Front. Eng. Manag. 2022, 9(4): 592–609
https://doi.org/10.1007/s42524-022-0227-z

REVIEW ARTICLE

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Review of sentiment analysis: An emotional product development view

Abstract Conveying consumers' specific emotions in new products, referred to as emotional product development or emotional design, is strategically crucial for manufacturers. Given that sentiment analysis (SA) can extract and analyze people's opinions, sentiments, attitudes, and perceptions regarding different products/services, SA-based emotional design may provide manufacturers with real-time, direct, and rapid decision support. Despite its considerable advancements and numerous survey and review articles, SA is seldom considered in emotional design. This study is among the first efforts to conduct a thorough review of SA from the view of emotional design. The comprehensive review of aspect-level SA reveals the following: 1) All studies focus on extracting product features by mixing technical product features and consumers' emotional perceptions. Consequently, such studies cannot capture the relationships between technical and emotional attributes and thus cannot convey specific emotions to the new products. 2) Most studies use the English language in SA, but other languages have recently received more interest in SA. Furthermore, after conceptualizing emotion as Kansei and introducing emotional product development and Kansei Engineering, a review of the data-driven emotional design is then conducted. A few efforts start to study emotional design with the help of SA. However, these studies only focus on either analyzing consumers' preferences on product features or extracting emotional opinions from online reviews, thus cannot realize data-driven emotional product development. Finally, some research opportunities are provided. This study opens a broad door to aspect-level SA and its integration with emotional product development.

Keywords sentiment analysis, emotion, product development, Kansei Engineering

1 Introduction

Nowadays, consumers often publish and share their reviews and experiences regarding using products/services via different web resources (Birjali et al., 2021). Sentiment analysis (SA), also called opinion mining, can extract and analyze people's opinions, sentiments, attitudes, and perceptions concerning different entities, including topics, products, and services. Over the last one and a half decade, SA has received great attention and has been widely used to understand the general public and consumers' opinions on different entities, including public social events, marketing business, and product/service preferences (Birjali et al., 2021).

Manufacturers must satisfy the functional needs of products (defined objectively) and the subjectively emotional needs (Petiot and Yannou, 2004; Yan et al., 2017). For instance, Apple's iMac is viewed as an aesthetic revolution in computing, indicating that computers' aesthetics plays a vital role in consumer purchase decisions (Postrel, 2001). Consequently, it is strategically important for manufacturers to convey consumers' specific emotions to the new products, referred to as emotional product development or emotional design, because positive emotions lead to higher market sales (Hertenstein et al., 2005). Consumer online reviews often express direct, real-time, and honest emotional perceptions concerning consumers' experiences of products/services (Liu, 2015). Thus, considering online reviews that drive emotional design with the help of SA is natural; it provides manufacturers real-time, direct, and rapid data-driven decision support for emotional product development. Unfortunately, SA-based emotional design is still considerably less common.

Received December 26, 2021; accepted July 27, 2022

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This study was supported by the National Natural Science Foundation of China (NSFC) under Grant Nos. 71871093, 72271092, 72131007, and 72140006.

Thus, the main focus of this paper is to provide a comprehensive review of SA from the perspective of emotional design. On the one hand, this paper may promote the research of SA itself. On the other hand, it may open up new research directions of emotional product development with the help of SA.

Over the past decade, numerous SA survey and review studies have been presented. For example, Liu and Zhang (2012) presented a survey of opinion mining and SA, where opinion mining was suggested to be addressed in the future. Ravi and Ravi (2015) surveyed published articles from 2002 to 2015 on the tasks, approaches, and applications of SA. Piryani et al. (2017) conducted a scientometric analysis of SA research ranging from 2000 to 2015 by a manual-detailed analysis to summarize the most popular approaches, the levels of SA, and the major application areas of SA. Birjali et al. (2021) classified and compared different approaches to SA. Regarding specific approaches and techniques, Do et al. (2019) and Yadav and Vishwakarma (2020) reviewed, compared, and discussed different deep learning models used in SA. With special attention to fine-grained SA, Rana and Cheah (2016) and Tubishat et al. (2018) reviewed and analyzed different approaches to identifying the aspects of SA. Furthermore, Schouten and Frasincar (2016) provided an in-depth overview of approaches to aspect identification and polarity detection.

To the best of our knowledge, existing surveys/reviews are often focused on approaches, techniques, and applications of SA but not from the view of emotional product development. Thus, the link between SA and emotional product development is missing. Furthermore, central to emotional product development is how to link emotional attributes with design attributes because design attributes can trigger emotions and evoke various meanings extending the use of products (Verganti, 2006). Thus, the fine-grained aspect-level SA, widely used due to its ability to find the sentiments of specific product features, is more suitable for emotional design. However, existing surveys/reviews usually only involve aspect identification and/or polarity detection phases, failing to provide a clear and detailed process for aspect-level SA.

A comprehensive review of aspect-level SA is firstly provided in terms of approaches, datasets, and applications to give an overview of SA from the perspective of emotional design. The approaches to aspect-level SA are summarized with respect to aspect identification, opinion extraction, and polarity detection. After conceptualizing emotion as Kansei and briefly introducing emotional product development and Kansei Engineering, a detailed review of SA-based emotion design is conducted to build the link between SA and emotional design. Finally, some future research directions are provided to realize data-driven emotional product development with the help of SA. The organization of this review is shown in Fig. 1.

The outline of this paper is as follows. Section 2 discusses the approaches, applications, and datasets of aspect-level SA. Section 3 reviews SA-based emotional product development. Section 4 presents some research opportunities and challenges. Section 5 concludes the paper.

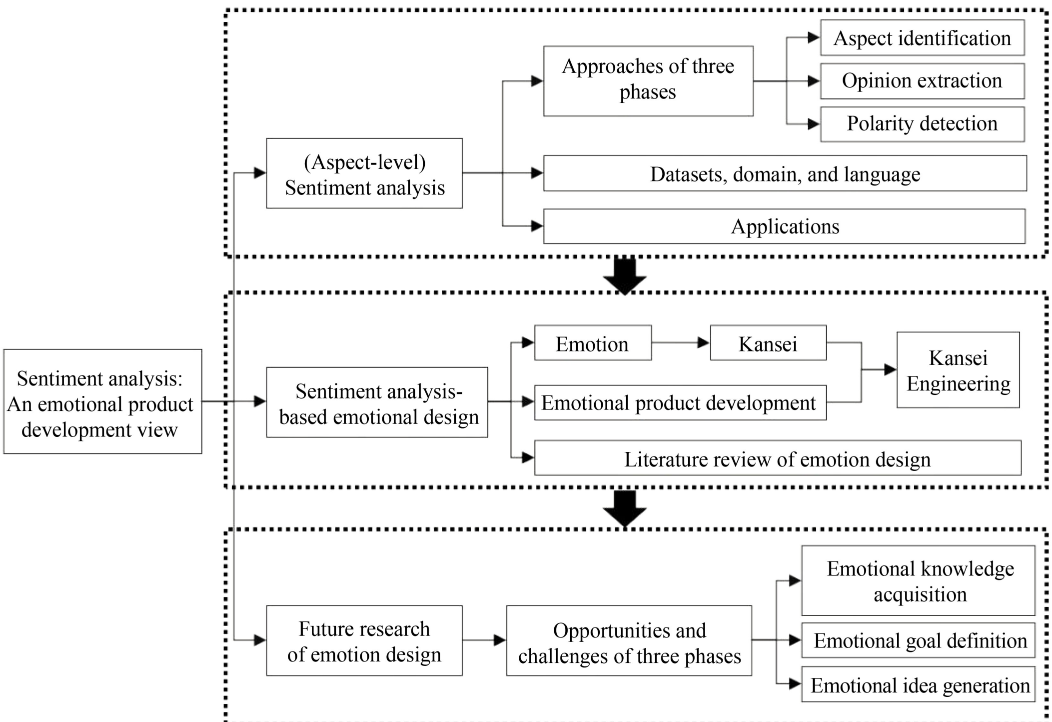


Fig. 1 Organization of the review.

