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Research Paper Open Access

Deep Learning-Based Customer Insight Analytics for Data-Driven Product Development and Innovation

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Abstract
The rapid growth of digital commerce has generated substantial volumes of customer reviews and product-related information. Extracting meaningful patterns from these data can help organizations understand customer experiences, identify product-related preferences, and support evidence-based product development. Deep-learning techniques provide opportunities to analyze customer-generated information systematically and transform complex feedback into actionable customer insights. This study aimed to apply deep-learning-based customer insight analytics to identify meaningful patterns in customer feedback and examine product- and category-level insights relevant to data-driven product development and innovation. The study used the Brazilian E-Commerce Public Dataset by Olist, incorporating customer reviews, product information, order-item records, and product-category information. Customer ratings were organized into feedback categories, and the available customer-generated information was processed to examine feedback patterns and differences across product categories. A deep-learning-oriented analytical framework was applied to derive customer insights relevant to product development and innovation. The analysis showed a predominance of positive customer feedback, while negative and neutral responses provided additional information concerning areas requiring further attention. Customer responses also varied across product categories, demonstrating differences in review volume and reported satisfaction. These patterns indicate that customer-generated information can provide meaningful evidence for identifying product-related strengths, potential improvement areas, and customer preferences. Deep-learning-based customer insight analytics provides a systematic approach for interpreting customer-generated information in digital commerce. Integrating customer feedback with product-level and category-level analysis can support evidence-based product development, customer-oriented decision-making, and innovation planning.

Keywords: Customer analytics, Deep learning, E-commerce, Product development, Product innovation

1. Introduction

Digital commerce has transformed the way organizations interact with customers, evaluate market responses, and develop products. Every online transaction can generate multiple forms of information, including customer ratings, written reviews, purchasing behavior, product preferences, and interaction patterns. The increasing availability of such information has created opportunities for organizations to move beyond conventional market research toward systematic, data-driven customer insight analytics (Adhikari *et al*., 2018). Big-data and machine-learning approaches can identify patterns within large and heterogeneous datasets and support evidence-based managerial decisions (Adewale *et al*., 2023). In retail environments, data-driven analytics can also provide insights into consumer engagement, customer experience, and purchasing behavior, thereby supporting more informed commercial strategies (Kliestik *et al*., 2022). Consequently, customer-generated data have become an important resource for understanding changing preferences and identifying opportunities for product improvement.

The value of customer insight analytics extends beyond describing historical purchasing behavior. Modern analytical approaches can integrate multiple dimensions of customer information to identify recurring patterns, relationships, and emerging preferences (Bhattacherjee and Badhan, 2024). Machine-learning techniques have increasingly been applied to predictive analytics because they can process complex datasets and generate information that supports data-driven decision-making across different industries (Boppiniti, 2019). Within e-commerce, machine-learning frameworks can similarly assist organizations in extracting actionable information from customer and transaction data (Mahmud *et al*., 2023). Customer segmentation is another important application because it enables organizations to distinguish groups according to behavioral characteristics and preferences, allowing marketing and product strategies to become more targeted (Rahaman *et al*., 2022). Therefore, customer insight analytics represents an analytical foundation for connecting customer-generated information with strategic product and business decisions.

The rapid growth of unstructured customer feedback has increased the need for analytical methods capable of interpreting textual information at scale. Customer reviews frequently contain detailed opinions concerning product quality, usability, performance, satisfaction, and specific product characteristics (Rachakatla *et al*., 2023). Traditional statistical approaches may provide useful descriptive summaries, but deep-learning techniques can model complex relationships within large volumes of data and extract higher-level patterns from textual and behavioral information. Artificial intelligence and machine learning are increasingly influencing business analytics by supporting automated pattern recognition, predictive analysis, and decision-making (Ahmed *et al*., 2025). Deep-learning and neural-network approaches are particularly relevant when customer information contains nonlinear relationships and unstructured textual content.

Deep-learning methods can also support customer-centric applications by learning representations from historical behavioral and feedback data. In financial services, neural-network-based predictive frameworks have been associated with customer-oriented analytical applications and innovation (Kannan, 2022). Similarly, machine-learning-based recommendation systems can use behavioral information to improve personalized user experiences (Liu *et al*., 2025). These developments demonstrate the broader potential of intelligent analytical systems to transform customer-generated information into useful insights. In the context of product analytics, deep learning can therefore be employed to classify customer feedback, identify patterns in customer preferences, and reveal differences in responses across product categories. Such capabilities provide a methodological basis for integrating customer feedback into data-driven product development.

