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Evolution In Consumer Sentiment and Purchase Pat-Tern: A Study on Work From Home Products Purchased During Covid-19

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FACULDADE DE **ECONOMIA**

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EVOLUTION IN CONSUMER SENTIMENT AND PURCHASE PATTERN: A STUDY ON WORK FROM HOME PRODUCTS PURCHASED DURING COVID-19

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Abstract

Consumers use social media to share their opinions about products, creating a valuable opportunity for Electronic Word of Mouth (eWOM) and generating massive user-generated content, which allows companies to identify significant disruptions. Covid-19 was one of the most severe disruptions in modern days, generating several meaningful shifts in consumer behaviour. This dissertation aims to assess if Covid-19 disrupted eWOM for Work From Home (WFH)-related products, test if Covid-19 changed people's sentiment toward WFH-related products and understand which online furniture stores had a more positive or negative impact during the covid-19 outbreak. To answer these goals, I analyse user-generated content from Twitter on responses for the top 20 online furniture stores in the US market, assessing the evolution of the interactions on Twitter and the changes in people's sentiment during the pandemic using sentiment analysis. The main findings are: (1) people posted more about their WFH products during Covid-19 lockdowns; (2) sentiment towards WFH products worsened due to Covid-19 restrictions and not the product itself; and (3) for some online furniture stores, the changes in sentiment for a specific period are explained by Covid-19 restrictions, but for the other periods, I identify some firms' idiosyncrasies that may explain the fall in customers' sentiment. This study mainly contributes to the literature by being the first to dynamically analyse eWOM and test if its dynamics may be influenced by external events, such as a pandemic.

Keywords: Covid-19, Electronic Word of Mouth, Sentiment Analysis, Twitter, Work From Home.

JEL Codes: M30, M31

Resumo

Consumidores usam as redes sociais para compartilhar as suas opiniões sobre produtos, criando uma valiosa oportunidade para Passa-Palavra Eletrónico (PPE) e gerando conteúdo massivo gerado pelo usuário, que permite às empresas identificar disrupções significativas. O Covid-19 foi uma das disrupções mais graves dos dias modernos, gerando várias mudanças significativas no comportamento do consumidor. Esta dissertação tem como objetivo avaliar se o Covid-19 impactou o PPE para produtos relacionados com o Trabalho Remoto (TR), testar se o Covid-19 mudou o sentimento das pessoas em relação aos produtos relacionados com o TR e entender quais lojas de móveis online tiveram um impacto mais positivo ou negativo durante o surto de Covid-19. Para responder a estes objetivos, analiso o conteúdo gerado no Twitter sobre as respostas das 20 principais lojas de móveis online do mercado dos EUA, avaliando a evolução das interações no Twitter e as mudanças no sentimento das pessoas durante a pandemia usando análise de sentimento. As principais descobertas são: (1) as pessoas postaram mais sobre os seus produtos de TR durante os confinamentos do Covid-19; (2) o sentimento em relação aos produtos de TR piorou devido às restrições do Covid-19 e não ao produto em si; e (3) para algumas lojas de móveis online, as mudanças de sentimento para um período específico são explicadas pelas restrições do Covid-19, mas para os outros períodos, identifico idiossincrasias de algumas empresas que podem explicar a queda no sentimento dos clientes. Este estudo contribui principalmente para a literatura por ser o primeiro a analisar dinamicamente o PPE e testar se a sua dinâmica pode ser influenciada por eventos externos, como uma pandemia.

Palavras-chave: Covid-19, Passa-Palavra Eletrónico, Análise de Sentimento, Twitter, Trabalho Remoto.

Código JEL: M30, M31

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1. INTRODUCTION

Social media has significantly changed how customers and businesses relate to each other. Nowadays, consumers use social media to share their opinion about products and services, creating a valuable opportunity for Electronic Word of Mouth (eWOM). Consequently, eWOM generates massive user-generated content allowing companies to identify important changes in customers' needs that may occur due to significant disruptions.

Covid-19 was one of the most severe disruptions in modern days, generating several meaningful shifts in consumer behaviour. On the one hand, as people had to work, study, and relax at home, professional and personal life boundaries have blended, changing existing habits exacerbated by digital technology. In fact, one of the most significant changes during Covid-19 that led to massive sales was Work from Home (WFH). On the other hand, several consumers tried digital and remoted experiences for the first time, naturally leading consumers to comment on these products on social media. Thus, during the pandemic, were there any changes in the eWOM related to WFH products? Did online stores seize the opportunity, and how did customers react on social media?

So far, the literature on consumer marketing during Covid-19 has developed into two strands. On the one hand, several studies have analysed how Covid-19 changed consumers' habits, such as payment methods, or hygiene and cosmetic standards (e.g. Akana, 2021; Mościcka et al., 2020). On the other hand, several studies have explored social media consumer reviews to infer changes in perceptions and sentiments during Covid-19 (e.g. W. K. Chen, Riantama, & Chen, 2021; Jung, Yoon, & Song, 2021).

Thus, most studies focus on understanding what social media users feel regarding topics of a generic nature, such as Work From Home, Online Education, and Digital Platforms. To the best of my knowledge, no study analyses disruptions in sentiment regarding any specific product or online furniture stores, exclusively to WFH-related products.

Thus, the goal of this dissertation is threefold. First, this dissertation aims to assess if Covid-19 disrupted eWOM for WFH-related products. Second, I test if Covid-19 changed people's sentiment toward WFH-related products. To answer these goals, I analyse user-generated content from Twitter on responses for the top 20 online furniture stores in the US market. The idea is to collect the posts on Twitter related to WFH. From this data, I assess the evolution of the interactions on Twitter and the changes in people's sentiment during the pandemic using sentiment analysis. Sentiment analysis allows me to evidence if people had a better (or worse).

My final goal is to understand which online furniture stores had a more positive or negative impact during the covid-19 outbreak, which can help companies adapt their strategy and offer new products or even continue to offer more products that are performing well.

This study contributes to the literature in three different ways. First, by using longitudinal data, this study is the first to dynamically analyse eWOM and test if its dynamics may be influenced by external events, such as a pandemic. Second, by performing a sentimental analysis in online furniture stores, this study is the first to compare sentiment along different players in the Furniture Sector. Third, by using Twitter content and machine learning to perform sentimental analysis for WFH product, the study is the first that analyse specific WFH products using that method.

My main findings are as follows. First, the results suggest that people posted more about their WFH products during Covid-19 lockdowns. Second, the results indicate that sentiment towards WFH products worsened due to Covid-19 restrictions and not the product itself. Third, for some online furniture stores, the changes in sentiment for a specific period are explained by Covid-19 restrictions. However, for the other periods, I identify some firms' idiosyncrasies that may explain the fall in customers' sentiment.

The study has several marketing and management implications. On the one hand, understanding customers' sentiment is necessary to perform a good service recovery or adjust the strategy. On the other hand, knowing about their competitors makes the company more competitive and merging IT and Marketing adds much value to the company.

