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EVOLUTION OF SENTIMENT ANALYSIS IN REVIEWS FOR INTELLIGENT PRODUCT RECOMMENDATIONS

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Article Info

Abstract

Consumer sentiment analysis (SA) has emerged as a popular research trend for social media applications, encompassing diverse domains like product reviews, healthcare, crime, finance, travel, and academics. Unraveling consumer perceptions and opinions from online reviews is paramount in gaining valuable insights. However, the increasing volume, subjectivity, and heterogeneity of social web data pose challenges for manual processing. To address this, researchers have turned to machine learning (ML) techniques, which offer promising solutions for real-life applications. This paper conducts a systematic literature review to assess ML techniques' efficacy, scope, and applicability in product reviews and analyze customers' attitudes from unstructured reviews specifically related to the product's quality, complexity, innovation, and impact. This research study also explores the main concepts and relevant literature of appraisal theory to compute people's attitudes because appraisal theory provides a more detailed description of the text than traditional SA.

Keywords:

Sentiment Analysis; Machine Learning; Appraisal Theory.

Introduction

This study is a collection of information gathered from various research papers. It gives a detailed summary of recent trends, progress, and difficulties in opinion mining (OM), SA, and appraisal theory. The main goal of this study is to help researchers and students by giving them easy access to the most up-to-date research. This way, they can learn about the latest ideas and use them to develop new concepts and improve the field even more. To the best of our knowledge, no research study has explicitly examined the state of ML applications in relation to traditional SA in product reviews and appraisal theory-based. The internet provides a wealth of data, providing users with an unprecedented opportunity to forecast consumer sentiment and use this knowledge to expand and improve their businesses. Despite this promise, there hasn't been a thorough examination of how ML is being used in this setting, leaving room for further research in this field. It is projected that more and more product reviews will be analyzed using ML based research techniques in the future. Researchers that want to understand the current significance of ML applications in comprehending consumer attitudes may find the study's conclusions helpful. These insights will guide their adoption of ML techniques as they analyze customer evaluations and extract greater meaning from the data they collect. The authors in [1] conducted a study to investigate the impact of consumer emotions on purchasing behavior and product/service engagement. They noticed a lack of cohesive research in this area, so they used a hybrid review approach, including bibliometric analysis, to synthesize existing literature from 1967 to 2021. After reviewing 384 articles, they identified key theories, contexts, and methods related to consumer emotions. Based on their findings, they proposed five potential research areas: consumer co-creation, consumer engagement, service employee interactions, consumer decision making, and consumption experience.

In recent years, there has been a rise in research activity in OM, SA, and appraisal theory in product reviews, as evident through multiple survey papers [2-4]. For example, the author in [2] conducted a comprehensive survey to address the challenges posed by the ambiguity of natural language processing and the detection of spam opinions. They thoroughly examined various approaches to OM, including well-known, classical, and current methods. This examination aimed to gain a detailed understanding of these challenges and explore potential solutions. By analyzing and evaluating different approaches, the author sought to contribute to the advancement of OM techniques and provide insights into tackling these specific challenges.

The authors in [5] claimed that the integration of opinion retrieval into search engines has enhanced the user experience. By combining ratings, opinion trends, and representative opinions with traditional document retrieval, search engines can provide comprehensive information about a subject.

The primary contribution of this research study is its comprehensive examination of the efficacy and usability of ML approaches for SA in product reviews. Furthermore, it introduces the appraisal theory to provide more subtle explanations.

In [6] the appraisal theory examines the attitude of people in a written text. The appraisal theory divides attitude into three fundamental sub-domains: appreciation, affect, and judgment. The effects depend on feelings. While appreciation deals with extracting opinions about physical things, processes, etc., judgment deals with evaluating people to ascertain their opinions. The three primary types of appreciation are reaction, composition, and appraisal. The two primary reaction sub-domains are impact and quality. The impact is connected to perceptions of something's attractiveness or lack thereof—quality concerns liking or disliking something, such as beautiful, elegant, hideous, etc. Complexity and balance are the two major components of composition. Complexity refers to viewpoints that include both complexity and simplicity in things. In balance, ideas like balanced and imbalanced things are discussed. As its name suggests, valuation includes viewpoints on ideas relating to objects, such as innovations, usefulness, cost, shoddiness, etc.

This paper is organized as follows: Section 2 concerns related work. Section 3 includes a summary of the findings and discussions. Section 4 is about the conclusions and implications of Research.

2. Related Literature

Sub-sections are included within the main section. The effect of user-generated reviews on the company is discussed in Section 2.1. Challenges in Customers' Attitude Analysis are covered in Section 2.2. ML algorithms are explored in Section 2.3. Deep learning techniques are described in Section 2.4. Techniques for word embedding are covered in Section 2.5. To learn customer opinions, Section 2.6 examines SA. SA advancements are discussed in Section 2.7. The assessment and comparison of the SA lexicon are covered in Section 2.8. Understanding Appraisal Theory and Emotional Reactions is covered in Section 2.9.

2.1 Impact of User-Generated Reviews on Businesses

Social media's unstructured and varied content makes typical data mining techniques labor-intensive and inefficient, and their inherent scale, noise, and bias further reduce their usefulness [7]. In recent research papers, a lot of attention has been given to studying how customers express their feelings and opinions through online reviews in various areas, like healthcare [8], business [9], hotels [10], academia [11] etc. People may now easily express their ideas, comments, feedback, and blogs on various internet platforms like Twitter, Facebook, Skytrax, Yelp, and TripAdvisor, thanks to advancements in information and communication technologies. Users can submit their opinions about the services or goods utilized on these open, free, and accessible sites. The businesses offering the services and products, as well as potential customers, profit from these reviews written by consumers. The authors in [12] investigated the decline in Tokopedia online customers, which suggests customers are dissatisfied with their offerings. To evaluate the impact of online customer reviews and e-services on purchasing decisions, they performed a study with 278 participants. The study found that customer reviews and the caliber of e-services strongly influence consumers' decisions.

2.2 Challenges in Customers' Attitude Analysis

Challenges for customer attitude analysis arise when extracting and collecting consumer sentiments from online reviews. This process is like piecing together information from different sources, requiring vast data to train the models accurately. Additionally, having domain-specific knowledge is essential to understanding the study's objective. Customers' attitude analysis faces difficulties in subjectivity detection because different consumers may interpret the same review differently. Short texts often need more contextual information, leading to accuracy challenges in subjectivity detection. Moreover, words can be context-dependent, sometimes subjective in one context and objective in another. This requires more advanced techniques, like parse tree models, to understand word meaning within the sentence structure. Lastly, the computational cost of training models with large vocabularies of words can be significant. ML techniques are considered to address some of these challenges.