Customer feedback provides organizations with direct evidence of how products are experienced after purchase. Ratings can indicate overall levels of satisfaction, whereas written reviews can provide more detailed information about perceived strengths, weaknesses, and product characteristics (Musanase *et al*., 2023). Integrating these forms of information can help organizations identify areas requiring improvement and recognize characteristics associated with favorable customer responses (Kim *et al*., 2024). Data-driven product development increasingly emphasizes the use of analytical evidence throughout the product innovation process rather than relying exclusively on intuition or conventional product research. Bertoni *et al*. (2020) proposed a data-driven design framework in which data analysis and visualization contribute to model-based decision-making during product innovation. Similarly, research on big data and artificial intelligence has highlighted their growing relevance to product design and development activities (Quan *et al*., 2023).

Machine-learning approaches can further strengthen this process by identifying relationships that may not be readily observable through conventional descriptive analysis. Research on machine-learning-enabled product and manufacturing applications has demonstrated the growing integration of artificial intelligence into product-related decision processes (Baviskar *et al*., 2023). Customer segmentation and text-mining approaches can additionally combine customer characteristics with feedback information to identify groups and product-related preferences relevant to development decisions (Maghsoudi *et al*., 2025). Thus, customer feedback can function not merely as an evaluation mechanism but as an analytical input for identifying potential product improvements, understanding category-level customer responses, and supporting evidence-based development priorities (Mortaji and Shateri, 2023).

Product innovation increasingly depends on an organization's ability to interpret rapidly changing market information and convert customer knowledge into development decisions. Data-driven innovation approaches provide a mechanism through which customer, market, and product information can be systematically analyzed to identify opportunities for new or improved products. Adikari *et al*. (2021) demonstrated the relevance of machine-learning-based data-driven approaches to value co-creation and open innovation, particularly in environments where large volumes of social-media information can contribute to innovation activities. More broadly, emerging digital technologies have been associated with data-driven innovation management and the development of analytical capabilities for organizational decision-making (Jain, 2026).

Deep learning can contribute to this process by enabling automated analysis of complex customer information and generating patterns that can support product-related decisions. Data-driven models have been increasingly examined for applications involving product design, innovation, and decision support. In retailing, machine-learning and neural-network algorithms have also been linked with consumer engagement, experience, and purchasing behavior. These developments indicate that intelligent customer analytics can connect customer experience with product-oriented decision processes. A deep-learning-based analytical framework can therefore provide a structured approach for transforming customer reviews and product-level information into insights that may assist organizations in identifying satisfaction patterns, areas for improvement, and opportunities for innovation.

Although previous studies have established the importance of big-data analytics, machine learning, customer segmentation, recommendation systems, and data-driven product design, an integrated application of deep learning to customer feedback for product development and innovation remains an important research area. Existing research has examined data-driven decision-making in e-commerce, consumer engagement and purchasing behavior in retailing, customer segmentation using machine learning and text mining, and data-driven product design using artificial intelligence. However, these streams of research are often focused on individual analytical tasks rather than connecting customer feedback analysis with product-development-oriented insights within a unified framework. Furthermore, customer reviews contain both quantitative ratings and qualitative textual information, requiring analytical approaches capable of considering these complementary forms of evidence. Addressing this gap requires a framework that applies deep learning to customer feedback while examining product-level and category-level patterns that can contribute to data-driven development and innovation.

The study aims to develop a deep-learning-based customer insight analytics framework for analyzing customer feedback and identifying patterns relevant to data-driven product development and innovation. Specifically, the study objectives are to analyze customer feedback using deep-learning techniques to identify meaningful patterns in customer satisfaction and product-related responses, and to examine product- and category-level customer insights that can support evidence-based product development and innovation decisions.