The rest of this dissertation is structured as follows. Section 2 presents the Literature Review, where all the relevant topics for this study in literature will be discussed. In Section 3, I present the methodology used in the study. Section 4 presents the data used in the analysis and the descriptive analysis. Section 5 presents the results of the study. Finally, Section 6 concludes.

2. LITERATURE REVIEW

2.1. Definitions

This dissertation has four key concepts: Electronic Word-of-Mouth (eWOM), Data Mining, Text Mining, and Sentiment Analysis. Firstly, according to Litvin, Goldsmith, & Pan (2008), eWOM can be defined as all informal communication related to goods or services and their vendors transmitted across consumers through Internet-based technologies.

Secondly, Fayyad, Piatetsky-Shapiro, & Smyth (1996) consider data mining as one of the steps in the Knowledge Discovery from Database (KDD) process. This process involves applying data analysis and algorithms to discover valuable patterns from large datasets (F. Chen et al., 2015). Besides discovering patterns, KDD can also produce patterns on top of the data (Fayyad et al., 1996) and may predict or describe behaviours using large amounts of data (Mukhopadhyay, Maulik, Bandyopadhyay, & Coello, 2014).

Thirdly, text mining deals with analysing text supported by a machine. This technique aims to extract essential information from texts, dealing with the imprecision and uncertainty of words through machine learning and statistical algorithms (Hotho, Nürnberger, & Paaß, 2005). Reaching new levels of usage, text mining is now being used in social media to understand consumer patterns (He, Zha, & Li, 2013).

Lastly, Sentimental Analysis (also known as Opinion Mining) is the field of study that analyses consumer opinions and feelings about products and services, focusing primarily on opinions that express or imply positive or negative feelings (B. Liu, 2012). Sentiment Analysis is a data mining technique that applies natural language processing, computational linguistics, and text analytics to interpret content from textual data (Chaturvedi, Mishra, & Mishra, 2017).

2.2. Electronic Word of Mouth

Electronic Word of Mouth (eWOM) plays an essential role in customer decisions once that kind of comment can directly influence the preference for a brand, product or service (Teng, Khong, Chong, & Lin, 2016; Viglia, Minazzi, & Buhalis, 2016). Once Word of Mouth became digital, marketers started to concern about the implications for some services, mainly the tourism and restaurant sectors. Starting with the Hospitality and Tourism sector, I highlight four studies that analysed eWOM. Firstly, Litvin et al. (2008) analyse how online interpersonal influence, or eWOM, can influence the sector. Throughout the study, the authors discuss strategies for harnessing media's power in the sector. As a result, they provide a conceptual model of eWOM for the hospitality and tourism sector, highlighting how marketers can manage eWOM from different online channels and the similarities between WOM and eWOM.

Secondly, Ye, Law, & Gu (2009) conduct an empirical study to investigate the impact of online customer-generated reviews on hotel room sales, using the largest travel website in China to collect the data. As a result, using a fixed effect log-linear regression model, they find a significant relationship between online user reviews and online hotel bookings.

Thirdly, using a different perspective, Vermeulen & Seegers (2009) apply consideration set theory to model the impact of online hotel reviews on consumer choice, using an experimental sample of 168 responses. As a result, the research confirms that exposure to online hotel reviews improves consumers' average probability of booking a room.

Lastly, Viglia et al. (2016), using similar methods as Ye et al. (2009), measure the impact of three dimensions (review score, review variance and review volume) on the occupancy rate of 346 hotels located in Rome, using the reviews found in websites such as booking.com, TripAdvisor and Venere.com. Their findings suggest that online reviews influence occupancy rate, with the review score having the highest impact.

Turning to the restaurant industry, the sector was also influenced by eWOM. For example, Z. Zhang, Ye, Law, & Li (2010) analyse how consumer-generated and editor-created reviews differently influence the behaviour of online users to eating at restaurants. Their findings suggest that consumer-generated reviews can significantly increase the online popularity of restaurants, whereas editor-created reviews may harm consumers' intentions.

Nowadays, emerging techniques in the machine-learning field have already opened new dimensions to eWOM (Verma & Yadav, 2021). Once people start to share their online opinions, social media and eWOM are targets of much research in Marketing (Alalwan, Rana, Dwivedi, & Algharabat, 2017). Due to the amounts of data people share in social networks, firms can better understand the market structure and competitors' products without interviewing a single person, using text-mining analysis (Netzer, Feldman, Goldenberg, & Fresko, 2012). Besides a large amount of user-generated content, textual contents have a significant power to predict consumer behaviour, explain a large part of product demand, and is more accurate than using just numeric information. (Archak, Ghose, & Ipeirotis, 2011).

2.3. Twitter

Twitter is different from other social media because the following relations do not require reciprocation, which means that you can follow a person, but one is not obligated to follow you back. Besides that, Twitter has gained popularity because of the possibility to share real-time trends and events (Kwak, Lee, Park, & Moon, 2010; Ranjan, Sood, & Verma, 2019). Nowadays, Twitter is the most popular micro-blog (Kaplan & Haenlein, 2011). On average, around 6000 tweets were made by second, representing 200 billion tweets per year (Internet Live Stats, 2021). In 2021 Q3, Twitter had around 56 million active users (Enberg, 2021).

Initially, user content from Twitter was used for eWOM branding. I highlight three studies that analyse the usage of eWOM branding. Firstly, Jansen et al. (2009) utilise more than 150.000 Twitter postings to investigate if microblogs are a trusting form of eWOM for consumer opinions regarding brands. Their results suggest that microblogging is an online tool for customers' eWOM, and marketers should discuss it for marketing strategy once web communications influence customer brand perceptions and purchasing decisions.

Secondly, Kim, Sung, & Kang (2014) investigate how the relationship between brands and customers influenced the engagement to retweet brand messages when brands started to use Twitter to communicate with customers. Their findings suggest that Twitter offers excellent opportunities for brands to promote eWOM via retweets, and consumer-brand relationships contribute to brand engagement.

Finally, Stone & Choi (2013) assess if Twitter is a viable content source for modelling sentiment analysis using Machine Learning. They conclude that Twitter user content for products is remarkably similar to other methods, suggesting that Twitter is a reliable user-generated source of information.

Besides branding, Twitter data were also analysed to understand tourism consumers' behaviour. For example, Sotiriadis & van Zyl (2013) explore how social media affects the purchase behaviour of tourists who use Twitter. The study's findings indicate three factors that influence the use of information originating from Twitter about tourism services: Twitter reliability, involvement degree, and user expertise.

Besides purchase behaviour, Twitter content can also be used to make predictions. To highlight those, I select three papers about election predictions. First, Tumasjan, Sprenger, Sandner, & Welpe (2010) study the German federal elections using more than 100.000 Twitter messages. Their findings suggest that Twitter can be considered a valid indicator of political opinion and election results.