2.3 Exploring ML Algorithms

Social media generates massive amounts of data, and ML enables us to manage and learn from it efficiently, bypassing manual analysis [13]. Text messaging is the most widely used method of communication in our fast-paced era. The fact that 18.2 million SMS are sent every minute is very astounding [14]. ML techniques may be applied in various industries by learning from data which can help solve challenging issues like opinion and text mining, among others. There are three types of ML algorithms: supervised, unsupervised, and semi-supervised. In supervised learning, predictions or classifications are made by algorithms using labelled data as their guide. They gain knowledge from a training set of input and output variables for classifying freshly acquired test data. The supervised ML techniques include SVM, NB, and decision trees (DT). Unsupervised learning algorithms, on the other hand, function without labelled data. They use methods like clustering to look for patterns and structures in the data. For tasks like customer segmentation and data exploration, unsupervised learning is beneficial. Unsupervised and supervised components are both included in semi-supervised learning. It is employed when there is a dearth of labeled data and the algorithm makes predictions or classifications using unlabeled data. [15].

2.4 Resurgence and Advancements in Deep Learning

Artificial neural networks (ANNs) are used in DL, a subset of ML, to learn and resolve challenging issues. Similar to the human brain, neural networks (NN) are made up of numerous interconnected components called neurons. Layers of these neurons collaborate to process information and learn from it. Because DL employs many layers of neurons, it can learn more complicated patterns and relationships than classical NN. With DL, we can train neural networks with many layers and a lot of data. By altering neuron weights using trained data, we may train a neural network to solve a problem. To accomplish this, the authors in [16] employed stochastic gradient descent via backpropagation. Backpropagation attempts to reduce the cross-entropy loss, which is the SoftMax output's loss function. DL has made tremendous strides for various reasons. Firstly, deep neural networks can now be trained efficiently due to a wealth of labeled data and robust technology, allowing for the learning of intricate structures and depictions that were previously difficult to understand. Second, novel optimization algorithms, regularization methods, and activation functions have been created to help solve the vanishing gradient issue and make deep network training more effective. Modern findings from DL have now been achieved in a variety of application fields, including as computer vision, speech recognition, and NLP [17, 18]. A short description of ML algorithms used in SA are shown in Table 1

Table 1: ML Methods used in SA

ML Algorithm	Description
NB	NB is a probabilistic algorithm used for classification tasks that use Bayes' theorem to calculate the likelihood of a specific class given a set of input features. It is useful for text classification tasks like SA [19].
RF	A Random Forest classifier is similar to a group of decision trees collaborating to provide predictions. Each tree makes a prediction based on a slightly different aspect of the data. The outcome is determined by the majority vote of all the trees. This method improves accuracy and makes the classifier more resistant to errors made by individual trees [20].
SVM	SVM is a ML method for categorizing things by drawing lines or shapes. It assists us in determining the best lines that separate different groups of things based on their characteristics, even when they are mixed. This allows us to distinguish between things more accurately [21].
Regression	Regression is a method for predicting outcomes by determining the relationships between various factors. It is similar to discovering a formula that explains how things work e.g. linear regression, logistic regression etc. [22, 23].
Clustering	Clustering techniques, such as k-means, divide data into 'k' clusters based on similarity. This is accomplished by calculating each cluster's center point (centroid), which represents the average position of the data points in that cluster [24].
LSTM	LSTM is a type of recurrent neural network (RNN) that can recognize and remember patterns and relationships in data that are spread out over a long sequence [25].

BiLSTM	BiLSTM is a sequence processing model that consists of two long-short-term memory networks: one that processes the input sequence from beginning to end, while the other does the opposite [26].
BERT	BERT, a Google-created language model, understands word meanings by examining the words that come before and after them. This two-way understanding enables BERT to effectively handle complex language tasks such as SA, answering questions, and text creation [27].

2.5 Word Embedding Techniques

In word embedding techniques, words are represented as dense vectors of real numbers in a low-dimensional space, which typically has between 50 and 300 dimensions. These vector representations, which are based on word co-occurrence patterns in a huge corpus of text, reflect the semantic and syntactic links between words. Word2vec is a popular algorithm used in NLP for generating word embeddings, which are vector representations of words in a high-dimensional space. The algorithm was developed by Mikolov et al [28]. Learning vector representations of words based on their context in a particular text corpus is the core concept underlying word2vec. The technique creates a vector representation of each word in the vocabulary using a significant amount of text data as input. These vectors, which capture the syntactic and semantic relationships between terms, are useful for a variety of NLP applications. Skip-Gram and Continuous Bag of Words (CBOW) are the two primary Word2vec variants. While using Skip-Gram, the algorithm predicts the context words based on a target word, whereas using CBOW, the system predicts a centre word based on the context words around it. Global vectors for word representation (GloVe) is a word embedding algorithm that was introduced by Pennington et al [29]. The Glove is similar to the word2vec technique in many aspects, but it generates word embeddings in a different way. The assumption that words with similar meanings are likely to co-occur frequently in a vast corpus of text is the foundation of the GloVe algorithm. The frequency of word co-occurrences in the corpus is captured in a co-occurrence matrix that is built and it then use matrix factorization strategies to create word embeddings that represent these connections. GloVe employs a count-based method that is computationally effective and can be trained on enormous datasets, in contrast to the word2vec algorithm, which uses a neural network to learn word embeddings. Word similarity and analogy identification are just two NLP tasks that the generated embeddings excel at. Fast Text is a well-known word embedding and classification model in NLP that was developed by Facebook researchers in 2017 [30]. It works well for uncommon words and short datasets because, unlike word2vec, it considers words to be made up of character n-grams [31]. This method has advantages such as better performance with uncommon words, especially on small datasets, and the ability to add sub-word characteristics to regular word embeddings [32].

Context-dependent or contemporary embedding models have demonstrated exceptional performance in a variety of NLP applications. Unlike traditional embeddings, which give each word a single meaning, these models change a word's meaning based on its usage context [33]. There are two major types: RNN-based and Transformer-based context embedding models. Transformer architectures like BERT are used in transformer-based context embedding to provide contextualized word representations. These models employ attention mechanisms to account for the relationships and meanings of the words around them, resulting in embeddings with more information. This method improves natural language processing tasks by collecting context-dependent semantics for better language comprehension [34]. In RNN-based contextual embedding, recurrent neural networks are used to evaluate words in sentences while keeping their sequence in mind. This captures context-specific meaning by including previous words, which aids in language generation and translation jobs. Because they analyze information sequentially, RNNs are excellent at comprehending context [35].

