INVESTIGATION OF CUSTOMER PREFERENCE CHANGES FOLLOWING COVID-19 MARKET DISRUPTION USING ONLINE REVIEW ANALYSIS

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ABSTRACT

COVID-19 pandemic has continued to pose a challenge to the society for almost three years, adversely affecting all segments of population in a scale unseen in the recent decades. Over the course of COVID-19 pandemic, many people have lost their jobs and income. These social and economic impacts have disrupted the market, potentially altering people's attitudes towards different product features. Therefore, this paper investigates the changes in customer preferences on various features of different products, before and after COVID-19 pandemic, using online review analysis. The proposed framework consists of four stages. Firstly, product review data is collected and preprocessed. Secondly, customer interest in product features is explored using latent Dirichlet allocation. Thirdly, customer sentiment for these features is analyzed with Valence Aware Dictionary and sEntiment Reasoner. Finally, the importance of each feature is calculated based on interpretable machine learning. The proposed method is tested on two real-world datasets – smartphone and laptop reviews. The result reveals the changes in customer sentiments and preferences for product features, thus helping companies quickly establish strategies in rapidly changing market environments.

Keywords: Market implications, User centred design, Semantic data processing, Machine learning

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1 INTRODUCTION

While there have been many natural disasters in the recent decades, COVID-19 pandemic has one of the most profound social and psychological impacts. Given its highly infectious nature and prolonged duration, people have been forced to work/study from home over an extended period of time. Due to the unprecedented social changes, the crisis has brought forth an implementation of various policies and practices that have impacted not only individuals' lives, but also our society, including governments, industrial companies, and academic institutions (Sarkis et al., 2020). Consequently, the global economic downturn has led to supply chain disruptions, shutdowns, plummeted demand, and unemployment (Aslam et al., 2020).

Due to the emergence of COVID-19, the social changes have affected people's lives, including their purchase behavior. These changes have caused uncertainties and challenges to product designers and manufacturers. The extended work/study-from-home in fear of infection in public spaces has potentially stimulated unconventional customer needs. For example, cameras, speakers, and microphones have become essential, because onsite lectures for students and meetings in company buildings have become online. For product development, it is crucial for companies to adapt to these potential shifts of customer preferences. However, to the best of our knowledge, not many studies have been done on dynamic changes in customer preferences for product features following a major crisis such as the COVID-19 pandemic.

This paper is to identify changes in customer preferences on various features of different products, before and after the COVID-19 pandemic, using publicly available online reviews. While traditional methods, such as surveys and interviews, have been used to study customer preferences, these methods are limited, expensive, and geographically restricted. In contrast, there is an abundance of online reviews, which are readily and publicly available on the Internet. Since the volume of online purchases has surged during COVID-19, analyzing online reviews allows us to investigate the potential shift of customer preferences in product features more effectively than traditional methods such as surveys and interviews. As such, this paper presents an empirical research that applies a semi-automatic framework to study customer preferences using online reviews before and during COVID-19. Our methodology includes four stages: (i) data collection and preprocessing, (ii) customer interest analysis, (iii) customer sentiment analysis, and (iv) feature importance analysis. To demonstrate its functionality, we have conducted two case studies using Amazon review data for two product categories: smartphones and laptops.

This paper is organized as follows: section 2 reviews relevant prior work/literature on customer preference elicitation and customer preference research in COVID-19 pandemic; section 3 describes our methodology; sections 4 and 5 present two case studies, one about smartphones and the other about laptops; section 6 concludes this paper.

2 LITERATURE REVIEW

2.1 Customer preference elicitation

Over the last decades, many researches have been conducted on improving product design using online reviews. As compared to conventional methods, such as questionnaires and surveys, which are usually expensive to scale in size and potentially prejudiced due to temporal and geographical limitations, methodologies using online reviews are easier and more economical to implement, while its results are potentially less biased. As customer preferences are manifested from their interaction with product attributes (Chen et al., 2013), Chen et al. (2013) proposed analytical discrete choice models to investigate different customer preferences and predict their purchase decisions. Tuarob and Tucker (2015) used the rule-based method with seed features and pre-defined rules for feature extraction. Recently, more literatures have been using sentiment analysis to elicit customer preferences from online reviews. Zhang et al. (2016) proposed an opinion mining algorithm to capture the relationship of product attributes. Jiang et al. (2017) proposed a method to infer the future product feature importance using a fuzzy time series model. Bag et al. (2019) developed a framework to build a prediction model based on the social perception score of the brand and review's polarity. Suryadi and Kim (2019) proposed a method to automatically obtain product usage context via machine learning models. Zhou et al. (2020) adopted latent Dirichlet allocation (LDA) for analyzing the review data.