Second, Choy, Cheong, Laik, & Shung (2012) predict US election results using more than 7 million tweets from the beginning of the campaign, suggesting two models to predict the election. As a result, both models indicated that Obama would win the 2012 election, which was validated by the election results.

Lastly, Budiharto & Meiliana (2018) use the tweets from President Candidates of Indonesia and relevant hashtags to predict the Indonesian Presidential election. Their findings confirm that Twitter is a valid poll for election results because their results were similar to four surveys conducted by institutes in Indonesia.

Traditional approaches to understanding consumer behaviour, such as surveys and focused groups, require large amounts of time and effort. Nowadays, Twitter can be used as an alternative to extract customer opinions about products, providing supportive information for producers. (Chamlertwat, Bhattarakosol, Rungkasiri, & Haruechaiyasak, 2012).

He et al. (2013) use Twitter to understand consumer patterns by applying text mining to analyse the content and extracting business value from the data for three large pizza chains: Pizza Hut, Domino's Pizza and Papa John's Pizza. As a result, they suggest that social media can be used to do competitive analysis on the leading ways, showing that the leaders actively engage their customers on social media, creating a bond.

Because of the amount of user-generated content, studies use Twitter to mine information from the users. One of the main goals of these studies is to understand the sentiment of a comment (Ranjan et al., 2019). Twitter is one of the most popular networks targeted by studies on social media (Kapoor et al., 2018).

Text Mining and Sentimental analysis are widely used to understand consumer opinion regarding several topics. Initiating with the automotive industry, Shukri, Yaghi, Aljarah, &

Alsawalqah (2015) apply sentimental analysis models of three leading automotive brands (BMW, Mercedes, and Audi) to extract the polarity and emotions of customers. Using Twitter content, their findings show different sentiments regarding each brand.

Using user-generated content from Twitter, Ibrahim, Wang, & Bourne (2017) apply text mining and sentimental analysis to understand the sentiment trends and engagement patterns between customers and brands in social media. Their findings suggest that Twitter is an excellent channel to explore market trends and improve companies' brand image and customer engagement.

In the same direction, Shirdastian, Laroche, & Richard (2019) analyse brand authenticity and sentiment polarity using Twitter comments about Starbucks. The authors propose a new framework to predict brand authenticity and sentiment polarity, achieving high accuracy in training and dataset.

He, Wang, & Akula (2017) propose an initial management framework for leveraging social media information and helping companies integrate Big Data analysis into the company scope. These authors use Twitter messages associated with retail industries to extract valuable knowledge and construct a useful model. Their findings suggest that the framework is sensible and fulfils the objective.

Twitter and Covid-19 were also analysed in recent studies. For example, several authors assess the sentiments about the outbreak. I highlight five studies about Covid-19 outbreak sentiment. First, Chintalapudi, Battineni, & Amenta (2021) study the tweets by Indian people throughout the Covid-19 lockdown using deep-learning models for text analysis (BERT). In this sense, they classify the tweets into four groups: fear, sadness, anger and joy. Moreover, these results encourage local governments to improve fact-checkers to overcome fake news. Secondly, Dubey (2020) studies the sentiments about Covid-19 in different countries using Twitter content. The findings point out that most countries took the lockdown with a positive and hopeful approach, although four countries showed signs of distrust and anger compared to the remaining eight countries. Thirdly, Pokharel (2020) focuses on sentiments for Covid-19 only in Nepal. As a result, the author concludes that most people from Nepal were positive and hopeful against the pandemic, but that sentiment can vary daily. Fourthly, Manguri, Ramadhan, & Amin (2020) extract Twitter content to perform sentimental analysis using the Naïve Bayes method to classify the tweets as Positive, Negative or Neutral to get insights from the data to help government organizations. The results indicate that people's reactions vary daily, and people have a more neutral sentiment. Lastly, Mansoor, Gurumurthy, Anantharam, & Prasad (2020) analyse global sentiment related to Coronavirus, Work From Home (WFH) and Online Learning and how people's sentiment in different countries has changed over time. To do so, they use Long Short Term Memory (LSTM) and Artificial Neural Networks (ANN) to classify people sentiment. As result, they find several inferences to understand the changing in sentiment over the months.

Besides the overall sentiment about the outbreak, several studies have analysed the impact of Covid-19 in the restaurant industry using sentiment analysis. Jung et al. (2021) use social media content to examine consumers' perceptions of dining-out before and during the Covid-19 outbreak. Their findings confirm that consumers changed their perceptions about dining-out due to Covid-19. Furthermore, the negative sentiment increased in 2020 after the outbreak compared to 2019.

In the same direction, Jia (2021) uses restaurant user-generated content posted by diners to describe customers' dining behaviours before and after the Covid-19 outbreak. The findings suggest that Covid-19 reduced customers' visits, ratings, and expenditures. Besides, factors that received too many complaints stopped being a priority for customers.

2.4. Covid-19 consumption change

According to Sheth (2020), consumption depends on the location and time, but that is not only limited to consumption. Consumer behaviour is highly predictable; that is why using past information to describe buying behaviour is so well spread. Thus, consumption is habitual but also contextual.

Sheth (2020) says that four major contexts can disrupt consumer habits. The first context is social when something changes in our routine, including workplace, community, neighbours and friends. The second context stands for technology when a technological breakthrough emerges. The third context stands for new rules and regulations, especially regarding public and shared spaces, such as indoor smoking. The fourth context stands for natural disasters, which is the case for global pandemics, including Covid-19 (Sheth, 2020).

Adopting new technologies, such as videoconferencing, e-learning, e-gaming, wearables, cashless payment, streaming and e-commerce (Brem, Viardot, & Nylund, 2021), will probably change the existing habits (Sheth, 2020).

Several studies aim to understand the changing habits after the covid period. Among those, I highlight three studies. Firstly, Janssen et al. (2021) focus on understanding the changes that occurred in Denmark, Germany, and Slovenia due to the Covid-19 outbreak, identifying the influence of different factors on individual food consumption. As a result, they find that changes were motivated by reduced shopping frequency and increased risk perception, driven by contextual and personal factors.

Secondly, Mościcka et al. (2020) aim to understand the changes in washing and cosmetic standards during the Covid-19 pandemic. They find that the washing and the usage of hand cream increased during the pandemic, whereas makeup and nails cosmetic decreased. Furthermore, nearly half of the respondents will maintain the new habits.

Lastly, Aristeidou & Cross (2021) study the impacts of distance learning on students' study habits (learning, assessment, and social activities), focusing on the factors associated with negative impacts. The findings support that Covid-19 harmed study habits for students in distance learning, intensifying the existing problems, even though the disruptive changes are less noticeable than in campus-based students.

WFH increased during Covid-19 outbreak. Indeed, people approved of that change, and it is believed to stay after the Covid-19 period. Besides, more than 73% of people have positive sentiments towards WFH (Dubey & Tripathi, 2020). Even though WFH is considered the most effective order at present, it can provoke a loss of work motivation for some occupations as teachers. Furthermore, the cost of electricity and the internet might increase (Purwanto et al., 2020).

