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An Automated Data-Driven Approach for Product Design Strategies to Respond to Market Disruption Following COVID-19

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Online reviews provide a source to identify customer needs. While many studies have analyzed online reviews during the pandemic, it is worth noting that many customer preference studies in this period were not conducted within a product design context. The societal challenges presented by the prolonged COVID-19 pandemic, spanning nearly three years, have significantly impacted all facets of the population in a manner unparalleled in recent decades. Therefore, this research delves into the post-COVID-19 landscape, examining shifts in consumer preferences for diverse product features through an analysis of online reviews. Our framework unfolds in five stages: First, it collects online reviews and second, delves into customer interest in product features. Third, it analyzes customer sentiments toward these features. Fourth, employing interpretable machine learning techniques, it determines the significance of each feature. Fifth, an importance-performance analysis (IPA) and Kano models are utilized to formulate and analyze product strategies. The developed method is assessed on two real-world datasets—smartphone and laptop reviews. The results reveal that after the pandemic, customer satisfaction for the screen and camera in smartphones decreased, whereas it increased for those in laptops. In addition, the importance of battery features in smartphones and laptops has increased. These insights will aid companies in promptly formulating strategies to navigate dynamic market environments. [DOI: 10.1115/1.4066684]

Keywords: COVID-19, online reviews, customer preference elicitation, sentiment analysis, interpretable machine learning

1 Introduction

While online review analysis has thrived during the pandemic, it is worth noting that many customer preference studies in this period were not conducted within a product design context. A substantial gap exists between the insights garnered from consumer reviews and their direct translation into practical guidance for product designers. This disconnection between customer sentiment and product design strategy is a missed opportunity for businesses looking to respond effectively to the evolving needs and expectations of their customers. Bridging this gap is essential for maximizing the utility of online review analysis [1,2], ensuring that it contributes directly to product design improvements that align with the shifting demands between pre-COVID and post-COVID periods. Analyzing changes in customer preferences across these distinct periods is crucial for product designers to develop innovations that meet new market expectations and comprehensively address evolving customer needs. Specifically, analysis of the pre-COVID period serves as an important benchmark to gauge the true extent of changes, while analysis of the post-COVID period is fundamentally essential for decision-making in response to both short-term and long-term customer needs. Pandemics such as SARS and COVID-19 have occurred in the past and are likely to recur in the future. Anticipating changes in customer preferences during these events can significantly aid in the development of new products.

The societal shifts triggered by the onset of COVID-19 have significantly impacted people's daily lives, influencing their purchasing behaviors [3]. These transformations have introduced uncertainties and challenges in the domains of product design and manufacturing [4,5]. The prolonged implementation of work/study-from-home policies, aimed at mitigating infection risks in public spaces, has created distinct customer needs compared to the pre-COVID era. Notably, features such as cameras, speakers, and microphones have become more essential due to the migration of student lectures and company meetings from physical locations to online platforms. Navigating these evolving customer preferences is paramount for companies engaged in product development. Numerous studies have been conducted to understand the changes in customer preferences before and after COVID-19 [6–8]. However, to our knowledge, only a limited number of studies have explored the dynamic shifts in customer preferences for

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product features within the domain of product design and manufacturing. Consequently, there is no established methodology that focuses on the changes in customer preferences before and after COVID-19 based on online reviews in the context of product design. This lack of methodology hinders manufacturers' ability to proactively respond to market disruptions and adapt their product designs accordingly.

Leveraging publicly accessible online reviews, this study aimed to develop a methodology to discern shifts in customer preferences for diverse product features following the COVID-19 pandemic. While numerous factors have the potential to influence the market, our study specifically concentrates on the most disruptive event, namely, the COVID-19 pandemic. In addition, one of the primary objectives of this study was to employ *automated* methodologies whenever feasible. Although traditional methods like surveys and interviews have historically been employed to investigate customer preferences, they are constrained by limitations such as cost and geographical constraints. Conversely, a wealth of online reviews is openly accessible on the internet, offering a rich and abundant data source. With the surge in online purchases during the COVID-19 pandemic, analyzing these online reviews provides a more efficient means of exploring potential shifts in customer preferences for product features compared to conventional methods such as surveys and interviews. This study developed an empirical research method that applies a semiautomatic framework to study customer preferences using online reviews before and during COVID-19. Our methodology comprises five stages: (i) data collection and preprocessing, (ii) customer interest analysis, (iii) customer sentiment analysis, (iv) feature importance analysis, and (v) product strategy analysis. To demonstrate its functionality, we conducted case studies on smartphones and laptops.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on customer preference research and elicitation in the COVID-19 pandemic. Section 3 describes our methodology, and Secs. 4 and 5 present two case studies on smartphones and laptops, respectively. Section 6 discusses the practical application of this research, as well as compares short-term and long-term changes regarding customer sentiments and feature importance. Section 7 summarizes the conclusions of our study.

2 Literature Review

2.1 Customer Preference Research in COVID-19 Pandemic. The COVID-19 pandemic stands out among natural disasters for its profound social and psychological repercussions [9]. To curb the virus's spread, numerous countries implemented lockdown measures and enforced social distancing protocols, leading to widespread shifts to remote work and learning environments [4,5]. Consequently, businesses, schools, and stores were shuttered, necessitating a transition to telecommuting. The consequent economic downturn shifted the purchase behavior of customers, which has changed the demand for products dramatically [10]. Various studies have investigated the changes in customer preferences due to COVID-19, using traditional methodologies such as questionnaires and interviews. Kim et al. [11] conducted an investigation on the dynamic changes in customer sentiments on product features following COVID-19 by sentiment analysis based on refurbished smartphone online reviews. Hotel customer satisfaction and its influencing factors changed significantly during COVID-19, e.g., during COVID-19, it was significantly influenced by service quality [12]. To study the shopping behaviors of customers during COVID-19, an investigation examined the effects of COVID-19 phobia, as a new exposure, on the psychological states of individuals and their resulting mobile shopping behavior [13]. The restaurant industry was severely affected during COVID-19; therefore, Kulshreshtha and Sharma [14] studied the effects of various factors responsible for the purchase decisions of generation Z in the context of cloud kitchens.

While numerous studies have explored shifts in customer preferences amidst the COVID-19 pandemic, few have specifically examined this phenomenon within the realm of product design. Therefore, the aim of this study is to address this research gap by conducting an empirical investigation focused on discerning alterations in customer preferences during the COVID-19 era, particularly within the context of product design.

2.2 Customer Preference Elicitation. In recent decades, numerous studies have focused on enhancing product design through the analysis of online reviews. Traditional methods like questionnaires and surveys often pose challenges in scalability due to their associated costs and can introduce biases stemming from temporal and geographical constraints. In contrast, methodologies utilizing online reviews offer a more accessible and cost-effective approach, potentially yielding less biased results. Given that customer preferences emerge from their interactions with product attributes, Chen et al. [15] introduced an analytical discrete choice model to explore various customer preferences and forecast their purchasing decisions. Similarly, Tuarob and Tucker [16] developed a rule-based method with seed features and pre-defined rules for feature extraction. Hou et al. [17] proposed a method which utilizes rule-based natural language processing to identify and structure product affordances from online reviews of two product generations, employing conjoint analysis inspired by the Kano model to quantify these affordances and detect changes in user expectations over time. Moreover, several methods for identifying significant customer reviews from the perspective of a product designer have been presented using text mining [18–23].

Although various approaches have been proposed in these studies, the overall systems primarily consist of three main components: (i) topic modeling, which is used to extract relevant product keywords and attributes from reviews written in natural languages; (ii) sentiment analysis, which is used to quantify preferences of customers over the extracted product attributes; (iii) importance analysis, which is used to identify the product attributes that a company should focus on based on their quantified importance and performance. The following subsections present some previous studies on these main components.

2.2.1 Topic Modeling. Topic modeling serves as a widely recognized analytical technique for data evaluation. Among the leading algorithms employed in text analysis across various domains are latent semantic analysis, non-negative matrix factorization, probabilistic latent semantic analysis, and latent Dirichlet allocation (LDA) [24].

Latent semantic analysis is an algebraic method based on singular value decomposition; it was proposed in 1990s by Deerwester et al. [25]. This method has been primarily applied in many different areas including information retrieval, natural language processing, and modeling of human language knowledge [26–28].

Both non-negative matrix factorization and probabilistic latent semantic analysis are dimension-reduction techniques. The former was proposed for environmental data [29], and subsequently has been adapted in many other research areas, including cancer identification using molecular gene expression datasets [30]. The latter is a technique developed based on bag of words for detecting semantic co-occurrence of terms using a probabilistic framework in a corpus [31].

LDA [32] is a generative statistical model that captures the statistical structures and distribution of documents across various topics. Specifically, each document includes different words and each topic can be associated with some of these words. Similar topics are assumed to have a cluster of similar words. This method has been applied in many research areas such as e-commerce [20,33–40].