2 Aspect-level sentiment analysis

2.1 Review methodology

The SA research can be divided into three granularity levels: Document-level, sentence-level, and aspect-level. The document-level SA is to classify a whole opinion document into a positive, negative, or neutral sentiment. The sentence-level SA aims to determine whether each opinion text expresses a positive, negative, or neutral opinion. The document-level and sentence-level SA can discover the sentiment polarity but not what people like and dislike exactly. Taking a different view, the aspect-level SA directly focuses on the opinion and its target (called opinion target), which can help manufacturers identify consumers' emotions about the specific aspects of products. In this article, aspect-level SA is considered because it can obtain more fine-grained results, which could be utilized in emotional product development.

The aspect-level SA can be mainly carried out in three phases: Aspect identification, opinion extraction, and polarity detection (Fig. 2). Given that aspect identification is fundamental to SA, introducing some basic concepts based on the pioneering work by Liu (2015) is necessary. An opinion can be expressed by a quadruple (g, s, h, t), where g is the target of the sentiment, s is the opinion sentiment with respect to the target g, h is the opinion holder, and t is the time when the opinion is expressed by the opinion holder. The sentiment target of an opinion can be the whole, a part, or attributes of an entity, upon which an opinion holder expresses his/her sentiment. The "entity" can be defined as a product, service, topic, person, organization, issue, or event. The "aspect" is viewed as a part of or an attribute of the entity.

We selected six major online databases to collect relevant studies for this review: Web of Science, ACM Digital Library, Springer Links, IEEE Xplore, Science Direct, and Scopus. To ensure the consistency of collection in the above databases, we constructed a generic string using the Boolean AND and OR as follows:
(("aspect" OR "opinion") AND ("identification" OR "extraction")) OR
("aspect level") AND ("sentiment analysis").

To ensure the relevance and accuracy of the collected articles, we read the articles carefully to check whether they could be considered based on the following criteria: The articles in English which involved one or more phases of aspect-level SA were included. An iterative procedure was adopted to obtain more relevant articles. Ultimately, 204 articles were selected for this review study. In the next subsection, approaches and techniques will be summarized and analyzed with respect to the three phases of aspect-level SA shown in Fig. 2.

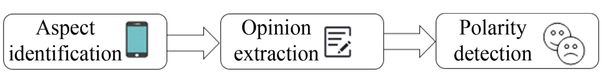


Fig. 2 Three phases of aspect-level sentiment analysis.

2.2 Three phases of aspect-level sentiment analysis

2.2.1 Aspect identification

Aspect expressions can be divided into explicit and implicit ones in terms of noun or verb phrases and adjectives. The aspect expression appearing in an opinion text in terms of nouns or noun phrases can be called an explicit one. On the other hand, the aspect expressions that are not expressed by nouns or noun phrases but indicate some aspects are referred to as implicit ones.

Furthermore, approaches to aspect identification can be classified into three types: Unsupervised, supervised, and semi-supervised. Unsupervised approaches utilize unannotated data to identify explicit or implicit aspects directly. Given that it does not require training, such a type costs less compared with other types of approaches (Maitama et al., 2020). The supervised type employs the concept of supervised learning to identify explicit and implicit aspects from online reviews, which leverage the annotated data to identify aspects of the target product. In other words, supervised approaches need to construct the aspects list manually and thus heavily depend on the trained datasets. Semi-supervised approaches use the concept of semi-supervised learning to identify aspects from online reviews, where limited annotated data are used to guide the feature learning process. Thus, such a type fits in between supervised and unsupervised types and will save much time and effort by utilizing the low-cost annotated data (Birjali et al., 2021). In the sequel, aspect identification will be summarized by the following six dimensions: (Explicit, Implicit) × (Supervised, Semi-supervised, Unsupervised); the summary of which is shown in Fig. 3.

(1) Aspect identification approaches: Explicit × Unsupervised

Regarding explicit aspect identification, all unsupervised approaches are discussed and divided into the following types: Frequency-based, relation-based, topic modeling, lexicon-based, and clustering.

① Frequency-based techniques

In online reviews, a limited set of words is much more often used than others. These frequently used words in terms of nouns and noun phrases are thus likely to be aspects. Therefore, frequency-based techniques are straightforward and quite powerful and have been widely utilized for explicit aspect identification in the literature (e.g., Schouten and Frasincar, 2016).

② Relation-based techniques

The relation-based techniques perform aspect identification using the associations between opinion words and aspects (Kang and Zhou, 2017; Luo et al., 2019; Rana