Work From Home (WFH) has a positive impact on performance. People sent to work in their houses consistently completed more calls than their counterparts who remained in the call centre (Bloom, 2014).

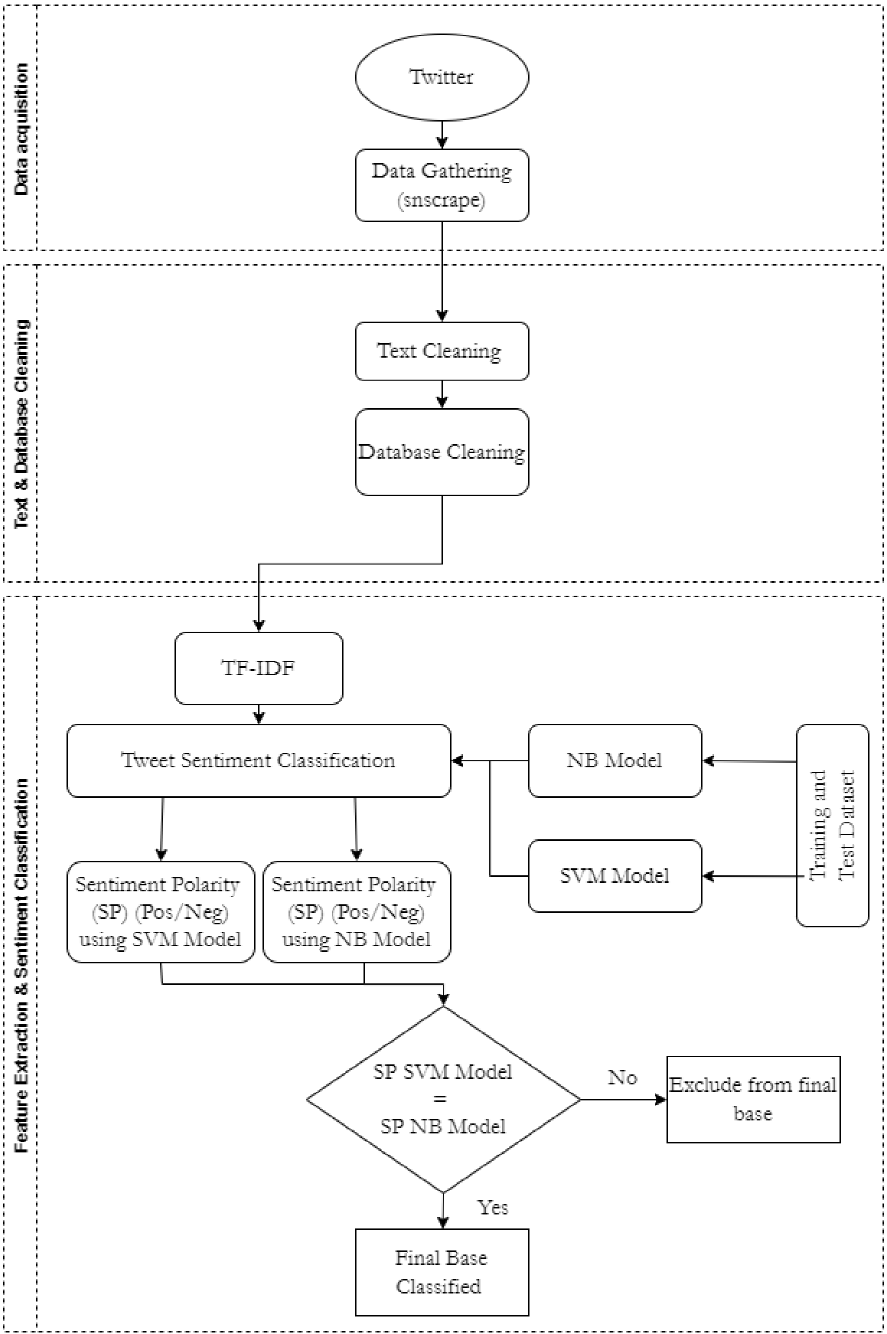
3. METHODOLOGY

This section describes the methodology of the study. SA is a multi-faceted problem, so several steps are needed to perform the analysis (Ravi & Ravi, 2015). To better describe the SA process, I adapt the initial model proposed by Medhat, Hassan, & Korashy (2014), using some insights from Ravi & Ravi (2015).

This model has three key stages. First, subsection 3.1. describes the data acquisition step. Second, subsection 3.2. details the second stage of the model: text and data cleaning. In this subsection, I present some examples of the data before and after this step. Third, subsection 3.3. discusses and reviews feature extraction and sentiment classification algorithms. Figure 1 plots the methodology used in this study.

Finally, subsection 3.4. presents the empirical design, detailing the specifications of each regression.

Figure 1 - Described architecture of the proposed method utilized



The figure presents the SA process. The arrow indicates the order of the process, starting with Twitter and finalizing in the Final Base Classified. Every sub-step inside the dashed box belongs to that step named in the vertical. Source: Adapted from Medhat et al. (2014) & Ravi & Ravi (2015).

3.1. Data Acquisition

Data Acquisition is the first step of the methodology of this study, as shown in Figure 1. This step stands for selecting where to gather the information and how the scrap will be executed.

In this study, the data source is Twitter. Data that come from Twitter are called tweets, which are a body of characters with an upper limit of 280 characters (Rosen, 2017). Given the unstructured characteristic of Twitter data (Stone & Choi, 2013), the first phase uses a Python library called snscrape to help collect information from Twitter. This library contains several functionalities that enable the user to collect tweets in different ways.

After choosing the data source, the data acquisition process has two steps. The first step is getting the unique ID from conversations. The conversation ID is important because it allows searching all tweets related to that conversation, increasing the number of occurrences. At this stage, I search some combined keywords through Twitter's Search Box using the snscrape function called "TwitterSearchScraper" to find all conversation IDs related to the topic.

Once in possession of the conversation IDs, in the second step, I search all tweets that belong to each conversation ID. To execute this step, I use the snscrape function called "TwitterTweetScraper", which allows finding all related information using a given ID.

Once in possession of the data, the next step is Text Cleaning and Feature Selection, which is described in the next section.

3.2. Text and Database Cleaning

Since twitter content information has much variability, text cleaning is a critical process step. In the study, this second step of the methodology performs several changes in the tweet corpus, keeping the original meaning. First, Twitter has several links inside the tweet that do not express sentiment and, thus, are removed from all tweets. Second, this step also removes from tweets usernames, double spaces between words, Html indexations (for example, "/n"), and special characters. To finalize the text cleaning step, I normalize all tweets to lower case.

