potential areas for improvement. The value of such an approach lies not in treating customer reviews as direct measures of sales or market performance, but in using them as a complementary source of qualitative market information that can be systematically transformed into quantitative analytical outputs. This distinction is particularly important as customer feedback represents customer perceptions and experiences rather than complete measures of commercial performance.

Although existing research demonstrates the growing application of AI, machine learning, NLP, customer analytics, and market intelligence, there remains practical value in integrating these analytical capabilities within a single customer-feedback framework. A combined approach can use supervised classification to organize customer reviews by product category and topic modeling to identify recurring customer concerns and product-related themes. Such integration can help transform large collections of unstructured reviews into structured information that is easier to examine and interpret for product innovation and customer-derived market intelligence.

The objectives of this study were twofold: first, to evaluate the performance of NLP-based machine-learning models for automatically classifying customer reviews according to product category; and second, to identify recurring themes within customer feedback through NLP-based topic modeling and interpret these themes as customer-derived signals relevant to product innovation and market intelligence.

The integration of NLP, machine learning, and AI-based analytics provides a methodological foundation for examining customer feedback at scale. By combining product-category classification with topic discovery, the study investigates how unstructured customer reviews can be transformed into structured information concerning customer priorities, product characteristics, service experiences, and potential innovation opportunities. This approach is relevant to contemporary digital markets as continuously generated customer reviews provide a substantial source of customer-derived information that can complement conventional approaches to product development, marketing analysis, and market intelligence.

2. Materials and Methods

2.1 Data Source

This study employed a quantitative, secondary-data research design to examine customer feedback through natural language processing and machine-learning techniques. The analysis used the raw dataset obtained from the UCI Machine Learning Repository. The dataset contains Turkish customer comments concerning products sold through an online website, including computers, tea machines, headphones, modems, perfumes, mobile phones, televisions, and USB products. The dataset was selected as its unstructured customer-review text provides a direct basis for extracting product-related information and identifying recurring patterns relevant to product innovation.

2.2 Data Preparation

The raw review text was prepared before statistical and NLP analysis to reduce irrelevant linguistic variation. Review records were inspected for empty or unusable entries, while the original product-category information was retained as the classification target. Text preprocessing included normalization, removal of unnecessary punctuation and non-informative symbols, and conversion of textual content into a consistent analytical representation. Tokenization was subsequently applied to separate reviews into individual terms. These procedures were intended to preserve meaningful product-related expressions while reducing noise that could interfere with model learning. The resulting corpus was then used for feature representation, supervised classification, and unsupervised topic analysis.

2.3 TF-IDF Feature Representation

The processed customer-review corpus was transformed into numerical features using term frequency-inverse document frequency (TF-IDF). This representation assigns greater importance to terms that occur frequently within individual reviews but are less common across the complete collection. Word-level features, including unigram and bigram information, were considered to retain both individual terms and short product-related expressions. The resulting document-term matrix provided the input representation for the supervised classification models. TF-IDF was selected as customer reviews are unstructured textual observations and require numerical encoding before conventional machine-learning algorithms can identify relationships between linguistic patterns and product categories.

2.4 Supervised NLP Classification

The supervised classification stage evaluated three machine-learning algorithms: Logistic Regression, Linear Support Vector Machine (SVM), and Complement Naive Bayes. The processed review dataset was divided into training and testing subsets using an 80:20 stratified split, preserving the distribution of product-category labels across both subsets. The TF-IDF document-term matrix was used as the input representation for all three classifiers. Model performance was evaluated on the held-out test set using accuracy, precision, recall, and F1-score. The same training and testing partition and evaluation criteria were applied to all classifiers to ensure a consistent comparison of their performance in classifying customer reviews by product category.