Despite different methods of topic modeling developed based on the context of datasets, many studies prefer LDA, which is more flexible and adaptive than other techniques. In this paper, an improved LDA method [35] has been used, because one of our focal points lies in the automated processes. Additionally, methodologies such as word2vec, Bidirectional Encoder Representations from Transformers (BERT), and Generative Pre-Trained Transformers (GPT) could be considered to identify topics, but they do not provide an automated methodology in preprocessing, so the improved LDA method [35] is preferred.

2.2.2 Sentiment Analysis. Sentiment analysis quantifies the opinions, sentiments, and subjectivity of a text. As it is an ongoing research field in text mining, many algorithms have been developed [41–45]. Typically, sentiment analysis can be classified into unsupervised (e.g., lexicon-based method) [46–48] and supervised [49–52] learning methods according to the working principle. The latter approaches are generally more accurate in the domains where they are trained, whereas the former approaches are less time consuming and have lower memory complexity [53].

In recent years, there has been a growing trend in utilizing sentiment analysis to extract customer preferences from online reviews. Zhang et al. [54] introduced an opinion mining algorithm aimed at capturing relationships among product attributes. Moreover, Jiang et al. [55] devised a method leveraging a fuzzy time series model to predict future product feature importance. Bag et al. [56] proposed a framework that integrates the social perception score of a brand and the polarity of reviews to construct a prediction model for customer purchase intention. To study the relation between online customer reviews and sales rank, Suryadi and Kim [57] developed a systematic methodology based on word embedding and sentiments identified using a dependency tree. Wang et al. [58] proposed a novel method for analyzing sentiment polarity from online videos on product reviews, utilizing LDA modeling and a newly designed multi-attention bidirectional long short-term memory (LSTM) to better capture complex relationships between a speaker's sentiments on different topics.

In this research paper, we have utilized the Valence Aware Dictionary and sEntiment Reasoner (VADER) method to conduct sentiment analysis. Given our emphasis on automation, VADER stands out as an ideal choice. It is an unsupervised method that eliminates the need for labeled data during training, rendering it particularly well suited for the analysis of social media text. In addition, VADER can be easily adapted to various domains and languages by updating its lexicon. In contrast, while other machine learning-based (ML-based) methods for sentiment analysis may produce slightly better performance, they may require extensive retraining or fine-tuning to attain similar performance in different contexts. Lastly, VADER typically requires fewer computational resources compared to many other ML-based methods, which can be important for applications with resource constraints.

2.2.3 Importance Analysis. Importance analysis stands as a widely employed technique for strategically enhancing customer satisfaction. Within the continuously evolving field of text mining, diverse methodologies have emerged for conducting importance analysis. One such approach involves measuring the significance of product attributes through the frequency of product-related terms, with attributes characterized by high frequencies and low sentiment scores being deemed of elevated importance [55,59]. In addition, importance can be classified into self-stated (i.e., relevance) and implicit (i.e., determinance) [60] importance. Self-stated importance is measured directly by asking customers, whereas implicit importance is a highly flexible concept that requires different handling. Decker and Trusov [61] proposed a negative binomial regression method based on sentiment scores and user ratings to estimate the implicit importance values of the pros and cons in a review. Recently, Bi et al. [62] presented a neural network for evaluating implicit importance in a natural language text. Furthermore, Joung and Kim [63] developed a method to apply information fusion-based Shapley additive explanation (SHAP) [64] to a deep neural network to understand product attribute importance.

The SHAP-based importance measurement method is used because it can accurately measure the influence of input variables on output variables in a prediction model based on high performance and interpretability. In this research paper, we have utilized the SHAP method to ascertain feature importance. This choice was driven by its capacity to offer a lucid and straightforward means of conveying model behavior and predictions. Moreover, its model-agnostic nature enables its seamless application to a diverse spectrum of machine learning models, including complex ones such as deep neural networks, without modifications. This adaptability empowers us to interpret a multitude of models within a unified framework.

Given that COVID-19 represents an unparalleled catastrophe in recent history, there is a scarcity of studies examining the fluctuating dynamics of customer preferences for product features during such a significant crisis. Leveraging the accessibility of online review analysis, product designers and manufacturers can promptly gather reliable data and adapt their strategies accordingly to enhance the overall customer experience.

3 Methodology

Figure 1 shows the overview of the proposed methodology, which consists of five stages: (i) collect and preprocess data, (ii) analyze customer interests for product features, (iii) analyze customer sentiments for features, (iii) analyze feature importance, and (v) derive product strategies. The details of each stage are presented in the following subsections.

3.1 Data Collection and Preprocessing. The first stage collects two sets of online reviews in different time divisions, pre-COVID and post-COVID. The reference point of time division can be determined by relevant indices, such as the employment rate and the number of new COVID cases. This study selects Apr. 1, 2020 as the timestamp, referring to US unemployment rates [65]. There exist two approaches to obtaining these review datasets. One is to collect current reviews and split them into two datasets based on the timestamp. Another is to use reviews collected during different times, e.g., the beginning (2020) and sometime after the pandemic (2022). This study adopted the second approach because recently collected data contain few reviews written in pre-COVID time. Specifically, most best-selling products on Amazon

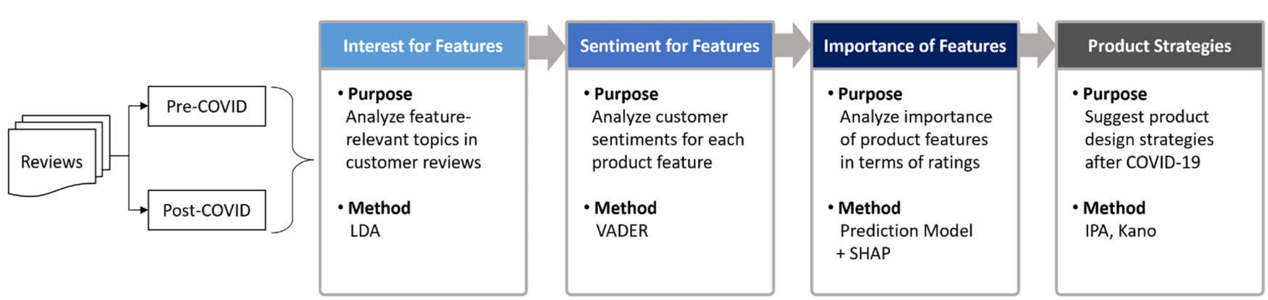

Fig. 1 Overview of developed methodology

were released after COVID-19. Therefore, collecting reviews written in the pre-COVID period was difficult.

Reviews of consumer products can be gathered from popular online marketplaces like Amazon and eBay. They provide useful data including reviewed products, ratings, review dates, and review content. This study collects the above data using a web scraping tool in PYTHON. The collected data are preprocessed before further analyses. Non-alphabetic characters, excluding punctuation, are eliminated from the reviews. Uppercase letters are converted to lowercase, and words undergo lemmatization. Subsequently, the reviews are filtered by brands; therefore, the two datasets comprise reviews for an identical list of brands.

As this study concentrates on customer attitudes toward product features, irrelevant words are removed. Product manuals, accessible from manufacturers' official websites and online commerce platforms, are employed for word filtering. Among the words in the review data, those not appearing in the product manuals are eliminated.

3.2 Features of Customer Interest. The second stage identifies product features that customers are interested in. LDA, one of the popular topic modeling methods in review analysis [35,62,66], is adopted. Product feature words are assumed to be nouns [34,57,67,68], and accordingly, a review-noun matrix is generated as the input for LDA. Because LDA requires manual input of the topic number (K), we use topic coherence to find the optimal K. The topic coherence measures the degree of semantic similarity between high-scoring words in each topic. This study tests multiple Ks and selects the one with the highest topic coherence. With this optimal K, LDA yields a matrix associating topics with keywords.

Since the LDA result may contain noise words, this research manually filters feature-relevant keywords from the top 30 nouns in each topic. These feature keywords are extended through the inclusion of synonyms, using word embedding [69].

(1) Generate vectors for all the nouns in the review data.
(2) Calculate the cosine similarity between a group of keywords and other nouns in the review data.
(3) Among the top 20 nouns with the highest similarity score, select feature-relevant words.
(4) Merge initial keywords and selected synonyms.

For example, let us assume that the first topic contains 20 keywords related to feature X. And let us say we collect 15 synonyms from step (4). Then, the number of final keywords for feature X is $20 + 15 = 35$. Open-source tools like the Gensim library in PYTHON or the Stanford Topic Modeling Toolbox can be employed for this purpose.

3.3 Sentiments for Features. This stage conducts sentiment analysis in two steps, i.e., define keywords and collect sentiment indices connected to these keywords. In this study, the keywords are feature-relevant words from the previous section. Regarding sentiment detection, Sec. 2.2.2 presents various algorithms that can be classified as supervised and unsupervised methods. This study employs an unsupervised method, VADER, because it is faster and more efficient than a supervised method as it does not require labeling.