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LDA returned the topic mentioned in reviews and those that are related to product features were selected. Park and Kim (2020) extracted phrases from the review data and embedded them using word vectors composing the phrase. Then, spectral clustering was applied to the embedded phrases. The method returned clusters consisting of sub-feature terms. Joung and Kim (Joung (a), 2021) proposed a method to apply information fusion-based SHapley Additive exPlanation (IFSHAP) in deep neural network to understand product attribute importance. Marion and Fixson (2021) explores the impact of digital tools on the innovation process, work dynamics, collaboration, and organization in the development of new products. Mertens et al. (2023) investigates the intellectual structure of product modularization in new product development over a 30-year period and identifies three key research perspectives, highlighting the need for a more common view and shared concepts to advance the field through interdisciplinary collaboration and further research.

However, there are few papers that investigate the dynamic changes in customer preferences about the product features in a time of major crisis. Given the ready availability and convenience of online review analysis, product designers and manufacturers can quickly gather valid data and modify their strategies accordingly to improve customer experience.

2.2 Customer preference research in COVID-19 pandemic

COVID-19 pandemic has one of the most profound social and psychological impacts. During COVID-19, many countries have adopted a lock-down policy by enforcing social distancing and work/study from home setting to prevent the spread of the virus. Consequently, stores, businesses, and schools were closed, and the working mode changed to telecommuting (Sarkis et al., 2020; Aslam et al., 2020). These economic downturn have forced consumers to change their purchase behavior, which has changed the demand dramatically (Dunn et al., 2020). A variety of researches have investigated the change of customer preferences due to COVID-19 through traditional methodologies, such as questionnaires and interviews. Kim et al. (2021) investigate the dynamic change of customer sentiment on product features following COVID-19 through sentiment analysis based on refurbished smartphone online reviews. Bhargava et al., (2020) studied the decline of customer consumption during COVID-19 for each retail category. According to the paper, although consumption of groceries and household supplies increased, other items (e.g., electronics, automobiles, gasoline, clothing, etc.) have decreased significantly. Fernandes (2020) investigated and estimated the impact of COVID-19 on the global economy through various scenarios based on recent data such as the stock market and GDP. The results of various scenarios showed that a global economic downturn is inevitable, and how long and deep it will depend on the success of the anti-COVID-19 spread prevention measures. Song et al. (2022) has discovered that hotel customer satisfaction and its influencing factors have changed significantly during COVID-19; hotel customer satisfaction during COVID-19 is greatly influenced by service quality. COVID-19 has affected the demand for new products as well as remanufactured/refurbished products. According to a report by re-commerce platform Cashify, Koshi et al. (2020) uncovered that the demand for refurbished smartphones has increased due to COVID-19. The results showed that customers became cautious about consumption during COVID-19, and consequently they became more concerned about price and affordability.

While many studies mentioned above have investigated and revealed the change of customer preferences during COVID-19, very few address the issue in the context of product design. The goal of this paper is to fill the research gap by conducting an empirical research on various electronic products, such as smartphones and laptops. These products are updated frequently based on the market feedback, which makes the results of this paper more meaningful and significant.

3 METHODOLOGY

The overall framework of this study is presented in Figure 1. The proposed methodology consists of four stages: (i) data collection and preprocessing, (ii) customer interest analysis, (iii) customer sentiment analysis, and (iv) feature importance analysis. The details of each stage are presented in the following subsections.

