Volume 17 • Issue 4 • 2025

Engineering Management in Production and Services

sciendo

received: 15 May 2024
accepted: 1 August 2025

pages: 1-14

Review of sentiment analysis in new product development: text, audio, visual, and multimodal data

Randi Eka Sanjaya
Ririn Diar Astanti
The Jin Ai

A B S T R A C T
This research provides a literature review on the application of sentiment analysis (SA) in the new product development (NPD) process. The literature review employs a systematic literature review methodology. The steps include selecting a review topic, searching and selecting relevant articles, assessing and synthesising the literature, and organising the writing of the review. Sentiment analysis is a subdomain of natural language processing (NLP) that examines user opinions. The sentiment analysis methodology has been employed in the new product development process to replace traditional methods. Sentiment analysis can be conducted across various modalities, including text, audio, image, and multimodal formats. Text modality for sentiment analysis has been used to enhance the lifetime of products and services. Audio data and image modalities represent alternative modalities; however, they receive significantly less attention. The limitation is that these modalities are predominantly executed in controlled environments, utilising open-source or benchmark datasets, and some still employ text modality sentiment analysis methods or lexicons. Multimodal data, conversely, aims to augment the informational dimension of the text modality and is typically executed using deep learning models. This modality encompasses numerous combinations with the primary objective of enhancing the performance of sentiment analysis, hence reducing bias. The findings suggest that future research in this domain should focus on improving multimodal sentiment analysis to improve the new product development process.

K E Y W O R D S
sentiment analysis, new product development, multimodal, literature review

10.2478/emj-2025-0023

The Jin Ai
Universitas Atma Jaya Yogyakarta
Jl. Babarsari 44, Sleman 55281, Indonesia
ORCID 0000-0002-5946-5027

Corresponding author:
email: the.jinai@uajy.ac.id

Randi Eka Sanjaya
Universitas Atma Jaya Yogyakarta
Jl. Babarsari 44, Sleman 55281, Indonesia
ORCID 0009-0009-4267-0524
e-mail: randi.eka1301@gmail.com

Ririn Diar Astanti
Universitas Atma Jaya Yogyakarta
Jl. Babarsari 44, Sleman 55281, Indonesia
ORCID 0000-0001-5234-0283
email: ririn.astanti@uajy.ac.id

Introduction

Product development is recognised as a vital activity that significantly contributes to a country's economic health, thereby supporting corporate survival and sustaining national economic prosperity (Craig & Hart, 1992). New Product Development (NPD) is a framework comprising a series of processes for developing new products. This terminology is used interchangeably with innovation and design, depending on the context, hence exemplifying the interdisciplinary essence of NPD. Until now, NPD has gained considerable interest and intensive research.

Sanjaya, R. E., Astanti, R. D. & Ai, T. J. (2025). Review of sentiment analysis in new product development: text, audio, visual, and multimodal data. *Engineering Management in Production and Services, 17*(4), 1-14. doi: 10.2478/emj-2025-0023

A brief literature review in Section 1 demonstrates the rapid development of the NPD field in terms of paradigms, methodologies, and tools used in NPD. An important issue discussed in NPD is how to gather the Voice of Customers (VoC). Current research has shifted from capturing VoC through sentiment analysis (SA) from text-only input data (Renganathan & Upadhya, 2022) to capturing VoC through multimodal sentiment analysis (MSA) from diverse input data formats such as text, images, audio, and video (Chandrasekaran et al., 2021).

Based on the brief review, existing literature reviews did not specifically study how SA and MSA enhance NPD in gathering VoC. To fill the gap, a literature review on this topic is re-conducted, which is SA with different modalities, to answer the following research questions:

- What is the drawback of text modality to represent VoC?
- Can other modalities be used to represent VoC in NPD?
- Which modality potentially produces better results for NPD?

After the short literature review presented in Section 1, the remainder of this article is outlined as follows. The methodology of this literature review is presented in Section 2. Section 3 summarises the literature review results by SA type. Section 4 discusses the roles of various SA types in enhancing NPD. Finally, the conclusion of this review is presented in Section 5.

1. Literature review

NPD is a framework of processes for developing new products or services. Initially, a manufacture-centric paradigm underlies NPD formulation. Later, this paradigm shifts to a customer-active paradigm (Von Hippel, 1978) that enhances it by placing the customer at its core; however, this approach is limited to instances where the client is explicitly aware of the need for a new product. In this paradigm, it is important to define lead product users as users who articulate future product needs that eventually become mainstream (Von Hippel, 1986). In producing successful NPD, technological and commercial information is fundamental to the NPD process, providing the foundation for assessment and decision-making (Craig & Hart, 1992). Consequently, information is an element that necessitates further both empirical and theoretical exploration.

Subsequently, Wind and Mahajan (1997) examined contemporary challenges in NPD and asserted that the need for NPD redesign should extend beyond conventional qualitative methodologies, including focus groups, user surveys, and experiments. The conventional approach is deemed costly and offers just temporary engagement (Hoyer et al., 2010). The innovative method should facilitate the identification, development, and evaluation of a product or service. A possible method for achieving NPD redesign is to get data from unconventional sources of customer insight, as NPD must prioritise gathering relevant, trustworthy, valid, timely, and cost-effective information regarding customers and other stakeholders. The NPD process development must also include alignment with market requirements. Customer involvement in NPD is regarded as beneficial when executed during the initial and subsequent phases, using lead users to achieve significant economic appeal. Subsequently, Hoyer et al. (2010) presented a conceptual framework for customer co-creation. Customer co-creation can enhance efficiency and effectiveness, but it may also introduce additional costs and risks.

March-Chordà et al. (2002) identified that demand and market conditions in product innovation represent the most significant obstacles in the development process, potentially leading to the failure of product innovation. Concerning this issue, prior studies employed conventional techniques, including surveys, questionnaires, and interviews (Altuntaş, 2019; Rianmora & Werawatganon, 2021; Kulcsár, 2022). The limitations of methods that address evolving customer needs include the manual identification of these needs through instruments such as surveys, interviews, focus groups, ethnographic observation, and lead user theory. These approaches require significant time, financial investment, and resources, while only encompassing a limited customer segment, thereby diminishing reliability (Ireland & Liu, 2018; Quan et al., 2023).

Meanwhile, in the domain of artificial intelligence, there is a great interest in developing natural language processing (NLP). NLP emphasises computational linguistics applicable to language comprehension. Sentiment analysis (SA) is utilised in the development or enhancement of product lifecycles through NLP. SA output is expressed as semantic orientation (SO) from various modalities such as text, audio, visual, and multimodal (Chandrasekaran et al., 2021). The implementation of SA can be used in several contexts, including social media sentiment analysis, marketing and product review (Zad et al., 2021), multimodal action recognition, market forecasting for trading systems, tourism sentiment analysis, health care, education and learning, human-computer interaction, recommendation systems, fraud detection, and sentiment regarding contemporary issues (Gandhi et al., 2023).

In their study, Schemmann et al. (2016) indicated that corporations are increasingly utilising crowdsourcing to gather innovative ideas from the general public in new product development (NPD). They demonstrated that crowdsourcing concepts from online platforms can enable organisations to harness collective intelligence to generate new ideas in new product development (NPD). The potential for idea generation from public opinion, coupled with SA capabilities, can effectively mitigate the drawbacks of the traditional NPD approach.