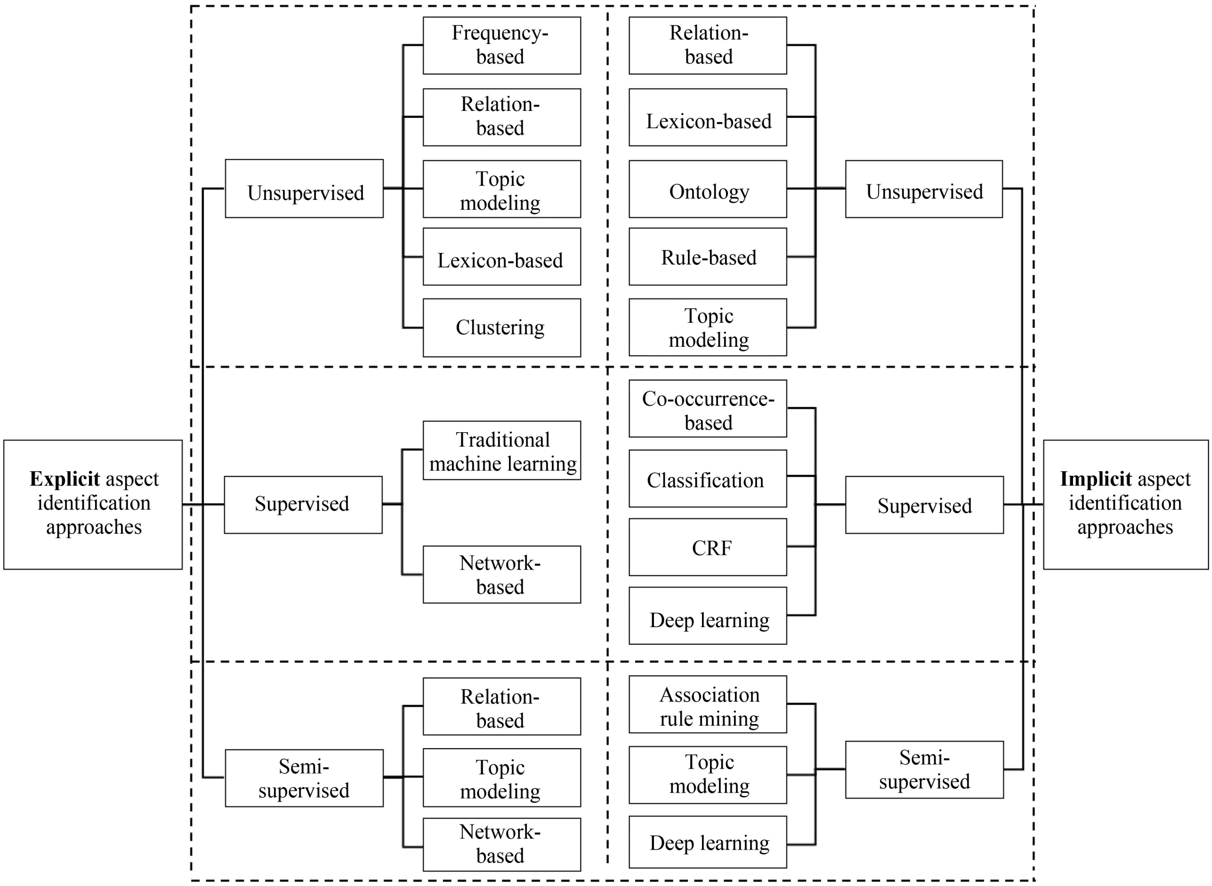


Fig. 3 Summary of approaches to aspect identification.

and Cheah, 2019). A simple and widely used relation between an opinion word and an aspect may be the adjectival modifier. Taking the text "amazing quality" as an example, the word "amazing" is an adjective describing the aspect "quality". One advantage of the relation-based techniques is that low-frequency aspects can be discovered. Given many associations between opinions, words, and aspects in online reviews, such as syntactical relations (Schouten and Frasincar, 2016), building a relational database for good coverage may be difficult.

③ Topic modeling techniques

Topic modeling techniques can identify topics and group similar aspect words under a single topic. In online reviews, the topics are aspects, and a set of similar words may refer to the same aspect (Rana et al., 2016). For instance, screen and LCD (liquid crystal display) are synonyms in the laptop domain and are grouped together in the same aspect. Summarized from the literature, two topic modeling techniques for aspect identification and categorization from online reviews are Probabilistic Latent Semantic Analysis (PLSA) (Basha and Rajput, 2019; Jeong et al., 2019) and Latent Dirichlet Allocation (LDA) (Moghaddam and Ester, 2011).

④ Lexicon-based and clustering techniques

The aspects could be identified by matching candidates with each aspect from the constructed lexicon or word lists, called lexicon-based techniques (Thet et al., 2010; Jiménez-Zafra et al., 2016). Clustering techniques are also used to identify aspects, which regard the clustering results of relevant term words as different aspects of evaluated entities (Fu et al., 2012).

(2) Aspect identification approaches: Explicit × Supervised

We now turn to identify explicit aspects by supervised approaches. Essentially, the task of aspect identification can be viewed as a sequence labeling problem. Consequently, many studies have utilized supervised algorithms and models to learn the process of aspect labeling, which can be generally classified into two main types: Traditional machine learning and network-based techniques. The type of traditional machine learning techniques consists of Random Forest (RF) (Venugopalan et al., 2021), Support Vector Machine (SVM) (Akhtar et al., 2017), Conditional Random Field (CRF) (Al-Smadi et al., 2019; Miao et al., 2021), and Hidden Markov Model (HMM) (Wang et al., 2017a).

As for the type of network-based techniques, Marcacini et al. (2018) proposed an aspect label propagation method by heterogeneous networks to extract aspects. Most other studies have exploited deep learning based on neural networks. As a sub-branch of machine learning, deep learning has been widely applied to SA in recent years because it can automatically learn complex features (Araque et al., 2017). Specifically, the neural network for aspect identification includes Convolutional Neural Network (CNN) (Poria et al., 2016), Recurrent Neural Network (RNN) (Wang et al., 2019a; 2019b; 2019c), Long Short-Term Memory (LSTM) (Chauhan et al., 2020), Gated Recurrent Units (GRU) (Wang et al., 2017b), Recursive Neural Network (RecNN) (Nguyen and Shirai, 2015), and Memory Network (MN) (Ma et al., 2019).

(3) Aspect identification approaches: Explicit × Semi-supervised

Some semi-supervised techniques are also proposed to identify the explicit aspects. For example, Liao et al. (2017) proposed a representation learning framework embedding the fusion relation by utilizing semantic structure-based relations and language expression feature-based relations to identify explicit aspects. Lin et al. (2012) and Wang et al. (2014) used topic modeling techniques to improve the performance by incorporating prior knowledge. Regarding network-based techniques, Matsuno et al. (2016) and Ding et al. (2017) applied a heterogeneous network and RNN to semi-supervised learning for aspect identification.

(4) Aspect identification approaches: Implicit × Unsupervised

We now turn to implicit aspect identification. The unsupervised approaches for identifying implicit aspects can be divided into five classes. The first class is called the (aspect-opinion) relation-based technique, which identifies implicit aspects by the association between the explicit aspect and opinion word, such as the co-occurrence relationship (Zhang et al., 2012; Bagheri et al., 2013; Hai et al., 2015; Afzaal et al., 2019a). The second and third classes are called lexicon-based (Alqaryouti et al., 2020) and ontology (Marstawi et al., 2017) techniques, respectively, which identify implicit aspects through semantic relations. Techniques that utilize specific rules and topic models are called rule-based (Wan et al., 2015) and topic modeling (Amplayo et al., 2018), respectively.

(5) Aspect identification approaches: Implicit × Supervised

The supervised approaches to implicit aspect identification can be divided into four classes. The first class, referred to as co-occurrence, identifies the implicit aspects through the co-occurrence relationship between annotated implicit aspects and other words in the reviews (Schouten and Frasincar, 2014). Classification is the second technique that uses a classifier to identify implicit aspects, for example, the Naïve Bayes (NB) classifier (Xu et al., 2020). The third one is CRF based on a sequential labeling technique (Chatterji et al., 2017). The last is deep learning techniques containing CNN (Feng et al., 2019) and LTSM (Ahmed et al., 2019).

(6) Aspect identification approaches: Implicit × Semi-supervised

The most common semi-supervised techniques for implicit aspect identification can be association rule mining, topic modeling, and deep learning. For example, Wang et al. (2013) used the association rules to identify implicit aspects. Xu et al. (2015) identified implicit aspects by constructing an explicit topic model incorporating prior knowledge. Ray and Chakrabarti (2022) proposed using a mixed approach of CNN and a rule-based technique to improve the performance of aspect identification.

(7) Statistical summary of recent research on aspect identification

A statistical summary of different techniques for identifying aspects is shown in Fig. 4. Compared with implicit aspects, more articles are focused on explicit aspect identification. Most researchers have regarded implicit aspect identification as the latest direction on aspect identification because of its inherent ambiguity. In terms of explicit and implicit aspects, unsupervised, supervised, and semi-supervised approaches accounted for 47%, 46%, and 7%, and 62%, 25%, and 13%, respectively. Therefore, unsupervised approaches are most commonly used to identify explicit and implicit aspects. The reason may be that the unsupervised approaches do not require annotation and training of data, which can save a lot of time. Compared with the other two types of approaches, semi-supervised approaches have not been explored sufficiently to identify explicit and implicit aspects, providing a future research direction.