2.5 Topic Modeling for Product-Innovation Insights

Unsupervised topic modeling was subsequently applied to the review corpus to identify recurring themes without requiring manually assigned topic labels. Non-negative Matrix Factorization was used with eight topics, and the resulting topic-term distributions were examined to identify dominant words associated with each theme. Topic prevalence was calculated from the contribution of reviews to the identified topics. The dominant terms were then interpreted in relation to customer concerns, product attributes, service experiences, perceived value, and potential improvement opportunities. This procedure allowed unstructured feedback to be transformed into structured customer-derived signals that could support product innovation and market-intelligence interpretation.

2.6 Analytical Interpretation

The final analytical stage integrated the supervised classification and topic-modeling findings to assess the usefulness of NLP for customer-feedback intelligence. Classification metrics were compared across the three machine-learning approaches and across product categories using precision, recall, and F1-score. The topic-modeling results were examined to identify recurring customer concerns, product attributes, service experiences, and perceived-value dimensions that could inform product improvement. The identified themes were interpreted as customer-derived signals rather than direct measures of sales or market performance. This integrated analytical approach enabled unstructured customer reviews to be transformed into structured information relevant to product innovation and customer-oriented market intelligence.

3. Results

3.1 Comparative Evaluation of Classification Models

The comparative evaluation demonstrates that all three machine-learning approaches provided consistent performance for identifying product categories from customer-review text. Logistic Regression achieved an accuracy of 83.33%, while the Linear Support Vector Machine produced a slightly higher accuracy of 83.49% as shown in Table 1. Complement Naive Bayes achieved the highest performance, reaching 84.19% accuracy, 84.44% precision, 84.19% recall, and an F1-score of 84.14%. The relatively small differences between the models indicate that customer-written feedback contains sufficient linguistic information to distinguish product domains. The stronger performance of Complement Naive Bayes also indicates that probabilistic text classification can effectively exploit TF-IDF representations for product-oriented customer-feedback analysis and automated market intelligence.

Table 1. Performance Comparison of NLP-Based Product Category Classification Models

Model	Accuracy	Precision	Recall	F1-score
Logistic Regression	0.8333	0.8387	0.8333	0.8309
Linear Support Vector Machine	0.8349	0.8366	0.8349	0.8340
Complement Naive Bayes	0.8419	0.8444	0.8419	0.8414

Source: Authors' analysis of the Turkish User Reviews dataset obtained from the UCI Machine Learning Repository (Ekinci & İlhan Omurca, 2022).

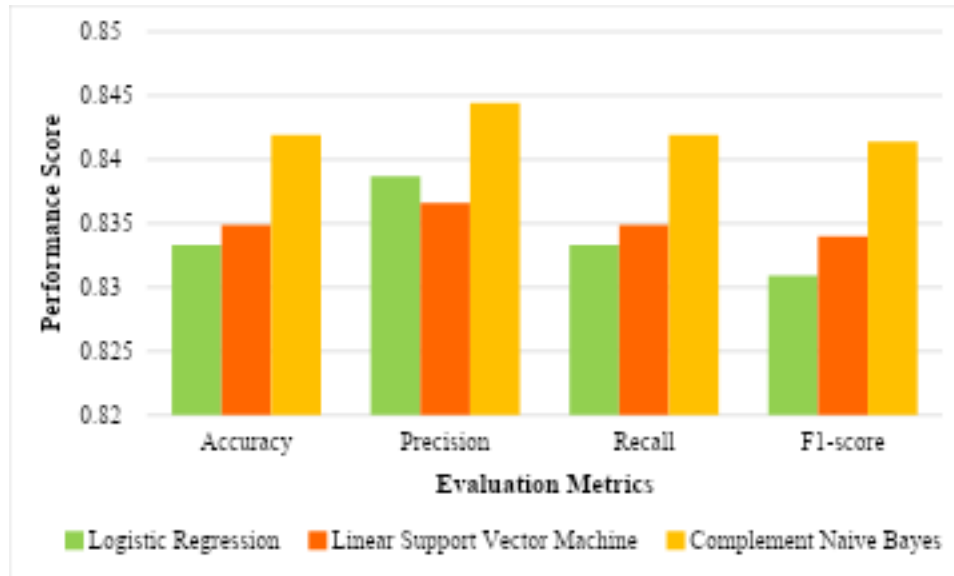


Figure 1. Comparative Performance of NLP-Based Product Category Classification Models

