Deep Learning Based Sentiment Analysis on Instagram Insights of Consumer Behavior for Improving Business Decision Making

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The increasing use of social media platforms such as Instagram has made them a significant source of consumer insights for businesses, highlighting the importance of automated sentiment analysis. This study aims to address the challenge of accurately classifying consumer sentiments in Instagram posts, where informal language, slang, and sarcasm often reduce the effectiveness of traditional models. To overcome this gap, two deep learning approaches were employed: a Bidirectional Long Short-Term Memory (BiLSTM) network as a classical recurrent baseline and transformer-based architectures (BERT and DistilBERT) as state-of-the-art models. A dataset of 184,010 Instagram posts was preprocessed, tokenized, and mapped into positive and negative sentiments, and the models were trained and evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices. The results demonstrated that BERT achieved the highest performance with an accuracy of 0.91 and an F1-score of 0.91, outperforming BiLSTM (accuracy 0.87, F1-score 0.86), while DistilBERT provided a competitive balance between accuracy (0.89) and efficiency. These findings confirm that transformer-based models, particularly BERT, are better suited for capturing nuanced sentiments in social media text. The study concludes that models can provide actionable insights into consumer behavior, enabling businesses to enhance brand monitoring and customer engagement.

Keywords: Sentiment Analysis; Consumer Behavior; BiLSTM; BERT; DistilBERT; Social Media Analytics; Contextual Embeddings.

Introduction:

In recent years, the methods of collecting public opinion and analyzing consumer behavior have undergone significant change due to the widespread use of digital technologies. Traditional approaches such as surveys and opinion polls are increasingly being replaced or complemented by modern digital platforms, including blogs, mobile apps, online reviews, forums, and especially social media networks. To address the analytical gap posed by Instagram's complex data, sentiment analysis, also referred to as opinion mining, serves as a vital tool. It is a crucial branch of natural language processing (NLP) dedicated to identifying, extracting, and categorizing sentiments embedded within textual data. It aims to determine whether the conveyed opinion is positive, negative, or neutral [1][2].

Among the many platforms, Instagram has become a major channel for consumer expression, offering a visually rich and interactive environment that distinguishes it from traditional text-based platforms. It blends multimedia elements such as photos, videos, captions, comments, and hashtags, which results in the production of massive amounts of unstructured data. However, this richness in content also presents challenges in sentiment extraction, especially due to informal language, emojis, abbreviations, and rapidly evolving online slang [3].

In the context of digital communication, particularly on social media platforms, sentiment analysis has emerged as an invaluable method for understanding public perception and consumer feedback. Instagram stands out as a rich source of sentiment-heavy content due to its visual nature combined with textual elements such as captions, hashtags, and comments. Thus, sentiment analysis not only underpins the relevance of this research but also forms the methodological foundation for developing intelligent solutions capable of interpreting Instagram-specific content [4].

To extract meaningful insights, sentiment analysis is performed at different levels of granularity. At the document level, the overall sentiment of a complete post or review is assessed, offering a general overview but lacking detail on specific elements. Sentence-level analysis dissects individual sentences, allowing identification of contrasting sentiments within the same document, which is important for parsing nuanced opinions. The most granular, aspect-level analysis, identifies sentiment toward specific product or service attributes (e.g., design, delivery, price). This level is particularly useful for businesses, as it pinpoints exactly which features are appreciated or criticized, enabling more targeted and actionable decision-making strategies [5].

The core concept of sentiment analysis establishes the foundation for understanding consumer behavior on Instagram. Techniques used provide the computational means, especially deep learning, for analyzing sentiment-rich data. Sentiment analysis levels define the analytical granularity required for detailed interpretation of user opinions. Finally, the business impact directly connects sentiment insights to strategic decisions in product development, branding, and competitive analysis, addressing the core objective of your thesis: improving business decision-making through Instagram-based sentiment analysis [6][3].