2.2.2 Opinion extraction

After identifying aspects, the next phase is to extract opinions concerning the identified aspects. The term

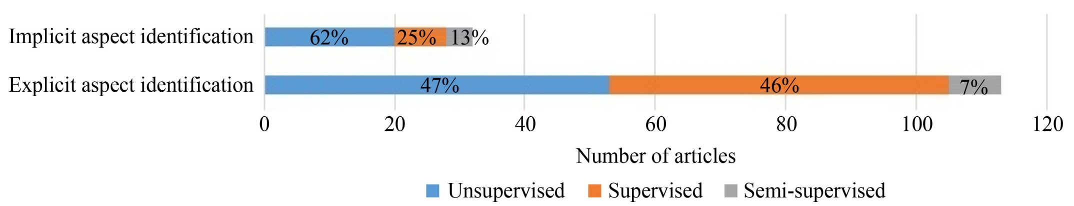


Fig. 4 Distribution of approaches to explicit and implicit aspect identification.

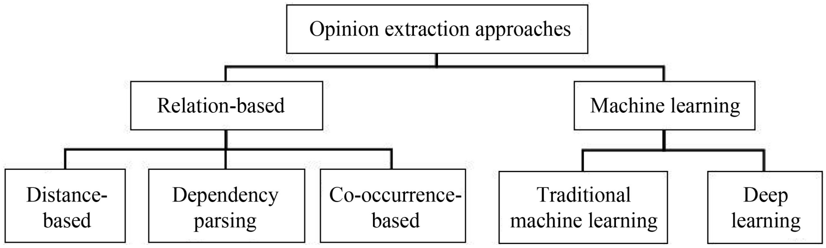


Fig. 5 Approaches to opinion extraction.

"opinion" refers to the words such as "good" and "bad" or "high" and "low", modifying the aspects, and can express a certain sentiment. We attempt to classify opinion extraction approaches into two main types: Relation-based and machine learning. The outline is shown in Fig. 5.

(1) Relation-based approaches

With the associations between aspects and opinions, the opinion words of the identified aspects can be extracted. In general, distance, syntactic dependency, and co-occurrence among them are always used to extract the opinion words of an aspect. When opinion words are extracted from the context at a certain distance from a specific aspect, we call it a distance-based technique (Nasim and Haider, 2017; Yadav and Roychoudhury, 2019). If opinion words modifying a specific aspect are extracted using the dependency parsing algorithm, we call it a dependency parsing technique (Quan and Ren, 2014; Afzaal et al., 2019b; Jiao and Qu, 2019; Wang et al., 2019a; 2019b; 2019c). Furthermore, the co-occurrence-based technique is also applied to extract opinions. For example, Fu et al. (2012) extracted opinion words of a specific aspect with the co-occurrence relationship between aspects and opinions.

(2) Machine learning approaches

Machine learning models consist of traditional models and deep learning models. According to the collected articles that extract opinions for aspect-level SA, the most commonly used traditional machine learning models are PLSA (Ali et al., 2020), LDA (Zheng et al., 2014), HMM (Wang et al., 2017a), and CRF (Miao et al., 2021). LSTM (Yu et al., 2019), GRU (Wang et al., 2017b), and RecNN (Aydin and Gungor, 2020) are commonly used deep learning models for opinion extraction in aspect-level SA. In summary, most of these models treat opinion expression extraction as a sequential labeling problem, which uses the conventional B-I-O tagging scheme to convert the original opinion expressions to sequences of tagging tokens.

(3) Statistical summary of opinion extraction research

In summary, 21 articles focus on the relation-based approaches to opinion extraction. These studies separate aspect identification and opinion extraction because opinion extraction depends on aspects. A total of 19 articles use machine learning approaches to opinion extraction, which primarily identify aspects and extract

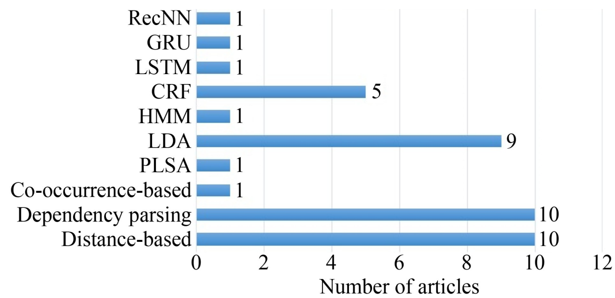


Fig. 6 Distribution of approaches to opinion extraction.

opinions simultaneously. Regarding specific techniques for opinion extraction, dependency parsing and distance-based techniques are the most frequently used ones by researchers, accounting for 50%, as shown in Fig. 6, perhaps because of their simplicity and convenience.

2.2.3 Polarity detection

The sentiments expressed by opinion words can be classified into positive, neutral, and negative. We attempt to classify polarity detection approaches into two main types: Lexicon-based and machine learning. The outline is shown in Fig. 7.

(1) Lexicon-based approaches

Lexicon-based approaches, also known as knowledge-based ones, require an opinion lexicon in terms of a predefined list of words, which associates the opinion words to their corresponding semantic orientations as positive, neutral, or negative words (Jurek et al., 2015). The orientation of each aspect is usually derived by summarizing the semantic orientations of all opinion words (Jiménez-Zafra et al., 2016).

(2) Machine learning approaches

Another type is using machine learning approaches to determine the sentiment polarity of the specific aspect by analyzing the opinion words or contextual contents. There are several traditional machine learning approaches to detect sentiment polarities: Decision Tree (DT) (Suciati and Budi, 2019), Logistic Regression (LR) (Nguyen and Shirai, 2015), Maximum Entropy (ME) (Hercig et al., 2016), SVM (Al-Smadi et al., 2018), Naïve Bayesian Model (NBM) (Afzaal et al., 2019b), LDA (Xu et al., 2013), and CRF (Miao et al., 2021). Deep learning

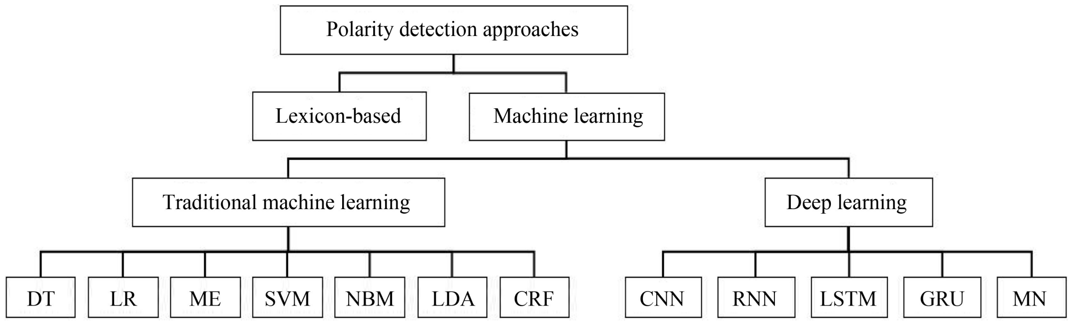


Fig. 7 Approaches to polarity detection.