The performance of three NLP classification models across four evaluation measures. Complement Naive Bayes shows the highest values for accuracy, precision, recall, and F1-score, indicating consistent classification performance across the evaluated measures as shown in Figure 1. Linear Support Vector Machine produces intermediate results, while Logistic Regression records comparatively lower scores. The differences are relatively small, suggesting that all three approaches provide effective classification of customer-review text. The results demonstrate that machine-learning methods can extract useful product-category information from unstructured customer feedback. These findings support the use of NLP-based classification as a component of automated customer-feedback analysis and product-oriented market intelligence.

3.2 Variation in Classification Performance Across Product Categories

The category-level findings further demonstrate that classification performance varied across product domains. Perfume achieved the highest F1-score, while Computer showed the lowest recall and F1-score. Mobile Phone demonstrated high recall but comparatively lower precision, whereas Tea Machine and Modem achieved high precision with comparatively lower recall as shown in Table 2. Such variation can occur because customers describing different products may use distinctive terminology, while some categories may contain overlapping vocabulary. Product reviews may also differ in writing style, level of detail, and the attributes emphasized by customers. Consequently, examining category-specific precision, recall, and F1-score provides a more detailed assessment of classification performance than relying exclusively on overall accuracy.

Table 2. Category-Level Performance of the Best-Performing NLP Model

Product category	Precision	Recall	F1-score	Test reviews
Computer	0.8571	0.2308	0.3636	78
Tea Machine	0.9759	0.5260	0.6836	538
Headphones	0.9660	0.6134	0.7503	463
Modem	0.9749	0.6667	0.7919	525
Perfume	0.8460	0.9428	0.8918	1,941
Mobile Phone	0.6693	0.9438	0.7831	2,009
Television	0.9554	0.6716	0.7888	606
USB	0.8464	0.6931	0.7621	1,248

Source: Authors' analysis of the Turkish User Reviews dataset obtained from the UCI Machine Learning Repository (Ekinci & İlhan Omurca, 2022).