Based on preliminary research, the use of the text mining technique to produce sentiment orientation has gained a lot of attention compared to other modalities (Jin et al., 2016; Zhang et al., 2018; Lyu et al., 2019; Botchway et al., 2020; Visalli et al., 2020; Chiarello et al., 2020; Park, 2020; Renganathan & Upadhya, 2022; Lovera et al., 2021; Ng et al., 2021; Awajan et al., 2021; Obayed et al., 2021; Benlahbib & Nfaoui, 2021; Jiang et al., 2022; Verza et al., 2023). In the NPD process, text modality has been used to improve the performance and robustness in gathering voice of the customer (VoC) at the initial stages. The application lies in concept development to gather novel ideas for developing new products (Verza et al., 2023). However, since SA can be produced from other modalities, several literature studies have been conducted to investigate whether different modalities can be applied to improve the NPD process (Quan et al., 2023; Chandrasekaran et al., 2021; Zad et al., 2021; Gandhi et al., 2023; Drus & Khalid, 2019; Seng & Ang, 2019). Zad et al. (2021) have contributed to the available techniques for sentiment analysis and its application. Drus and Khalid (2019) contributed by depicting the use of sentiment analysis in social media and its application. Chandrasekaran et al. (2021) later expanded the review by investigating the current landscape of multimodal sentiment analysis (MSA), preprocessing, feature extraction, and fusion techniques, and by comparing SA techniques on several modalities. Seng and Ang (2019) also demonstrated SA for each modality and for multimodal combinations. Gandhi et al. (2023) later investigated the available dataset, the fusion method, and the future implications for MSA application. In their paper, Quan et al. (2023) proposed how data analytics techniques, using structured or unstructured data, can specifically improve product design activity by examining the traditional method.

2. Research methods

The literature study is conducted following the methodology proposed by Bodolica and Spraggon (2018). The initial step is to select a review topic. This step highlights identifying search keywords based on the author's preferences for this topic of interest. The range of topics starts with specific, focused subjects: "Sentiment Analysis", "Product Development", "Text", "Audio", "Visual", and "Multimodal". These keywords were chosen to acquire foundational theories, facilitate theory development, and implement them in SA to support the product development process. The subsequent step involves searching for and selecting appropriate articles. This step emphasises the systematic identification of topics with relevant information. The literature domain includes theoretical representations, review articles, and empirical research articles.

The search involved several group keywords with different modalities and open-access journals only. Text modality ("Sentiment Analysis", "Text", "Product Development") was used in 254 sources of literature; audio modality ("Audio", "Sentiment Analysis", "Product *") - in 554, and ("Sentiment Analysis" AND "Product" AND "Development" AND "Speech") - in 1410 sources of literature. Image modality ("Sentiment Analysis", "Visual", "Product *") was found in 89 sources of literature, ({Sentiment Analysis} AND {Visual} AND {Product *}) - in 1481, ("Sentiment Analysis", "Product", "Development", "Image") - in 1952, and ("Emotion", "Recognition", "Product", "Development", "Image") - in 4296 sources of literature. Multimodality ("Sentiment Analysis", "Multimodal", and "Product *") yielded 1356 sources of literature. The second attempt was made with a limit on open-access journals and a search within the abstract title, abstract, and keywords, with a broader keyword definition for image and multimodal modality. Image modality ("Sentiment Analysis", "Image") yielded 265 sources of literature. Multimodal modality ("Product Review", "Sentiment Analysis", "Multimodal") was used in 19 sources of literature, and ("Product *", "Multimodal Sentiment Analysis") yielded 32 sources of literature.

All keywords were obtained using the Scopus database. The search results were refined by selecting relevant titles and a brief reading of abstracts. The pruning resulted in the text modality keywords yielding 21 references, audio modality keywords - 26 references, image modality keywords - 13 references, and multimodal keywords - seven references.

The next step involved analysing and synthesising the literature. This step underscores the necessity of scrutinising each reference and synthesising information depending on the article's compilation. The elimination process entails a concise examination of the abstract, methodology, conclusion, and its relevance to the application of SA and the implementation. For the context of the keywords "Sentiment Analysis", "Text", and "Product Development", the journals had to include SA and case studies, as they are exclusively focused on the product lifecycle; thus, any literature outside this scope was considered irrelevant. Consequently, the final compilation comprised 15 literature sources in text modality, three in audio modality, five in image modality, and eight in the multimodal category, with a total of 31 sources of literature.

The last step is organising review writing. This step emphasises the importance of structured review, facilitating readers' comprehension of the topic, and conducting a literature review in the same way. Based on the previously chosen publications, the author analyses and synthesises the topic from SA and product development. Each modality topic encompasses theory development and its application. This approach allows for journal mapping.

The study aims to illustrate the current landscape of the SA technique and identify a potential approach to leverage the product cycle, especially in the NPD context. Each keyword group undergoes a literature review and is mapped manually in draw.io. Synthesis is made to accommodate all keyword groups to form future research on how the NPD process can be enhanced using the best SA method.

3. Research results

NLP is recognised as a series of application domains within the computational linguistic community, employing various strategies for language comprehension (Bates, 1995). The NLP implementation in the product lifecycle encompasses SA, text summarisation, and subject modelling. SA is a computer method for recognising and classifying various ideas presented in textual format. SA is also commonly referred to as "opinion mining" and interprets user attitudes towards an object (Ding & Liu, 2007). Customer sentiment is a crucial factor for manufacturers to better understand their markets. Producers can use sentiment analysis to acquire client feedback on their product and subsequently enhance or modify it to address the issue.

In recent years, the use of SA has become increasingly important with the massive amount of data, known as Big Data, characterised by the 5Vs: volume, veracity, velocity, value, and variety (Quan et al., 2023). Other data types, such as audio, image, video, and multimodal modalities, have gained attention and may be used to improve SA. Several studies have proposed SA techniques for each of the modalities mentioned above.

The results of this review are classified into three subsections. The first subsection reviews textual data, the earliest and most common mode used for SA. The second subsection reviews results on single-mode, non-textual data to explore the SA potential using the non-textual mode. The third subsection reviews SA results using multimodal data types, in which more than one mode is used as input for the SA process.

3.1. Sentiment analysis on text data

Compared to other modalities, SA using text modality has attracted the most attention. Several studies have been conducted to improve product lifecycles. Research results on text data in the area of SA are presented in Fig. 1 and summarised in Table 1. In this subsection, the results are divided into four parts based on their application: tangible product, service, product and service, and others.