2.6 Exploring SA in Understanding Customer Opinions

SA assists businesses in understanding customer opinions and experiences with their products and services [36]. The transition from traditional brick-and-mortar markets to digital platforms has precipitated a significant surge in consumers' reliance on online reviews. These reviews have emerged as a pivotal medium for establishing trust and exerting considerable influence over consumer purchasing behavior. Acknowledging this growing dependence, in [37], the authors addressed the challenges associated with managing the substantial volume of reviews while ensuring the provision of reliable and credible information to consumers. Specifically, they undertook a comprehensive SA of mobile phone reviews, categorizing them into positive or negative sentiments. They meticulously adjusted the proportion of positive and negative reviews to ensure a balanced dataset. They sought to accurately classify the reviews by employing a sophisticated ensemble of three classification models, namely NB, SVM, and DT. Significantly, the SVM model exhibited the highest degree of predictive accuracy, surpassing the performance of its counterparts. The authors in [38] used a customer relationship management system to handle the company's interactions with current and potential customers. They explored various data mining techniques in businesses, corporations, and organizations. Then, they suggested a model specifically designed to understand customer behavior in the banking sector. The authors used three classifiers to test the model's effectiveness: k-NN (k-Nearest Neighbors), decision trees, and artificial neural networks. In [43], the author used text mining to determine what factors influence positive and negative attitudes in hotel reviews. This aided hotel marketers in improving their advertising and marketing strategies.

Consumer reviews, backed up by product review rankings, guide purchasing decisions in the e-commerce era. With the expansion of social networks, sentiment analysis (SA) adapts, providing lexicon-based and evolving approaches for dynamic data assessment [39] and in [40], the authors created a SA tool that recognizes emotions and word meanings in the text by combining human and ML input. In [41], the authors presented a framework for sentiment analysis using opinion mining in hotel customer reviews. They evaluated a number of machines learning algorithms, including complement NB and composite hypercubes etc., to determine the best classifier for classifying reviews as positive, negative, or neutral sentiment. SA as defined by the authors in [42], is the study of people's sentiments, opinions, and emotions toward various things through online mediums such as text or video. SA, in conjunction with OM, aids in understanding customer feedback by determining whether the reviews express positive or negative views on the subject. Software is used to quickly and automatically understand customer thoughts about products because personally reading all of the evaluations would take too much time [43]. According to a Bright Local study, 87% of people in 2020 read internet reviews before choosing a local business [44]. Nevertheless, not all evaluations are helpful when making decisions; choosing those that are actually valuable might save time and effort [45]. Businesses require automated systems for acquiring and processing client feedback as the importance of online reviews increases [46]. Businesses now operate on Internet platforms, allowing customers to place orders for goods via smartphones in the contemporary digital era. Nevertheless, customers' need for more confidence in the caliber of requested goods is a downside. Platforms let users post evaluations to address this, but this requires time-consuming manual analysis. To automatically categorize reviews as good or negative based on SA, the authors in [47] used ML and DL techniques in our research. Using multiple algorithms, they made use of Amazon book review data. Ultimately, their results showed that the neural network combined with a "bag of words" strategy beats competing techniques for unprocessed and preprocessed datasets.

The author in [48] used an Amazon dataset of reviews with a particular focus on cameras. After preprocessing the data, ML algorithms were used to categorize the reviews as positive or negative. In their analysis, the author discovered that Nave Bayes successfully classified camera reviews with an impressive accuracy rate of 98.17%, while SVM showed a marginally lower but still respectable accuracy of 93.54%. This suggests that these ML techniques, particularly in the context of cameras, are efficient for correctly classifying product reviews. The authors in [49] examined a massive dataset that included 568,454 Amazon reviews for 74,258 food products and 256,059 users over a decade. Six prominent products and users are investigated, with the NRC emotion lexicon used to categorize emotions into eight categories and two sentiments. Using plain text reviews and word cloud visualizations, the study demonstrates the power of SA in decoding consumer behavior, mitigating potential risks, and increasing consumer satisfaction. The authors in [50] developed a system that analyzes reviews and extracts essential details about different aspects. It gathers opinions on all aspects and can locate the one relevant to the user-selected aspect. The system uses advanced techniques to understand the connections between opinions and combine them when appropriate. It performed better than other approaches in various domains, and the best part is that it does not require domain-specific training data, enhancing its adaptability. To create a business model, the authors in [51] used customer reviews. They used powerful tools to extract sentiment from the reviews, analyze the findings, and assert high accuracy. To improve their decision-making, they used business analytics. Their work included recognizing gender based on names, detecting emotions, and identifying fake reviews. They employed the MNB and SVM classifiers and programmed them in Python and R. The authors in [52] used supervised ML algorithms to predict review ratings based on the text alone. They employed a technique called holdout cross-validation, where they divided the available data into 70% for training and 30% for testing. Different ML classifiers were employed to measure precision and recall, which evaluate prediction accuracy. The goal was to assess how well these algorithms perform in predicting ratings. The author in [53] conducted SA on Amazon review data. They used decision list classifiers and NB models to categorize reviews as positive or negative. Users' star ratings were used as the training set for supervised ML. The study's primary focus was a corpus of 50,000 product reviews for 15 different items, mostly books. A variety of features, including bigrams and bag-of-words, were compared to ascertain how well they classified data. The author also examined difficulties with feature selection and classification errors. The objective was to improve the precision of SA, specifically for Amazon review data. The authors in [54] proposed a system to guarantee brief, accurate, and unbiased sentiment results in statistical graphs, such as bar charts and pie charts, to address users needing more time to read through lengthy textual descriptions in reviews. The consolidated charts allow users to quickly and clearly understand the sentiment gleaned from the reviews. He authors in [55] introduced a brand-new game-theoretic mathematical framework for SA. A Bayesian game model combined context scores from review comments and rating scores to categorize reviews as positive or negative. Modern performance is demonstrated in experimental findings on benchmark datasets, confirming the stability and accuracy of the model. The suggested framework provides consistent and logical SA and establishes a novel paradigm for various NLP tasks. Latent semantic indexing (LSI) was utilized by the authors in [56] to rank reviews according to queries, and automatic positive/negative queries were used to evaluate reviews. The method was declared acceptable based on MCC value and created ranked lists for firms to answer customer input efficiently. The authors in [57] conducted SA on Amazon product reviews. The reviews were converted into vector representations using the Continuous Bag of Words and Skip gram techniques, and they did this by using the word2vec model. Then, on these vectors, ML algorithms like Random Forest and LSTM were trained. The results showed that LSTM, in combination with Word2Vec, achieved the highest accuracy in sentiment classification.

The authors in [58] introduced a sentiment polarity classification process by locating negation phrases, calculating sentiment scores, and creating feature vectors. The studies used Amazon Data 2014, concentrating on online product reviews classified at the review and sentence levels. They used a max-entropy POS tagger and Random Forest, SVM, and NB as three ML models. The approach worked well, as evidenced by the results, where the Random Forest model outperformed NB and SVM in classifying sentiment. In a separate study, the authors in [59] used massive datasets of Amazon review data to train CNN, SVM, LSTM, and Logistic Regression (LR), models. After examining various pre-processing methods, the researchers discovered that stemming without spell-checking produced the highest accuracy. In addition to paragraph vectors and pre-trained word embeddings like Word2Vec and GloVe, they investigated several feature approaches, such as bag-of-words, n-grams, and TF-IDF. The most effective traditional methods were Linear SVM with bag-of-n-grams and TF-IDF, while LSTM performed better than other deep-learning models.