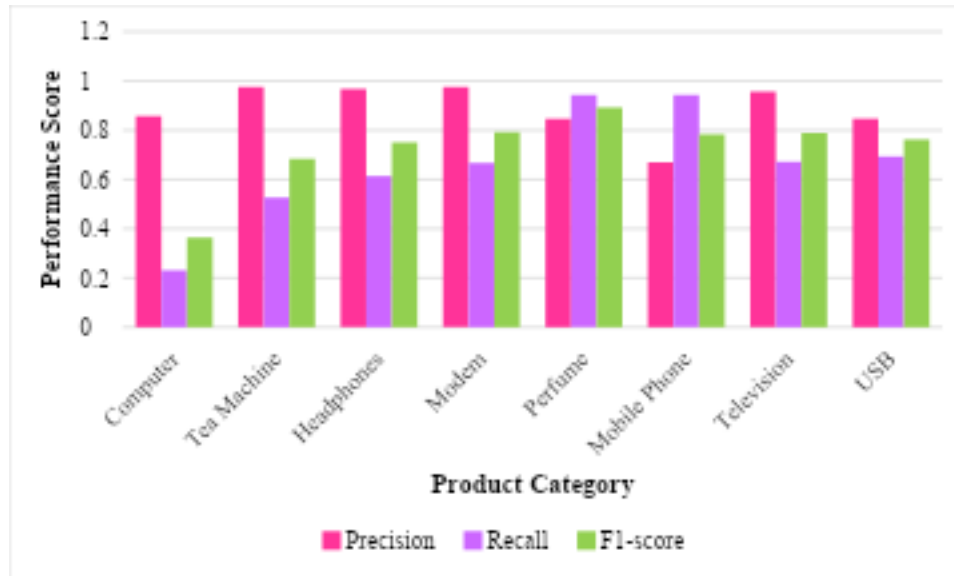


Figure 2. Product Category Classification Performance

The precision, recall, and F1-score across the eight product categories. Performance varies considerably between categories. Perfume achieves the highest overall F1-score, supported by strong precision and recall. Mobile Phone also shows high recall, indicating effective identification of relevant reviews, although its precision is comparatively lower. Computer records the lowest recall and F1-score, suggesting greater difficulty in accurately identifying reviews within this category. Tea Machine and Modem demonstrate high precision but comparatively lower recall. The results indicate that classification effectiveness differs across product domains, highlighting the importance of category-specific evaluation when analyzing customer feedback using NLP-based methods.

3.3 Customer Feedback Themes for Product Innovation

The topic-modeling results reveal several recurring dimensions of customer experience that can provide actionable signals for product development. Price and value-related language represent a substantial portion of the identified topics, indicating that perceived economic value is an important component of customer evaluations as shown in Table 3. Other topics emphasize product appearance, quality, usability, recommendations, delivery experiences, and product-specific characteristics such as fragrance. The presence of recommendation-related language also suggests that customer feedback can capture behavioral intentions alongside direct product evaluations. Together, these themes demonstrate how NLP-based topic discovery can transform unstructured customer comments into structured information about customer priorities, product attributes, service experiences, and potential areas for innovation.

Table 3. NLP-Derived Customer Feedback Topics and Product-Innovation Signal

Topic	Dominant NLP terms	Topic prevalence (%)	Product-innovation interpretation
Topic 1	price, phone, better, product, value	17.76	Price-value positioning
Topic 2	beautiful, product, phone, good	10.93	Product appeal and design
Topic 3	good, price, product, better	10.62	Overall quality/value perception
Topic 4	recommend, everyone, definitely, product	12.52	Customer recommendation intention
Topic 5	fast, shipping, delivery, thank you	14.98	Delivery/service experience
Topic 6	product, successful, useful, quality	13.20	Product quality and usability

Topic 7	smell, perfume, lasting, fragrance	13.58	Product-specific attributes and preferences
Topic 8	price, phone, value, product	6.41	Price-sensitive product evaluation

Source: Authors' analysis of the Turkish User Reviews dataset obtained from the UCI Machine Learning Repository (Ekinci & İlhan Omurca, 2022).