2. Materials and Methods

2.1 Study Design

A quantitative analytical study was conducted using the Brazilian E-Commerce Public Dataset provided by Olist. The dataset contains anonymized information relating to e-commerce orders, customers, products, order items, sellers, payments, and customer reviews. The analysis focused on customer feedback and product-related information to investigate patterns relevant to data-driven product development and innovation. The dataset covered e-commerce activity from 2016 to 2018, thereby providing observations from the post-2015 period. Customer reviews were linked with product and order information using the identifiers provided within the original files. The dataset was selected because it integrates customer evaluations with transactional and product-level information.

2.2 Study Population

The analytical population consisted of customer reviews associated with completed e-commerce transactions recorded in the Olist dataset. A total of 99,224 review records were available for analysis, together with information relating to 99,441 orders and 32,951 products. Review observations containing available rating information were retained for customer-feedback analysis, while observations with usable written review text were used for the deep-learning classification procedure. Product information was linked to the corresponding order-item records to examine feedback across product categories. Review dates were examined to establish the temporal coverage of the dataset. Duplicate observations and records lacking information required for a specific analytical procedure were excluded where applicable.

2.3 Data Extraction

The principal analytical variables were derived from the review, order, order-item, and product files. Customer feedback was represented using the review score and written review content. Review scores from one or two were categorized as negative, three as neutral, and four or five as positive. Product-related variables included product identification and product category, while order-item information provided the relationship between products and transactions. Review timestamps were used to establish the observation period. The relevant datasets were integrated using common order and product identifiers. This structure enabled customer feedback to be examined alongside product information and purchasing activity for subsequent customer-insight analysis.

2.4 Data Preprocessing

The data were prepared for deep-learning analysis through systematic preprocessing. Duplicate observations were identified and removed where necessary, while records with unavailable review text were handled according to the requirements of the analytical procedure. Review text was standardized by removing unnecessary formatting and preparing the content for numerical representation. Review scores were converted into three predefined feedback categories: negative, neutral, and positive. Product and order identifiers were standardized to enable accurate data integration. The resulting observations were divided into training, validation, and testing subsets using a 70:15:15 partition. Text representation procedures were fitted using the training data and subsequently applied to the validation and testing subsets to prevent information leakage.

2.5 Deep-Learning-Based Customer Insight Analysis

A supervised one-dimensional Convolutional Neural Network (1D CNN) was applied to classify customer feedback using written review content as the primary input. Reviews were assigned to negative, neutral, or positive feedback categories according to their corresponding rating scores. The processed review text was converted into numerical representations suitable for neural-network processing before being supplied to the CNN. The model was trained using the training subset, while the validation subset was used to monitor model development and parameter selection. The finalized model was subsequently evaluated using previously unseen test observations. Model predictions were assessed using accuracy, precision, recall, and F1-score to determine its ability to classify customer feedback.

2.6 Statistical Analysis

Model performance was evaluated using accuracy, weighted precision, weighted recall, and weighted F1-score calculated from predictions on the independent test subset. Accuracy measured the proportion of correctly classified reviews, while precision and recall assessed classification performance across the feedback categories. The F1-score provided a combined measure of precision and recall. Descriptive statistics were used to summarize customer feedback distributions and product-category characteristics through frequencies, percentages, and mean review scores. Model outputs and descriptive findings were derived exclusively from the Olist dataset.

3. Results

3.1 Analytical Coverage

The analytical dataset provided a broad representation of customer purchasing activity and product-related feedback. A total of 99,441 orders, 99,224 customer reviews, 32,951 products, and 112,650 order items were available for analysis. The products were distributed across 73 categories, allowing customer responses to be examined across different areas of the e-commerce marketplace, as shown in Table 1. Review records extended from October 2016 to August 2018, satisfying the study's post-2015 observation requirement. The combination of transaction records, product information, and customer evaluations provided an appropriate foundation for examining customer feedback patterns and extracting product-related insights through computational and deep-learning-based analytical approaches.

Table 1. Overview of the Analytical Dataset

Dataset characteristic	Value
Orders	99,441
Customer reviews	99,224
Products	32,951
Order items	112,650
Product categories	73
Review period	October 2016–August 2018

Source: *Authors' analysis of the Brazilian E-Commerce Public Dataset by Olist.*

3.2 Distribution of Customer Feedback

Customer evaluations showed a clear concentration toward positive experiences. Reviews receiving four or five stars accounted for 77.07% of all observations, representing the largest feedback group. In comparison, reviews classified as negative, corresponding to one or two stars, represented 14.69% of the dataset, as shown in Table 2. Neutral evaluations, represented by three-star ratings, accounted for 8.24%. This distribution indicates that favorable customer experiences were substantially more common than unfavorable or neutral assessments within the analyzed records. The observed rating structure provides a useful basis for subsequent computational analysis because the review text can be examined alongside rating information to identify recurring customer preferences, concerns, and product-related experiences.