VADER provides the sentiment polarity and intensity for the input text. Given the potential for a reviewer to mention the same feature multiple times, this study calculates the average sentiment score of relevant sentences. For example, a reviewer said "As everyone says, the camera is the best. The Night Sight is amazing. Battery life is good. I used GPS for about 3 hours, and the screen was set at the max, only used about 35% of the battery. The phone is not lacking or slow for daily use such as email or some Youtubing and Facebooking." When we focus on the battery feature, the third and fourth sentences are selected as relevant reviews. The sentiment score for each sentence is 0.6369 and 0.4404. The final score of this review is an equally weighted average of these two values, which is $(0.6369 + 0.4404)/2 = 0.5387$. It means that the reviewer has positive sentiments for the battery feature of the product. The sentiments for all product features are calculated in each review. If a reviewer does not mention any feature keyword for feature i, the sentiment for i remains null.

One downside of VADER is that it does not distinguish different sentiments in one sentence. For example, for "The screen is good, but the battery is poor," VADER returns an average score of good and bad for the screen and battery. The solution for this limitation will be studied in future research. Dividing a sentence by punctuation or coordinating conjunctions can be a feasible approach.

3.4 Importance of Features. The fourth stage analyzes the importance of product features based on the sentiments from the previous stage. The assumption behind this approach is that if a feature is important, then its sentiment can impact the review rating more significantly. A SHAP-based method suggested by Joung and Kim [63] is adopted in this study. SHAP [64] is one of the most well-known interpretable machine learning techniques. It analyzes the effects of all input variables on the output, and thus it can interpret a black box-like neural network model. A flowchart for importance estimation is shown in Fig. 2. First, the method constructs a review-sentiment/rating matrix, shown in Table 1. Each review has two types of data: (i) an array of the sentiment score for each product feature (f_i) which becomes the input data for a prediction model and (ii) star rating which is the output data of the model. The sentiment scores acquired in Sec. 3.3 span from -1 to 1, with -1 denoting a highly negative sentiment, 0 representing neutrality, and 1 indicating a highly positive sentiment. If a reviewer does not reference feature i, the sentiment score for that feature is zero because the input data to the prediction model cannot be null. The reviews with only zero scores are removed due to no benefit in star rating predictions. The star ratings consist of integer values ranging from 1 to 5 and are divided into two categories. To be specific, class 0 includes ratings from 1 to 3, indicating low satisfaction or complaints about products. Class 1 includes ratings 4 and 5, representing that customers are satisfied with the products. Because most customers give 4 or 5 ratings in their reviews, the result is highly imbalanced resulting in poor accuracy of the trained model. To address this problem, this study filters class 1 with review sentiments, i.e., the sentiment score of entire sentences in a review. For example, if a review has a rating of 4, and its sentiment score is above a threshold θ, it is classified into class 1. When a review has a rating of 5, but its sentiment is lower than θ, it is removed from the dataset. Then using these data, the method trains a model that predicts review ratings based on customer sentiments associated with product features. This study tested four different models (support vector machine, light gradient boosting machine, extreme gradient boosting, and neural network) and selected that with the best performance (F1 score). After training, the model is interpreted by SHAP, and the obtained SHAP values are further analyzed by Eqs. (1) and (2). In Eq. (1), $|\mathrm{SHAP}^k_{ni}|$ denotes the absolute SHAP value for feature i in review n, and k indicates that the value comes from the kth model in

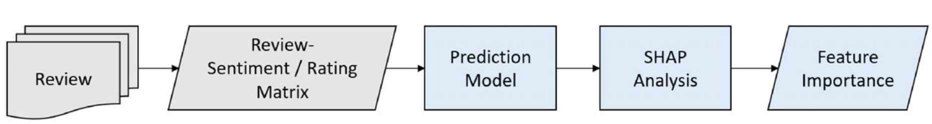

Fig. 2 Flowchart of feature importance estimation

Table 1 Dataset for importance estimation

Review	f_1	f_2	$\cdots$	f_i	Star rating
1	0.0	0.6	$\cdots$	−0.2	1
2	0.4	0.0	$\cdots$	0.3	1
3	−0.2	0.1	$\cdots$	0.0	0
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
N			$\cdots$		0

K-fold validation. W_k indicates the model performance (F1 score in this study) of the kth model and is normalized to become the weight for |SHAP| values. $\overline{\text{SHAP}_{ni}^k}$ is the normalized $w^k|\text{SHAP}_{ni}^k|$ with regard to all features. In Eq. (2), Imp_i calculates the importance of feature i by averaging $\overline{\text{SHAP}_{ni}^k}$ over all datasets.

$$\overline{SHAP_{ni}^k} = \frac{w^k|SHAP_{ni}^k|}{\sum_j w^K|SHAP_{nj}^k|}, \qquad w^k = \frac{W_k}{\sum_{k'} W_{k'}} \tag{1}$$

$$Imp_i = \frac{\sum_{k=1}^K \sum_{n=1}^N \overline{SHAP_{ni}^k}}{KN} \tag{2}$$

3.5 Product Strategy Analysis. This study employs importance-performance analysis (IPA) and Kano categorization to derive product strategies.

3.5.1 Importance-Performance Analysis. IPA, introduced by Martilla and James [70], aims to identify attributes of products or services that companies need to focus on. Specifically, IPA maps selected attributes into quadrants based on their importance and performance. In quadrant I, both performance and importance are high, which implies "keep up the good work" as a product development strategy. Quadrant II suggests "concentrate here" due to its low performance and high importance. Quadrant III has low performance and importance, so the attributes in this quadrant have "low priority." The strategy for those in quadrant IV is "possible overkill" because performance is high while importance is low. This study adopts the method of Joung and Kim [34] to perform IPA. The sentiment score from Sec. 3.3 represents performance, and the importance score from Sec. 3.4 indicates importance. The cross-hairs are determined by the mean of each dataset.

3.5.2 Kano Model. The Kano categorization, suggested by Kano et al. [71], aims to determine the priority of product features for new product development. The model analyzes the roles of features in satisfying customer needs and divides the features into different categories. This study employs the method of Joung and Kim [63] to conduct Kano categorization. While details can be found in Ref. [63], we assume it is necessary to summarize the method for converting SHAP results into Kano categories. In Eq. (3), $\hat{\text{SHAP}}_{\text{ink}}$ is the weighted SHAP value of feature i, review n in the kth model. The weight is the normalized model performance (F1 score). E_i^{POS} represents the average $\hat{\text{SHAP}}$ of feature i among reviews with positive sentiments for feature i. Specifically, $\text{Sent}R_i^{\text{POS}}$ is the number of reviews expressing positive sentiments toward feature i, and $\hat{\text{SHAP}}_{\text{ink}}^{\text{POS}}$ is the SHAP value of feature i within those reviews. Likewise, E_i^{NEG} is the average $\hat{\text{SHAP}}$ of feature i among reviews expressing negative sentiments for feature i. Then, each feature i is assigned to quadrants where E_i^{POS} is x-axis, and E_i^{NEG} is y-axis. The characteristics of each quadrant are defined as follows.

$$\begin{aligned} \hat{SHAP}_{ink} &= \frac{w_k}{\sum_{k'} w_{k'}} SHAP_{ink} \\ E_i^{POS} &= \frac{\sum_k \sum_n \hat{SHAP}_{ink}^{POS}}{SentR_i^{POS}} \\ E_i^{NEG} &= \frac{\sum_k \sum_n \hat{SHAP}_{ink}^{NEG}}{SentR_i^{NEG}} \end{aligned} \tag{3}$$

- Quadrant I (performance feature): fulfillment of this category is positively related to customer satisfaction. In other words, the product feature will result in dissatisfaction when not fulfilled and satisfaction when fulfilled.
- Quadrant II (must-be feature): when the product feature of this category is fulfilled, customers are just neutral, but customers will be very dissatisfied when the feature is not fulfilled.
- Quadrant III (reverse feature): this category of product features will result in an increase in dissatisfaction with the degree of fulfillment increases.
- Quadrant IV (attractive feature): this category offers customer satisfaction when fulfilled but does not give rise to dissatisfaction when it is not fulfilled.

4 Case Study—Smartphone

This paper chose a smartphone as a case study, given the unprecedented decline experienced by the smartphone market (1Q20-1Q19, −20.2%) due to the pandemic [72]. In this section, the analysis results of customer reviews for smartphone products are presented.

4.1 Data. This research collected two datasets: (i) online customer reviews and (ii) product manual documents. The smartphone review data were collected on different time stamps, as explained in Sec. 3.1. The pre-COVID and post-COVID data were collected from the top 100 best-selling products of Amazon on Jul. 11, 2020 and March 25, 2022, respectively. Therefore, each dataset contained the reviews for the latest/popular products at each time division. Then the collected reviews were filtered by the review date so they encompassed the identical date range, spanning two years before and after the onset of the COVID-19 outbreak. Subsequently, the data underwent brand-based filtering to ensure both datasets comprised reviews for the same set of brands. This study exclusively utilized verified reviews from Amazon to ensure data authenticity, and Table 2 provides an overview of the review dataset. The total count of pre-COVID reviews is 7293, spanning from Apr. 1, 2018 to Mar. 31, 2020, across 29 reviewed products. The post-COVID dataset consists of 4338 reviews for 17 products, composed between Apr. 1, 2020 and Mar. 25, 2022.