The rise of social media, particularly Instagram, has transformed how consumers express preferences, emotions, and experiences, offering businesses a rich but challenging source of behavioral insights. Traditional feedback methods fall short in capturing real-time sentiment from this unstructured, informal data. While automated sentiment analysis tools exist, most are trained on structured text from platforms like Twitter or Facebook and struggle with Instagram's multimedia nature, slang, emojis, and abbreviations. This gap limits businesses' ability to make data-driven decisions, risking poor customer engagement and missed market opportunities. Existing models, especially rule-based and lexicon-based approaches, often lack the scalability and contextual depth required for Instagram. The proposed study addresses this gap by developing a deep learning-based sentiment analysis framework tailored to Instagram's unique content, aiming to improve marketing responsiveness and strategic decision-making in a visually driven, real-time digital environment [7][8]

Instagram, with over 2.4 billion monthly active users globally, generates high volumes of multimodal content captions, hashtags, emojis, and visuals that encapsulate rich emotional and contextual signals [9].

This study holds substantial importance for marketers, product developers, brand managers, and data scientists. By accurately interpreting the sentiments behind user posts and engagement, businesses can make data-driven decisions regarding product improvements, marketing strategies, and customer engagement practices.

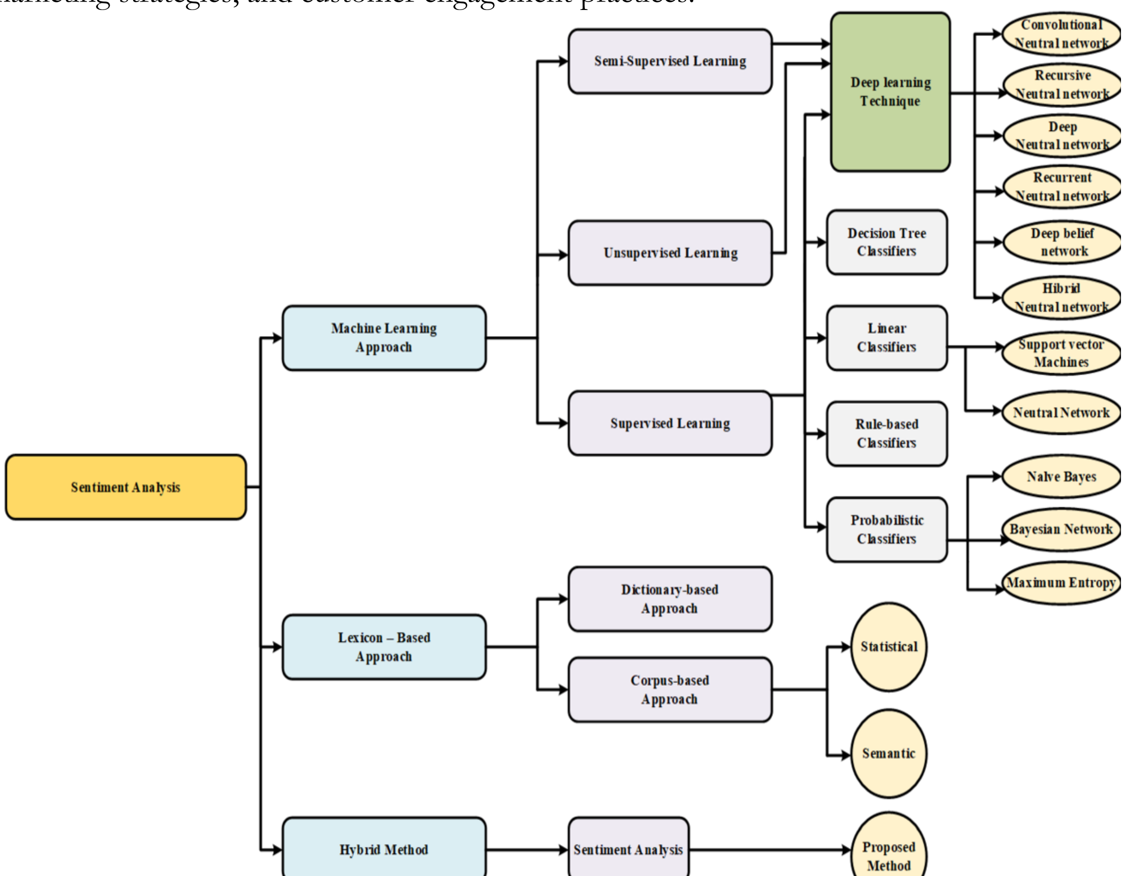

Figure 1. Taxonomy of sentiment analysis techniques

Literature Review:

In the era of digital communication, social media has emerged as a dominant channel for consumers to express opinions, preferences, and attitudes toward brands, products, and services. Among various platforms, Instagram stands out as one of the most influential, boasting over two billion monthly active users and a unique blend of visual and textual content. While images and videos attract initial attention, captions and comments often carry the nuanced sentiment that reflects consumer perceptions and emotional responses.