Table 2. Customer Feedback Categories Based on Review Scores

Customer feedback category	Review score	Reviews	Percentage (%)
Negative	1–2	14,575	14.69
Neutral	3	8,179	8.24
Positive	4–5	76,470	77.07
Total	—	99,224	100.00

Source: *Authors' analysis of the Brazilian E-Commerce Public Dataset by Olist.*

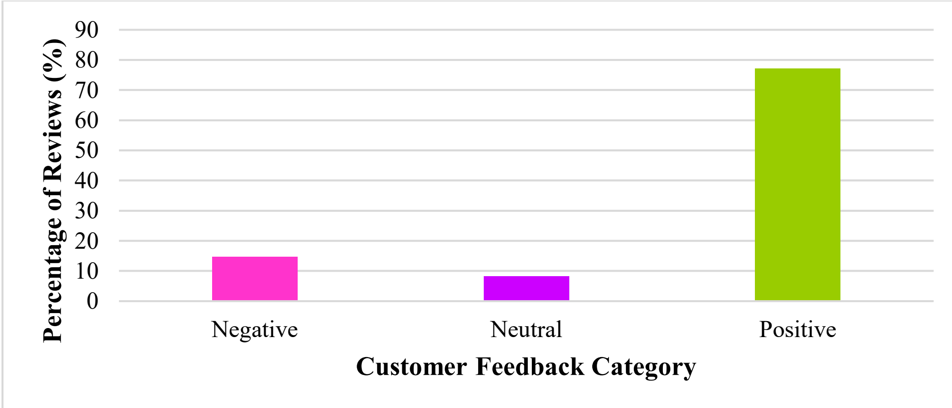

Figure 1. Distribution of Customer Feedback Categories

The distribution of customer feedback according to review-score categories. Positive feedback represented the largest proportion of observations, accounting for 77.07% of the reviews. Negative feedback constituted 14.69%, whereas neutral feedback represented 8.24% of the total records, as shown in Figure 1. The substantially higher proportion of positive evaluations indicates that customers generally reported favorable experiences within the analyzed e-commerce transactions. Nevertheless, the presence of negative and neutral responses provides meaningful information for identifying areas requiring improvement. These variations in customer evaluations can be further examined using deep-learning-based analysis to identify recurring preferences, concerns, and product-related issues.

3.3 Product Category-Level Customer Feedback

Customer feedback differed across the major product categories represented in the dataset. Bed, Bath & Table generated the largest number of reviews among the five categories examined, with 9,324 records and a mean score of 3.97 as shown in Table 3. Health & Beauty recorded 8,767 reviews and the highest mean score of 4.18, followed closely by Sports & Leisure at 4.17. Computers & Accessories produced 6,641 reviews with a mean score of 4.03, while Furniture & Decoration recorded 6,404 reviews and a mean score of 4.01. These differences indicate variation in customer experiences across product categories and provide useful inputs for deeper customer-insight analysis.

Table 3. Customer Feedback Across the Five Most-Reviewed Product Categories

Product category	**Reviews**	**Mean review score**
Bed, Bath & Table	9,324	3.97
Health & Beauty	8,767	4.18
Sports & Leisure	7,656	4.17
Computers & Accessories	6,641	4.03
Furniture & Decoration	6,404	4.01