For product manuals, this research utilized manual documentation for seven distinct smartphone products, which manufacturers distribute and make available online. Since the features and functions of smartphones are similar, it is assumed that a smaller number of manual documents is adequate to encompass representative product features. Words in the review data that did not appear in the manual documents were subsequently excluded.

4.2 Result

4.2.1 Features of Customer Interest. Table 3 lists the topics obtained from LDA. The first column provides the different time divisions, and the second column reports the topic labels representing the product features mentioned by customers. Feature-relevant keywords are listed in the third column. The results show that customer interest in smartphone features has not changed. They reference identical features both before and after COVID-19. Notably, there is a variation in the feature keywords related to the price. Specifically, in the post-COVID reviews, new keywords like "quality" and "performance" emerge. This suggests that customers look for cheaper products due to reduced incomes but still care about their specs. They say, "For about the same price as I paid in 2016, I got 8 cores instead of 4, 32g over 16g, bigger screen, Nfc, etc. [$\cdots$] Many advanced features from a "midrange" phone," "The battery life is good, it is decently powerful for the price." Regarding the camera feature, despite the emergence of the new keyword "zoom" in the post-COVID period, it is not associated with the pandemic. The majority of reviews referencing "zoom" are discussing the enhanced zoom capabilities of smartphone cameras, rather than

Table 2 Details of smartphone review data

	Pre-COVID	Post-COVID
Range of dates	Apr. 1, 2018—Mar. 31, 2020	Apr. 1, 2020—Mar. 25, 2022
Number of reviews	7293	4338
Number of products	23	17
List of brands	Apple, Samsung, Google, Motorola, OnePlus, ZTE	

Table 3 Smartphone features of customer interest

	Topic label	Keywords	# Reviews	Ratio	Change
Pre-COVID (7293)	Network[a]	card, service, carrier, text, cell, datum, message, signal, etc.	1675	23%	–
	Screen[a]	screen, protector, screen_protector, touch, glass, display	1370	19%	–
	Camera[a]	camera, picture, photo, video, picture_quality	1613	22%	–
	Battery[a]	battery, life, battery_life, power, charger	1786	24%	–
	Security[a]	fingerprint, reader, finger, print, sensor, face, recognition, etc.	767	11%	–
	Price	price, sale, money	1721	24%	–
Post-COVID (4338)	Network[a]	card, service, carrier, text, cell, datum, message, signal, etc.	1371	32%	+ 9%P
	Screen[a]	screen, protector, screen_protector, touch, glass	966	22%	+ 3%P
	Camera[a]	camera, picture, photo, video, zoom	1097	25%	+ 3%P
	Battery[a]	battery, life, battery_life, power, port	1453	33%	+ 9%P
	Security[a]	fingerprint, reader, finger, print, sensor, face, recognition, etc.	736	17%	+ 6%P
	Price	price, quality, performance	1071	25%	+ 1%P

[a]Result is statistically significant at $\alpha = 0.0001$ (*Z*-test).

the "Zoom meeting" application. The reviewers said "Camera is dramatically better at 10× zoom and higher" and "The Pixel 6 does an excellent job with image effects, bokeh, zoom, etc." No noticeable difference is observed in other features.

To examine alterations in the level of interest in smartphone features, this study calculates the review ratio by Eq. (4).

$$\text{Ratio} = \frac{\text{Number of reviews mentioning feature } k}{\text{Number of total reviews}} \quad (4)$$

In Table 3, the last column shows the increased interest in all features after COVID-19. Moreover, all features except the price show statistically significant changes at $\alpha = 0.0001$. The findings suggest that customers provided feedback on product features with greater frequency after COVID-19. This may be due to the increased price sensitivity of consumers during the pandemic [73]. Higher interest in "values of money" would make them more care about product quality and features.

4.2.2 Sentiment for Features. COVID-19 also affected the sentiments of customers regarding product features. Figure 3(*a*) illustrates the shifts in customer sentiment regarding smartphone features pre- and post-COVID. The *x*-axis presents the product features derived from LDA, while the *y*-axis depicts the sentiment score associated with each feature. A normality test on the sentiment values showed that they did not have a normal distribution; therefore, this study employed a rank sum test instead of a two-sample *t*-test for the statistical analysis. The result shows that the sentiment scores for the screen, camera, and price are significantly decreased. Given the swift rise in the unemployment rate post-COVID-19 [65], it is anticipated that consumers would seek out affordable or lower-tier smartphones. Complaints about high-tier products may arise, as reflected in the decreased sentiment regarding the price. Changes in the screen and camera feature likely stem from shifts in smartphone usage patterns. With most states in the US implementing lockdown after the pandemic, opportunities for in-person meetings were limited. As individuals sought alternatives, such as video calls and online meetings, the use of camera and screen would increase.

For example, customers said "Unfortunately will return this since the primary need is for video calls and the front camera performs worse than a $100 phone." The sentiment for the screen and camera decreased as customers expressed unmet needs in new usage.

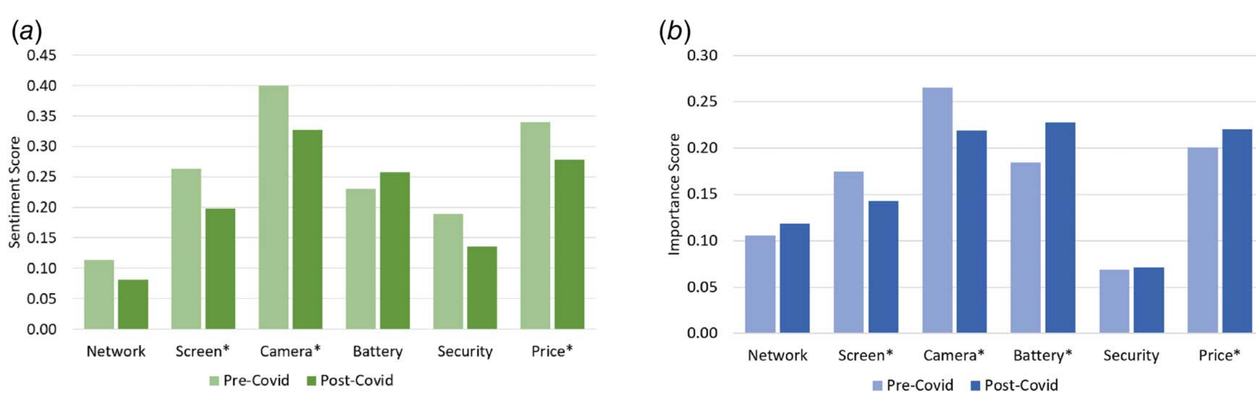

Fig. 3 (*a*) Customer sentiments for smartphone features in pre/post-COVID-19 times and (*b*) importance of smartphone features in pre/post-COVID-19 times. *Result is statistically significant at $\alpha = 0.0001$ (rank sum test).

moved from "performance" to "attractive," which means customers do not care even when these features are not fulfilled. After the pandemic, people stayed at home most of the time and had little outdoor activities, so they may be less concerned about taking photos and locking their smartphones.

4.2.3 Importance of Features. In addition to the sentiments associated with product features, this study analyzed their respective importance. The outcomes are presented in Fig. 3(*b*), where the *y*-axis illustrates the importance score for each product feature. These scores have been normalized to ensure a cumulative sum of 1. The figure illustrates shifts in both the importance scores and ranks of the product features. The statistical verification with the rank sum test shows significant changes in the screen, camera, battery, and price. Regarding ranking, the most important feature was the camera pre-COVID but changed to the battery post-COVID. This shift is likely attributed to a decrease in outdoor activities after the pandemic. As customers spend more time using smartphones, they care more about the battery life. Even though charging is possible at any time indoors, there are various restrictions on using a smartphone while charging, so people place importance on battery time. For example, customers said, "So far it is good phone battery does last all day [$\cdots$] I do use my phone all day internet radio like pandora [$\cdots$]" and "This smartphone is performing very well, the camera is very good, and the battery is great. Under normal use, it can easily last two days." Customers mentioned the battery feature more frequently, as can be seen from Table 3, and became satisfied with the battery performance, as shown in Fig. 3(*a*). The price is the second-most significant feature in post-COVID. As previously stated, the impact of COVID-19 on customer income levels led to a decline in sentiments. Understandably, in post-COVID, the price is an important factor when purchasing smartphones.

4.2.4 Product Strategy. This section describes product strategies obtained from IPA and Kano categorization. Figure 4 illustrates IPA results before and after COVID-19. It is observed that the battery feature moved from quadrant II (concentrate here) to quadrant I (keep up the good work). The increased importance is probably due to the increased smartphone usage, and the increased performance is because of the improved battery capacity after COVID-19. The average capacity is 3665 mA h in pre-COVID and 4492 mA h in post-COVID. Another change in IPA is the screen. It moved from quadrant I (keep up the good work) to quadrant III (low priority). The decreased importance may be due to the alternatives at home, e.g., desktop monitor or TV. The decreased sentiment is probably a consequence of small improvements in the screen features. For example, the average screen size slightly increases from 6.2 in. to 6.4 in., but there are little changes in resolution and type.