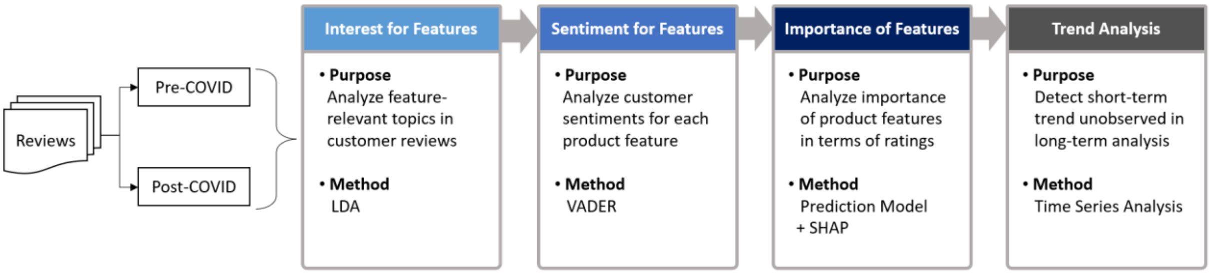

Figure 1. Overview of the proposed methodology

3.1 Data collection and preprocessing

The input data is online reviews of a target product, divided into pre-COVID and post-COVID time divisions. The reference point for data division can be determined by relevant indices, such as the ratio of positive-COVID cases and the unemployment rate. There are different approaches to obtaining two review datasets depending on the time of collection. The first approach is to collect customer reviews now and divide them into two datasets. The second approach is to use the review data collected during different periods, e.g., around the outbreak of COVID (2020) and a while after the pandemic (2022). This study adopts the second approach because the reviews collected in 2022 contains little data for the pre-COVID period. For example, a list of the top 100 best-selling items includes recently released products. Therefore, the reviews for these products were written in Post-COVID period.

Online reviews for consumer products can be collected from well-known e-commerce websites, such as Amazon and eBay. The data from these websites contain review products, review dates, ratings, and review titles and contents. The collected data go through preprocessing before further analyses. Non-alphabetic characters except punctuation are removed from review text, and punctuation marks indicating the end of a sentence are replaced with a period. An uppercase is converted to a lowercase, and words are lemmatized. Next, the reviews are filtered by brands so that two datasets contain the reviews for the same list of brands.

Since this research focuses on customer preferences toward product features, the words irrelevant to product features are removed. This study utilizes product manual documents for word filtering. The product manuals can be obtained from the official websites of manufacturers and online commerce websites. Among words in the review data, those not appear in the product manuals are removed.

3.2 Interest for features

This stage identifies product features of customer interests. LDA is employed in this study because it is one of the most popular models in online review analysis (Bi et al, 2019, Joung (a), 2021, Wang et al., 2018). Product feature words are assumed to be nouns (Guo et al, 2009, Hu, 2004, Joung (b), 2021, Suryadi, 2018), so a review-noun matrix is generated as the input for LDA. The number of topics is determined based on the topic coherence, and the output of LDA is a topic-keyword matrix. Since the input data contains nouns only, all the keywords are also nouns. Each topic is labeled based on the keywords in the topic. These labels represent product features of customer interests (Bi et al, 2019, Joung (a), 2021, Wang et al., 2018).

The feature keywords can be extended by adding synonyms. This study adopts word embedding (Mikolov et al., 2013) for synonym extraction. First, feature-relevant keywords are selected from the top 30 nouns in each topic. Then the top 20 words most similar to selected nouns are extracted from word vectors. The union of these word sets becomes feature keywords. Some open-source libraries or software, such as the Gensim library of Python and the Stanford Topic Modeling Toolbox, can be utilized for this task.

3.3 Sentiment for features

Sentiment analysis is conducted by two steps - define target words and collect sentiment indices connected to those words. In this study, target words are feature keywords obtained in Section 3.2. Regarding sentiment detection, there exist various indices, such as review ratings, the sentiment score of sentences mentioning target words, and that of adjectives connected to the target word.