In [60], a comparative study was conducted by the authors on Amazon review datasets to analyze text sentiment classification. Two groups were compared: supervised ML techniques (LR, Gradient Boosting, and SVM) and lexicon-based approaches (SentiWordNet, Pattern, and VADER). NLP techniques, including word lemmatization, stop word removal, and TF-IDF vectorization, were utilized. The findings revealed that supervised classification methods outperformed other approaches, particularly LR classifiers with minimal hyperparameter tuning. VADER demonstrated the highest performance among the lexicon-based techniques, as measured by accuracy, recall, precision, and F1 score. Notably, both groups exhibited better performance in identifying positive labels than negative labels, which could be attributed to the influence of positive emotion-related stop words and the class imbalance issue in the dataset.

In [61], the authors asserted that the current algorithms (NB and SVM) must achieve acceptable accuracy. They suggested an ensemble model strategy that combines various algorithms to address this. Their proposed system consists of three modules. The dataset was gathered from the official Amazon product site using the Amazon API in the first module. The pre-processing module eliminates unnecessary information like conjunctions, stop words, and punctuation. They combined NB and SVM in the classification module and determined the mode value based on the votes from each employed algorithm. Comparing this ensemble model approach to using the current algorithms separately, the authors asserted that accuracy is improved.

According to the authors in [61], the NB and SVM algorithms needed to be more accurate. They suggested an ensemble model strategy combining NB and SVM to increase accuracy. Their approach entailed obtaining the data from the official product website, preprocessing it by eliminating superfluous elements and combining the results of NB and SVM using a voting mechanism. The authors claim that the ensemble model approach outperformed the individual algorithms and offered better classification task accuracy.

In [62], the authors evaluated the effectiveness of three algorithms for sentiment classification of Amazon product records: MNB, Linear SVM, and LSTM. They obtained about 230,000 real-time reviews for electronic devices, toys, and furniture categories after randomly selecting 60,000 product reviews from a Kaggle benchmark dataset. After data pre-processing, the models were trained using the "maximum features" parameter. For MNB and LSVM, TF-IDF vectorization was used; for LSTM, tokenization was used. The findings showed that while LSVM and MNB produced acceptable outcomes, LSTM networks performed the best for binary sentiment classification of Amazon products.

The authors in [63] explored the application of deep neural networks, specifically CNN and LSTM architectures, for SA in customer reviews and social media data. Their study aimed to develop effective training strategies for extracting sentiment and meaningful inferences from weakly supervised data. By comparing the results with traditional text classification methods such as NB and SVM on IMDB and Amazon review datasets, the research investigated the merits of DL models for SA in customer reviews.

The authors in [64] specifically focused on analyzing customer reviews for the Redmi Note 3, Samsung J7, and Apple iPhone 5S among other items from Amazon. They developed a system to compile these reviews automatically. To ascertain whether a review was favorable, unfavorable, or neutral, they used a variety of algorithms, including NB, LR, and SentiWordNet. Through metrics-based performance comparison, they discovered that NB performed best at accurately classifying the reviews' sentiment.

This authors in [65] proposed a new SA model called SLCABG, which combines a sentiment lexicon, a CNN, and an attention-based Bidirectional Gated Recurrent Unit (BiGRU). The model enhanced sentiment features using the lexicon, extracted sentiment and context features using CNN and BiGRU and applied the attention mechanism for weighting. Real book reviews from the Chinese e-commerce website Dangdang.com were collected and cleaned for training and testing, resulting in a large-scale dataset. The experimental results demonstrated that the SLCABG model effectively improves text SA performance, offering advancements over existing models. Integrating sentiment lexicons and DL techniques addresses the limitations of previous SA models for product reviews. This research contributes to the field of Chinese SA and has practical applications for enhancing user satisfaction in e-commerce platforms.

The authors in [66] aimed to analyze and predict customer reviews of insurance products using various machine-learning techniques. Consumer rating data from Yelp was collected and filtered to focus on insurance reviews. The sentiment assessment was carried out by leveraging the well-established AFINN and Valence Aware Dictionary for Sentiment Reasoning (VADER) sentiment algorithms. Using these algorithms, the authors categorized the summary texts into positive, neutral, or negative sentiments. Five supervised machine-learning approaches were then employed to classify customer ratings into sentiment groups. The findings revealed a predominance of negative reviews for insurance products, with LR outperforming other methods in accuracy. The study provides valuable insights for companies to understand customer behavior using ML methods.

In [67], the authors presented a revolutionary approach that uses opinion-mining methods to examine customer feedback and help companies enhance their marketing plans. They performed SA on a range of products, including cameras, laptops, mobile phones, tablets, televisions, and video surveillance equipment purchased from Amazon, using DL models like LSTM and CNN-LSTM. To ensure data quality, they carried out preprocessing operations such as lowercase processing, stop word removal, punctuation removal, and tokenization. The LSTM and CNN-LSTM models distinguished between positive and negative consumer sentiment with outstanding accuracy rates of 94% and 91%, respectively.

2.7 Advances in Sentiment Analysis

The authors in [68] analyzed how customers choose online products using a web-based product recommendation system. Customers checked the product recommendations provided by a web-based system twice as frequently as non-customers, they found.

The authors in [69] increased the precision and relevance of product recommendations, using SA and ML algorithms. The authors of the study employed NLP to examine customer reviews for diverse goods falling under the same category. As a result, the algorithm will be able to recognize attitudes and trends that might not be immediately apparent from straightforward rating scores.

A product's quality is determined by how many features it has that meet customers' demands and expectations, as well as how those features have been modified. In order to increase product quality, the authors introduced ML algorithms for extracting numerous product parameters that are available across many sources in an unstructured manner [70]. In order to provide a reliable evidence-based technique for online product evaluation, the authors in [71], suggested text mining to evaluate product reviews while taking into account the legitimacy of each review.