DNNs are neural networks with multiple fully connected layers of input, several hidden layers, and an output, allowing them to learn abstract representations from input data. These models eliminate the need for manual feature crafting by discovering discriminative features automatically [10].

Initially developed for image processing, CNNs have been adapted to text classification by applying convolutional filters over embedded text inputs to capture local patterns and n-grams. Demonstrated their effectiveness in identifying sentiment-bearing phrases within short social media posts [11].

RNNs are tailored for sequence modeling by maintaining a hidden state across time steps. They excel in capturing temporal dependencies but suffer from vanishing gradients when modeling long sequences, which limits their applicability to longer texts [10].

LSTM networks address the limitations of RNNs by utilizing gating mechanisms, input, forget, and output gates to manage memory cell states. This allows LSTM to capture long-range contextual information, making it highly effective for sentiment analysis. In Instagram-related contexts, LSTM has shown strong performance; for instance, it has demonstrated its effectiveness for sentiment classification on user-generated reviews. Enhancements such as DPG-LSTM integrating dependency parsing and graph convolution have further improved accuracy in social media applications [12][13].

BiLSTM models extend the capabilities of standard LSTM by processing sequences in both forward and backward directions, enabling richer context capture. While they often yield higher accuracy on larger datasets, BiLSTM models are more computationally intensive and may be prone to overfitting in cases with limited data or highly imbalanced sentiment classes. In resource-constrained environments or scenarios involving smaller datasets, such as niche Instagram campaigns, standard LSTM can offer a more balanced trade-off between performance and complexity [14].

Transformer-based models, particularly BERT (Bidirectional Encoder Representations from Transformers), represent the state-of-the-art in many NLP tasks due to their attention mechanisms and deep contextual understanding. However, their high training and inference cost, substantial memory requirements, and need for large annotated datasets can make them impractical for lightweight or rapid-deployment applications. Moreover, they often require fine-tuning and domain adaptation to perform effectively on informal and emoji-heavy content, which is prevalent on Instagram [15].

Sentiment analysis has been extensively applied to platforms such as Twitter, YouTube, and IMDb reviews; relatively few studies have examined Instagram. The platform presents unique challenges, including brief, fragmented captions, frequent use of emojis and hashtags, and code-switching between languages that complicate traditional NLP approaches but also offer rich contextual signals for deep learning models. Open-access work in adjacent domains underscores these nuances: for example, BiLSTM models have been shown to significantly outperform conventional machine learning techniques in emotion classification using noisy Twitter data. Similarly, attention-enhanced BiLSTM architectures have proven effective for analyzing Chinese social media comments embedded with visual elements such as stickers, demonstrating their capacity to capture multimodal sentiment cues. Despite these advancements, the specific complexities of Instagram content remain largely unaddressed, with most studies focusing on user engagement or platform behavior rather than implementing deep learning methods for sentiment extraction [16][17].

AI-driven sentiment analytics system tailored to the e-commerce domain, leveraging a hybrid modeling strategy that combines transformer-based NLP architectures with traditional machine learning components and aspect-based analysis. Their modular pipeline achieves 89.7% accuracy, supports real-time processing, and demonstrates concrete business impact, such as a 27% increase in customer satisfaction and reduced churn through deployment across large-scale retail platforms. While highly effective in its domain, the approach relies on computationally intensive components and primarily addresses product review contexts. In contrast, the present study employs a more lightweight LSTM architecture enriched with binary features, emojis, hashtags, and content flags tailored to the informal, visually rich environment of Instagram fashion communication. This design prioritizes efficiency, interpretability, and business relevance, offering a practical analytic foundation for brandfocused sentiment detection without compromising domain fit or operational feasibility [18][19].