Source: *Authors' analysis of the Brazilian E-Commerce Public Dataset by Olist.*

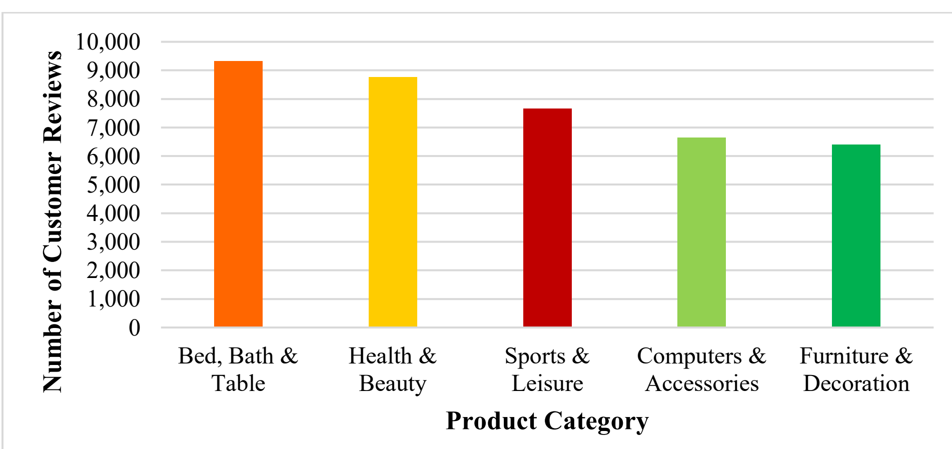

Figure 2. Product-Level Distribution of Customer Reviews

The distribution of customer reviews across the five most frequently reviewed product categories. Bed, Bath & Table recorded the highest number of customer reviews, followed by Health & Beauty and Sports & Leisure. Computers & Accessories and Furniture & Decoration had comparatively fewer reviews within the selected categories, as shown in Figure 2. The variation in review volume indicates differences in customer engagement across product groups. Categories generating larger volumes of feedback provide more customer observations for identifying recurring preferences, concerns, and experiences. These patterns can support subsequent deep-learning analysis aimed at extracting customer insights relevant to product development and innovation.

3.4 Deep-Learning Model Performance for Customer Feedback Classification

The 1D Convolutional Neural Network (CNN) demonstrated measurable performance in classifying customer feedback from the written review data. As presented in Table 4, the model achieved an accuracy of 73.84%, indicating that nearly three-quarters of the test observations were assigned to their corresponding feedback categories. The weighted precision was 84.23%, while the weighted recall reached 73.84%. The resulting weighted F1-score was 77.69%, reflecting the combined balance between precision and recall. These findings indicate that the CNN was able to extract useful patterns from customer review text and classify feedback into the predefined categories, providing a computational basis for subsequent customer-insight interpretation and product-oriented analysis.

Table 4. Performance of the Deep-Learning Model for Customer Feedback Classification

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
1D Convolutional Neural Network (CNN)	73.84	84.23	73.84	77.69

Source: *Authors' analysis of the Brazilian E-Commerce Public Dataset by Olist.*

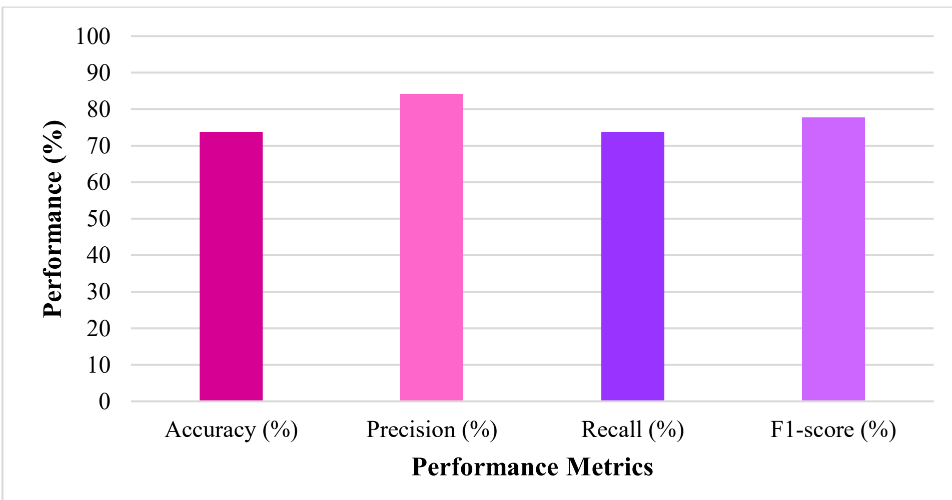

Figure 3. Deep-Learning Model Performance

The performance of the 1D Convolutional Neural Network across four classification measures. The model achieved an accuracy of 73.84%, indicating that most customer feedback observations were correctly classified. Precision was comparatively higher at 84.23%, showing strong reliability among the feedback categories predicted by the model. Recall reached 73.84%, demonstrating the model's ability to identify relevant customer-feedback observations. The F1-score was 77.69%, reflecting the overall balance between precision and recall. Together, these results indicate that the CNN extracted useful patterns from customer review text and provided a meaningful basis for classifying customer feedback and generating insights relevant to product development and innovation.