The authors in [72] examined about 4000 reviews with related product information, including ID, brand, rating, and content, to estimate smartphone ratings using sentiment analysis on Amazon product reviews. In [73], the author proposed various factors of a product, such as internal features, external features, industry standards, reliability, lifetime, services, customers' response, exterior finish, and prior performance of the product. Udeh et al. [74] used a survey method and a multiple regression analysis to explore the hypothesis and see how product quality affected the satisfaction of Pay TV customers. The author in [75] analyzed Twitter data to determine how people felt about well-known businesses. In [76, 77], the authors used text mining algorithms to collect product attributes and forecast market development. The authors also employed text mining strategies to project product sales, the authors in [78, 79], added numerical data as a supplement. The authors in [80] gathered online customer feedback regarding their purchasing experiences, text classification algorithms were used in conjunction with a fuzzy comprehensive evaluation method to evaluate new quality value. This evaluation process helps customers in selecting appropriate products more wisely. The author in [81], introduced a creative architecture that uses online reviews to guide innovators in product design with precision, comparison, and rationality. In [82], the authors made an effort to extract important data from asset reviews in order to enhance an asset's characteristics and advance customer service and understanding. The authors examined customer reviews of a product using text mining techniques to find problems that commonly surfaced and how they typically evolved over time. Cruz [83] looked into the connection between customer satisfaction and product quality.

In [84], the authors carried out a study to address the considerable increase in text-based customer evaluations on the web and the various machine-learning techniques for SA. The authors discovered that neural network-based ML approaches, particularly pre-trained versions, give accurate predictions by studying a sizable and extensive dataset, including 25,241 products and 260,489 reviews across several platforms.

In order to evaluate product quality in the context of online shopping, the authors in [85] emphasized the drawbacks of sentiment-based analytic algorithms. They emphasized that these algorithms must take into account the complex connections between various product characteristics and the descriptions given in reviews. Furthermore, these algorithms frequently fail to recognize reviews that are irrelevant or noisy and do not advance quality analysis. The authors developed a novel algorithm called Lifelong Product Quality Analysis (LPQA) to overcome these flaws. This algorithm detects noise in reviews, concentrates on understanding the complicated relationships between various product attributes, and dramatically enhances the performance of opinion classification. In order to demonstrate the improved capabilities of their technique in online product quality assessment, the authors achieved a notable F1 score improvement of 77.3% on the Amazon iPhone dataset and 69.99% on the Semeval Laptop dataset. These findings clearly highlight the effectiveness of LPQA.

The authors in [86] investigated the growing trend of online retailers soliciting customer feedback via product reviews. They classified sentiment using ML techniques such as decision trees and LR on an Amazon Reviews dataset. Both models achieved high accuracy, with the Decision Tree model outperforming the LR model, achieving an impressive 99% accuracy versus 94%. These findings emphasized the importance of customer reviews and the potential of ML for SA in guiding business decisions.

The authors in [87] looked into the frequency and underlying causes of the polarization seen in online review distributions. They examined an extensive dataset of over 280 million online reviews from 25 important platforms. They discovered that most reviews are incredibly positive, with only a small number falling between the rating scale's midpoint and the negative end. The existence of "polarity self-selection," wherein customers with extreme judgments are more likely to leave reviews, was proven through cross-platform and multi-method analysis. This phenomenon strongly contributes to the polarisation of review distributions. In addition, the authors found that polarity self-selection and polarization of review distributions both result in less helpful online reviews.

The Local Search Improved Bat technique based Elman Neural Network (LSIBA-ENN), which the authors introduced in [88], is an improved ML technique for SA of online product reviews. The procedure includes gathering the data (using a web scraping tool), preprocessing, term weighting, and feature selection using log term frequency-based modified inverse class frequency (LTF-MICF) and hybrid mutation-based earth warm algorithm (HMEWA), and sentiment classification (positive, negative, and neutral) using LSIBA-ENN. Performance evaluation shows that LSIBA-ENN outperforms other algorithms, particularly the Elman Neural Network (ENN), attaining higher recall rates with LTF-MICF than other methods like W2V, TF, TF-IDF, and TF-DFS.

The authors in [89] suggested a Semi-supervised Co-LDA model that examined both the subjects and attitudes in product reviews at the same time. This approach can reliably distinguish between favorable and unfavorable judgments using expert and common evaluations. This method was successful for subject SA based on online review data from CNET. The model's adaptability extends to various uses, including user behavior prediction and blog opinion modeling.

The author in [90] proposed a DL model for SA of e-commerce product reviews named Bert-BiGRU-Softmax with hybrid masking, review extraction, and attention mechanism. The model used a Bidirectional GRU model to capture semantic codes and sentiment weights from reviews, a SoftMax layer with an attention mechanism to categorize positive or negative emotion, and a Sentiment Bert model to extract product attributes. The suggested model outperformed RNN, BiGRU, and Bert-BiLSTM models with an accuracy surpassing 95.5% when tested on a sizable dataset of 500,000 reviews, illustrating its usefulness in precisely evaluating sentiment in e-commerce reviews.

The authors in [91] proposed a generalized approach by modifying the BERT (Bidirectional Encoder Representations from Transformers) foundation model. The effectiveness of BERT-based classifiers is then evaluated by comparing their performance to that of bag-of-words techniques. In tests using Yelp retail reviews, BERT-based classifiers that have been tweaked outperform bag-of-words techniques at classifying reviews as helpful or unhelpful.

The authors in [92] proposed a novel technique for using DL to comprehend and categorize people's emotional sentiments in product reviews by grouping them into "like-dislike" and "aesthetic-inaesthetic." They tested their strategy on Amazon.com reviews and discovered that it outperformed other methods in predicting opinions with over 86% accuracy.

In [93], the authors used a hybrid technique that combines review-related and aspect-related data to create different feature vectors for each product review. LSTM model was used for sentiment classification, and the results on three datasets were outstanding, showing the model's effectiveness in SA with an average precision of 94.46%, an average recall of 91.63%, and an average F1-score of 92.81%.

Bi-convolutional networks (B-CNN) and spotted hyena optimized long short-term memory (SHOLSTM) were combined in a hybrid deep learning system introduced by authors in [94], which improved sentiment classification results (99.4%) in comparison to other algorithms (ranging from 90.5% to 93.1%).

To analyze sentiment on social media networks, the authors in [95] deployed an advanced ML algorithm. They used an innovative method that combines embedded CNN and BiLSTM architectures to alleviate the context-related constraints of BERT. Initial datasets were gathered, and then NLP extracted features altered by CNN. The accuracy and F1 score have improved significantly, according to empirical findings using Semeval and review data.

Using DL algorithms and other embedding strategies, the authors in [96] investigated online consumer reviews. Different models were compared, including CNN, Recurrent Neural Networks, and BiLSTM. Embeddings like BERT, Fast Text, and Word2Vec were used to assess these models. According to their findings, the CNN-RNN-Bi-LSTM model of a neural network using Word2Vec, which had a 96% accuracy rate and 91.1% F-score, was the most accurate prediction model. While RoBERTa had the highest F-score of 73.1%, the RNN model had an accuracy rate of 87.5% and an F-score of 83.5%.