Once the text cleaning is finalized, this step proceeds to clean the database. Since it is common knowledge that tweets have several bots, which may influence the results (Broniatowski et al., 2018; Mønsted, Sapieżyński, Ferrara, & Lehmann, 2017), this step identifies these bots and remove the tweets from these bots. To do so, I identify the main usernames that have several tweets with promotions campaigns or spam. Tweets with promotions campaigns or spam were defined as any tweet that was very similar to the previous one and contained any type of advertising (e.g. deal, sales, coupon) in the content. Table 1 presents six examples of tweets that were classified as "bot". I identify these profiles manually. After these bots were identified, all tweets from these accounts were removed from the database.

To see the impact of this methodological step, Table 2 presents three examples of original tweets and the corresponding final texts. In the first and second tweets of Table 2, I removed all high cases from the phrase, the punctuation, HTML indexation and links. Those corrections maintain the main component of the tweet with the same meaning but remove all the unnecessary information that may affect the sentiment classification model. In the third tweet, I removed it from the database because it is not considered a personal opinion.

Table 1 – Examples of tweets that were identified as bots

Username	Tweet
shadowconn	Furmax Office Chair Desk Leather Gaming Chair, High Back Ergonomic Adjustable Racing Chair,Task @amazon #sponsored #chair #office https://t.co/BtulOtIneS
shadowconn	Gaiam Balance Disc Wobble Cushion Stability Core Trainer for Home or Office Desk Chair #ergonimics #officesupplies @amazon https://t.co/1SmzR3QQzr
bestdailydisc	37% OFF #sale #save #officedesk #workingstation #sauder @amazon Sauder 417586 Harbor View Corner Computer Desk A2, Salt Oak https://t.co/UxFoy3GFKQ https://t.co/bTwhOIoVrZ
bestdailydisc	37% OFF #sale #save #gamingchair #gaming @amazon Furmax Gaming Chair High Back Racing Chair, Ergonomic Swivel Computer Chair Executive Leather Desk Chair With Footrest, Bucket Seat and Lumbar Support (Blue) https://t.co/dqUMIPlRWv https://t.co/10j113ak7b

The table presents examples of tweets that were classified as a bot. The Column 1 is the Twitter username that was identified as bot and Column 2 is the tweet presented in the original form. Source: Developed by the author.

Table 2 – Table comparing Original Tweet and Cleaned Tweets

Original Tweet	Cleaned Tweet
"My heated footrest just arrived!! So excited for 3 reasons.\n1. I can sit at a desk w/o my feet propped on the base of my chair.\n2. I can turn down the climate control in the rest of the room.\n3. Those little nubbies are a surprisingly good massage. https://t.co/vwx9ESX52x @amazon"	"my heated footrest just arrived so excited for 3 reasons 1 naïve can sit at a desk w o my feet propped on the base of my chair 2 naïve can turn down the climate control in the rest of the room 3 those little nubbies are a surprisingly good massage."
"@Wayfair could you explain why it is taking over A MONTH to deliver a desk that was ordered in February? Now the delivery date has been extended... I look forward to your response."	"could you explain why it is taking over a month to deliver a desk that was ordered in 15ebruary now the delivery date has been extended naïve look forward to your response"
"37% OFF #sale #save #officedesk #workingstation #sauder @amazon Sauder 417586 Harbor View Corner Computer Desk A2, Salt Oak https://t.co/UxFoy3GFKQ https://t.co/bTwhOIoVrZ"	(Removed from the database)

The table presents a comparison between the Original Tweet and the same Tweet after being cleaned. The Column 1 stands for the original tweet and Column 2 stands for the same tweet cleaned. Source: Developed by the author.

3.3. Sentiment Classification

The final step, Sentiment classification, determines a classification of a given text in matters of sentiment (Ravi & Ravi, 2015). This section describes all the steps to classify a given tweet as Positive or Negative. The first step is Feature extraction. That step addresses the problem of finding the most compact and informative set of features, to improve efficiency and processing (Guyon, Gunn, Nikravesh, & Zadeh, 2006). For this study, I chose the method based on TF-IDF. The final step is Sentiment classification, which can be divided into Machine Learning approaches and Lexicon-based approaches (Medhat et al., 2014). For this study, I choose a Machine Learning approach; more specifically, two supervised learning methods called Support Vector Machines (SVM) and Naïve Bayes (NB) (C. C. Aggarwal & Zhai, 2012).

Before proceeding with the explanations of the methods, it is important to mention that supervised approaches need trained datasets to perform the classification. Several trained datasets are available, and I chose a dataset created by Go, Bhayani, & Huang (2009), a well-used dataset that provides a training and test database with more than 1.5 million tweets already classified as positive and negative.

I now present both methods and end the section describing the classification itself.

3.3.1. Feature Extraction based on TF-IDF

To calculate the sentiment of a tweet properly, it is important to calculate the weight of each word using TF-IDF, a well-defused method used in text mining research (Dadgar, Araghi, & Farahani, 2016). TF-IDF determines the relative frequency of words (TF) in a specific tweet compared to the inverse proportion of that word over the entire document corpus (IDF). This calculation determines how relevant a specific word is in a particular document. (Ramos, 2003)

Equation (1) is a classic TF-IDF equation used to calculate weight:

$$W_i = tf_i * \log \frac{N}{df_i} \tag{1}$$

where W_i is the weight of the word i in the database, tf_i is the frequency of the word i in the database, N is the number of words in the database and df_i is the number of tweets containing the word i.

3.3.2. Support Vector Machine Model

The support vector machine is a classification technique. This powerful model is a supervised learning algorithm based on Structural Risk Minimization (SRM), controlling the generalization ability of the decision function by limiting the flexibility of the set of candidate functions (Karaçalı, Ramanath, & Snyder, 2004). When training the model, the algorithm creates a hyperplane to best separate positive and negative samples (Dadgar et al., 2016). Then, it classifies the samples by positioning the text on the hyperplane, using the TF-IDF feature.

As explained by W. Zhang, Yoshida, & Tang, (2011), for linearly separable space, the decision surface is a hyperplane which can be written as shown in Equation (2):

$$wx + b = 0 \tag{2}$$

where x is an object to be classified; the vector w and constant b are learned from a training set of linearly separable objects.

3.3.3. Multinomial Naïve Bayes Model

Naive Bayes is a learning algorithm frequently used for text classification because it is fast and easy to implement (Domingos & Pazzani, 1996). What differentiates Naïve Bayes models is the use of the Bayes theorem, which states the conditional probability of an event to occur. Equation (3) describe Bayes Theorem:

$$P(A|B) = \frac{P(B|A) * P(A)}{P(B)} \tag{3}$$

Using this theorem, textual classification becomes a simple matter of selecting the most probable class. (McCallum & Nigam, 1998) In order to do so, the multinomial model captures word frequency information in documents to better classify the text. (McCallum & Nigam, 1998) Consider, for example, a classified database where all the tweets are mapped with a positive and negative sentiments. Every word in this database is listed in a "bag of words". A tweet is then treated as a sequence of words, assuming that each word position is generated independently from the others. After that, the algorithm applies Bayes Rule to estimate if the tweet has more probability of being positive or negative.