3.1.1. SA application for a product

Jin et al. (2016) proposed an approach for opinion data mining from customer reviews using Lexicon WordNet, the Kalman filter, and the Bayesian method on a smartphone product review. They analysed customer opinion data from the product designer's perspective. Zhang et al. (2018) proposed the Aspect Sentiment Collaborative Filtering (ASCF) method to capture different attitudes towards a product using SA on smartphone purchase records. ASCF uses a combination of SA and the Fuzzy Kano model to output a user's degree of desire and importance for a product feature. They also stated that different product categories may have distinctive characteristics. Also, this method is unsuitable for a small dataset on user purchasing behaviour. Special marketing

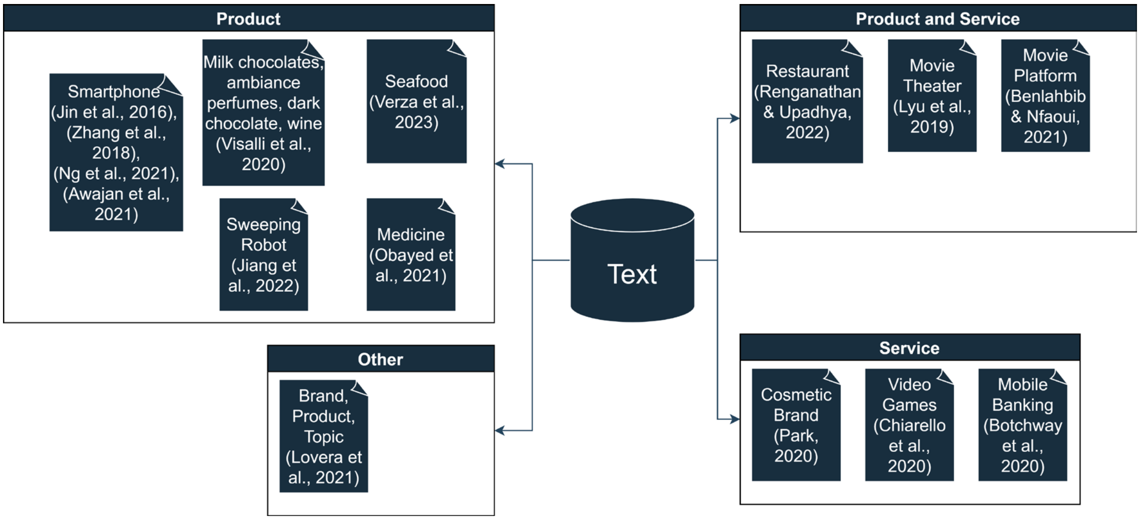

Fig. 1. Schematic diagram of sentiment analysis of text data

Tab. 1. Summary of research in the area of sentiment analysis of text data

Method	Language / Tools	Library / Add-On	Reference
Lexicon, Kalman Filter	Java	MIT Java WordNet	Jin et al., 2016
ItemCF, Fuzzy Kano Model	Python	NLTK	Zhang et al., 2018
Dynamic Topic Analysis (DTA), Autoregressive Heat-Sentiment (ARHS)	-	-	Lyu et al., 2019
Lexicon	Python	NLTK, VADER, SentiWordNet, AFINN	Botchway et al., 2020
Lexicon	R	Microsoft Text Analytics API	Visalli et al., 2020
Lexicon	-	-	Chiarello et al., 2020
Lexicon, TF-IDF	R, RapidMiner	Rvest	Park, 2020
Lexicon	R	TM, NLP, Syuzhet, Ggplot2	Renganathan & Upadhya, 2022
Knowledge Graph (KG), Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BiLSTM), Local Interpretable Model-agnostic Explanations (LIME)	Python 3	TensorFlow	Lovera et al., 2021
Lexicon, K-Means	-	-	Ng et al., 2021
Lexicon, Simplified Neutrosophic Number Weighted Average Operator (SNNWA), Cosine Similarity, Score Function	Python, ScrapeStorm	NLTK	Awajan et al., 2021
Global Vectors for Word Representation (Glove), Bidirectional Long Short-Term Memory (BiLSTM)	-	-	Obayed et al., 2021
Embedding for Language Model (ELMo), Multinomial Naïve Bayes	ScrapeStorm	-	Benlahbib & Nfaoui, 2021
Particle Swarm Optimisation (PSO), Dynamic Evolving Neural-Fuzzy Inference (DENFIS)	Excel	Semantria	Jiang et al., 2022
Latent Dirichlet Allocation (LDA), Lexicon	Java, R	Machine Learning for Language Toolkit (MALLET), NRC Emotion Lexicon	Verza et al., 2023

activities affect sentiment, therefore creating bias for the Kano Model. Visalli et al. (2020) investigated the potential of the Microsoft API for sentiment prediction, measuring sentiment, liking, and the correlation from product sensory data. Their research concluded that sentiment analysis is not as reliable as an indirect measure of the liking score, especially when products differ slightly. They also stated that a score of 0.5 can express either a neutral stance or indetermination; that the ML model is not specifically designed for sensory data; and that, in a few cases, sentiment is simply dubious because it was created for long texts. Ng et al. (2021) proposed a framework for product evaluation using a lexicon and the K-Means algorithm for smartphone products from a Facebook fan page. Their research contributed a logical and practical solution for handling user-generated content (UGC). The drawbacks of their framework, including performance, are that it is highly affected by other product models for comparison, the involvement of expert judgement is required to compare products, and the use of a lexicon may be insufficient and imprecise, with varying opinions. Awajan et al. (2021) proposed a method for ranking products based on online customer reviews (OCR) using an integrated lexicon, the Simplified Neutrosophic Number Weighted Average Operator (SNNWA), cosine similarity, and a score function for smartphone reviews on Twitter. Their method combines the VADER lexicon with a neutrosophic number and later implements the cosine similarity to rank the product. Accuracy can be enhanced by integrating more neutral words from social media, and generalising neutrosophic logic can capture more uncertainty. Obayed et al. (2021) proposed a binary classification on the sentiment analysis of a pharmaceutical product using Global Vectors for Word Representation (GloVe) and Bidirectional Long Short-Term Memory (BiLSTM) on a review dataset. Jiang et al. (2022) proposed a model to depict the dynamics of customer preferences using a Particle Swarm Optimisation (PSO)-based Dynamic Evolving Neural-Fuzzy Inference System (DENFIS) trained on Amazon product reviews of a sweeping robot. Their research concerned customer preferences, which introduce variability and can be depicted as time-series data, given the ambiguity of emotions expressed by customers in online reviews. The relationship between product design attributes and customer preferences is crucial. However, this research has drawbacks: problems of neutrality and ambivalence are not considered in terms of sentiment analysis, and parameter tuning takes a long time. Verza et al. (2023) proposed a framework for NPD using a combination of Latent Dirichlet Allocation (LDA) topic modelling and a lexicon derived from online discussions for a seafood product concept. This research found that customer involvement in NPD could provide assistance and new market opportunities. Online discussion data can be used as an alternative to ethically formed data acquisition. Differentiating customers based on certain attributes can provide NPD that addresses a sample dimension. The drawbacks lie in limited customer involvement, which may result in only addressing personal preference; product ideas derived from consumers may not align with their purchasing behaviour.

3.1.2. SA application for service

Botchway et al. (2020) proposed an SA approach using a lexicon to better understand customer opinions towards mobile banking products. They suggested that a lexicon for text mining can help companies focus on vital cases, convey and exchange information fast, and enhance newly released products. The drawbacks of their research include using a single social media platform, the lack of other techniques such as topic modelling or the fuzzy rule-based method, and the use of only English tweets. Chiarello et al. (2020) developed a lexicon based on the advantages and drawbacks of products, associated with functional or physical underpinnings and using a newly released video game. They filtered data from Twitter in the context that the new product delivered more relevant, unambiguous information, identified reasoned and balanced customer opinions of their experience and could shed light on issues. Information from social media has drawbacks: it is difficult to untangle and understand in depth, and a risk may arise of underestimating endogenous extraction of opinions and beliefs.