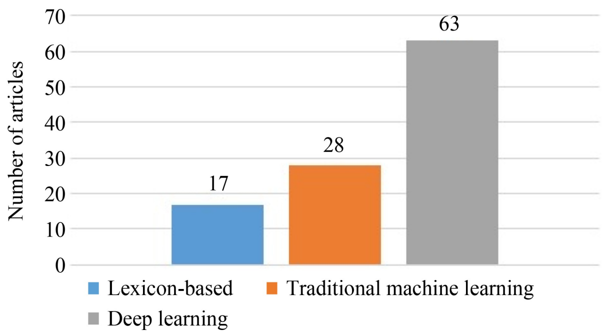


Fig. 8 Distribution of polarity detection approaches.

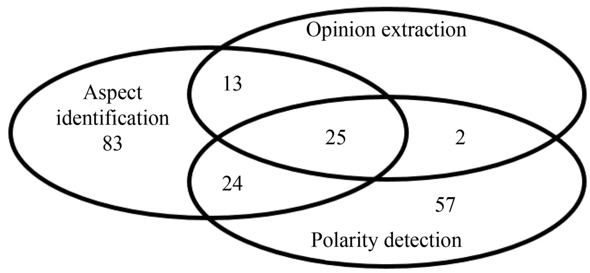


Fig. 9 Distribution of articles in three phases of aspect-level sentiment analysis.

approaches have also been used to determine the sentiment polarity of the specific aspect, including the ones based on Multiple Attention Mechanism Network (MAMN) (Wang et al., 2021), CNN (Wu et al., 2021; Ye et al., 2021), RNN (Chen et al., 2017), LSTM (Song et al., 2019; Liu et al., 2021; Lv et al., 2021), GRU (Ali et al., 2021), and MN (Zhang et al., 2020; Chen et al., 2021).

(3) Statistical summary of polarity detection research

As shown in Fig. 8, 63 papers used deep learning techniques, followed by traditional machine learning (28) and lexicon-based techniques (17), revealing that researchers favor machine learning techniques to detect polarity for aspect-level SA. Deep learning is more commonly used than traditional machine learning for three reasons. First, deep learning can reduce the time of feature design by automatically extracting the required features. Second, it has a better performance with a large amount of data. Third, it can also obtain data's nonlinear and complex relationships through a multi-layer structure (Yadav and Vishwakarma, 2020).

2.2.4 Statistical summary of the three phases of sentiment analysis

As a conclusion of comprehensively reviewing the three phases of SA, 204 articles are statistically summarized from the perspective of the three phases of aspect-level SA, as graphically shown in Fig. 9.

The numbers of articles on aspect identification, opinion extraction, and polarity detection are 145, 40, and 108, respectively. Through further analysis, the number of articles that have simultaneously studied all three phases is 25. For example, Miao et al. (2021) regarded aspect-level SA as a sequential labeling problem by combing the bidirectional long-short-term memory network and the CRF model, which can simultaneously identify aspects, extract opinions, and detect polarities. However, fewer articles focused on opinion extraction than on aspect identification and polarity detection. The main reason for such a phenomenon is that many articles regarded the context of the aspects as a whole to conduct aspect-level SA, but they did not point out the opinion words expressing the given aspect.

2.3 Datasets, domains, and languages

(1) Datasets

The datasets used in SA are often collected from websites and e-commerce platforms such as Amazon, Taobao, and JD.COM. Some benchmark datasets appeared several times in the literature, including the customer reviews dataset collected by Hu and Liu (2004) and three review datasets released by International Workshop on Semantic Evaluation (SemEval 2014, SemEval 2015, and SemEval 2016), the frequency distribution of which is shown in Fig. 10.

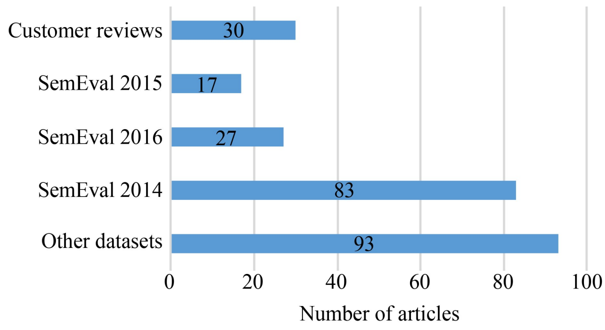


Fig. 10 Distribution of benchmark datasets.

(2) Domains and languages

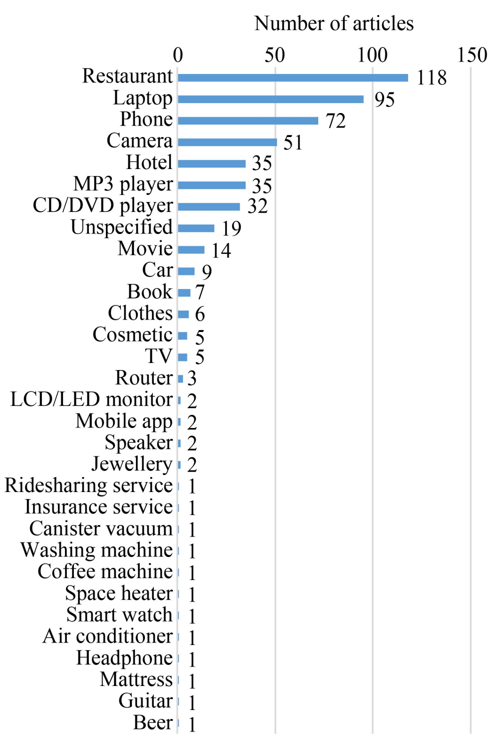
The data utilized in the collected articles cover both product and service domains. Our analysis shows that 31 specific product/service domains are in aspect-level SA, as shown on the left side of Fig. 11. Restaurant, laptop/computer, cell/mobile/smartphone, and camera reviews are the most frequently used data domains because of the open accessibility of the benchmark datasets, such as the SemEval 2014 dataset and customer reviews dataset.

Regarding data language, 17 languages are applied in the collected articles, as shown on the right side of Fig. 11. The most frequently used language is English (72%), followed by Chinese (14%). However, German, Russian, Korean, and Italian languages have a low frequency. Further analysis shows that the performance of approaches to aspect-level SA depends heavily on the language type of the datasets.

2.4 Applications

With its considerable advancements in approaches and techniques, (aspect-level) SA has been applied to various fields, such as business intelligence, government intelligence, and healthcare and medical domain, to achieve real-time monitoring, accurate predictions, and recommendations, as summarized in Table 1.