Table 4 presents the changes in Kano categorization of smartphone features post-COVID. The network and price changed from "performance" to "must-be," indicating they became essential features. This change is reasonable because online communications, such as Zoom meetings and face talk, have become essential after the pandemic. Also, reduced incomes led to customer need for affordable smartphones. On the other hand, the camera and security moved from "performance" to "attractive," which means customers do not care even when these features are not fulfilled. After the pandemic, people stayed at home most of the time and had little outdoor activities, so they may be less concerned about taking photos and locking their smartphones.

5 Case Study—Laptop

In the second case study, we conducted an analysis of laptop reviews sourced from Amazon. The usage of laptops has experienced a significant surge since the onset of the COVID-19 pandemic, primarily due to the widespread adoption of extended work and study from home policies. This section provides the findings derived from our analysis of customer reviews pertaining to laptop products.

5.1 Data. Similar to the previous case study, this study collected two types of data: (i) online customer reviews and (ii) product manual documents. The laptop review data were collected from Amazon.com. The pre-COVID and post-COVID reviews were collected on Jul. 11, 2020 and Mar. 25, 2022, respectively. The filtering process of the dataset was the same as in the previous case study. Table 5 summarizes the details of the filtered review data. The total number of pre-COVID reviews is 32,188, written from Apr. 1, 2018 to Mar. 31, 2020. The number of reviewed products is 155. The post-COVID data contain 24,487 reviews for 103 products, written between Apr. 1, 2020 and Mar. 25, 2022.

In this study, product manuals for seven distinct laptop models were utilized. These manuals, disseminated by manufacturers and accessible online, served as the primary source of information. Similar to the previous case study, it was presumed that the features and functionalities of laptops across various brands were comparable. Hence, analyzing the manuals of these seven different models was deemed adequate to encompass representative laptop features. To streamline the analysis, any words in the review data not found in the manual documents were excluded.

5.2 Results

5.2.1 Features of Interest. Table 6 lists the topics obtained from LDA. The first column lists the different time divisions, and the second column provides the topic labels representing the product features mentioned by customers. Feature-relevant keywords are listed in the third column. The results show that interest of the customers in the laptop features remains almost unchanged post-COVID, except for performance_ventilation and the Internet. Performance_ventilation only occurs in the pre-COVID dataset, whereas the Internet occurs only in the post-COVID dataset. This change is probably caused by the increased demand for online work owing to COVID-19; therefore, customers express more

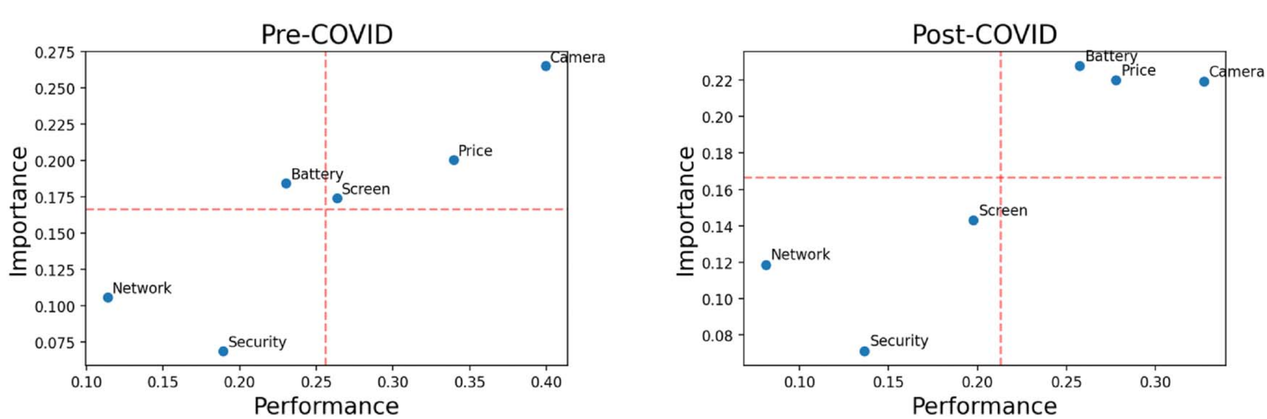

Fig. 4 IPA—smartphone

Table 4 Kano—smartphone

Feature	Pre-COVID	Post-COVID
Network	Performance	Must-be
Screen	Performance	Performance
Camera	Performance	Attractive
Battery	Performance	Performance
Security	Performance	Attractive
Price	Performance	Must-be

Table 5 Details of laptop review data

	Pre-COVID	Post-COVID
Range of dates	Apr. 1, 2018–Mar. 31, 2020	Apr. 1, 2020–Mar. 25, 2022
Number of reviews	32,188	24,487
Number of products	155	103
List of brands	ASUS, Acer, Apple, Dell, HP, Lenovo	

concern regarding features associated to the Internet after COVID-19. Feature keywords in the product features common in pre-COVID and post-COVID show very slight changes.

To observe the changes in the degree of interest in laptop features, this study analyzed the ratio of reviews mentioning each feature. Table 6 highlights notable trends, with increased interest observed across all features following the onset of COVID-19. Specifically, the ratios for screen_camera and speaker features witnessed an uptick, while those for other common laptop features experienced a decline. Except for the speaker, these changes were statistically significant at the $\alpha = 0.0001$ level. In contrast to the findings of the previous case study, results from this analysis reveal divergent shifts in customer interest toward various laptop features post-COVID-19. These distinct changes are likely attributed to the altered work and study environments before and after the pandemic. Before COVID-19, people probably needed to bring their laptops to their work spaces (such as company buildings and lecture halls), and this need was reduced after COVID-19, because people have been required to work/study from home. This shift of need probably impacted the decision of a customer when potentially purchasing a new laptop.

5.2.2 Sentiment for Features. The COVID-19 pandemic also had a notable impact on customer sentiments toward product features. Figure 5(*a*) illustrates the shifts in customer sentiments regarding laptop features before and after the pandemic. The *x*-axis represents the product features derived from LDA, while the *y*-axis indicates the sentiment score associated with each feature. Due to the non-normal distribution of sentiment values, this study employed a rank sum test for statistical analysis instead of a two-sample *t*-test. Asterisks (*) in the graph denote statistically significant differences at $\alpha = 0.0001$.

While all common laptop features exhibit varying sentiment values pre- and post-COVID-19, only the differences for memory, speaker, and malfunction are statistically significant. Before the pandemic, concerns about speaker quality might have been relatively low as most work occurred on-site. However, with the transition to remote work and online meetings, the quality of speakers (including headphones) became critical for a satisfactory user experience, leading to heightened scrutiny and criticism in reviews. Similarly, malfunctioning laptops severely hinder online work capabilities, resulting in intensely negative sentiment reflected in customer reviews.

Interestingly, unlike the previous case study where the sentiment scores for screen and camera features significantly decreased, this study observed similar sentiment scores for screen_camera features both pre- and post-COVID-19. This discrepancy could be attributed to the availability of external devices to compensate for subpar features that fail to meet customer needs. For laptops, customers have the option to purchase external cameras if the built-in camera falls short of their expectations. However, such external solutions are less common in the smartphone market.

5.2.3 Importance of Features. Similar to the previous case study, in addition to sentiment analysis, we conducted an importance analysis on the laptop features. The results are depicted in Fig. 5(*b*), where the *y*-axis denotes the importance score attributed to each product feature. These scores have been normalized, thus summing up to 1. The figure illustrates shifts in the importance scores and rankings of the product features. As detailed in

Table 6 Laptop features of customer interest

	Topic label	Keywords	# Reviews	Ratio	Change
Pre-COVID (22,302)	Screen_Camera[a]	screen, display, monitor, camera, resolution, etc.	9758	30%	–
	Speaker	speaker, sound, volume, audio, microphone, etc.	2541	8%	–
	Malfunction[a]	malfunction, problem, error, solution, protection, etc.	6376	20%	–
	Keyboard_Mouse[a]	keyboard, mouse, touchpad, keypad, button, etc.	5987	19%	–
	Software_Application[a]	window, system, software, application, bios, microsoft_office, etc.	10,745	33%	–
	Memory[a]	drive, ssd, memory, storage, processor, space, hdd, etc.	6557	20%	–
	Battery	battery, life, battery_life, charger, etc.	6472	20%	–
	Customer_Service	customer_service, support, warranty, service, repair, return, help, tech_support, etc.	5306	16%	–
	Performance and Ventilation	fan, performance, cpu, turbo_mode, temperature, etc.	5108	16%	–
Post-COVID (17,421)	Screen_Camera[a]	screen, display, monitor, camera, resolution, etc.	9127	37%	+7%P
	Speaker	speaker, sound, volume, audio, microphone, etc.	2024	8%	–
	Malfunction[a]	malfunction, problem, error, solution, protection, etc.	3162	13%	−7%P
	Keyboard_Mouse[a]	keyboard, mouse, touchpad, keypad, button, etc.	4073	17%	−2%P
	Software_Application[a]	window, system, software, application, bios, microsoft_office, etc.	6860	28%	−5%P
	Memory[a]	drive, ssd, memory, storage, processor, space, hdd, etc.	3192	13%	−7%P
	Battery	battery, life, battery_life, charger, etc.	4746	19%	−1%P
	Customer_Service	customer_service, support, warranty, service, repair, return, help, tech_support, etc.	3812	16%	–
	Internet	internet, email, work, account, network, vpn, ethernet, etc.	7746	32%	–

[a]Result is statistically significant at $\alpha = 0.0001$ (*Z*-test).