This paper employs the second approach, the sentiment of sentences since it is the most widely used approach. Specifically, this study estimates customer sentiments for product features using VADER,

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an unsupervised machine learning model based on lexicons and rules to measure the sentiments of text data (Hutto, 2014). This model can be easily applied to other fields because it does not require manual labeling for the training data. The VADER sentiment analysis provides the polarity and intensity of the given sentence. Since a reviewer may mention the same feature more than once, this study calculates the average sentiment score of relevant sentences. For example, a customer says *"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."* The first and the third sentences are selected as reviews for the battery feature. The sentiment score by VADER is 0.6369 and 0.4404 respectively. The reviewer's sentiment for the battery is (0.6369+0.4404)/2 = 0.5387. For each review, the sentiments for all product features are calculated. If the reviewer does not mention any feature keywords for feature K, the sentiment for K remains empty.

3.4 Importance of features

This stage analyzes the importance of product features, which means the effect of each feature on the review ratings. This study modifies the method suggested by Joung & Kim (Joung (b), 2021) based on interpretable machine learning. It is considered necessary to summarize the method for importance estimation while the details are available in the reference (Joung (b), 2021).
Figure 2 shows a flowchart of feature importance estimation. The dataset for this analysis is a review-sentiment/rating matrix. Table 1 shows an example of this input data. Each review has a vector of sentiment scores for product features and a star rating. The sentiment scores are obtained in Section 3.3 and range from -1 to 1, where -1 is very negative, 0 is neutral, and 1 is very positive. The input data for the prediction model cannot be empty. Therefore, when a reviewer does not mention feature K, the sentiment for K is filled with 0. The reviews with 0 scores for all features are removed because they have no benefits in predicting star ratings. The star ratings have integer values between 1 and 5, and they are classified into two categories. Ratings 4 and 5 are assigned to class 1 representing that customers are highly satisfied with products. The remaining values are class 0 indicating low satisfaction or complaints about products. Next, the method trains a model that predicts review ratings based on customer sentiment for product features. This research tests four different models (SVM, LGBM, XGBoost, and neural networks) and chooses the one with the best performance (F1 score). In the final step, the trained model is interpreted by SHAP, one of the most popular interpretable machine learning techniques, and the obtained SHAP values are further analyzed. Specifically, this study calculates the mean of the absolute values of SHAP results for each product feature, and the resultant value represents the importance of each feature.

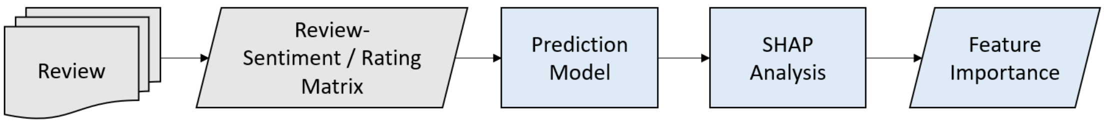

Figure 2. Flowchart of feature importance estimation

Table 1. A dataset for importance estimation

Review	f1	f2	…	fk	Review Rating
1	0.0	0.6	…	-0.2	1
2	0.4	0.0	…	0.3	1
3	-0.2	0.1	…	0.0	0
…	…	…	…	…	…
N			…		0

4 CASE STUDY - 1

This paper selected a smartphone as one of the case studies because the smartphone market has experienced the worst decline in history (1Q20-1Q19, -20.2%) due to the pandemic (Gartner, 2020). This section presents the analysis result of customer reviews for smartphone products.

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4.1 Data

This study collects two types of data: (i) online customer reviews; (ii) product manual documents.

The smartphone review data was collected from Amazon.com. The reviews for pre-COVID was collected on July 11, 2020, and those for post-COVID was collected on March 25, 2022. The reference point for dividing before and after COVID was set to April 1, 2020, referring to the US unemployment rate (US Labor, 2022). Each dataset was filtered by review date so that each one contains the same range of dates, i.e., two years before and after the outbreak of COVID-19. Next, the data was filtered by brand so that two datasets have reviews for the same list of brands. This study considered reviews for new smartphones and used only verified reviews provided by Amazon for the authenticity of the data. The total number of reviews for pre-COVID is 7,293, written from April 1, 2018 to March 31, 2020. The number of reviewed products is 29. The post-COVID data contains 4,338 reviews for 17 products written between April 1, 2020 and March 25, 2022.