3.1.3. SA application for both product and service

Lyu et al. (2019) proposed the Dynamic Topic Analysis (DTA) framework to handle electronic word of mouth (eWOM) data to extract heat and sentiment from movie daily ticket sales. They also proposed an autoregressive heat-sentiment (ARHS) model to enhance forecasted daily sales by integrating heat and sentiment into a predictive model; thus, it could be used to monitor customer feedback, issue warnings during collaborative brand attacks, and better predict performance for sales. The drawback of this method is that it benefits only social media marketing for products and brands with massive social media data, and it integrates only eWOM and social media data. Renganathan and Upadhya (2022) proposed a sentiment analysis model on tourist restaurant reviews using a lexicon. This approach can help tourists find a suitable restaurant and compare restaurants within their categories. The drawback is that the use of a lexicon is unsuitable for comparison with machine learning (ML) or deep learning (DL) models; thus, it can be enhanced by using a hybrid method that comprises the lexicon-ML model to measure accuracy. Benlahbib and Nfaoui (2021) proposed a reputation system based on opinion mining and semantic analysis using Multinomial Naive Bayes. This approach results in a reputation value and visualisation to inform the user about the movie-related performance. Park (2020) proposed a framework to analyse relative customer satisfaction and its determinants in cosmetic brands using a sentiment analysis lexicon approach, statistics, and TF-IDF. This paper stated that using sentiment analysis can replace traditional methods, such as customer satisfaction surveys. The drawbacks, including dependency on a general lexicon, make analysis prone to bias, and sentient activation or deactivation is not considered, which potentially lowers the accuracy.

3.1.4. Other applications

Lovera et al. (2021) proposed an SA framework that uses knowledge graphs (KG) and DL techniques on Twitter short document data. The Local Interpretable Model-agnostic Explanations (LIME) model is used to uncover the so-called "black box", thus enhancing the truth in a predictive model. Using KG, the proposed framework captures tweet structural information with its meaning. This framework may produce an underfitting model since it uses only a limited amount of data. Therefore, as one of the disadvantages of this framework, it is sometimes unable to generalise the rules and distinguish sentiment.

3.2. Sentiment analysis of non-text data

Sentiment analysis has stretched beyond using text modality to produce sentiment orientation. Data in audio and image modalities are two modalities that interest many researchers and have ever-growing data availability that the Internet produces each day, especially through social media and e-commerce. Several pieces of literature have been studied to depict each modality used for product development. A schematic diagram of research results on SA into non-text data is presented in Fig. 2 and summarised in Table 2. In this subsection, the results are divided into two parts based on their modality: audio and image.

3.2.1. Audio modality

Sentiment analysis using audio modality has been applied for tangible products (Setchi & Asikhia, 2019; Ko et al., 2022). Setcho and Asikhia (2019) proposed a method for linking user sentiment with specific product design features by an ontology of image schemas and a lexicon in an offline session using alarm clock products. This approach can be chosen to investigate user interaction with products to help design intuitive use. This research stated that affectivity can influence user perception towards usability. Its drawback is that it excludes the use of interjection words to signify emotion. Ko et al. (2022)

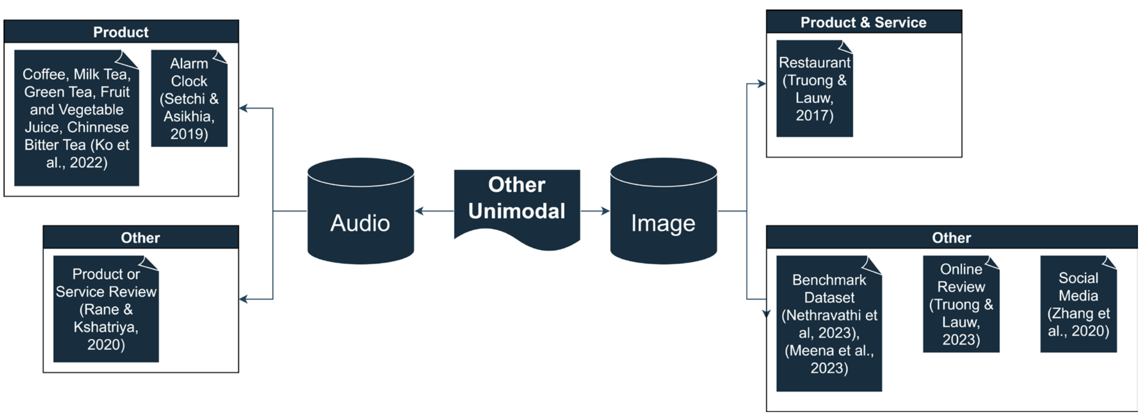

Fig. 2. Schematic diagram of sentiment analysis on non-text data

Tab. 2. Summary of research in the area of sentiment analysis on non-text data

Modality	Method	Language / Tools	Library / Add-On	Reference
Audio	API	Google Sheet, Liv.ai, Meaning Cloud	-	Rane & Kshatriya (2020)
Audio	Long Short-Term Memory (LSTM), MFCC, Support Vector Machine (SVM)	Audacity	-	Ko et al. (2022)
Audio	Lexicon, Ontology of Image Schema	C++	-	Setchi & Asikhia (2019)
Image	Convolutional Neural Network (CNN)	-	-	Truong & Lauw (2017)
Image	Convolutional Neural Network (CNN), Viola and Jones Algorithm	Python	TensorFlow	Nethravathi et al. (2022)
Image	Inception-V3 CNN	Python 3.9	TensorFlow 2.5	Meena et al. (2023)
Image	Vision Transformer (ViT)	-	-	Truong & Lauw (2023)
Image	Discriminant Correlation Analysis (DCA), Machine Learning Classifier, Sample Refinement (SR)	-	-	Zhang et al. (2020)

proposed a discriminative model to detect customer satisfaction via audio data using a Mel-Frequency Cepstral Coefficient (MFCC), LSTM, and a support vector machine (SVM) in an offline session interview about a food product. This research stated that acoustic analysis can be used to enhance customer relationship management (CRM). The drawback of this study is that it only uses the Mandarin language, and research has been done in a controlled environment, which makes it prone to bias in real-world applications.

Meanwhile, other applications of SA are found using audio modality. Rane and Kshatriya (2020) proposed an audio opinion mining and sentiment analysis framework for product or service reviews using phone calls. This framework utilises an API for speech recognition and sentiment analysis to generate reports. The drawback is that this research only uses a specific set of questions, therefore, outputting static feedback.

3.2.2. Image modality

SA using the image modality has also been investigated by Truong and Lauw (2017), who applied it to both products and services. They proposed an approach to infer sentiment from images using a convolutional neural network (CNN) on food product reviews. Image sentiment analysis of reviews may be affected by three factors: image factor, item factor, and user factor. Thus, items and user factors with facial recognition are proposed using CNNs to capture the interaction between image features and user expressions or items. The drawback is the bias from items, which can be positive in one context and negative in another.