In the business intelligence domain, SA can help companies optimize product design, marketing decisions, and market predictions by exploiting user feedback. For example, Li and Li (2013) constructed a framework for analyzing microblog posts, which can support managers in understanding market trends and making marketing strategies more accurately by tracking sentiment changes. Kang and Park (2014) presented a framework for measuring customer satisfaction by combing SA and VIKOR. As for a business prediction, Kraaijeveld and de Smedt (2020) noted that the price returns of some digital currencies could be predicted by a cryptocurrency-specific lexicon-based SA approach. Ho et al. (2017) confirmed the time-varying relationship between social media sentiments and future stock returns. Similarly, Yu et al. (2012) and Pai and Liu (2018) showed that SA has strong predictive power in box office revenues and monthly total vehicle sales, respectively. Users' preferences could be predicted through SA, and an intelligent recommendation system that aims to suggest relevant products or services to users also could be generated. For example, Shen et al. (2019)



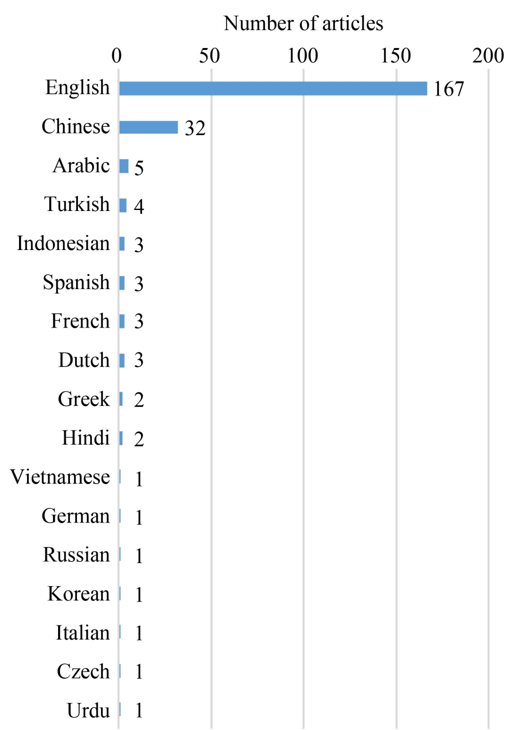


Fig. 11 Distribution of data domains (left) and languages (right).

Table 1 Applications of sentiment analysis

	Business intelligence	Government intelligence	Healthcare and medical domain
Monitoring	Products and services optimization Marketing strategy formulation	Public opinion monitoring	Healthcare surveillance
Prediction	Market and forex prediction	Politics prediction	Disease detection
Recommendation	Intelligent recommendation system		

introduced the sentiment-based matric factorization with a reliability algorithm for accurate recommendations, which can recommend products to users by mining sentiment information contained in online reviews.

SA could be used in government intelligence to monitor public opinions on government policies and predict the results of specific political activities. For example, Georgiadou et al. (2020) introduced the SA of the Twitter dataset to the case of the Brexit negotiations, which can provide the government with a real-time barometer of public sentiment and a basis for making decisions. Ceron et al. (2015) applied SA of tweets from voters to electoral campaigns and accurately predicted the results of the US 2012 Presidential Election and the Italian Centre-left 2012 Primaries by mining political preferences and voting intention of voters.

Finally, SA has been used in the healthcare and medical domain. It could allow healthcare professionals to find information about adverse drug reactions; identify patients' emotions about diseases, medications, doctors, and treatments; and surveil public health. For example, Akay et al. (2015) analyzed 920 posts on lung cancer forums using positive, negative, and side effects word lists. They found that consumer opinion on Erlotinib, a lung cancer drug, can provide the pharmaceutical industry with the direction of drug improvement. UI Hassan et al. (2017) proposed a framework for detecting depression level from posts. Each post can be classified as positive, neutral, or negative by the SVM, NB, and ME classifiers.

2.5 Summary

With the above comprehensive review analysis, we can conclude that prior research has dramatically advanced aspect-level SA. Nevertheless, all studies are focused on extracting product features by mixing technical product features and consumers' emotional perceptions of either the approaches or the applications of SA. For example, "convenience" and "system" features regarding a mobile phone are treated as product features. "Convenience" reflects consumers' emotional needs, which are triggered by technical product features, whereas "system" expresses the technical feature of the mobile phone.

Design often uses technology and materials efficiently and effectively to create a reliable product, and it can be viewed as a tool to trigger various cognitive and emotional responses, consequently affecting the processes of product selection and retention (Eisenman, 2013). The design attributes layering the symbolic facets of products can trigger emotions (e.g., joy) and elicit various meanings extending the use of products (Verganti, 2006). Online reviews often capture direct and real-time emotional expressions concerning product usage experiences (Liu, 2015). Thus, online reviews driven by emotional product development can be realized with the help of (aspect-level) SA. Unfortunately, existing SA studies cannot capture the relationships between technical attributes and emotional attributes and thus cannot convey specific emotions to the new products. Thus, we turn to the discussion of emotional product development in the next section.

3 Sentiment analysis-based emotional product development

3.1 Concept of emotion

3.1.1 Conceptualization of emotion as Kansei

A prerequisite step to linking SA with emotional product development is understanding how to conceptualize emotion. We must differentiate several similar terms to answer this question. In the literature, many terms are used inconsistently, such as "emotion", "affect", "attitude", and "sentiment". Emotion is a very complicated, multi-dimensional characteristic reflecting the personality and behavioral traits of humans. By definition, emotion can be viewed as "a mental state of readiness arising from the cognitive appraisals or events or thoughts" (Bagozzi et al., 1999) and "typically elicited by events, objects or persons" (Ladhari et al., 2017; Shigemoto, 2019). Bagozzi et al. (1999) stated, "Emotions are a type of state created by the preexisting mood of an individual, tempered by responses to his environmental surroundings."

In line with Bagozzi et al. (1999), the term "affect" is regarded as a set of more specific mental processes, which includes emotions, moods, and attitudes. Thus, "affect" could be viewed as a general category for mental feeling processes but not a particular psychological process. The term "attitude" is often viewed as an instance of affect used occasionally to express emotions and attitudes (e.g., unpleasant–pleasant and sad–happy). The term "sentiment" is defined as a mental attitude created by the existence of the emotion (i.e., the expression of emotions). In summary, as stated by Munezero et al. (2014), "emotions and sentiments are often viewed as replaceable terms, but sentiments represent a more general idea — the polarity of emotion (i.e., positive, neutral, or negative)".

Another way to conceptualize "emotion" may be using the Japanese word "Kansei" (Yan and Li, 2021). Dahlgaard et al. (2008) indicated that the methodology of Kansei Engineering could help design and develop products/services, which satisfies customers' emotional, psychological feelings, and needs. The term "Kansei" means the feeling or impression sensitivity and some kinds of emotion (Ishihara et al., 1997), which is "an individual subjective impression from a certain artifact, environment, or situation using all senses of sight, hearing, feeling, smell, taste, and balance, as well as their recognition" (Schütte et al., 2004; Grimsæth, 2005). "Kansei" can incorporate all the meanings of the following words: Sensitivity, sense, aesthetics, feelings, emotions, affection, and intuition (Lee et al., 2002). Consequently, the term "emotion" can be conceptualized in terms of Kansei in behavioral service design (Yan and Li, 2021), which will also be used in this paper.

3.1.2 Measuring emotions in terms of bipolar Kansei words

We now discuss how to measure emotions, which are often caused by a stimulus with subsequent cognitive attention (Bagozzi et al., 1999). In their pioneering work, Bagozzi et al. (1999) stated that "emotions are often accompanied by physiological processes and can be expressed physically in gestures, posture, and facial features". Such physical expressions may result in specific actions to affirm or cope with the emotions, according to their nature and meaning for the person having them. Emotions are measured using two methods. Dasu and Chase (2013) defined emotions simply as discrete primary emotions, such as "anger" or "happiness". Elfenbein (2007) suggested that cognition (appraisal) and emotion occur together in response to a stimulus. Barrett et al. (2007) suggested one should ask people to relate their experiences in their own words to capture people's emotions. Rychalski and Hudson (2017) defined emotions by mixing cognitive appraisals and emotions, which are felt by individuals subjectively.