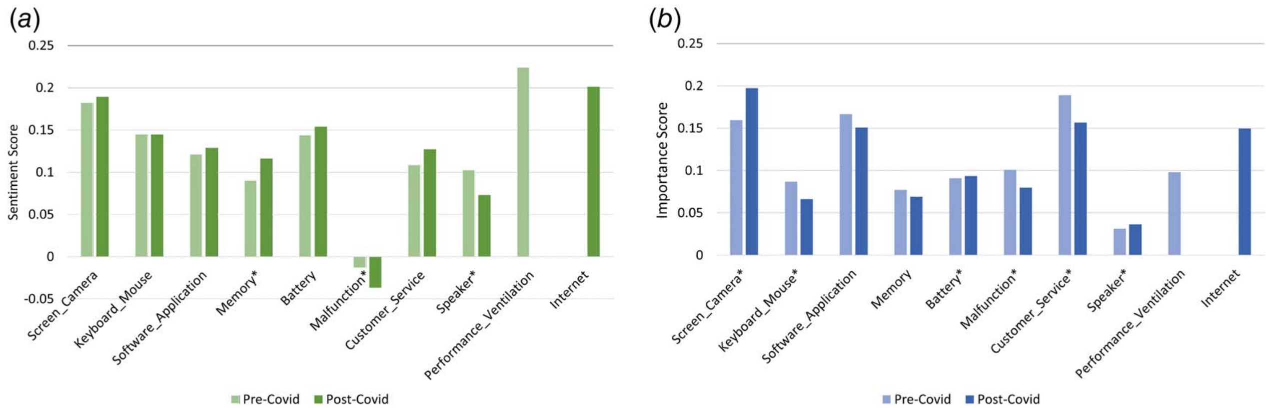

Fig. 5 (*a*) Customer sentiment for laptop features in pre/post-COVID-19 times and (*b*) importance of laptop features in pre/post-COVID-19 times. *Result is statistically significant at $\alpha = 0.0001$ (rank sum test).

Sec. 3.4, importance estimation relied on the absolute values of the SHAP results, leading to non-normally distributed data. Consequently, a rank sum test was employed to determine the significance of changes in importance scores.

The figure reveals significant differences in the importance scores for screen_camera, keyboard_mouse, battery, malfunction, customer_service, and speaker. Among these laptop features, screen_camera emerged as the most pivotal one post-COVID-19. This outcome is unsurprising, considering the lockdown measures during the pandemic compelled people to rely heavily on laptops for interpersonal communication, thereby elevating the significance of screen_camera, the primary medium through which individuals interact with the external world. Indeed, as indicated in Table 6, the ratio of screen_camera mentions increased post-COVID-19, further underscoring its importance.

5.2.4 Product Strategy. This section describes product strategies obtained from IPA and Kano categorization. Figure 6 illustrates IPA results of laptops before and after COVID-19. From the figures, it is observed that the customer_service feature moved from quadrant II (concentrate here) to quadrant I (keep up the good work). The change is probably due to the increased focus on customer satisfaction. The economic impact of the pandemic may have led businesses to prioritize customer satisfaction and loyalty. Investing in better customer service can lead to positive word-of-mouth, repeat business, and a more resilient brand image. In addition, it is observed that the software_application feature moved from quadrant II (concentrate here) to quadrant I (keep up the good work). The change is probably due to the user feedback and adaptation. Increased reliance on software during the pandemic might have generated valuable user feedback. Developers could use this feedback to identify pain points and areas for improvement, leading to updates and enhancements in post-COVID software releases.

Table 7 shows the changes in Kano categorization of laptop features after COVID-19. It is observed that both the screen_camera and speaker moved to "must-be" from "performance" and "attractive," respectively. The change is probably due to the increased demand for online communication. The pandemic led to a widespread shift to remote work, making the quality of laptop screens, cameras, and speakers crucial. People working from home rely heavily on their laptop screens for tasks ranging from video conferencing to document editing, while good speakers and headphones are essential for effective communication during video conferences, virtual presentations, and team collaborations. In addition, it is observed that battery moved from "must-be" to "attractive." The change is probably due to the shift in usage patterns. Work habits and lifestyles might have changed drastically during the pandemic. Before COVID, people traveling to work might wish to remain "unleashed" and thus prefer longer battery life. However, after COVID, most of the people were working from home, making it less crucial to have extended battery life, thanks to the access to power outlets in their apartments.

6 Discussion

6.1 Practical Applications. The findings of this research can help companies devise appropriate strategies for their products post-COVID. Regarding the smartphone case, the first analysis (LDA)

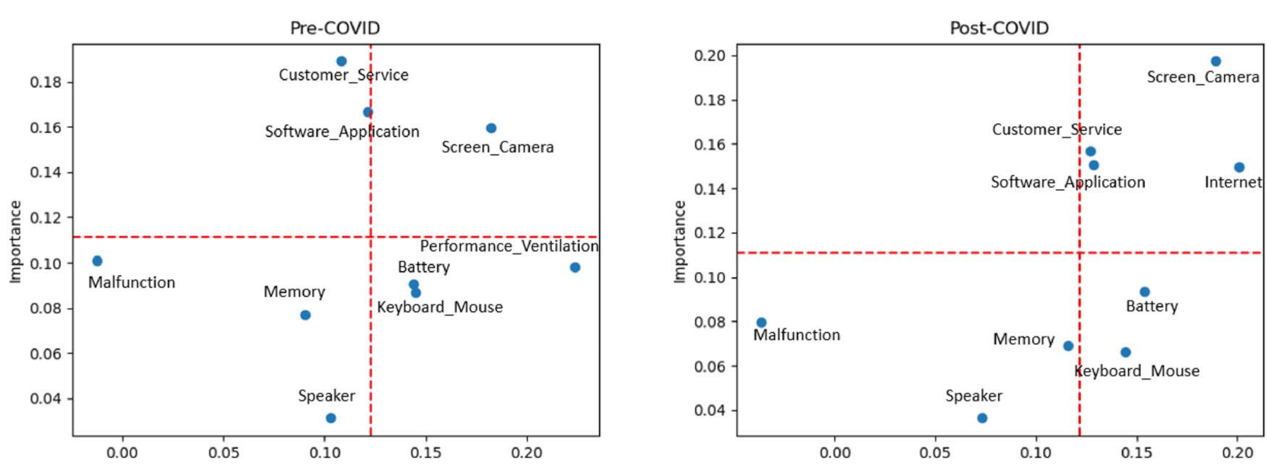

Fig. 6 IPA—laptop

Table 7 Kano—laptop

Feature	Pre-COVID	Post-COVID
Screen_Camera	Performance	Must-be
Speaker	Attractive	Must-be
Malfunction	Performance	Performance
Keyboard_Mouse	Performance	Performance
Software_Application	Performance	Performance
Memory	Performance	Performance
Battery	Must-be	Attractive
Customer_Service	Must-be	Must-be

showed no changes in the list of smartphone features of customer interest. This suggests that designers can focus on the same features, i.e., network, screen, camera, battery, security, and price for the next generation. However, the second analysis, whose results are shown in Fig. 3(*a*), revealed changes in the customer sentiments for the product features. Particularly, the screen, camera, and price showed statistically significant decreases. This result suggests that COVID-19 negatively affected customer satisfaction for these features; therefore, companies should enhance their quality/specification. The third analysis, whose results are shown in Fig. 3(*b*), also revealed changes in the importance of smartphone features. The price became the most significant feature in post-COVID, followed by the battery and the camera. Therefore, an affordable smartphone focusing on the battery and camera will be a better strategy than a high-tier smartphone with improvements in other features.

Regarding the laptop case, the first analysis (LDA) showed a new feature (Internet) replacing an existing feature (performance and ventilation) after COVID-19. The change in environment due to work/study from home increased the demand of the Internet for laptops, as otherwise their work capability may be severely hampered. Consequently, LDA extracted the Internet feature from the reviews after the outbreak of COVID-19. For the existing features, the second analysis, whose results are in Fig. 5(*a*), revealed changes in the customer sentiments for product features. In particular, memory presented a statistically significant increase in sentiment, whereas malfunction and speaker showed reverse statistically significant results. These results suggest that companies may need to improve their quality control (to reduce malfunctions) as well as enhance the quality of speakers (including microphones). The third analysis, whose results are in Fig. 5(*b*), also presented changes in the importance of smartphone features. After the outbreak of COVID-19, screen and camera became increasingly important, possibly owing to the work/study from home restriction, where most meetings shifted from in-person to online. Along with the results from the previous analysis, a better strategy is to focus on screen and camera as well as speakers, all of which are essential components for a quality online conferences/meetings/lectures, while simultaneously reducing the rate of malfunction by improving quality control. This is because failed laptops may hamper the working experiences of customers more than before.