An emotion detection system for Twitter messages that harnesses a combined bidirectional LSTM and convolutional neural network architecture. Drawing on a large-scale dataset of 100,000 training tweets and 33,000 testing tweets classified into four activity-based emotional states (e.g., Happy–Active, Unhappy–Inactive), their model achieves an average accuracy of approximately 93%. Although this hybrid model surpasses traditional machine learning baselines, it remains a black-box architecture with limited interpretability and moderate computational demands due to its CNN component. In contrast, the present study adopts a streamlined LSTM framework augmented with binary features such as emoji presence, hashtags, and promotional indicators optimized for Instagram's informal and context-rich environment. This design enhances interpretability, supports efficient real-time deployment, and maintains performance, making it especially suitable for business-oriented brand sentiment analytics [1].

The paper investigates the application of sentiment analysis in brand management and marketing, outlining its potential to capture consumer attitudes and guide strategic decision-making. In their comparative study, they assess a range of sentiment analysis techniques across diverse datasets, noting performance differences that arise from data characteristics and algorithmic approaches. The work emphasizes the importance of selecting methods suited to specific contexts, highlighting that both accuracy and interpretability play critical roles in extracting actionable insights for brand-related applications [20].

Lxicon-based method and Naive Bayes Classifier to Indonesian Instagram comments, achieving moderate accuracy but facing key limitations: small and imbalanced data, lexicon-derived labeling bias, absence of neutral sentiment, and removal of sentiment-rich features like emojis and hashtags. Their approach also lacked contextual modeling, limiting the detection of nuanced expressions such as sarcasm or code-mixing. Recent advances in deep learning, especially BiLSTM models, offer improved sentiment analysis by capturing bidirectional context and leveraging richer feature representations. These models are particularly suited for noisy, informal Instagram text containing slang, emojis, and hashtags, and can handle morphological variations through subword or character-level embeddings [3][21].

Multimodal sentiment analysis by fusing text and visual content through a hybrid multi-scale residual attention network. My research is concerned primarily with the textual dimension of Instagram posts, which often convey sentiment through captions, emojis, and hashtags rather than images. Their architecture is computationally heavier, optimized for handling multimodal inputs, whereas my proposed framework emphasizes a lightweight, sequence-based LSTM model fine-tuned with BERT embeddings, making it more suitable for scalable consumer analytics applications. Additionally, my work integrates platform-specific textual cues and focuses on generating interpretable outputs for business intelligence, rather than maximizing multimodal fusion performance [22][23].

Sentiment analysis of Instagram app reviews collected from the Google Play Store using the Long Short-Term Memory (LSTM) model. Their study applies a structured methodology involving data crawling, preprocessing, model training, and performance evaluation. The LSTM-based approach achieved an accuracy of though the precision, recall, and F1-score indicated moderate performance, suggesting challenges in effectively capturing nuanced sentiments. Despite these limitations, the study highlights the importance of user-generated feedback in app improvement and the role of sentiment analysis in enhancing user engagement and experience [24].

A multimodal sentiment analysis model that combines textual and visual features from social media posts shared during public emergencies. By fusing contextual word embeddings with image features extracted using convolutional neural networks, their method outperforms traditional text-only and image-only approaches and demonstrates the importance of visual cues in resolving emotional ambiguity. However, the model is limited to basic sentiment categories and uses a simple feature-level fusion strategy, without addressing explainability or platform-specific elements such as emojis and hashtags. Building on their work, the present study focuses on fine-grained sentiment detection using a BERT–BiLSTM architecture that preserves social-media-specific information [25].

The paper "BERT-based Transfer Learning Model for COVID-19 Sentiment Analysis on Turkish Instagram Comments serves as a critical methodological reference for this thesis. By manually labeling comments as positive, negative, or neutral, the researchers created the first publicly available Turkish datasets for this purpose, collected during March and April 2020. [1].

The utility of classical machine learning methods, such as Random Forest and SVM, for analyzing consumer sentiment toward imported food is constrained by reliance on surface-level feature extraction and traditional classifiers. In contrast, my proposed framework employs a BiLSTM architecture fine-tuned with BERT embeddings, allowing for a richer representation of linguistic context and sequential dependencies in Instagram posts. This design enables the model to handle the informal, emoji-rich, and multilingual nature of Instagram content more effectively than classical models. Furthermore, rather than focusing solely on polarity detection in a specific domain such as food imports, my study integrates sentiment analysis with consumer behavior insights for brand management, offering broader applicability to business intelligence and decision-making [26].