In the community of Kansei Engineering, different methods could measure Kansei: Words (Yan et al., 2017; Yan and Li, 2021), physiological responses (Balters and Steinert, 2017), people's behaviors and actions (Satterfield et al., 2008), and facial and body expressions (Elokla et al., 2010). Despite the different methods, the most commonly used to measure Kansei is human words, that is, the external descriptions of the internal Kansei within a human mind (Grimsæth, 2005). In this paper, user emotions will be extracted from online reviews and expressed in terms of bipolar pairs of words, called Kansei attributes. Given that Kansei Engineering can capture the relationships between design attributes and users' emotional needs (Nagamachi, 2002; Schütte et al., 2004; Grimsæth, 2005), creating a systematic procedure for emotional product development is possible.

3.2 Emotional product development

New product development (NPD) transforms a market opportunity and a set of assumptions about product technology into a product available for sale (Krishnan and Ulrich, 2001). The NPD process is generally classified into two constructs: Fuzzy front end (FFE, from knowledge acquisition to idea generation) and back end (from concept definition to product-process engineering) (Yan and Ma, 2015; Tsang et al., 2022). As stated by Schneider and Hall (2011), the most critical problem in NPD may be that companies focus too much on product design and manufacturing but lack consideration and preparation in the market phase. Thus, business organizations should design products that best satisfy customer needs at the stage of FFE, which is perhaps the most challenging and uncertain part of the NPD process (Tsang et al., 2022) and is also the main focus of this part.

The emotional dimension of products and services has become a critical success factor in many sectors (Norman, 2004). An example is that emotional attachment to products plays an important role in consumer purchase decisions (Krishna, 2012). Nevertheless, most existing tools focus too much on the back end to measure the "emotional content" of a concept already formed. Only a few tools can support the idea generation of the innovation process (Alaniz and Biazzo, 2019). Emotional product development can be classified into three phases: Emotional knowledge acquisition, emotional goal definition, and emotional idea generation (Alaniz and Biazzo, 2019). In emotional NPD, the professionals responsible for designing and developing new products must be very familiar with the techniques and tools to understand the emotions and then convey the specific emotions into the new products. Thus, a very complex challenge is to generate products with significant emotional features by professionals.

3.3 Kansei Engineering as a powerful methodology

As a methodology of consumer-oriented product development, Kansei Engineering aims to transform a customer's ambiguous image of a product into a detailed design (Nagamachi, 1995; 2002), which focuses on customers' psychological feelings, rather than the manufacturer's intention of the product. Kansei Engineering is also known as "sensory engineering" or "emotional usability" (Grimsæth, 2005). With its inception in the 1970s, Kansei Engineering has been successfully used in a wide range of physical products (artefacts). Recent studies prove that Kansei Engineering can also be successfully used in service design (Schütte et al., 2004; Yan and Li, 2021). As a systematic design support tool for developing a new product or improving an existing product, once choosing a domain, the Kansei Engineering methodology can be mainly conducted by spanning attributes, Kansei experiment, and model building, as shown in Fig. 12.

We summarize the three main stages of Kansei Engineering based on our previous work (Yan and Li, 2021). In the first stage, we should span a set of Kansei attributes, each of which corresponds to a bipolar pair of Kansei words. The Kansei words can be collected from all available sources: Magazines, literature, manuals, experts, and user experiences (Grimsæth, 2005). Similarly, the process of spanning design attributes can be conducted by the following two steps (Schütte et al., 2004; Yan and Li, 2021): 1) to collect all possible design attributes from all available sources (e.g., technical manuals, experts, and related Kansei studies) and 2) to choose the desired design attributes by a focus group. In the second stage, human Kansei is obtained by a Kansei experiment with a set of experimental stimuli. The final stage aims to model the relationships between design attributes and Kansei attributes to convey specific emotions to the new products.

3.4 Data-driven emotional product development based on sentiment analysis

To assist product development, some researchers recently started to analyze consumers' preferences on product features from online reviews with the help of SA. For example, Jin et al. (2015) presented a data-driven framework of quality function deployment by a probabilistic approach to link online reviews with product design attributes, the implementation of which invokes a better understanding of consumer preferences on product technical features. Jin et al. (2016) identified product features and sentiment polarities from online reviews to understand the changes in consumer preferences on product features and their competitive advantages. Xiao et al. (2016) analyzed online product reviews for preference measurement based on a modified, ordered choice model and a marginal effect-based Kano model, where product features and the reviewers' sentiment polarities were extracted from online product reviews. Qi et al. (2016) developed a product improvement strategy from online reviews to classify product features using conjoint analysis and Kano model, where sentiment polarities represented consumer utilities toward products. Nevertheless, such studies do not extract technical product features and consumers' emotional perceptions and do not focus on the relationship between technical attributes and emotional attributes. Thus, they cannot convey specific emotions to the new products.

Another line of research has used SA to extract consumers' emotions from online reviews (Liu, 2015). For example, Atzeni et al. (2018) extracted consumers' emotions from online reviews by frame-based resources. Wang et al. (2018) proposed a Kansei text mining approach, where product features and their corresponding affective responses are automatically extracted and summarized from product descriptions and online reviews. Jiao and Qu (2019) proposed a computerized method to extract emotional knowledge from online reviews. Some studies also focused on ranking products by online reviews (e.g., Turney and Littman, 2003). However, most of them focused mainly on polarity classification, which lacks the specifics of emotions and may thus be insufficient for emotional product development. Recently, Wang et al. (2019a) extracted emotional opinions from online reviews and classified them into pairs of emotional words by a heuristic deep learning method. Kim et al. (2019) applied a self-organizing map to cluster the collected opinion words. They detected 15 categories of affective variables, among which "comfort" was the most commonly used to express affective experiences about reclining chairs. Li et al. (2020) clustered adjectives and adverbs into four pairs of affective attributes and five categories of affective degree, respectively. However, these studies only extracted consumers' emotional perceptions from online reviews. They did not include technical product features that trigger corresponding emotions. Thus, they cannot transfer specific emotions into a new product design.

Given that Kansei Engineering is a powerful tool in

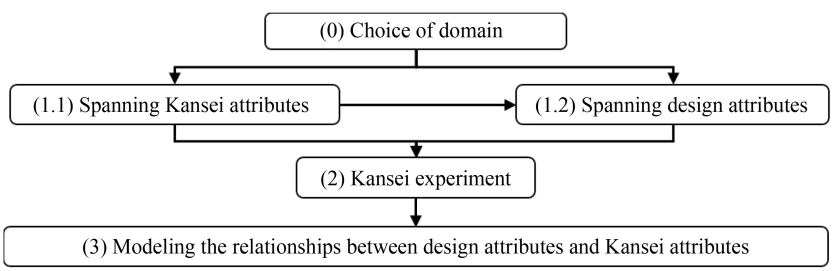


Fig. 12 Procedure of Kansei Engineering methodology.

emotional product development, some researchers have attempted incorporating SA into Kansei Engineering for emotional product development. For instance, Hsiao et al. (2017) integrated Kansei Engineering and text-mining-based online content analysis for logistics service design. Chiu and Lin (2018) utilized text-mining techniques and Kansei Engineering to support data-driven conceptual design. Nevertheless, these studies have been focused on extracting Kansei attributes from online reviews, then conducting an off-line Kansei experiment to collect Kansei evaluation data, and finally using the traditional modeling approaches to model the relationships between design attributes and emotional attributes.