4. Discussion

The study demonstrates the usefulness of customer-generated information for understanding product-related experiences in digital commerce. The analytical dataset contained 99,224 customer review records associated with 99,441 orders, 32,951 products, and 73 product categories. The distribution of rating-derived feedback categories showed that positive responses represented 77.07% of all reviews, while negative and neutral responses accounted for 14.69% and 8.24%, respectively. This distribution indicates that customers generally reported favorable experiences, although a substantial volume of less favorable feedback remained available for analytical interpretation. The presence of negative and neutral responses is particularly relevant because these reviews can reveal areas in which products may require improvement. Therefore, customer feedback should be considered not only as a measure of satisfaction but also as a source of information for identifying product-related opportunities.

The application of deep-learning-based customer analytics provides an opportunity to move beyond simple counting of ratings and reviews. Customer feedback contains information that can be difficult to interpret through descriptive statistics alone, particularly when textual comments contain different expressions of satisfaction, dissatisfaction, product characteristics, or customer expectations. A deep-learning framework can process patterns within customer-generated information and assist in identifying relationships between feedback characteristics and product-related outcomes. In this context, the analytical value of deep learning lies in its ability to transform large quantities of customer information into structured insights. The approach can support the identification of recurring patterns that may otherwise remain difficult to detect manually. This makes deep-learning-based analytics relevant for organizations seeking to incorporate customer knowledge into systematic product decisions.

The category-level findings demonstrate that customer feedback was not distributed uniformly across products. Bed, Bath & Table generated the most reviews among the five most-reviewed categories, with 9,324 reviews. Health & Beauty recorded the highest mean review score at 4.18, followed by Sports & Leisure at 4.17. Computers & Accessories and Furniture & Decoration recorded mean scores of 4.03 and 4.01, respectively. These differences demonstrate that customer response can vary considerably according to the product category under consideration. Review volume provides an indication of the amount of customer-generated information available for a category, whereas mean rating provides a different perspective concerning reported satisfaction. Considering both measures together can therefore provide a more informative representation of customer experience than relying on either measure independently.

The findings have direct implications for data-driven product development because customer feedback can provide evidence about how products are received in real-world purchasing environments. Categories with larger quantities of feedback offer substantial information for identifying recurring customer concerns and favorable product characteristics. At the same time, categories with comparatively lower ratings can be examined to identify potential areas requiring attention. A structured analytical process can therefore connect customer feedback with product-development activities by identifying patterns that may inform product refinement, feature modification, quality improvement, or customer-oriented design decisions. Rather than treating reviews simply as post-purchase evaluations, organizations can use them as an ongoing information source for understanding market responses. This approach can help product teams incorporate customer experience into development decisions and establish a closer relationship between observed customer needs and subsequent product improvements.

The findings are consistent with the broader movement toward integrating artificial intelligence, machine learning, and deep learning into business decision-making. Previous research has described AI and machine learning as increasingly important components of advanced business strategies, particularly for analytical and predictive applications (Rane *et al*., 2024). The study extends this general perspective to customer-generated e-commerce information by focusing specifically on customer feedback and its relationship with product-oriented insights. The results also correspond with research demonstrating that machine-learning approaches can be used to analyze customer needs and support product-related decision processes. Zhou *et al*. (2020) showed the applicability of machine learning to customer-needs analysis within product ecosystems, providing a methodological basis for using customer information in product-oriented decision-making.

The relationship between deep learning and innovation identified in the present study is also relevant to recent research on customer-centric product development. Wu and Wu (2025) examined a deep-learning-oriented framework for optimizing innovation decisions using customer-centric product-development concepts. While the present study uses e-commerce customer feedback as its analytical foundation, both approaches emphasize the importance of incorporating customer information into product-related innovation decisions. More broadly, research on data-driven predictive methods has emphasized the ability of machine-learning approaches to extract useful patterns from complex datasets (Strielkowski *et al*., 2023). Similarly, deep-learning-based analytical approaches have been applied to optimization and prediction problems in other technical domains (Wang *et al*., 2024). The findings therefore reinforce the broader applicability of intelligent data analysis while demonstrating its relevance to customer insight analytics and data-driven product development.