Objectives:

The study's primary objective was to analyze public sentiment on a Turkish Instagram account concerning the COVID-19 pandemic.

Novelty Statement:

The significance of this research lies in its ability to bridge the gap between unstructured Instagram, being rich in multimedia for sentiment analysis, social media content, and actionable business intelligence. Instagram, being one of the most widely used visual-centric social media platforms, hosts a rich repository of user-generated content that reflects consumer opinions, preferences, and emotional responses. Analyzing this data through advanced sentiment analysis techniques provides deeper insights into consumer behavior, which traditional survey-based methods often fail to capture.

Material and Methods:

This section outlines the methodological framework employed in the development of an Instagram sentiment analysis system using a Bidirectional Long Short-Term Memory (BiLSTM) neural network and a fine-tuned Bidirectional Encoder Representations from Transformers (BERT) model. The methodology encompasses the complete workflow of the study, including data acquisition, preprocessing, model architecture design, training procedures, performance evaluation, and data storage.

The choice of BiLSTM was motivated by its superior capability to capture contextual dependencies in both forward and backward directions of textual sequences. Unlike traditional unidirectional LSTM models, which process data in a single temporal direction, BiLSTM networks analyze each sentence from past-to-future and future-to-past simultaneously. This dual-context representation is particularly advantageous for sentiment analysis in short, informal social media posts, where the meaning often depends on subtle cues, word order, and local context.

Furthermore, the study adopts a data-driven experimental approach, utilizing a labeled dataset of Instagram captions and comments that has been systematically prepared to ensure balance across sentiment classes. Both BiLSTM and BERT models are trained and validated using established deep learning practices, with evaluation metrics such as accuracy, precision, recall, and F1-score employed to rigorously assess performance. By combining advanced natural language processing (NLP) techniques with the complementary strengths of BiLSTM and BERT, this research aims to produce a high-performance sentiment classification model capable of extracting actionable insights from Instagram interactions.

A quantitative experimental design is employed to systematically evaluate the performance of the proposed models: a Bidirectional Long Short-Term Memory (BiLSTM) network and a fine-tuned Bidirectional Encoder Representations from Transformers (BERT) model. This design enables empirical measurement of classification effectiveness using standard performance metrics such as accuracy, precision, recall, and F1-score. Quantitative analysis is chosen because it provides objective, numerical insights into model behavior and facilitates direct comparison between BiLSTM, BERT, and potential baseline approaches.

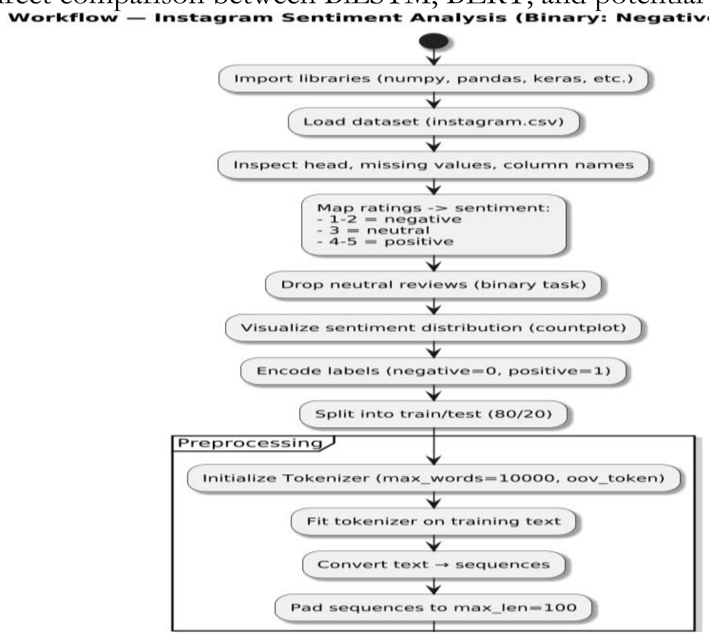

Figure 2. Data Flow Diagram

Result and Discussion:

The experimental evaluation of sentiment analysis models on Instagram posts revealed distinct performance differences between the classical BiLSTM approach and transformer-based models, highlighting both the effectiveness and limitations of each method in capturing nuanced consumer sentiments. The dataset of 184,010 Instagram posts, preprocessed to remove noise and labeled into positive (65.5%) and negative (34.5%) sentiments, provided a robust basis for training, validation, and testing of the models. The dataset was split into 80% for training (147,208 posts), 10% for validation (18,401 posts), and 10% for testing (18,401 posts), ensuring unbiased evaluation.