3.3.4. Tweet Sentiment Classification

As described in previous sections, both methods classify textual information in a very precise way, although with different approaches. Although both models have a good classification accuracy, they may produce different results for the same tweet.

This dissidence arises from differences in the approach of each model. To overcome this limitation, I only classify the tweets when both models point to the same sentiment. Thus, I classify a tweet as positive (negative) when it is classified as positive (negative) using both SVM and MNB.

Beyond classification, it is important to define how overall sentiment is calculated. Several studies suggest different ways to compute sentiment. For example, Valle-Cruz, Fernandez-Cortez, López-Chau & Sandoval-Almazán (2022) compute and normalize using Euclidean norm. Agarwal, Xie, Vovsha, Rambow, & Passonneau (2011) use the scoring method for each sentiment word and then normalize the sum scores.

In this study, I calculate the share of positive tweets in the number of classified tweets. Thus, the method shows us the average evolution of people's feelings over the days. Therefore, Sentiment can be defined as the Equation (4) below:

$$Sentiment_t = \frac{\sum Positive\ Tweet_t}{\sum Positive\ Tweet_t + \sum Negative\ Tweet_t} \qquad (4)$$

Where $Positive\ Tweet_t$ are all the positive tweets at time t and $Negative\ Tweet_t$ are all the negatives Tweets at time t.

The next section describes the empirical design of this study.

3.4. Empirical Design

As mentioned before, this study contributes in three different directions. First, I test whether Twitter was a valid platform for eWOM during the pandemic. The idea behind this test is that, after the first lockdown, people were forced to purchase some equipment to work from home. Consequently, if Twitter is a good platform for electronic word-of-mouth, people should have tweeted more significantly on WFH subjects during the lockdowns.

To do so, I propose the following regression defined in Equation (5):

$$Num\ of\ WFH\ tweets_t = \alpha + \beta \times COVID_t + \varepsilon_t \tag{5}$$

where $Num\ of\ WFH\ tweets_t$ is the number of tweets that are related to products of work from home at month t, and $COVID_t$ is a measure of lockdowns at time t.

To measure lockdowns ($COVID_t$), I use the Stringency Index. This index, obtained from ourworldindata.org, is expected to capture the severity of government actions to control covid-19, using nine metrics to calculate severity. The index varies between 0 and 100, and 100 indicates the strictest response. For the USA, the max value obtained is approximately 73. This index has been widely used in the literature (e.g. S. Aggarwal, Nawn, & Dugar, 2021; M. Liu, Choo, & Lee, 2020; Ritchie, Mathieu, et al., 2020).

Second, I test the impact of lockdown on the overall people's sentiment toward products related to WFH. It is already known that people have positive sentiments toward WFH (Dubey & Tripathi, 2020) and positive and hopeful sentiments toward the Covid-19 outbreak (Dubey, 2020), but for some activities, negative sentiments could have increased (Jung et al., 2021). Thus, as sentiment can vary depending on the topic, I test whether lockdowns affected the sentiment towards WFH products. To do so, I propose the following regression defined in Equation (6):

$$Sentiment_t = \alpha + \beta \times COVID_t + \varepsilon_t \tag{6}$$

where $Sentiment_t$ is the sentiment score for products that are related to work from home at month t, $COVID_t$ is a measure of lockdowns at time t, α is the coefficient associated with the constant term, and β indicates the response of sentiment to the changes in lockdown policy.

In the sequence of the previous topic, the third contribution stands for the different ways online furniture stores have dealt with Covid-19. Covid-19 significantly impacted online furniture stores worldwide, increasing their sales rapidly because of the lockdowns (Bhatti et al., 2020). It is also known that due to the high market growth rates, companies tend to have little incentive to deal with consumer complaints (Estelami, 1999). Thus, it is expected that as online furniture stores grew during the Covid-19 outbreak, more people started to complain about the service and the products offered by the stores. To do so, I propose the following regression defined in Equation (7):

$$\ln\left(Sentiment_{i,t}\right) = \alpha_i + \beta \times COVID_t + \Omega \times D_i \times COVID_t + \varepsilon_{i,t} \tag{7}$$

where $Sentiment_{i,t}$ is the sentiment score for products that are related to work from home at month t for the online stores i, $COVID_t$ is a measure of lockdowns at month t, α_i are online stores fixed effects, β is the coefficient associated with the measure of lockdowns, and the vector Ω indicate how the sentiment towards each online furniture stores has been affected by the measure of lockdowns.

4. DATA

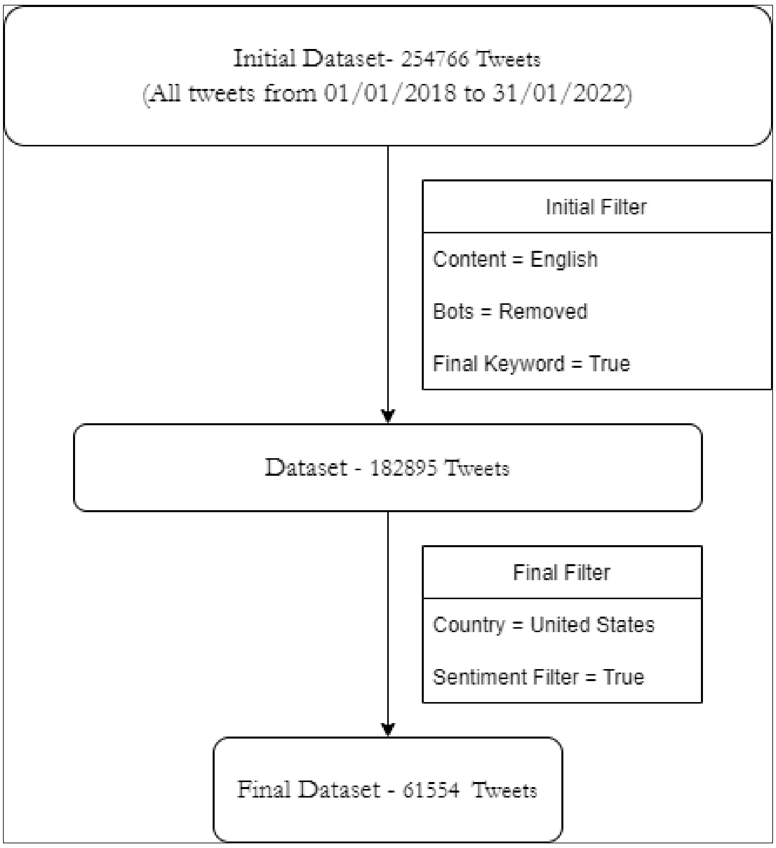
4.1. Data Gathering

Figure 2 presents the steps of the data collection process and the impact on the size of the Dataset. The initial Dataset includes daily tweets from 01/01/2018 to 31/01/2022. The size of the initial Dataset is 254,766 tweets. Although Twitter data is collected daily, I choose to analyze monthly data because daily information has many timelines breaks due to missing data. Thus, all observations are grouped by month.