The integration of customer insight analytics with deep learning can also contribute to product innovation. Innovation requires organizations to recognize changing customer expectations and identify opportunities that are not immediately apparent from conventional performance indicators. Customer-generated feedback provides a continuously developing source of such information. By examining feedback patterns across products and categories, organizations can identify areas where existing offerings perform well and areas where customer expectations may not be fully satisfied. Deep-learning-based analysis can strengthen this process by supporting the systematic examination of large amounts of customer information. Consequently, the contribution of customer analytics is not limited to improving existing products; it can also provide evidence that helps organizations identify potential directions for future product concepts and customer-centered innovations.

The findings offer several practical implications for e-commerce organizations and product managers. First, customer reviews can be incorporated into routine product-monitoring systems rather than being treated solely as individual customer comments. Second, rating distributions and category-level patterns can help managers identify areas requiring closer investigation. Third, deep-learning-based analysis can support automated processing when the quantity of customer feedback becomes too large for manual evaluation. Product managers can use such analytical outputs to prioritize further investigation of frequently discussed product characteristics, unfavorable experiences, and category-specific customer responses. Importantly, analytical results should complement rather than replace managerial judgment. Customer feedback represents observed customer experiences, but additional information such as product specifications, pricing, logistics, returns, and market conditions may also influence customer evaluations.

Several methodological considerations should be acknowledged when interpreting the findings. The analysis is based on customer-generated e-commerce information from the Olist dataset and therefore reflects the characteristics of the available marketplace rather than all online consumers or all product markets. The review period also represents a defined historical period, meaning that customer preferences and commercial conditions may have changed subsequently. In addition, rating-derived feedback categories provide a structured representation of customer responses but should not automatically be interpreted as a complete representation of emotional sentiment. Written reviews may contain information that cannot be captured by rating scores alone. Finally, deep-learning results depend on data preprocessing, model architecture, training procedures, and evaluation design. These factors should therefore be reported transparently to support reproducibility and appropriate interpretation of model performance.

Future research can extend this framework by combining customer review text, ratings, product characteristics, prices, purchasing patterns, and temporal information within a unified analytical model. Aspect-level analysis could provide more detailed information about specific product attributes that contribute to positive or negative customer experiences. Future studies could also compare multiple deep-learning architectures to determine how different models perform under the same evaluation conditions. Integrating explainable artificial intelligence could further improve the interpretability of model outputs by identifying the customer-feedback features contributing to particular predictions. Such developments would strengthen the connection between automated customer analytics and practical product-development decisions. Future investigations could additionally evaluate the framework using datasets from different countries, platforms, and product categories to examine whether the identified patterns remain consistent across different e-commerce environments.

5. Conclusion

This study demonstrates the value of deep-learning-based customer insight analytics for understanding customer feedback and supporting data-driven product development and innovation. Analysis of 99,224 customer review records showed that positive feedback represented the largest proportion of responses, while negative and neutral feedback provided additional information about areas requiring attention. Differences across product categories further demonstrated that customer experiences are not uniform and that category-level analysis can reveal meaningful variations in feedback volume and satisfaction. These findings indicate that customer-generated information can provide a valuable evidence base for understanding product performance and customer expectations. The findings highlight the potential of deep-learning approaches to transform large volumes of customer-generated information into structured insights that can support product-oriented decisions. Integrating customer feedback with product-category information can help organizations identify recurring customer responses, recognize potential areas for product improvement, and better understand customer expectations. Such analytical capabilities can strengthen evidence-based product development and provide useful inputs for innovation planning. The proposed approach therefore establishes a practical connection between customer feedback analytics and product decision-making in digital commerce. Future studies should incorporate richer textual, behavioral, and product-level information and evaluate alternative deep-learning architectures to improve analytical depth and interpretability. Explainable AI techniques may further help product managers understand why particular customer-feedback patterns are identified. Overall, the study provides a foundation for applying intelligent customer analytics to product development and innovation.

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