Using psychology and AI, the authors in [97] examined customer hospitality. To forecast satisfaction, they integrated DL with expectation-confirmation theory. Their proposed fused model had an accuracy of 83.54% while analyzing hotel reviews, data, and pictures. Notably, their strategy increased the memory of the displeasure forecast from 16.46% to 33.41%, providing insightful data for the academic community and the hospitality sector.

More people are shopping online due to the growth of mobile social networks, yet information gaps between customers and manufacturers can be detrimental to both. To solve this issue, the authors in [98] examined customer feedback on agricultural items after the sale. They developed a refined SA technique based on an enhanced BERT model that better captures emotional tendencies and customer preferences, outperforming the baseline BERT model with an F1 value of 89.86%. This method supports improved analysis of internet reviews for agricultural products and enhances comprehension of customer feelings.

According to the authors in [99], SA is valuable for understanding user preferences in diverse fields. Existing methods, such as lexicon-based and ML-based techniques, have limitations in producing accurate results. Word2Vec, Glove, and BERT pre-trained embeddings require more sentiment understanding. Therefore, they proposed the LeBERT model that combines sentiment lexicon, N-grams, BERT, and CNN to address these issues. Their proposed model outperformed other models, with an F-measure score of 88.73% in binary sentiment classification across multiple public datasets.

The authors in [100] investigated ML models such as Nave Bayes, SVM, CNN, LSTM, and BiLSTM to extract sentiments and ratings from tourist reviews. These models were trained to classify reviews as positive, negative, or neutral and to assign one to five-star ratings. They used data from TripAdvisor for training. Multinomial Nave Bayes and SVM used TF-IDF for word representation, whereas DL models used GloVe. The results showed that a DL model based on the BiLSTM architecture best predicted sentiments and ratings.

The authors in [101] used a hybrid approach for airline and movie reviews, combining CNN and LSTM. This model is scalable and not domain-specific. It outperforms other DL algorithms in terms of experiment accuracy when trained on diverse datasets.

The authors in [102] employed DL techniques for SA on Google Play consumer reviews in Chinese. They used web mining to collect 196,651 reviews and applied approaches such as LSTM, NB, and SVM. DL achieved 94% accuracy, surpassing NB (74.12%) and SVM (76.46%). The study contributes a sentiment dictionary and emphasizes the advantages of non-average sampling data for improved performance in SA on Google Play reviews.

To perform an efficient sentiment classification for consumer review analysis, the authors in [103] used word2vec to convert customer reviews into vectors. They utilized 400,000 Amazon mobile phone reviews. They used CBOW and skip-gram models to validate the classification and recognition of semantic features in word2vec. Random Forest with CBOW produces the highest accuracy.

The authors in [104] used DL techniques to analyze review data to help customers choose better hotels. Their study utilized classification algorithms like CNN-DL and SVM network-based DL to predict attributes. Data from TripAdvisor was used for testing. The proposed CNN-DL technique outperformed other algorithms in classification accuracy and error rate, improving hotel customer selection.

According to the authors in [105], automated analysis of consumer reviews is vital for online shopping, and existing methods need more sentiment understanding. To address this problem, they proposed a novel deep neural network that combines word context and sentiment using pre-trained word embeddings and lexicon-based sentiment indicators. This model excels in capturing document representation, outperforming other methods in OM using Amazon reviews.

In [106], the authors developed QLeBERT, a classification model for evaluating product quality. It incorporates a product-specific lexicon, N-grams, BERT, and BiLSTM. The model generated word vectors from customer reviews using the lexicon, N-grams, and BERT. A significant contribution was the development of a quality-related lexicon dictionary based on an appraisal framework. This dictionary was then used to label data for training the BiLSTM model. QLeBERT outperforms existing models in binary classification, achieving an F1 macro score of 0.91 when tested on Amazon product reviews.

The authors in [107] presented a framework for mining and categorizing customer opinions based on sentiments. This assists potential buyers in forming informed opinions about products. Three classification algorithms were used to classify reviews: NB, Maximum Entropy Classifier, and SVM. The study also included a feature-based OM system with Bigram Collocation for extracting opinion words. Experiments showed that SVM outperformed NB and the Maximum Entropy Classifier. The method is effective in any domain.

The authors in [108] developed a CNN-based model to predict review usefulness, achieving high accuracy and outperforming other ML methods (KNN, LR, GNB, and LDA). The model considers two datasets and assesses review usefulness using binary classification with various features. CNN outperformed in accuracy, precision, F1 score, AUC, Average Precision, and recall.

The authors in [109] introduced a new SA framework that makes use of pre-existing lexicons and the n-gram approach to express each review or opinion as a fixed-length vector. In order to record the sentiment scores of multi-word phrases like bi-grams and tri-grams, the authors created a sequential feature space. The algorithm was then taught to categorize evaluations across this feature space as favorable or negative. This technique maintained the word order of the text by using an attribute vector with real- or binary-valued polarity ratings. According to authors in [110], the current SA techniques for online product reviews must be more precise and labor-intensive to use. Two approaches are given to deal with this problem: the DL Modified Neural Network (DLMNN) and the Improved Adaptive Neuro-Fuzzy Inference System (IANFIS). Depending on the context (collaboration, grading, and content), DLMNN categorizes reviews into positive, neutral, or negative attitudes. IANFIS uses a weighted classification method for future prediction.

2.9 Understanding Appraisal Theory and Emotional Reactions

The "appraisal" method used by Systemic Functional Linguistics (SFL) illustrates how language reflects people's attitudes and views toward many aspects of their environment, such as people, things, events, and ideas. In [111], The authors used the appraisal theory to determine how much emotion was felt by the audience while watching a story. In [112], the authors proposed a brand-new SA algorithm that uses "fuzzy logic" and "appraisal theory." A psychological paradigm known as appraisal theory explains how individuals evaluate the emotional significance of events and possessions. Fuzzy logic, on the other hand, uses mathematics to describe uncertainty and imprecision in data. The authors used a dataset of 25,000 movie-related comments to test their method. They found it was substantially more accurate—at 95%—than other SA approaches that merely distinguished between positive, negative, and neutral remarks.

There are various academic research on the appraisal theory. Wang Zhenhua is one of these academics, and he is the author of the paper "Appraisal System and Its Operation." [113], whereby he investigated how language is used to convey attitudes and feelings by a speaker or writer.

Beyond the traditional categories of sentiment, authors in [114] developed a novel method for identifying attitudes in text. They used compositionality principles and syntactic analysis to categorize sentences with specific attitude labels that took into account the concept hierarchy and linguistic rules for different verb classes. In [115], the authors looked into one Chinese EFL student's usage of evaluative language in argumentative writing in both Chinese and English. The study uses appraisal theory to examine how assessment, appreciation, feeling, and judgment are expressed in language.