Two types of keywords were used to filter the tweets. First, I selected the tweets that mention the top 20 United States online furniture stores identified by eCommerceDB (2022). Second, the other type of keywords reflects the WFH categorization. To select the most appropriate keywords, I did a pre-search using only keywords from WFH categorization (e.g. desk chairs, computer desk, chair, computer armoire). After that pre-search, I selected the four keywords that returned more than 10,000 tweets across all online furniture stores: “desk chair”, “office desk”, “office chair”, and “desk”. Thus, the final keywords were created by composing the name of the online furniture store and the WFH categorization (e.g. amazon desk chair, ikea office desk, wayfair office chair). After that, I apply the text and database cleaning described in Section 3.2 and select only English content. At the end of that step, the Dataset comprises 182,895 tweets.

Finally, as stated in Section 3.3.4, I only select the tweets in which both classification models point to the same sentiment and are generated in USA. At the end of this process, the dataset comprises 61,554 tweets.

Figure 2 – Evolution of size of Dataset used in the study



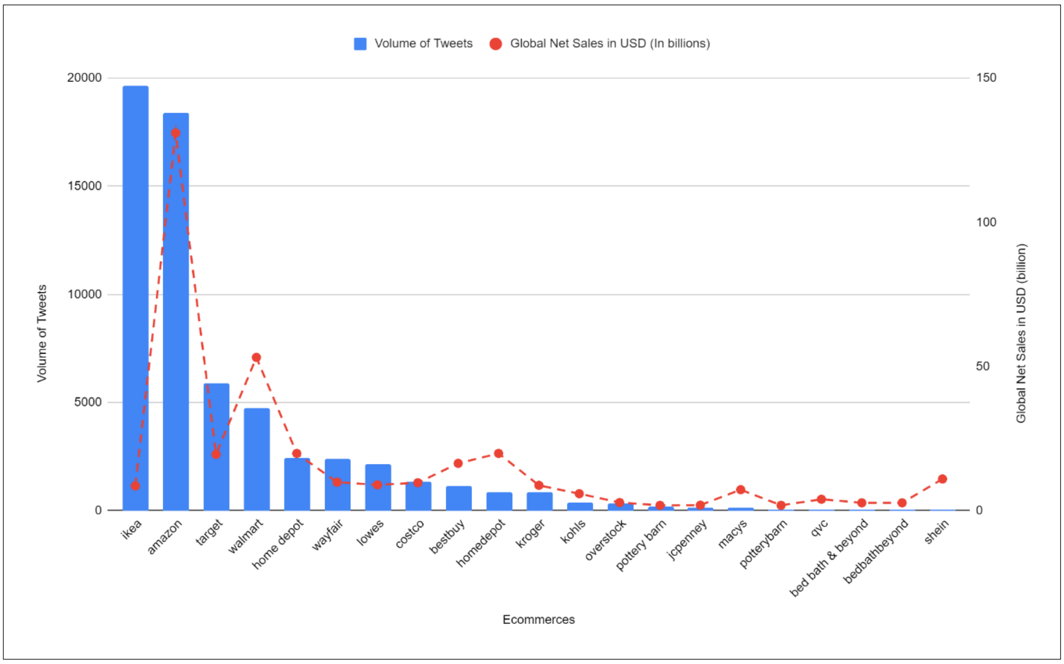
The figure presents the evolution of Initial Dataset after applying the methodology and filters. The Initial Dataset is the raw base, with no corrections. The arrow indicates the order of the process. The filters are the corrections applied between every Dataset. Source: Developed by the author.

4.2. Descriptive Analysis

I start by analyzing the major online furniture stores in the United States and their presence on Twitter. According to eCommerceDB (2022), by 2021, Amazon's net sales were approximately 131 billion dollars, followed by Walmart with approximately 53 billion dollars (eCommerceDB, 2022). Figure 3 plots the global net sales in USD in 2021 for the top 20 online furniture stores.

Despite the huge numbers in sales, this is not indicative that the presence on social networks is guaranteed. Figure 3 also plots the number of tweets related to WFH. From this figure, Ikea ranks first in the number of tweets but has earned approximately 8 billion dollars in 2021. It is important to mention that only two online furniture stores have a significant presence on Twitter, followed by two with an intermediary presence. The other 16 stores have a feeble presence on Twitter. Looking from the company perspective, this discrepancy between the numbers of tweets across companies suggests that building a solid presence on Twitter may require a high investment in time and money.

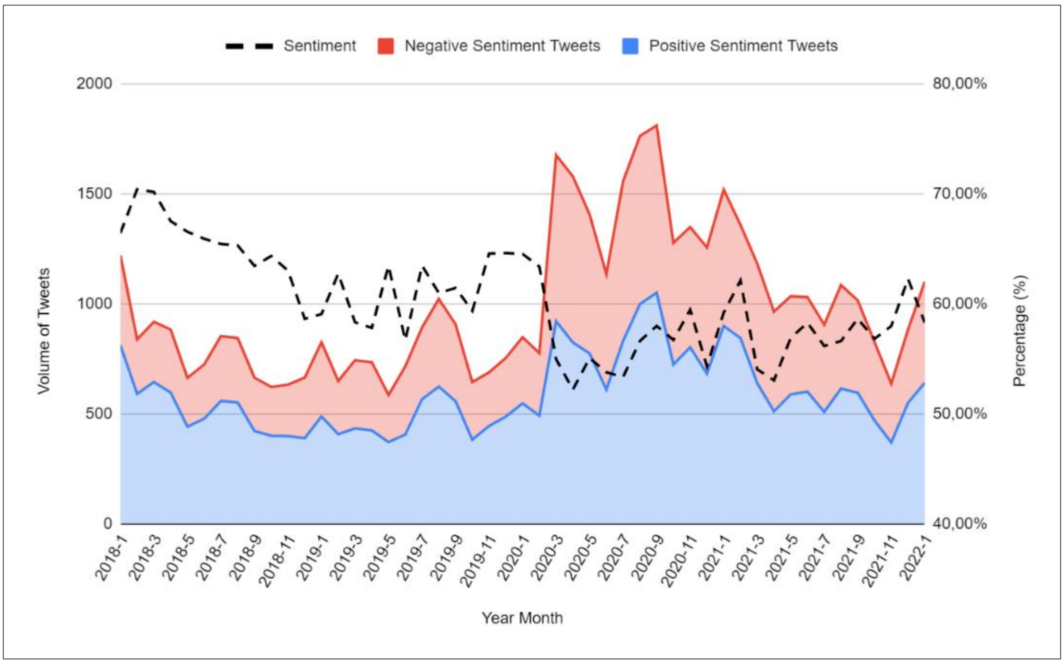
Figure 3 – Histogram of Volume of Tweets related to WFH Products and Global Net Sales



The graph presents the comparison between Volume of Tweets and Global Net Sales for the top 20 online furniture stores. The blue bars plot the Volume of Tweets (Left Axis) and the red line plot the Global Net Sales (Right Axis). Source: Data consolidated by the author & eCommerceDB (2022).