Regarding product manuals, this study used manual documents for seven different smartphone products. These documents are distributed by manufacturers and available online. Although this is a smaller number than the number of smartphones covered in this study, it is assumed that the features and functions of smartphones are similar, so it will be sufficient to cover the representative smartphone features by analyzing the smartphone manuals of these seven different models. Among words in the review data, those not appearing in the manual documents were removed.

4.2 Result

The list of topics obtained from LDA is [network, screen, camera, battery, security, price]. Customers mentioned the same feature categories before and after COVID-19. Regarding feature keywords, there exists a difference in the price feature. Specifically, new keywords `quality' and `performance' appear in the post-COVID reviews. It can be interpreted that customers are more concerned about product performance versus price due to decreased income. 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. [...] Many advanced features from a "midrange" phone.", "The battery life is good, it is decently powerful for the price."* For the camera feature, although a new keyword 'zoom' appears in post-COVID, it's not related to the pandemic. Most reviews mentioning 'zoom' talk about the advanced zoom functions of smartphone cameras, not the 'Zoom meeting' application. There were not any noticeable differences in the keywords of the remaining features.

To observe the changes in the degree of interest in smartphone features, this study analyzed the ratio of reviews mentioning each feature. All features except for the price show statistically significant increases in the ratio at $\alpha=0.0001$. This result indicates that customers express their opinions about product features more frequently after COVID-19. It is probably because customers become more meticulous about product quality versus price, as mentioned above.

COVID-19 also affects customers' sentiments toward product features. Figure 3 (a) shows the changes in customer sentiment for smartphone features before and after COVID-19. The x-axis lists the product features from LDA, and the y-axis represents the sentiment score for each feature. The sentiment values do not have a normal distribution, so this study used a rank sum test instead of a two-sample t-test for statistical analysis. In the graph, the asterisk (*) means that the difference is statistically significant at the level of $\alpha=0.0001$. The result shows that the sentiment score for the screen, camera, and price has significantly decreased. Considering the unemployment rate rapidly rising after COVID-19 (US Labor, 2022), it is expected that consumers look for affordable or low-tier smartphones. Customers may have complaints about high-tier smartphones, which has been reflected in the decreased sentiment for the price. The changes in the screen and camera are probably due to the changes in smartphone usage. After the breakout of COVID-19, most states in the US enforced lockdown, so people had little chances for in-person meetings. Since their needs for interaction were not met, people would look for alternatives, such as face talk and online meetings. As a result, users more care about the interface for input (camera) and output (screen). For example, customers say *"Unfortunately will return this since the primary need is for video calls and the front camera performs worse than a 100$ phone."* They want a better interface for online meetings, so the sentiments for current screen and camera features have decreased.

* The result is statistically significant at the α = 0.0001 (Rank Sum Test)

Figure 3. (a) Customer sentiment for smartphone features in pre/post-COVID-19, (b) Importance of smartphone features in pre/post-COVID-19

In this study, not only the sentiment for product features but also the importance of each feature was analyzed. The result is shown in Figure 3 (b). The y-axis represents the importance score of each product feature. The scores are normalized so that they are summed up to 1. The figure shows changes in the importance scores and the ranks of product features. As mentioned in Section 3.4., the importance estimation is based on the absolute value of SHAP results, therefore the data is not normally distributed. A rank sum test was performed to assess whether the changes in the importance scores were significant. As a result of statistical verification, there were significant differences in the screen, camera, battery, and price. In terms of ranking, the top 3 important features have been changed. The most important feature was changed from the camera to the price. As mentioned above, COVID-19 negatively affected the customer's income level resulting in decreased sentiments. Naturally, the price became the most significant feature when purchasing smartphones. The battery was the third-most important feature in pre-COVID and has risen to second place in post-COVID. It is probably because people have less outdoor activity after the pandemic. As customers spend more time using smartphones, they care more about battery life. For example, customers say *"So far it is good phone battery does last all day [...] I do use my phone all day internet radio like pandora [...]", "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 mention the battery feature more frequently and are satisfied with the battery performance, as shown in Figure 3 (a).

5 CASE STUDY - 2

In the second case study, we study the reviews of laptops from Amazon. Since the COVID-19 pandemic, the usage of laptops increases tremendously due to the extended work/study from home policy. This section presents the analysis result of customer reviews for laptop products.