Several other applications of SA using image modality have been offered (Nethravathi et al., 2022; Meena et al., 2023; Zhang et al., 2020; Truong & Lauw, 2023). Nethravathi et al. (2022) proposed using multiple CNNs to identify head posture and face emotion in customer engagement with an advertisement. First, CNN estimates head posture; then, it is used for face segmentation; and finally, it proceeds with face recognition and classification. This method is suitable for marketing, product likeability, client interest, and boosting sales. Meena et al. (2023) used an Inception-V3 transfer learning approach for the SA of image data. Inception-V3 transfer learning is a CNN-based method that can focus on the human body, which is a significant advantage over traditional CNNs. This research used benchmark datasets, such as FER2013, JAFFE, and Cohn-Kanade (CK+). It stated that image SA can be used in several contexts, including understanding customer perceptions of a product or service, building customer relations and loyalty, improving customer service, and utilising emotional marketing. The drawback of this research is the effort to manually tune parameters. Zhang et al. (2020) proposed the Multidimensional Extra Evidence Mining (ME2N) method for image SA, focusing on cross-modal sentimental semantics mining and the sample refinement (SR) process. The proposed model incorporates SR, Cross-Modal Sentimental Semantics Mining (CSS), and the ML classification algorithm. It was tested using social media and social networking websites. Based on this research, image SA can capture people's emotions, analyse mental states, and benefit social or economic contexts. Truong and Lauw (2023) later proposed an image sentiment analysis by enhancing the Vision Transformer (ViT) model by incorporating concept orientation into the self-attention mechanism named SentiViT, which was tested on several online product reviews. This research stated that image sentiment classification could be used for measuring customer satisfaction and opinions on social media.

3.3. Sentiment analysis on multimodal data

This subsection reviews several research efforts that applied SA to multimodal data. Based on the modality used in the SA, these results can be categorised into (i) text and image modality, (ii) text, image, and behavioural features, and (iii) text and audio modality. A schematic diagram for the results of existing research in the area of SA on multimodal data is presented in Fig. 3 and summarised in Table 3.

3.3.1. Text and image modality

Ye et al. (2019) proposed the Deep Tucker Fusion (DTF) method for multimodal sentiment analysis (MSA) of the text and image modality and created a dataset for the modality, Product Reviews-150K (PR-150K), consisting of online shopping website data. The DTF method uses a CNN and a Gated Recurrent Unit (GRU) to predict sentiment.

Hou et al. proposed the VisdaNet framework for text and image MSA of restaurant online reviews (Hou et al., 2023a). This framework uses the Contrastive Language-Image Pre-Training (CLIP) model and the Bidirectional Gated Recurrent Unit (BiGRU) to perform sentiment classification based on visual distillation and attention mechanism. The CLIP model can distil knowledge by reducing either noise in a long text or missing information in a short text. CLIP-based visual attention fuses cross-modal features and information of a single text and multiple images.

Huang et al. (2019) proposed Deep Multimodal Attentive Fusion (DMAF) to perform image-text sentiment analysis with a semantic attention mechanism and mixed fusion using manual and machine-labelled data from social image websites. This model works by performing unimodal SA of each image and text modality first, then using an intermediate fusion-based multimodal attention model to depict internal correlation between modalities, and finally, performing a late fusion for final sentiment prediction. Later, Huang et al. (2020) proposed the Attention-Based Modality-Gated Network (AMGN) model to perform MSA using CNN and Modality-Gated LSTM using manual and machine-labelled data from social image websites. This approach analyses the correlation and discriminative information between modalities. A visual-textual attention model is used to learn a word-relative visual feature first, then, selection of a more emotional modality feature is performed using modality-gated LSTM; thus, a semantic self-attention model is employed to select a discriminative feature for sentiment prediction. However, this model is created based on an assumption that there is a fine-grained relationship between text-image pairs.

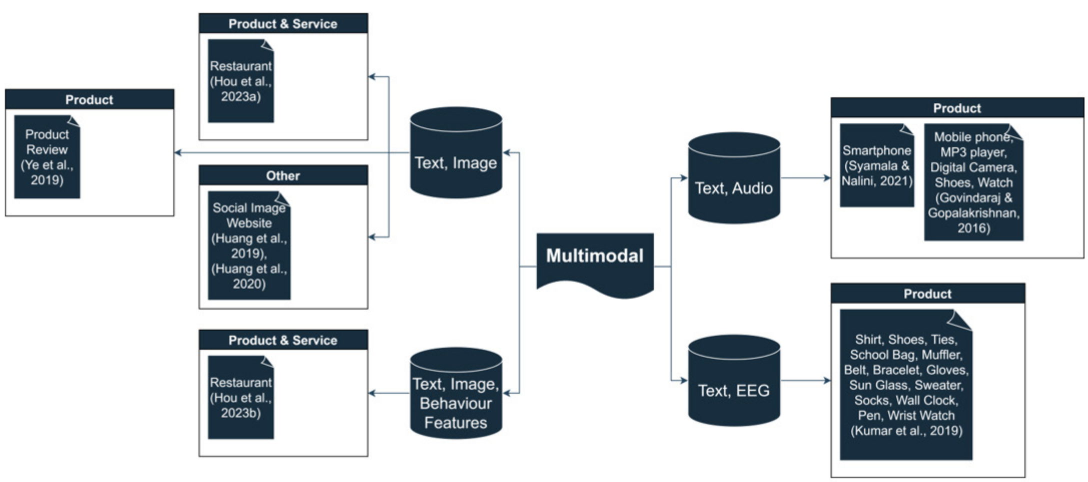

Fig. 3. Schematic diagram of sentiment analysis on multimodal data

Tab. 3. Summary of research on sentiment analysis of multimodal data

Modality	Method	Language / Tools	Library / Add-On	Reference
Text, Audio	Lexicon, OpenEAR + MFCC, Support Vector Machine (SVM)	-	-	Govindaraj & Gopalakrishnan (2016)
Text, Audio	Lexicon, Latent Dirichlet Allocation (LDA), Efficient Named Entity Recognition (E-NER), Convolutional Neural Network (CNN), Bidirectional Recurrent Neural Network (Bi-RNN), Normalised Weighted Aspect Extraction (NWAE)	Python	Gensim, Idamallet, WordNet	Syamala & Nalini (2021)
Text, EEG	Lexicon, Random Forest Regression, Artificial Bee Colony Algorithm (ABC), DWT Algorithm	-	-	Kumar et al. (2019)
Text, Image	Deep Tucker Fusion (DTF), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU)	Python	PyTorch	Ye et al. (2019)
Text, Image	Contrastive Language-Image Pre-Training (CLIP), Bidirectional Gated Recurrent Unit (BiGRU)	Python 3.6	TensorFlow 1.14.0	Hou et al. (2023a)
Text, Image	Convolutional Neural Network (CNN), Modality-Gated Long Short-Term Memory (LSTM)	-	TensorFlow	Huang et al. (2020)
Text, Image	Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM)	-	TensorFlow	Huang et al. (2019)
Text, Image, and Behaviour Features	Contrastive Language-Image Pre-Training (CLIP), Bidirectional Gated Recurrent Unit (BiGRU)	Python 3.6	TensorFlow 1.14.0	Hou et al. (2023a)

3.3.2. Text, image, and behavioural features

Hou et al. (2023b) proposed the UsbVisdaNet model for MSA that emphasises reducing user bias in product reviews by adding psychological behaviour into VisdaNet for restaurant online reviews. This model is proposed because SA often struggles to consider the user attitude, whether it is constantly negative or positive. This approach improves sentiment classification, which is affected by user reviews using behaviour information.