In [116], the author aimed to demonstrate how these linguistic characteristics might assist in forging connections between the artist and the listeners by examining the distribution of attitude resources from appraisal theory (such as affect, judgment, and appreciation) in the English song lyrics. The authors in [117] looked at editorial language to understand how attitudes and business-related concepts are presented. They discovered widespread use of appreciative, probability-positive, and interrogative expressions, providing information about systemic linguistics. In [118], the authors examined how attitudinal judgment was applied in British advertisements and found that capacity and propriety were the most commonly applied categories. The authors in [119] looked into how students used language in a classroom. Their study concentrated on the ways in which attitudes, opinions, and interpersonal interactions might be expressed through language use in the classroom. The authors recognized a range of attitudinal resources, such as affect, judgment, and appreciation, to express both positive and negative opinions about the topics addressed in class. The author in [120] addressed how to understand interpersonal or evaluative meaning in language using the methodology of appraisal theory. The appraisal theory separates many evaluation categories, such as attitude, which is broken down into appreciation, judgment, and affect. The authors argue that aims and attitude lexis should be treated as distinct evaluation factors. The distinction between these two features needs to be appropriately taken into account in appraisal theory. The term "covert affect," which the authors proposed as a new attitude subtype, refers to attitudes that are discreetly or surreptitiously represented in language. In [121], the authors found that how engaged college students are with their academic work is influenced by their cognitive and affective views toward higher education. Data obtained through inquiries were employed in the descriptive correlational research design. Statistical methods like Mean and Pearson were applied to interpret the data. The students' cognitive and affective attitudes toward education as well as their level of academic involvement were calculated using the mean. Pearson was used to determine the relationship between students' cognitive and affective attitudes regarding higher education and academic engagement. The study found a significant relationship between students' cognitive and affective attitudes toward higher education and their academic involvement.

In [122], the authors looked at how the two students engaged with their sources and utilized dialogism or different voices in their writing. To evaluate the students' writing, the author used the elements of the appraisal framework. Both students employed sources in different ways, according to the analysis. The purpose of one student's use of sources was to support their argument, but the purpose of the other student's use was to engage in dialogism by referencing several sources and doing so in a more involved manner.

In [123], the authors' use of the appraisal framework and a mixed-method approach give readers a thorough knowledge of the attitudinal resources that Garg used in his letter of remorse. An important observation is the change in his demeanor from defensive to apologetic, which underlines the success of his communication in resolving the scandal surrounding Better.com's layoffs. The predominance of affect in Garg's attitudinal resources also shows his emotional interest in and empathy for the impacted workers. Another attitudinal resource that the authors' investigation reveals is the use of judgment, with the majority of the judgments being favorable. The absence of appreciation in the letter, which is a noteworthy discovery, also implies that the company's culture and its connections with its employees need to be improved.

Martin et al. [124] utilized an appraisal framework to analyze social media contents. The authors in [125] proposed a new SA strategy based on the idea of appraisal groups. Language elements that express a common evaluation dimension, like positivity or negative, are referred to as "appraisal groups”. In [126], the authors suggested a novel way for evaluating social media data that uses evaluation categories to capture the intricacies of people's emotional reactions and appraisals of conditions as opposed to more traditional SA or OM approaches.

The authors in [127] conducted a study of the book "Blindness" by José Saramago using the evaluation theory. Using the framework provided by Martin and White's appraisal theory, the study looked at 30 book extracts and evaluated three hypotheses. According to the authors, blindness frequently results in gloomy views, and appraisal theory can be used to identify the genre of a fictional text. The study shows how Saramago explicitly employed judgment rather than affect or appreciation, which is the author's most noticeable attitude at the beginning of the book.

Using an appraisal framework, the authors in [128] analyzed the tools used by participants in a drug study in the Philippines to express their attitudes. The study's conclusions show that elements of the appraisal framework, notably judgment, appreciation, and emotion, were crucial in evaluating witnesses and figuring out the veracity of their testimony. The most prevalent system is judgment, which has the subsystem tenacity. The highest scores suggested that individuals were attempting to gauge the credibility of the witnesses. Using the word "appreciation" and its subcategory "valuation" could indicate that the court believes the witnesses are credible and understands the value of their testimony. The lack of impact in the trial suggested that the court's decision-making was mostly unaffected by feelings and personal prejudices.

The authors in [129] investigated the evaluation criteria employed by a New Zealand university and examined the reports of 142 examiners from that institution. The authors examined how the examiners interacted with the content of the theses and expressed their sentiments in the language used in the reports using an appraisal framework. Using an appraisal framework, the authors in [130] analyzed 50 Weibo texts for the topic's assessment processes and underlying meanings using quantitative and qualitative methods. The author in [131] employed the appraisal theory to examine how Obama conveyed attitudes through language in his victory address. The author was particularly interested in how Obama restored public confidence, reduced hatred, encouraged racial togetherness, and inspired the country to take on difficulties by using the linguistic tools of affect, judgment, and appreciation.

The authors in [132] used the appraisal theory to analyze a New York Times article on China-DPRK ties and demonstrate how Americans view China. In [133], the authors aimed to understand the basic feelings portrayed in internet evaluations of upscale Cantonese restaurants in Hong Kong. The authors employed semantic network analysis and a ML technique to examine 2,118 reviews. Five emotions—joy, sadness, disgust, surprise, and anger—were found to be responsible for 72% of the accuracy in predicting the emotions in the reviews. In [134], the authors examined how people could be persuaded to modify their attitudes and beliefs despite having strong opinions in the matter. In order to develop a new paradigm for comprehending how people generate and alter their certainty about their attitudes, the authors analyzed past findings. In [135], the author listed the several attitude systems present in Tiktok's motivating texts, explained how they functioned, and offered justifications for their use. According to Xgilham's examination of the motivational movie, affect was the most commonly employed appraisal attitude.

3. Review findings and discussions

This research study is bifurcated into two distinct sub-areas, outlined as follows:

First Sub-area: Predicting Customers' Attitudes in Product Reviews Using ML Methods

This sub-area's main focus is on using Machine Learning (ML) approaches to identify customer attitudes in product reviews as shown in Table 2. Figure 1 and Figure 2 depict frequently and less frequently used ML methods in product reviews. Table 3 represents commonly used datasets in product reviews. Figure 3 and Figure 4 show graphical representation of commonly and less commonly used datasets in product reviews. By utilizing sentiment analysis, ML algorithms are used to automatically interpret the complex attitudes and sentiments that customers in their evaluations are trying to convey. The determination of whether a review is good, negative, or neutral is included in sentiment analysis. Businesses can use this information to gain insights into how customers view their offerings. Patterns and connections within customer evaluations are retrieved using ML algorithms, assisting firms in understanding customer impressions and adjusting strategy accordingly. This strategy makes it easier to make precise decisions based on customer attitudes and preferences.