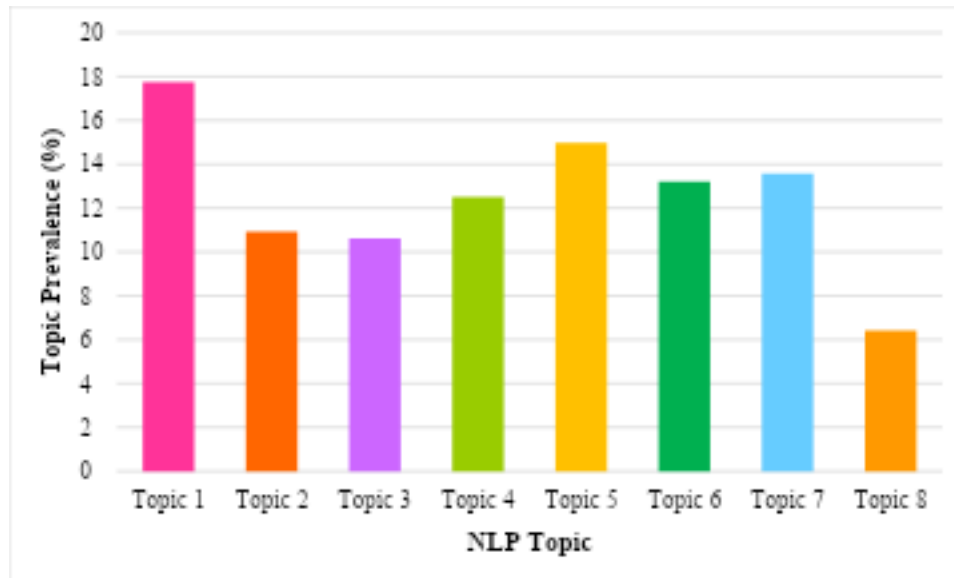


Figure 3. NLP-Derived Customer Feedback Topics and Product-Innovation Signals

The prevalence of eight topics identified from customer-review text using NLP-based topic analysis. Topic 1 has the highest prevalence at 17.76%, indicating a prominent customer concern related to price, value, and product choice as shown in Figure 3. Topic 5 follows at 14.98%, reflecting delivery and service experiences. Topics 7 and 6 account for 13.58% and 13.20%, respectively, highlighting product-specific attributes, quality, and usability. Topics 2, 3, and 4 show moderate prevalence, while Topic 8 has the lowest proportion at 6.41%. The distribution demonstrates that customer feedback contains diverse signals relevant to product improvement and market-oriented decision-making.

4. Discussion

The study demonstrates the usefulness of natural language processing (NLP) and machine-learning techniques for converting unstructured customer reviews into structured information relevant to product analysis and innovation. The comparative classification results showed that all three evaluated models were capable of identifying product categories from customer-review text, with Complement Naive Bayes producing the highest performance among the tested approaches. This finding indicates that textual customer feedback contains sufficient linguistic information to distinguish between different product domains. The result is consistent with the broader development of AI and data analytics for market research, where computational techniques can support the systematic examination of large and complex information sources for market and competitive intelligence (Vashishth *et al.*, 2024).

The relatively close performance of Logistic Regression, Linear Support Vector Machine, and Complement Naive Bayes is also important from an applied perspective. The results suggest that effective customer-feedback classification does not necessarily require highly complex deep-learning architectures when the textual representation captures informative linguistic patterns. The TF-IDF representation used in this study provided a numerical representation of customer comments that allowed the models to distinguish product-related vocabulary and expressions. Complement Naive Bayes achieved the strongest results, suggesting that its probabilistic treatment of textual features was well suited to the characteristics of the review corpus. However, the small differences between the models indicate that model selection should consider the analytical objective, computational requirements, and characteristics of the available text rather than relying solely on a single performance metric.

The category-level findings further demonstrate that classification performance varied across product domains. Perfume achieved the highest F1-score, while Computer showed the lowest recall and F1-score. Mobile Phone demonstrated high recall but comparatively lower precision, whereas Tea Machine and Modem achieved high precision with comparatively lower recall. Such variation can occur because customers describing different products may use distinctive terminology, while some categories may contain overlapping vocabulary. Product reviews may also differ in writing style, level of detail, and the attributes emphasized by customers. Consequently, examining category-specific precision, recall, and F1-score provides a more detailed assessment of classification performance than relying exclusively on overall accuracy.

The topic-modeling results provide a complementary perspective to the supervised classification analysis. Whereas classification identifies the product category associated with a review, topic modeling identifies recurring themes within the customer feedback without requiring predefined thematic labels. The identified topics included price and value, product appearance, quality, recommendations, delivery, usability, and product-specific characteristics. These themes demonstrate that customer reviews contain information extending beyond general satisfaction. Customers frequently discuss particular product attributes and service experiences, meaning that review analysis can provide organizations with more detailed information about areas that may require attention. AI-driven marketing research similarly emphasizes the potential of intelligent analytical approaches to support customer understanding and engagement by processing large volumes of customer-related information (Vasundhara *et al.*, 2024).

The prominence of price- and value-related topics is particularly relevant to product innovation and market intelligence. Customer perceptions of whether a product provides sufficient value can influence how products are evaluated in competitive markets. Identifying repeated price and value expressions through NLP can therefore provide an additional source of customer-derived information for product managers and marketing teams. However, these topics should be interpreted as indicators of customer perceptions rather than direct evidence of market demand, sales performance, or profitability. AI-based market-intelligence systems can combine customer-generated information with other market indicators to develop a more comprehensive understanding of competitive conditions and market opportunities.