3.3.3. Text and audio modality

Govindaraj and Gopalakrishnan (2016) proposed integration of sentiment and emotion analysis with text-speech modality for customer service product reviews to intensify sentiment. A lexicon was used for SA, then OpenEar and MFCC were performed for emotion recognition, and finally, a support vector machine (SVM) was used for sentiment classification. This method is proposed for automated customer behaviour analysis, customer redress systems, customised retail services, and business process quality improvement. Syamala and Nalini (2021) proposed a hybrid aspect-based sentiment analysis using fusion from the text-speech modality for reviews of a smartphone. This research proposes a speech-to-text model using a deep learning framework and a bi-gram language model to enhance the text transcript. Three text analysis models, including lexicon, topic modelling, and E-NER, are performed, thus using decision-level fusion to generate the final sentiment.

4. Discussion of the results

Verza et al. (2023) stated that new product success can be achieved by involving consumers in the first NPD phase, using a co-creation approach. Nowadays, customer review data can be easily obtained from social media, e-commerce, and blogs, revealing major customer requirements. This data can play a significant role in market-driven product design (Jin et al., 2016). Given the opportunity, many researchers use online review data to develop or enhance various products and services. The conventional way of preprocessing such data is to use sentiment analysis (SA) to provide a customer perspective on products or services.

Traditionally, SA and ER are obtained from the text modality. But in recent years, SA advancement resulted from Big Data, which can be characterised by 5Vs: volume, variety, velocity, veracity, and value

(Quan et al., 2023). Nowadays, SA can be obtained using several modalities, including text, images, speech, and multimodal. Thus, a literature review was performed to identify the current SA landscape in terms of several modalities for products or services. Each modality includes categories of product, service, product and service, and others. Products are used in literature sources that specifically use products as objects, and the same can be said for services. Some objects comprise both products and services, e.g., restaurants. Others do not belong to any category but state the usability of a product or service.

SA has concentrated on deriving Semantic Orientation (SO) from textual data. Sentiment analysis is commonly utilised in product or service evaluation data, including documents, websites, and online reviews. Numerous studies have examined the efficacy of online product reviews in text modality (Jin et al., 2016; Zhang et al., 2018; Lyu et al., 2019; Botchway et al., 2020; Visalli et al., 2020; Chiarello et al., 2020; Park, 2020; Renganathan & Upadhya, 2022; Lovera et al., 2021; Ng et al., 2021; Awajan et al., 2021; Obayed et al., 2021; Benlahbib & Nfaoui, 2021; Jiang et al., 2022; Verza et al., 2023). In terms of products, SA used the text modality to determine sentiment towards a product, product ranking, perceive trends, compare products, determine the degree of desire and importance of product features, product evaluation, analyse the dynamics of customer preferences, and develop ideas for NPD. In terms of a service, SA used the text modality to analyse customer satisfaction and advantages or drawbacks of products with functional or physical underpinnings. Several cases also addressed both product and service, which used SA for a recommendation system, reputation system, and extracting heat and product sentiment. However, several drawbacks can be identified, such as the use of a general lexicon, which can make the analysis prone to bias. Thus, it can be replaced by another approach considered more robust, i.e., topic modelling, the fuzzy rules-based method, or the hybrid lexicon-ML model (Botchway et al., 2020; Park, 2020; Renganathan & Upadhya, 2022). A lexicon also caused the output's unsuitability for comparing with an ML or DL algorithm and not giving sufficient and precise results with varying options (Renganathan & Upadhya, 2022; Ng et al., 2021). Special marketing activities will affect sentiment, thus blurring the real customer opinion (Zhang et al., 2018). Information from social media is difficult to untangle and understand in depth (Chiarello et al., 2020). Expert judgements are still necessary to produce a meaningful analysis (Ng et al., 2021). With limitations on customer involvement, it may yield results only addressing personal preference (Verza et al., 2023).

Significantly less frequent use of SA is found in the context of non-text modalities, including audio (Setchi & Asikhia, 2019; Ko et al., 2022; Rane & Kshatriya, 2020) and image (Truong & Lauw, 2017; Nethravathi et al., 2022; Meena et al., 2023; Zhang et al., 2020; Truong & Lauw, 2023) modalities for products or services. In terms of products, SA used the audio modality for opinion mining, detecting customer satisfaction, and linking product features with sentiment. For other cases, SA used the audio modality for opinion mining and sentiment analysis. However, several drawbacks can be identified, such as audio SA testing used in a controlled environment only (Setchi & Asikhia, 2019; Ko et al., 2022) and mostly treating audio SA as text SA, because audio data is transcribed into text (Setchi & Asikhia, 2019; Rane & Kshatriya, 2020). For the image modality, the use of SA is divided into products and services, and others. For products, SA captures the interaction of image features with user expression or items. For other cases, SA identifies emotions, classifies sentiments, and measures customer satisfaction and opinions. However, several drawbacks can be identified, such as a suggestion to monitor facial expression over time using object tracking and localisation (Nethravathi et al., 2022). The use of image modality in SA can be enhanced by integrating text to perform MSA (Truong & Lauw, 2017) and further refined by using a cross-modal analysis model, a GAN-based data augment model for sample refinement and integrating colour features for predicting the final sentiment (Zhang et al., 2020).

In recent years, SA has started using multimodality. Multimodality has many different combinations: first, text-image, which has been used for products, product and service, and others. In all those categories, this combination is used for sentiment classification. Second, text-image-behavioural features, which have been used for products. This combination is used for sentiment classification with consideration of user behaviour. Third, text-EEG, which has been used for products. This combination is used for product rating predictions. The last combination uses text and audio for the product category. It is used for sentiment intensification and aspect-based sentiment analysis. However, several drawbacks can be identified, such as performing research in a controlled environment (Kumar et al., 2019), in text and image pairs, and assuming that both modalities have a fine-grained relation (Huang et al., 2020).

Conclusions

Natural language processing (NLP) emphasises computational linguistics applicable to language comprehension. One application of NLP in enhancing the product lifecycle is sentiment analysis (SA). SA has concentrated on deriving semantic orientation (SO) from textual data. Sentiment analysis is commonly used to evaluate product or service reviews, presented in documents, websites, and online assessments. This data can serve as a resource to enhance the product development cycle, particularly given that extensive studies have focused on text data. Social media data continues to grow, with large amounts generated by users. Big Data has 5V characteristics: volume, veracity, velocity, value, and variety. One social media characteristic is the availability of non-text data, such as images, audio, and video. With advances in SA, especially deep learning (DL) techniques, the non-text modalities can be used to produce sentiment orientation (SO).