5.1 Data

Similar to the previous case study, this study collects two types of data: (i) online customer reviews; (ii) product manual documents. Under the same data preprocessing procedures, the total number of reviews for pre-COVID is 32,188, written from April 1, 2018 to March 31, 2020. The number of reviewed products is 155. The post-COVID data contains 24,487 reviews for 103 products written between April 1, 2020 and March 25, 2022.

Regarding product manuals, this study used manual documents for seven different laptop products. These documents are distributed by manufacturers and available online. Similar to the previous case study, it is assumed that the features and functions of laptops across different brands are close, so it will be sufficient to cover the representative laptop features by analyzing the laptop manuals of these seven different models. Among words in the review data, those not appearing in the manual documents were removed.

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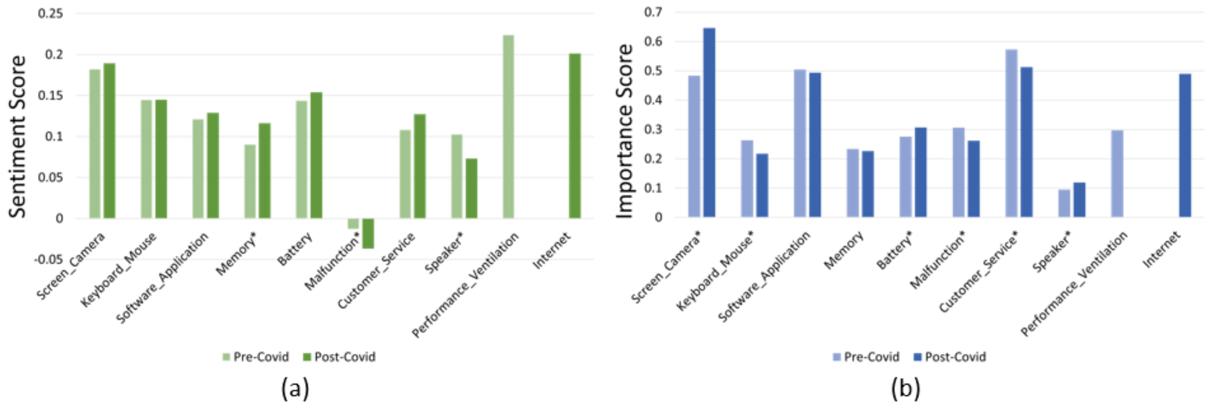
5.2 Result

Based on LDA, the list of topics obtained for pre-COVID is [screen_camera, speaker, malfunction, keyboard_mouse, software_application, memory, battery, customer_service, performance_ventilation], and the list for post-COVID is [screen_camera, speaker, malfunction, keyboard_mouse, software_application, memory, battery, customer_service, internet]. Different from smartphone case study, pre-COVID and post-COVID topics are not entirely identical: performance_ventilation only occurs in pre-COVID dataset, whereas internet occurs only in post-COVID dataset. This change is probably caused by the increased demand for online work due to COVID-19, so that customers may express more concern regarding features associated to Internet after COVID-19 has happened.

To observe the changes in the degree of interest in laptop features, this study analyzed the ratio of reviews mentioning each feature. It is observed that the ratios of screen_camera and speaker increase, whereas the of ratios associated the remaining laptop features decrease. These changes, besides the one associated to speaker, are all statistically significant at α=0.0001. Different from that of the previous case study, this result indicates that customers' interests towards different laptop features have changed in different directions after COVID-19. It is surmised that these different changes are caused by the different work/study environment pre-COVID and post-COVID. Before COVID-19, people may need to bring their laptops to their work spaces (such as company buildings and lecture halls), but this need has been reduced after COVID-19, because people have been required to work/study from home. This shift of need may impact customers' decisions when potentially purchasing a new laptop.