3.5 Summary

As a strong support tool in emotional product development, Kansei Engineering is still critically challenged by the use of surveys or interviews to gather and identify Kansei attributes and Kansei evaluation data during the initial procedure of emotional product development. Such a procedure is costly, time-consuming, and labor-intensive. However, the size of the available data set is usually on a small scale (Hsiao et al., 2017). Given the high market competition, rapid increase in the number of new products, and rapid change in customer preferences, more and more new products are launched to the market within a very short period (Wang et al., 2018). Thus, developing a real-time Kansei Engineering methodology is crucial to improve the emotional development results continuously. Finally, the respondents in Kansei experiments may not be the real consumers of the target products.

Few efforts have studied emotional design with the help of SA. Essentially, data-driven product development may achieve greater flexibility and self-improvement in the evolution of product development. Prior research has tried to conduct online reviews driven by emotional product development. However, these studies only focus on either analyzing consumers' preferences on product features or extracting emotional opinions from online reviews, thus cannot convey specific emotions to the new products. To the best of our knowledge, only two articles tried to incorporate SA into Kansei Engineering for emotional product development, where consumer emotions were extracted from online reviews as an alternative for the attributes spanning of Kansei Engineering (Stage 1 in Fig. 12), and the rest two stages were the same as traditional ones shown in Fig. 12.

4 Research opportunities and challenges

With the comprehensive reviews of aspect-level SA and its integration with emotional product development, this article opens a broad door to data-driven emotional product development with the help of aspect-level SA. Given that emotional product development may be divided into three phases, namely, emotional knowledge acquisition, emotional goal definition, and emotional idea generation (Alaniz and Biazzo, 2019), future research will discuss the possible research opportunities and challenges from these three phases.

4.1 Emotional knowledge acquisition

The phase of "emotional knowledge acquisition" is particularly critical because professionals have to develop the emotional competence of the new products to generate emotion-focused ideas. Essentially, such a phase focuses on supporting the design team in creating a profile of emotions for the new product. In practice, generating new products with significant emotional features is a very complex challenge.

Although recently, some researchers have begun extracting emotional knowledge based on SA, more research problems need to be addressed. Existing approaches of aspect-level SA only mix technical product features and consumers' emotional perceptions. The first research question may be how to extract technical product features and consumers' emotional perceptions by proposing or revising the existing approaches to aspect-level SA in Section 2.2.

The performance of approaches to aspect-level SA depends heavily on the language type of the datasets. Given a product/service type, emotion knowledge may be different with different language types. Thus, the second research question may be to propose new (suitable) approaches to extracting product/service technical attributes and consumers' emotional needs to investigate the main differences in emotional needs concerning different languages.

Consumers may have different emotional needs with respect to different product/service domains (i.e., consumers' emotional needs are domain-dependent). Thus, the final research question may propose new (suitable) approaches to extracting product/service technical attributes and consumers' emotional needs and investigate the main differences in emotional needs concerning different product/service domains.

4.2 Emotional goal definition

In the process of emotional product development, the phase of "emotional goal definition" aims at defining the emotional goals of the new products with the following two challenges: 1) to strategically choose specific emotions that the new products have to evoke and 2) to transform the chosen emotions into the new products.

Traditionally, human Kansei is obtained by a Kansei experiment with a set of experimental stimuli. In the Kansei experiment, a survey is usually designed by the semantic differential method. However, many SA studies mainly focus on polarity classification, which lacks emotion specifics and may thus be insufficient for emotional product development.

Consequently, in this phase, the first research question may be to extract consumers' emotional evaluations concerning different emotional needs by a scale similar to the semantic differential method in the Kansei experiment. With consumers' emotional evaluations extracted, another research question may be to conduct marketing strategic analysis of consumers' emotional evaluations to determine emotional goals in product development.

4.3 Emotional idea generation

The final phase aims at translating the emotional goals into the new products. This phase is focused not on generating many emotional ideas but rather on delivering a few strong and meaningful ideas (called "thick ideas"). The term "thick idea" represents the emotional ideas of the new products that contain rich details about how the chosen emotions will be evoked in the new products.

In Kansei Engineering, linear regression models are often used to model the relationships between design attributes and Kansei attributes. Among them, the (partial) least square method is usually used. However, a recent study showed that nonlinear relationships exist between design attributes and Kansei attributes (Yan and Li, 2021). Furthermore, Kansei Engineering is an uncertain process. In most cases, the accurate relationships derived by linear regression models may thus lack flexibility and efficiency. Recently, Yan and Li (2021) proposed an uncertain Kansei Engineering methodology for a behavioral service design based on a probabilistic interpretation of Kansei data.

In online reviews, although many consumers can provide their emotional expressions towards targeted products, the products consumers evaluated may be on a very small scale. Moreover, each consumer may present an opinion regarding different products on different emotional attributes, which is a sparse evaluation matrix; the illustration of which is shown in Fig. 13. Thus, a critical research question is how to model the nonlinear and uncertain relationships between design attributes and Kansei attributes with the sparse matrix to generate ideas for emotional product development.

Reviews	Design attributes				Emotional needs			
	X_1	X_2	X_3	X_4	Y_1	Y_2	Y_3	Y_4
Review #1	✓	✓	✓		✓	✓		
Review #2			✓	✓		✓	✓	

Fig. 13 Illustration of sparse evaluation matrix.

5 Conclusions

This study presented a comprehensive overview of aspect-level SA from the perspective of emotional product development. First, aspect-level SA was reviewed with the following phases: 1) Aspect identification was summarized by the dimensions of (Explicit, Implicit) × (Supervised, Semi-supervised, Unsupervised). 2) Opinion extraction was reviewed according to two main types: Relation-based and machine learning techniques. 3) Polarity classification was reviewed according to two main types: Lexicon-based and machine learning techniques. Second, the datasets of aspect-level SA were reviewed. Third, the applications of SA were reviewed, revealing the following: 1) All studies are focused on extracting product features by mixing technical product features and consumers' emotional perceptions. Consequently, such studies cannot model the relationships between technical attributes and emotional attributes and thus cannot convey specific emotions in the new products. 2) Most studies use English in SA, but other languages have received more interest in SA recently.

Regarding SA-based emotional product development, after conceptualizing emotion as Kansei and briefly introducing emotional product development and Kansei Engineering, a detailed review of data-driven emotional product development was then conducted. Results revealed that a few efforts have studied emotional development with the help of SA. However, these studies were focused on either analyzing consumers' preferences on product features or extracting emotional opinions from online reviews and thus cannot convey specific emotions to the new products. Only two articles tried to incorporate SA into Kansei Engineering for emotional product development, where consumer emotions are extracted from online reviews as an alternative for the attributes spanning of Kansei Engineering. The other two stages are the same as the traditional ones.

Finally, some research opportunities were presented according to the three phases of emotional product development: Emotional knowledge acquisition, emotional goal definition, and emotional idea generation. In this way, we believe this review will open a broad door to data-driven emotional product development with the help of aspect-level SA. This review will promote the research of SA and open up new research directions for data-driven emotional product development.

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