Based on a literature review, SA used the text modality to improve product and service lifecycles. Most approaches use a lexicon, which has inherent limitations and is intended for general use; therefore, it could introduce ambiguity into the produced sentiment. Audio data and image data, respectively, are other possible SA modalities, but they gain substantially less attention compared to the text modality. These modalities are usually used with a DL and a pretrained model, potentially providing better SO than the text modality. The drawback is that both modalities are mostly used in controlled environments, with open-source or benchmark datasets, and some audio modalities still rely on the text modality SA (lexicon). Multimodal data, on the other hand, proposes to add dimensions of information from the text modality. It is commonly performed using the DL model. This modality has many combinations, as discussed above. The overall aim of the multimodal sentiment analysis (MSA) is to improve SA by combining modalities, thereby reducing bias in SO production.

Based on the insights from this paper, future research can focus on using MSA to improve the NPD process, especially in the ideation phase, by replacing traditional approaches such as surveys, questionnaires, and interviews.

Acknowledgements

The authors thank the editor and the anonymous reviewers for their valuable comments and suggestions to improve the quality of this paper. Lembaga Penelitian dan Pengabdian pada Masyarakat (LPPM), Universitas Atma Jaya Yogyakarta, partially funds this work

Literature

Altuntaş, S., Özsoy, E. B., & Mor, Ş. (2019). Innovative new product development: a case study. *Procedia Computer Science*, *158*, 214-221. doi: 10.1016/j.procs.2019.09.044

Awajan, I., Mohamad, M. S., & Al-Quran, A. (2021). Sentiment analysis technique and neutrosophic set theory for mining and ranking big data from online reviews. *IEEE Access*, *9*, 47338-47353. doi: 10.1109/access.2021.3067844

Bates, M. (1995). Models of natural language understanding. *Proceedings of the National Academy of Sciences of the United States of America*, *92*(22), 9977-9982. doi: 10.1073/pnas.92.22.9977

Benlahbib, A., & Nfaoui, E. H. (2021). MTVRep: A movie and TV show reputation system based on fine-grained sentiment and semantic analysis. *International Journal of Power Electronics and Drive Systems/International Journal of Electrical and Computer Engineering*, *11*(2), 1613. doi: 10.11591/ijece.v11i2.pp1613-1626

Bodolica, V., & Spraggon, M. (2018). An end-to-end process of writing and publishing influential literature review articles. *Management Decision*, *56*(11), 2472-2486. doi: 10.1108/md-03-2018-0253

Botchway, R. K., Jibril, A. B., Oplatková, Z. K., & Chovancová, M. (2020). Deductions from a Sub-Saharan African Bank's Tweets: A sentiment analysis approach. *Cogent Economics & Finance*, *8*(1), 1776006. doi: 10.1080/23322039.2020.1776006

Chandrasekaran, G., Nguyen, T. N., & Hemanth, D. J. (2021). Multimodal sentimental analysis for social media applications: A comprehensive review. *Wiley Interdisciplinary Reviews. Data Mining and Knowledge Discovery*, *11*(5). doi: 10.1002/widm.1415

Chiarello, F., Bonaccorsi, A., & Fantoni, G. (2020). Technical Sentiment Analysis. Measuring advantages and drawbacks of new products using social media. *Computers in Industry*, *123*, 103299. doi: 10.1016/j.compind.2020.103299

Craig, A., & Hart, S. (1992). Where to now in new product development research? *European Journal of Marketing*, *26*(11), 2-49. doi: 10.1108/03090569210023037

Ding, X., & Liu, B. (2007). The utility of linguistic rules in opinion mining. *Proceedings of the 30th annual international ACM SIGIR conference on Research* *and development in information retrieval*. doi: 10.1145/1277741.1277921

Drus, Z., & Khalid, H. (2019). Sentiment Analysis in Social Media and its Application: Systematic Literature review. *Procedia Computer Science*, *161*, 707-714. doi: 10.1016/j.procs.2019.11.174

Gandhi, A., Adhvaryu, K., Poria, S., Cambria, E., & Hussain, A. (2023). Multimodal sentiment analysis: A systematic review of history, datasets, multimodal fusion methods, applications, challenges and future directions. *Information Fusion*, *91*, 424-444. doi: 10.1016/j.inffus.2022.09.025

Govindaraj, S., & Gopalakrishnan, K. (2016). Intensified Sentiment Analysis of Customer Care Audio using Acoustic and Textual Features. *ETRI Journal*, *8*(3), 494-501. doi: 10.4218/etrij.16.0115.0684

Hou, S., Tuerhong, G., & Wushouer, M. (2023a). VISDANET: Visual Distillation and Attention Network for Multimodal Sentiment Classification. *Sensors*, *23*(2), 661. doi: 10.3390/s23020661

Hou, S., Tuerhong, G., & Wushouer, M. (2023b). USBVISDANET: User Behavior Visual Distillation and Attention Network for Multimodal Sentiment Classification. *Sensors*, *23*(10), 4829. doi: 10.3390/s23104829

Hoyer, W. D., Chandy, R., Dorotić, M., Krafft, M., & Singh, S. S. (2010). Consumer cocreation in new product development. *Journal of Service Research*, *13*(3), 283-296. doi: 10.1177/1094670510375604

Huang, F., Wei, K., Weng, J., & Li, Z. (2020). Attention-Based Modality-Gated networks for Image-Text Sentiment analysis. *ACM Transactions on Multimedia Computing, Communications and Applications/ACM Transactions on Multimedia Computing Communications and Applications*, *16*(3), 1-19. doi: 10.1145/3388861

Huang, F., Zhang, X., Zhao, Z., Xu, J., & Li, Z. (2019). Image-text sentiment analysis via deep multimodal attentive fusion. *Knowledge-based Systems*, *167*, 26-37. doi: 10.1016/j.knosys.2019.01.019

Ireland, R., & Liu, A. (2018). Application of data analytics for product design: Sentiment analysis of online product reviews. *CIRP Journal of Manufacturing Science and Technology*, *23*, 128-144. doi: 10.1016/j.cirpj.2018.06.003

Jiang, H., Guo, G., Sabetzadeh, F., & Chan, K. Y. (2022). Model variational consumer preferences based on online reviews using sentiment analysis and PSO-based DENFIS approaches. *Journal of Intelligent & Fuzzy Systems*, *43*(3), 2407-2418. doi: 10.3233/jifs-213057

Jin, J., Li, Y., Ji, P., & Liu, H. (2016). Understanding big consumer opinion data for market-driven product design. *International Journal of Production Research*, *54*(10), 3019-3041. doi: 10.1080/00207543.2016.1154208

Ko, Y. H., Hsu, P., Liu, Y., & Yang, P. (2022). Confirming customer satisfaction with tones of speech. *IEEE Access*, *10*, 83236-83248. doi: 10.1109/access.2022.3196733

Kulcsár, E., Gyurika, I. G., & Csiszér, T. (2022). Network-based - Quality Function Deployment (NB-QFD): The combination of traditional QFD with network science approach and techniques. *Computers in Industry*, *136*, 103592. doi: 10.1016/j.compind.2021.103592