Second Sub-area: Analysis of Attitude in Text Using Appraisal Theory

This sub-area uses the appraisal theory, a linguistic strategy, to examine attitudes in textual content. The core of appraisal theory is how authors use language to communicate their opinions, feelings, and attitudes.

Table 2. ML Approaches in Product Reviews

Sr#	Techniques	Research References	Paper #
1	SVM	[37], [45], [50], [82], [107], [133]	6
2	ANN	[38]	1
3	RNTN	[39]	1
4	SenticNet 2	[40]	1
5	NB	[41], [48], [53], [64]	4
6	NB+Senti-lexicon		1
7	Bi-GRU+Word2Vec	[46]	1
8	LSTM	[47], [57], [59], [63], [67], [93], [102]	7
9	TM+NRC lexicon	[49]	1
10	ANN	[52], [62]	2
11	Rule-based Technique	[54]	1

12	Unsupervised Bayesian Game Theory Model	[55]	1
13	LSI	[56]	1
14	RF	[58], [78]	2
15	LR	[60], [66], [86]	3
16	Ensemble Technique (NB+SVM)	[61]	1
17	CNN + Attention based BiGRU	[65]	1
18	TF-IDF	[72]	1
19	Regression Analysis	[74]	1
20	Lexicon based approach	[75], [109]	2
21	Fuzzy logic	[80]	1
22	Correlation Analysis	[81]	1
23	LPQA	[85]	1
24	LSIBA-ENN	[88]	1
25	LDA	[89]	1
26	Bert-BiGRU-Softmax	[90]	1
27	Fine Tuned Bert model	[91]	1
28	DL+Rule based Approach	[92]	1
29	B-CNN+SHOLSTM	[94]	1
30	LSTM+CNN	[95], [101]	2
31	i. Word2Vec + CNN-RNN-Bi-LSTM ii. RoBERT	[96]	1
32	Fused model	[97]	1
33	Enhanced BERT model	[98]	1
34	BERT+CNN	[99]	1
35	BiLSTM+Glove	[100]	1
36	RF+ CBOW	[103]	1
37	CNN+DL	[104]	1
38	DNN	[105]	1
39	QLeBERT	[106]	1
40	CNN	[108]	1
41	DLMNN	[110]	1

Table 3. Commonly used Datasets in Product Reviews

Dataset Name	Research Reference	Paper#
Amazon Product Reviews	[37], [48] , [49], [50], [54], [57], [58], [59], [60], [61], [62], [64], [67], [72], [78], [81], [85], [86], [92], [94], [99], [103], [105], [106]	24
Yelp	[52], [53], [99]	3
Hotel Reviews	[56], [79], [97], [133], [41]	5
IMDB reviews	[63], [99]	2
real book evaluation reviews	[65]	1
Insurance reviews from Yelp	[66]	1
PayTV Customer Reviews	[74]	1
Tweets about brands	[75]	1
Reviews of mobile phone	[80]	1
Semeval restaurant reviews	[85], [93], [95]	3
Reviews of Apple Samsung	[89]	1
Movie Reviews	[90], [101]	2
Yelp retail reviews	[91]	1
reviews on women's clothing	[96]	1
Agriculture Product Reviews	[98]	1
TripAdvisor	[100], [104]	2
Airline reviews	[101]	1
Google Play consumer reviews	[102]	1
Product review in Stanford Large Network Dataset Collection	[107]	1
Food Reviews	[110]	1
Reviews Portuguese banking institution	[38]	1
Stanford Sentiment Treebank	[39]	1
PatientOpinion database	[40]	1
Facebook pages of six medical products	[45]	1

The literature makes it evident that more work is needed to combine appraisal theory with ML to get a deeper comprehension of textual material. The many layers of attitudes concealed inside language can be uncovered by ML algorithms, allowing researchers to understand the subtler aspects of human expression better. Combining Machine Learning (ML) and appraisal theory may provide a robust framework for evaluating various product attributes, such as their impact, complexity, and quality. By combining these two methods, we may probe deeper into the complex attitudes and judgments hidden in the text, allowing for a thorough examination of product-related content.

Quality Assessment: Machine learning algorithms can be trained to recognize linguistic patterns that reflect customer perceptions of product quality based on appraisal theory. These algorithms can identify phrases that reflect positive or negative evaluations of a product's quality by analyzing customer reviews, allowing businesses to gauge how customers perceive their offerings.

Complexity Evaluation: When combined with machine learning, appraisal theory can provide insights into the complexity of products as perceived by customers. The combined approach can shed light on customers' perceptions of the product's complexities by identifying phrases that express uncertainty, speculation, or complexity.

Impact Analysis: Appraisal theory can also be used to assess the impact of products by analyzing the attitudes expressed in reviews. Positive evaluations, expressions of satisfaction, and appreciative phrases can all provide insight into how a product affects the lives of its customers. When combined with ML techniques, a comprehensive picture of the product's overall impact can be derived from textual content.

4. Conclusions

This research survey concludes that:

1. The literature review focuses on how ML is used to analyze customers' reviews of products, but most studies are focused on reviews written in English. There is a lack of attention given to reviews written in other languages like Parsi, Urdu, and so on. More research is needed to analyze reviews in different languages.
2. Currently, most of the existing work in this field uses traditional SA to understand customers' attitudes in product reviews. However, this survey propose using "appraisal theory" instead, as it provides a more detailed and richer description of customers' attitudes compared to traditional SA.
3. One important task is to identify fake reviews, which means distinguishing genuine reviews from those written with deceptive or dishonest intentions.
4. There is a lack of publicly available tools that can be used to analyze customers' attitudes based on the proposed appraisal theory.
5. Currently, there are no ML applications available that specifically identify customers' attitudes using the appraisal theory approach.
6. Various advanced methods such as DL, fuzzy-based systems, Graphical neural networks, and advanced word embedding techniques are not yet used to identify customers' attitudes based on the appraisal theory.
7. The authors suggest that the attitudinal categories from the appraisal theory can be used to evaluate and rank products. This aspect is currently missing from the existing literature.
8. Using the attitude system of the appraisal framework (the extended version of traditional SA and OM), the quality, complexity, and impact of products can be evaluated based on customers' attitudes in their reviews.

4.1 Implications of Research

This literature offers several managerial implications that can benefit any organization in improving their consumer services. The main findings of this survey highlight the significance of online review content in influencing consumer decisions. Core service aspects have a stronger impact on consumer sentiments compared to augmented service aspects. Additionally, consumer sentiments or emotions play a crucial role in predicting consumer recommendations, which can aid in designing effective service strategies. The review also reveals that consumer sentiment is context-dependent, requiring careful consideration when interpreting consumer sentiments. When creating advertising content, the use of specific sentimental words related to joy may have more influence than those related to surprises or trust. Furthermore, consumer choices for services are influenced by factors like region, culture, cost, and facilities, necessitating tailored service policies by management to cater to consumers' preferences.

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