6.2 Comparison of Short-Term and Long-Term Changes. Regarding customer sentiments and feature importance, we conducted further analysis to compare the short-term and long-term changes. First, the review data were split into different time divisions. This study applied a semi-yearly division, but other criteria (monthly, quarterly, or yearly) can be applied. And then, the data from Secs. 4 and 5 are plotted and analyzed. The observations from the graphs reveal differences in the short and long-term trends. Table 8 summarizes results, and the details are presented in the following sections. The number of reviews per period is provided in the Appendix.

6.2.1 Case 1—Smartphone. The study conducted a time series analysis to detect short-term changes unseen in the previous analyses. Figure 7 shows semi-annual trends of customer sentiments for the product features. The *x*-axis is a timeline, and the *y*-axis represents the sentiment scores. The arrow on the graph indicates the outbreak of COVID-19. Overall, the long-term trend in the graph matches the sentiment analysis results in Fig. 3(*a*). The sentiments for all features except the battery decreased after the pandemic. In terms of comparison analysis, the results are divided into two categories: (i) short-term changes align with long-term trends and (ii) short-term trends are inconsistent with long-term trends. Based on Fig. 7, the screen feature belongs to the first category, i.e., aligned short-term and long-term trends. The sentiment for the screen decreases in the short term as well as in the long term. All other features belong to the second category, i.e., inconsistent short-term and long-term trends. Regarding the network and battery features, a noticeable change occurred immediately after the pandemic, which is against the long-term trend. The camera and price features show little change in the short term, whereas they show decreased sentiment after some time. The security feature shows a significant drop and recovery in its sentiment score, but it has little change in the long term.

Figure 8 shows the semi-annual trends of the importance of the product features. Overall, the trend is consistent with the result in Fig. 3(*b*). Again, the results can be divided into two categories mentioned above. Unlike the case of feature sentiments, the importance of most features belongs to the first category, i.e., the short-term and long-term trends align. The only feature with inconsistent trends is security. It shows a rapid drop and recovery near the breakout of the pandemic, whereas its importance in the long term shows little change.

6.2.2 Case 2—Laptop. The same analysis was conducted for the laptop case. Figure 9 shows semi-annual trends of the customer sentiments for the product features. Overall, the long-term trend is similar to the sentiment analysis results in Fig. 5(*a*). The sentiments for all features, except for the malfunction, are increased after the pandemic. Similar to the previous subsection, the results can be divided into two categories. In Fig. 9, malfunction, memory, and customer service belong to the first category (aligned short-term and long-term trends) whereas other features belong to the second category (inconsistent short-term and long-term trends). Malfunction shows a significant drop immediately after COVID-19; its short-term decrease is consistent with its long-term decrease.

Table 8 Comparison of short-term and long-term changes

		Similar short- and long-term trends	Dissimilar short- and long-term trends
Smartphone	Feature sentiment	screen	network, camera, battery, security, price
	Feature importance	network, screen, camera,[a] battery, price	security
Laptop	Feature sentiment	malfunction, memory, customer_service	screen_camera, speaker, battery keyboard_mouse, software_application
	Feature importance	screen_camera,[a] malfunction, speaker, keyboard_mouse,[a] software_application, battery, memory, customer_service[a]	–

[a]Features showing statistically significant disrupts at the COVID breakout, 2020 H1 versus 2020 H2 (rank sum test, $\alpha = 0.01$).

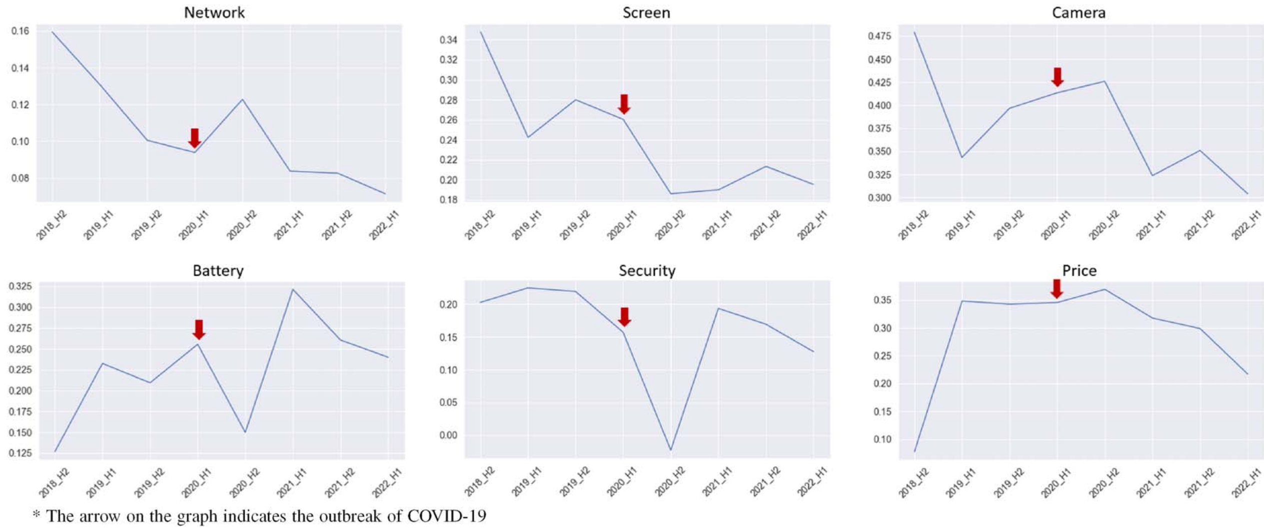

Fig. 7 Smartphone feature sentiment trend: $y-$axis = sentiment scores, $x-$axis = timeline. *The arrow on the graph indicates the outbreak of COVID-19.

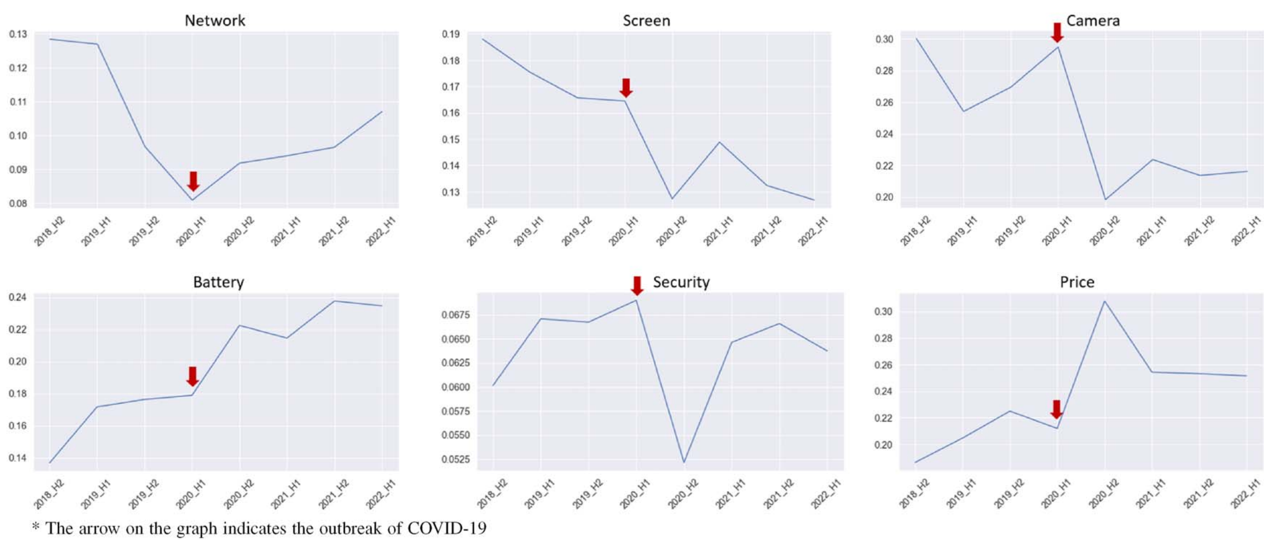

Fig. 8 Smartphone feature importance trend: $y-$axis = importance scores, $x-$axis = timeline. *The arrow on the graph indicates the outbreak of COVID-19.