* The result is statistically significant at the α = 0.0001 (Rank Sum Test)

Figure 4. (a) Customer sentiment for laptop features in pre/post-COVID-19, (b) Importance of laptop features in pre/post-COVID-19

COVID-19 also affects customers' sentiments toward product features. Figure 4 (a) shows the changes in customer sentiment for laptop features before and after COVID-19. The x-axis lists the product features from LDA, and the y-axis represents the sentiment score for each feature. The sentiment values do not have a normal distribution, so this study used a rank sum test instead of a two-sample t-test for statistical analysis. In the graph, the asterisk (*) means that the difference is statistically significant at the level of α=0.0001. According to the figure, while all common laptop features display different sentiment values pre-COVID and post-COVID, only the differences in memory, speaker, and malfunction are statistically significant. Previously before COVID-19, people may not be too concerned about the quality of speaker, because most of the work is supposed to be done on-site. However, in the online work/study from home setting, people have to use laptops for online discussions and meetings. As such, the quality of speaker (which includes headphones), which will determine their user experience in online meetings, is given more attention and consequently, more criticism. Similarly, when a laptop is not functioning properly, customers will be severely hampered in their capabilities of working online. Their workflow will be disrupted, and thus this intensely negative sentiment is reflected in their reviews. On the other hand, different from the previous case study, where screen and camera have shown statistically significant decrease, in this case study, we observe similar sentiment scores in screen_samera pre-COVID and post-COVID. This difference may be potentially explained by the availability of external devices to make up for the sub-par features that do

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not satisfy the needs of customers. When using a laptop, customers can purchase an independent and external camera, if the camera on the original laptop does not satisfy their requirement. However, this kind of external camera is very rare in the smartphone markets.

Similar to the previous case study, besides sentiment analysis, we have also conducted an importance analysis on laptop features. The result is shown in Figure 4 (b). The y-axis represents the importance score of each product feature. The scores are normalized so that they are summed up to 1. The figure shows changes in the importance scores and the ranks of product features. As mentioned in Section 3.4., the importance estimation is based on the absolute value of SHAP results, therefore the data is not normally distributed. A rank sum test was performed to assess whether the changes in the importance scores were significant. According to the figure, there are significant differences in the screen_camera, keyboard_mouse, battery, malfunction, customer_service, and speaker. Among these laptop features, screen_camera has risen to the most important after COVID-19. This is expected; the lock-down during COVID-19 has forced people to interact with others via laptops, and thus screen_camera, being the media with which people are making interaction with the external world, has certainly gained more attention.

6 CONCLUSION & FUTURE WORK

This paper has identified the change in customer preferences on both smartphones and laptops, pre-COVID and post-COVID, using an automatic framework as well as publicly available online reviews. According to our empirical research, change of preferences towards certain product features in response to the policies implemented during COVID-19 is captured by our framework. Specifically, product designers and manufacturers in smartphone domain may want to look into features such as Camera, Price, and Battery; whereas those in laptop domain may want to look into Screen_Camera, Software_Application, and Customer_Service. The proposed method of identifying customer needs not only provides increased business opportunities, but also enables companies to drive customer-driven innovation, which is essential for responding to changing customer needs during times of crisis. By collecting and analyzing large amounts of online data, companies can swiftly detect market disruptions and develop timely responses in their next-generation products.

In addition, the methodologies and findings of this study can shed light on product design practices during a pandemic similar to COVID-19. Since the volume of online purchases has surged during COVID-19, analyzing online reviews allows us to investigate the potential shift of customer preferences in product features more effectively than traditional methods such as surveys and interviews, thus allowing product designers and manufacturers to quickly adjust their plans and strategies to cater to the changing customers' needs.

This study has some limitations. First, this study has only investigated electronic products, while there are many other different categories that are affected by COVID-19 in a different way. In addition, the chosen products for our case studies - smartphones and laptops - are both closely associated to the lock-down policies introduced in COVID-19. Thus, the implication drawn from these products may not be applicable to other products that are not as closely associated to the lock-down policies as smartphones and laptops. Second, this study has only reached out to the online reviews from Amazon, while there are many other online platforms, such as eBay and BestBuy, etc. In addition, the scope of online reviews has been confined primarily to North America customers, who mainly speak English. In our future work, we may extend our scope to include online reviews in different languages from different online platforms. Third, while this paper has identified changes in customer preferences on both smartphones and laptops before and after COVID-19 outbreak, whether COVID-19 is the sole cause for this change remains to be a question for future research.

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