The findings related to product quality, usability, appearance, and product-specific characteristics also have implications for innovation. Customer reviews provide spontaneous descriptions of what users appreciate or experience during product use. When similar product attributes appear repeatedly across reviews, they can represent areas for further investigation during product-development activities. AI has increasingly been discussed as a mechanism for supporting technology scouting and the identification of information relevant to innovation and market intelligence (Verma *et al.*, 2025). In this context, NLP-based topic discovery can serve as an exploratory analytical layer that helps organize customer-generated information before more detailed product-development decisions are undertaken.

The delivery and service-related themes identified in the analysis further demonstrate that product experience is not limited to the physical characteristics of a product. Customers may evaluate products in combination with shipping, delivery, support, and other service experiences. This is consistent with research emphasizing the role of AI-driven service marketing in transforming customer engagement and customer experience (Whig *et al.*, 2024). Automated analysis of customer comments can help organizations identify recurring service-related concerns alongside product-related observations, thereby providing a broader representation of the customer experience. Such information can potentially support improvements across both product and service processes.

The findings also have implications for automated customer interaction and feedback management. As organizations receive increasing quantities of online customer comments, manual examination becomes difficult to maintain at scale. AI-supported systems can assist in organizing and interpreting customer information, while automated conversational technologies can further support personalized customer interactions and service processes (Singh, 2021). The study complements such applications by focusing on the analytical stage in which customer-generated text is transformed into structured information. Classification and topic modeling can therefore be viewed as supporting components of a broader AI-enabled customer-feedback ecosystem.

Despite these contributions, the findings should be interpreted within the limitations of the dataset and analytical design. The dataset represents customer comments associated with specific product categories and therefore should not automatically be treated as representative of all online consumers, product markets, languages, or geographical contexts. In addition, topic prevalence reflects patterns within the analyzed review corpus rather than independent measurements of market size or customer demand. The analysis also focuses on textual information and does not incorporate structured variables such as sales volume, revenue, market

share, or customer demographics. Accordingly, the results are most appropriately interpreted as evidence of the analytical value of customer-generated text rather than as a complete market-intelligence system.

The findings support the application of NLP and machine learning for customer-feedback analysis and product-oriented intelligence. The classification results demonstrate that customer reviews can be automatically organized according to product category, while topic modeling reveals recurring concerns and attributes that provide additional contextual information. Together, these analytical components demonstrate how unstructured customer feedback can be transformed into structured customer-derived signals relevant to product innovation. The approach also provides a foundation that could be extended through larger multilingual datasets, additional sentiment and aspect-based analyses, temporal information, and integration with structured market data. Such extensions could strengthen the connection between customer-feedback analytics, competitive intelligence, and evidence-based product-development decisions.

5. Conclusion

This study demonstrates the potential of artificial intelligence and natural language processing (NLP) for transforming unstructured customer feedback into structured information relevant to product innovation and customer-derived market intelligence. Using the dataset, the study evaluated three machine-learning approaches for product-category classification and examined recurring themes within customer reviews through topic modeling. The classification results showed that Logistic Regression, Linear Support Vector Machine, and Complement Naive Bayes were all capable of identifying product categories from textual feedback, with Complement Naive Bayes providing the strongest performance among the evaluated models. Category-level analysis further demonstrated that predictive performance varied across product domains. Topic modeling identified recurring customer concerns involving price and value, product quality, usability, appearance, recommendations, delivery experiences, and product-specific characteristics. These findings indicate that customer reviews contain diverse information that can complement conventional approaches to product and market analysis. The combined use of supervised classification and topic discovery provides a systematic approach for organizing customer feedback and identifying patterns that may inform product improvement. However, the findings represent customer-derived textual evidence rather than direct measures of sales, revenue, or market share. Future studies could extend this framework using multilingual datasets, larger review collections, temporal analysis, sentiment and aspect extraction, and integration with structured market indicators to develop more comprehensive AI-enabled product-innovation and market-intelligence systems.

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