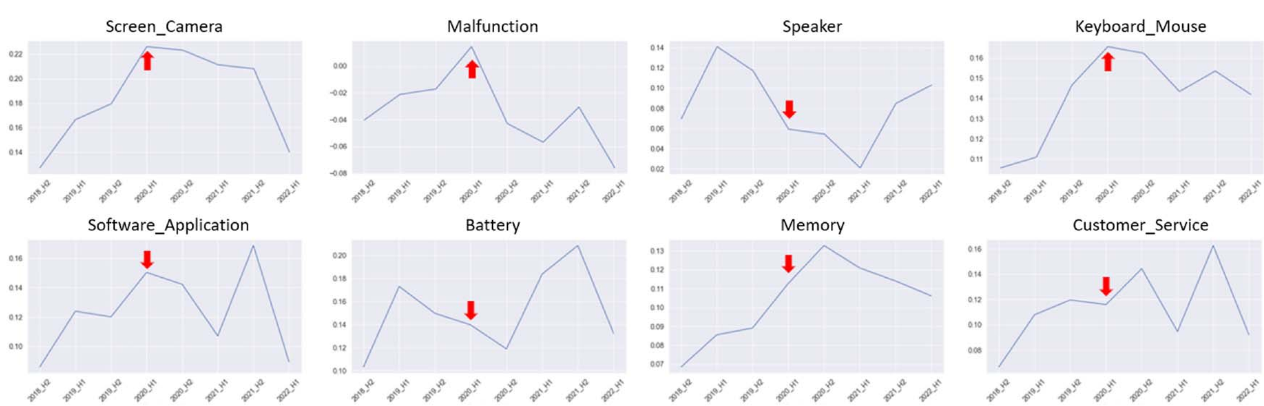

Fig. 9 Laptop feature sentiment trend: $y-$axis = sentiment scores, $x-$axis = timeline

However, screen and camera present a steadily increasing trend before COVID-19, which starts to reverse after it. A similar scenario is also observed for the keyboard, mouse, and software application.

Figure 10 shows the semi-annual trends for the importance of the product features. Overall, the trend is consistent with the results in Fig. 5(*b*). Again, the results can be divided into two categories mentioned above. Unlike the case of feature sentiments, the importance

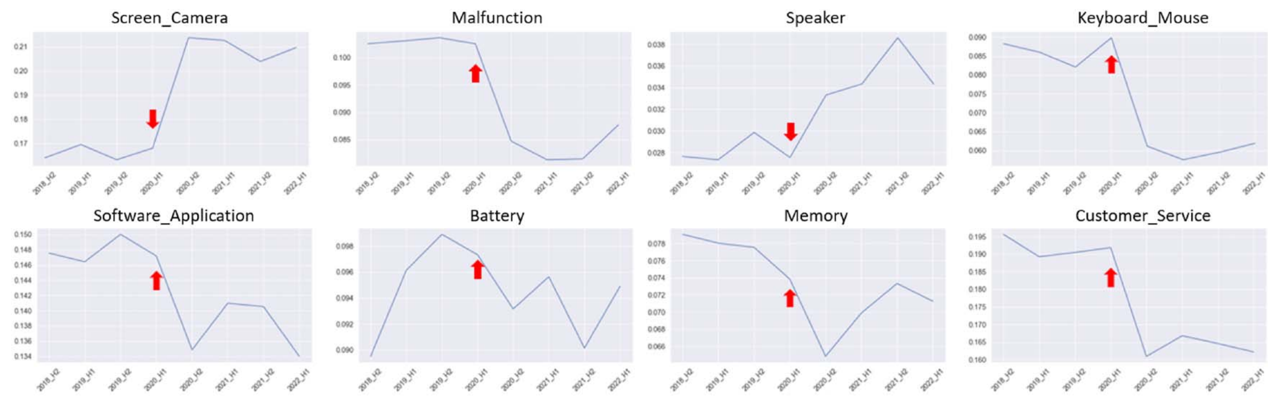

Fig. 10 Laptop feature importance trend: y − axis = importance scores, x − axis = timeline

of all features belong to the first category, i.e., the short-term and long-term trends are aligned.

6.3 General Applicability of the Methodology. In this study, we have developed a general methodology applicable to any user-generated text data to understand changes in customer preferences during significant events. This versatile tool is adaptable to various contexts and datasets, broadening its potential applications. Our methodology offers several advantages:

(1) Economical and unbiased: By utilizing publicly available online review data, which encompasses customers from across the United States, our approach is both cost-effective and geographically unbiased. In contrast, traditional methods using surveys and questionnaires would be more costly and localized.
(2) Data-driven: The methodology enables the identification of patterns and trends, providing valuable insights. This data-driven approach supports informed decision-making and enhances the overall effectiveness of our analysis.
(3) Scalability: The framework is scalable, allowing for the analysis of multiple products across different platforms with large quantities of text reviews, given sufficient computing power.
(4) Product-agnostic: A key advantage of our methodology is its product-agnostic design; it can be applied to any product without requiring significant modifications to the pipeline. This flexibility is crucial in a rapidly evolving market landscape, where the ability to quickly adapt and analyze different products is essential. By maintaining a consistent analytical framework, our methodology allows for seamless integration of various product datasets, facilitating comparative analyses and trend identification across diverse product categories.

However, it is important to acknowledge a limitation of our methodology: it cannot establish causal relationships between events and observed changes. For instance, in our case study, although we identified both short-term and long-term changes, we cannot definitively attribute these changes solely to COVID-19 or other influencing factors. Also, a comparative study with a benchmark model is required to verify the above points. We will conduct additional experiments on this in our future research.

7 Conclusion and Future Works

This study employed an automated framework and publicly accessible online reviews to discern shifts in customer preferences for smartphones and laptops, both before and after the onset of the COVID-19 pandemic. Our empirical investigation revealed that our framework effectively captured alterations in preferences for specific product features prompted by the policy changes implemented during COVID-19. Specifically, our findings suggest that in the smartphone sector, attention may need to be directed toward features such as the camera, price, and battery. Conversely, for the laptop market, emphasis may be placed on aspects like the screen/camera, software applications, and customer service. These insights could prove invaluable for product designers and manufacturers seeking to align their strategies with evolving consumer needs in the post-pandemic landscape.

Furthermore, the methodologies and insights gleaned from this study offer valuable insights into product design strategies amid pandemics akin to COVID-19. The surge in online purchases during the pandemic underscored the efficacy of analyzing online reviews in uncovering potential shifts in customer preferences for product features, surpassing the effectiveness of traditional methods like surveys and interviews. This will enable product designers and manufacturers to quickly adjust their plans and strategies to cater to the changing needs of their customers.

However, it is important to acknowledge that, despite our analysis results, we cannot establish causal relationships between events and observed changes. While COVID-19 is undeniably a significant event, it remains uncertain whether it is the sole cause for the shift in customer preferences. Other latent factors may also influence these preferences. Nonetheless, it is noteworthy that many of the reviews used in our case study exhibit signs of contexts related to COVID-19. Some of these signs come with direct keywords such as COVID and pandemic; for example, "Tonight, while using it to do homework while being home from school for the Covid-19 lockdowns, it started sparking, smoking and got very hot with sparks coming from the blackened portion in the photo …" Other signs come with indirect keywords such as zoom meeting and work from home; for example, "Recently i found out the reason for poor audio in zoom meeting since the embedded microphone is of worst quality …" These examples serve as evidence that COVID-19 has impacted customer preferences, with customers expressing concerns about product features in the context of activities associated with the pandemic. Therefore, while we may not determine if COVID-19 is the sole cause for the shift in customer preferences, we can infer that it has had a significant impact on these changes.

This study is subject to several limitations. First, it exclusively focused on electronic products, while COVID-19 impacted various product categories differently. Furthermore, the selected products for our case studies were closely linked to the lockdown policies implemented during the pandemic. Consequently, the implications drawn from these products may not be universally applicable to others less affected by such policies. Second, the study relied solely on online reviews from Amazon, overlooking the wealth of feedback available on platforms like eBay and BestBuy. Additionally, the analysis primarily encompassed reviews from North American customers, predominantly English speakers. Future research endeavors will aim to broaden the scope by incorporating reviews in diverse languages from various online platforms. Third, the proposed method has a limitation in detecting implicit features in review data. The keyword detection would miss the review “This smartphone shows a great performance.” which indicates a CPU without mentioning keywords for the CPU. In future research, we plan to utilize the context-based approach using state-of-the-art language models, such as BERT and GPT, to address this limitation. Lastly, while this study successfully identified shifts in customer preferences for smartphones and laptops before and after the COVID-19 outbreak, attributing these changes exclusively to the pandemic remains a topic warranting further investigation. For example, enhancements in product features may bias the sentiments and feature importance. Similarly, Sec. 6.2 reveals disparities in short-term and long-term trends for some product features, but the underlying reasons for this incongruence remain undiscovered. Subsequent research endeavors will delve into uncovering the causes of this inconsistency.

Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The datasets generated and supporting the findings of this article are obtainable from the corresponding author upon reasonable request.

Appendix: Number of Reviews Per Period

Table 9 provides the number of reviews per period in Figs. 7–10 after data preprocessing.

Table 9 Number of reviews per period

Period	Smartphone	Laptop
2018 H2	633	4450
2019 H1	912	3381
2019 H2	3326	7180
2020 H1	2422	5192
2020 H2	326	2806
2021 H1	1170	4213
2021 H2	1712	4243
2022 H1	1034	2368

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