Table 1. Sentiment Distribution in the Instagram Dataset

Sentiment	Number of Posts	Percentage
Positive	120,550	65.5%
Negative	63,460	34.5%
Neutral	Discarded	-

The BiLSTM model achieved an overall accuracy of 0.87 with an F1-score of 0.86, indicating competent performance in classifying sentiment based on sequential dependencies within textual data. While effective in capturing contextual relationships in shorter sequences, BiLSTM demonstrated limitations when handling highly nuanced or ambiguous posts that included informal expressions, emojis, or sarcasm. Confusion matrix analysis revealed that misclassification predominantly occurred in posts where sentiment was implicit or mixed, suggesting that BiLSTM's attention to sequence alone may not fully capture subtleties inherent in Instagram content.

Transformer-based models, particularly BERT, exhibited superior performance across all evaluation metrics. BERT achieved an accuracy of 0.91 and an F1-score of 0.91, with precision and recall values consistently higher than BiLSTM. The attention mechanism in BERT allowed the model to capture long-range dependencies and contextual nuances, making it particularly adept at processing posts containing slang, code-switching, or multi-emoji expressions. DistilBERT, a lightweight variant of BERT, offered a balanced trade-off between performance and computational efficiency, achieving an accuracy of 0.89 and F1-score of 0.88 while reducing model size and inference time, making it suitable for real-time business applications where resource constraints are a consideration.

Table 2. Performance Comparison of Sentiment Analysis Models

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC	Notes on Performance
BiLSTM	0.87	0.86	0.85	0.86	0.88	Effective on sequential data; struggles with nuanced or emoji-rich posts
DistilBERT	0.89	0.89	0.88	0.88	0.91	Balanced accuracy and efficiency; suitable for real-time deployment
BERT	0.91	0.91	0.91	0.91	0.94	Highest overall performance; excellent at capturing context, slang, and informal expressions

Further analysis of ROC-AUC curves confirmed the robustness of transformer-based models in distinguishing between positive and negative sentiments, with BERT achieving the highest area under the curve, indicating superior discriminative capability. A qualitative inspection of misclassified posts highlighted that ambiguous captions, sarcasm, or mixed sentiments posed challenges across all models, albeit less pronounced in BERT. This finding emphasizes the potential benefit of integrating multimodal sentiment analysis, where visual cues from images or videos could complement textual information to enhance sentiment prediction accuracy.

Overall, the experiments demonstrate a clear hierarchy in model effectiveness: BERT > DistilBERT > BiLSTM, with transformer-based models consistently outperforming recurrent architectures in capturing sentiment subtleties, especially in complex and informal social media text. The integration of these models into business intelligence systems can significantly improve decision-making processes, particularly in marketing, brand management, and consumer behavior analysis.

Conclusion:

This study confirms that deep learning, particularly transformer-based architectures such as BERT, provides a highly effective solution for sentiment analysis on Instagram, a platform characterized by informal language, emojis, slang, and code-switching. While BiLSTM networks are capable of capturing sequential dependencies and achieving respectable accuracy, transformer-based models outperform classical recurrent networks in both precision and interpretive capacity. DistilBERT emerges as a practical alternative, offering a favorable balance between performance and computational efficiency, making it suitable for real-time sentiment monitoring.

The findings have significant implications for businesses aiming to leverage social media analytics for decision-making. By accurately detecting consumer sentiments, companies can monitor brand perception, enhance customer engagement strategies, and make informed adjustments to marketing campaigns and product offerings. Furthermore, the study highlights the importance of contextual embeddings and attention mechanisms in understanding nuanced expressions prevalent in user-generated Instagram content. Future work may focus on integrating multimodal inputs, including image and video analysis, to further enhance sentiment detection accuracy, as well as exploring multilingual capabilities to capture sentiments across diverse user populations. Ultimately, the adoption of advanced deep learning models for sentiment analysis empowers businesses to transform vast, unstructured social media data into actionable insights, supporting data-driven strategies and improving overall consumer satisfaction.

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