Kumar, S., Yadava, M., & Roy, P. P. (2019). Fusion of EEG response and sentiment analysis of products review to predict customer satisfaction. *Information Fusion*, *52*, 41-52. doi: 10.1016/j.inffus.2018.11.001

Lovera, F. A., Cardinale, Y., & Homsi, M. N. (2021). Sentiment analysis in Twitter based on knowledge graph and deep learning classification. *Electronics*, *10*(22), 2739. doi: 10.3390/electronics10222739

Lyu, X., Jiang, C., Ding, Y., Zhao, W., & Liu, Y. (2019). Sales prediction by integrating the heat and sentiments of product dimensions. *Sustainability*, *11*(3), 913. doi: 10.3390/su11030913

March-Chordà, I., Gunasekaran, A., & Lloria-Aramburo, B. (2002). Product development process in Spanish SMEs: an empirical research. *Technovation*, *22*(5), 301-312. doi: 10.1016/s0166-4972(01)00021-9

Meena, G., Mohbey, K. K., & Kumar, S. (2023). Sentiment analysis on images using convolutional neural networks based Inception-V3 transfer learning approach. *International Journal of Information Management Data Insights*, 3(1), 100174. doi: 10.1016/j.jjimei.2023.100174

Nethravathi, P. S., Koti, M. S., Taramol, K. G., Anwar, S., Babu, G. J., & Thinakaran, R. (2022). Real Time Customer Satisfaction Analysis using Facial Expressions and Head-pose Estimation. *International Journal of Advanced Computer Science and Applications/International Journal of Advanced Computer Science & Applications*, *13*(10). doi: 10.14569/ijacsa.2022.0131029

Ng, C. Y., Law, K. M. Y., & Ip, W. H. (2021). Assessing public opinions of products through sentiment analysis. *Journal of Organizational and End User Computing*, *33*(4), 125-141. doi: 10.4018/joeuc.20210701.oa6

Obayed, H. K., Al-Turaihi, F. S., & Alhussayni, K. H. (2021). Sentiment classification of user's reviews on drugs based on global vectors for word representation and bidirectional long short-term memory recurrent neural network. *Indonesian Journal of Electrical Engineering and Computer Science*, *23*(1), 345. doi: 10.11591/ijeecs.v23.i1.pp345-353

Park, J. (2020). Framework for Sentiment-Driven Evaluation of Customer Satisfaction with Cosmetics Brands. *IEEE Access*, *8*, 98526-98538. doi: 10.1109/access.2020.2997522

Quan, H., Li, S., Zeng, C., Wei, H., & Hu, J. (2023). Big Data and AI-Driven Product Design: A survey. *Applied Sciences*, *13*(16), 9433. doi: 10.3390/app13169433

Rane, A. L., & Kshatriya, A. R. (2020). Audio Opinion Mining and Sentiment Analysis of Customer Product or Services Reviews. In *ICDSMLA 2019: Proceedings of the 1st International Conference on Data Science, Machine Learning and Applications* (pp. 282-293). Singapore: Springer Singapore.

Renganathan, V., & Upadhya, A. (2022). Dubai Restaurants: A Sentiment Analysis of Tourist Reviews. *Academica Turistica*, 165-174. doi: 10.26493/2335-4194.14.165-174

Rianmora, S., & Werawatganon, S. (2021). Applying quality function deployment in open innovation engineering. *Journal of Open Innovation*, *7*(1), 26. doi: 10.3390/joitmc7010026

Schemmann, B., Herrmann, A., Chappin, M. M., & Heimeriks, G. (2016). Crowdsourcing ideas: Involving ordinary users in the ideation phase of new product development. *Research Policy*, *45*(6), 1145-1154. doi: 10.1016/j.respol.2016.02.003

Seng, J. K. P., & Ang, L. (2019). Multimodal Emotion and Sentiment Modeling From Unstructured Big Data: Challenges, Architecture, & Techniques. *IEEE Access*, *7*, 90982-90998. doi: 10.1109/access.2019.2926751

Setchi, R., & Asikhia, O. K. (2019). Exploring User Experience with Image Schemas, Sentiments, and Semantics. *IEEE Transactions on Affective Computing*, *10*(2), 182-195. doi: 10.1109/taffc.2017.2705691

Syamala, M., & Nalini, N. (2021). An Efficient Aspect based Sentiment Analysis Model by the Hybrid Fusion of Speech and Text Aspects. *International Journal of Advanced Computer Science and Applications/International Journal of Advanced Computer Science & Applications*, *12*(9). doi: 10.14569/ijacsa.2021.0120920

Truong, Q., & Lauw, H. W. (2023). Concept-Oriented Transformers for Visual Sentiment Analysis. *Proceedings of the 16th ACM International Conference on Web Search and Data Mining*. doi: 10.1145/3539597.3570437

Truong, Q.T., & Lauw H.W. (2017) isual sentiment analysis for review images with item-oriented and user-oriented CNN. In *Proceedings of the 25th ACM international conference on Multimedia* (pp. 1274-1282). doi: 10.1145/3123266.3123374

Verza, M., Camanzi, L., Rota, C., Cerjak, M., Mulazzani, L., & Malorgio, G. (2023). Consumer Sentiments and emotions in new seafood Product Concept Development: A Co-Creation approach using online discussion rooms in Croatia, Italy and Spain. *Foods*, *12*(8), 1729. doi: 10.3390/foods12081729

Visalli, M., Mahieu, B., Thomas, A., & Schlich, P. (2020). Automated sentiment analysis of Free-Comment: An indirect liking measurement? *Food Quality and Preference*, *82*, 103888. doi: 10.1016/j.foodqual.2020.103888

Von Hippel, E. (1978). Successful Industrial Products from Customer Ideas. *Journal of Marketing*, *42*(1), 39. doi: 10.2307/1250327

Von Hippel, E. (1986). Lead users: a source of novel product concepts. *Management Science*, *32*(7), 791-805. doi: 10.1287/mnsc.32.7.791

Wind, J., & Mahajan, V. (1997). Issues and Opportunities in new product Development: An introduction to the special issue. *Journal of Marketing Research*, *34*(1), 1-12. doi: 10.1177/002224379703400101

Ye, J., Peng, X., Qiao, Y., Xing, H., Li, J., & Ji, R. (2019). Visual-Textual Sentiment Analysis in Product Reviews. *IEEE International Conference on Image Processing*, 869-873. doi: 10.1109/icip.2019.8802992

Zad, S., Heidari, M., Jones, J. H., & Uzuner, Ö. (2021). *A Survey on Concept-Level Sentiment Analysis Techniques of Textual Data*. doi: 10.1109/aiiot52608.2021.9454169

Zhang, H., Wu, J., Shi, H., Jiang, Z., Ji, D., Yuan, T., & Li, G. (2020). Multidimensional extra evidence mining for image sentiment analysis. *IEEE Access*, *8*, 103619-103634. doi: 10.1109/access.2020.2999128

Zhang, J., Chen, D., & Lu, M. (2018). Combining sentiment analysis with a fuzzy Kano model for product aspect preference recommendation. *IEEE Access*, *6*, 59163-59172. doi: 10.1109/access.2018.2875026