In parallel, the pandemic completely changed how we work (Sheth, 2020). In fact, Figure 4 plots the number of tweets related to products that belong to the WFH category for the top 4 online furniture stores' Twitter presence. From this figure, I can see that, in March 2020, there was a significant increase in the number of tweets, going from more than 1500 tweets a month. While the total number of tweets increased for the period, the sentiment decreased.

Figure 4 – Evolution of Volume of Tweets and Sentiment



The graph presents the evolution along time of Volume of Tweets and Sentiment. The red area and blue area (Left Axis) indicate Negative and Positive Tweets, in other. Both areas are stacked, the high points indicate the Volume of Tweets. The dashed line (Right Axis) indicate the Sentiment defined in equation (4). Source: Developed by the author.

Figure 4 also seems to indicate that there was a reduction in sentiment after the outbreak of the pandemics. In this sense, I test whether there was a change after March 2020 using the ANOVA test for both volumes of tweets and sentiment. Table 3 presents the descriptive statistics and the results of the test. The results suggest a change in consumer sentiment towards WFH products ($\alpha < 1\%$) and the Number of Tweets ($\alpha < 1\%$). Performing the test store by store, the results suggest that Amazon ($\alpha < 1\%$), Ikea ($\alpha < 1\%$) and Walmart ($\alpha < 5\%$) suffered changes in sentiment. Target is the only big store with no significant difference in sentiment, but with a significant change in the Number of Tweets ($\alpha < 1\%$), suggesting stability in the proportion of positive reviews. In the next chapter, I deepen the discussions and present the results.

Table 3 – Descriptive Statistics and ANOVA Test for Number of Tweets and Sentiment[a]

Variables	Number of Tweets			Sentiment		
	Before Covid-19 | After Covid-19 Outbreak					
	Mean	**Std**	**ANOVA Test**	**Mean**	**Std**	**ANOVA Test**
Total	**1002.15** **1543.39**	**145.86** **389.53**	**43.416*** **	**0.637** **0.565**	**0.028** **0.029**	**76.522*** **
Amazon	312.23 446.69	84.41 120.21	20.904***	0.677 0.586	0.059 0.052	32.251***
Ikea	278.57 539.52	72.30 181.11	45.823***	0.645 0.577	0.038 0.039	37.183***
Walmart	86.96 108.04	40.00 45.62	2.970*	0.452 0.405	0.070 0.091	4.137**
Target	104.26 139.30	26.71 36.01	15.181***	0.607 0.580	0.080 0.066	1.569
Others	220.11 309.82	40.24 104.91	16.330***	0.646 0.556	0.043 0.059	37.351***

[a] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

The table presents the ANOVA Test for all online furniture stores. Column 1 stands for stores whereas the first line is the Total online furniture stores results. Columns 2 to 4 stand for the Number of Tweet ANOVA test. Columns 5 to 6 stand for the Sentiment ANOVA test. The upper line of each online furniture store shows the values before Covid-19, and the bottom line shows the values after the Covid-19 outbreak. All the results were truncated in the third decimal point.

5. RESULTS

5.1. Covid-19 and The Number of WFH Tweets

Table 4 presents estimations for the number of WFH Tweets per month specified in equation (5) in subsection 3.4. The table displays the coefficients for the variables Stringency Index and the constant for the model. In the brackets, standard errors are estimated robustly, and the statistics part presents the number of observations, R2 and, the F-stat.

Table 4 - OLS Estimations of Number of WFH Twets[a,b]

Variables	Model (1) Number of WFH Tweets
Stringency Index	7.7180***
	(1.0027)
Constant	770.0860***
	(43.6936)
Statistics	
Number of Observations	49
R^2	0.5459
F stat	56.51

[a] Robust standard deviations in brackets
[b] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

The table presents regression estimates for Equation (5) presented in Chapter 3.4. Heteroskedasticity-consistent standard errors are presented in parentheses.

From Table 4, two remarks are in order. First, the positive value for the constant in the model indicates that people tend to post about WFH products even before the Covid-19 outbreak, i.e. users already interacted about these products through tweets. The estimate of

770.08 indicates that, when there were no restrictions by Covid-19, consumers tweeted, on average, 770 times per month related to WFH products.

Second, the positive relationship between the Stringency Index and the number of WFH Tweets suggests that the Covid-19 restrictions increased people's participation on Twitter for WFH products. The estimate of 7.7180 indicates that, on average, when the Index increases one unit, the number of tweets approximately increases by eight. Since the Stringency Index is a scale that varies between 0 and 73, in the most restrictive period of the Covid-19 outbreak, the number of WFH tweets increased by approximately 563 tweets, which is an increase of 73% in comparison to the average of 770 tweets before the Covid-19 outbreak.

In sum, these results indicate that when people were at home due to the Covid-19 restrictions, they used Twitter to talk more about their new products related to WFH. Thus, these results are in line with three strands of literature. First, the increase in tweets may be linked to an increase in the purchase of these products, which is aligned with studies that indicate habits changed due to Covid-19 (Brem et al., 2021; Sheth, 2020). Second, my results indicate that Twitter is a good platform for extracting user-generated content. Lastly, the results suggest that people use Twitter to share their opinion, which may influence the purchase behavior of other consumers, creating a valid space where eWOM can exist. The fact that Twitter is a valid space for eWOM has been pointed out by several studies (Jansen et al., 2009; Kim et al., 2014; Stone & Choi, 2013).

5.2. Covid-19 and Overall Sentiment from WFH Tweets

Table 5 presents estimations for Sentiment (described in equation 1 in subsection 3.3.4) specified in equation (6) in subsection 3.4. The table follows the same presentation strategy as the previous one, displaying the coefficients for the variables Stringency Index and the constant for the model.

Table 5 underlines that the sentiment toward WFH products tends to be positive, pointed out by the positive value for the constant in the model. In other words, before the Covid-19 outbreak, people made more positive tweets toward WFH products than negative tweets. The value of 0.6337 presented in the constant indicates that in the period when there were no restrictions by Covid-19, the sentiment towards WFH products, on average, was 63.37%. In other words, considering all tweets, 63.37% are classified as positive tweets.

Table 5 – OLS Estimations of Overall Sentiment from WFH Tweets[a,b]

Variables	**Model (2)** **Sentiment**
Stringency Index	-0.0011***
	(0.0001)
Constant	0.6337***
	(0.0062)
Statistics	
Number of Observations	49
R^2	0.5345
F stat	53.97

[a] Robust standard deviations in brackets
[b] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

The table presents regression estimates for Equation (6) presented in Chapter 3.4. Heteroskedasticity-consistent standard errors are presented in parentheses.

Moreover, the negative coefficient for the Stringency Index suggests that the greater restrictions due to Covid-19, the more negatively people react to WFH products. The negative value of -0.0011 presented in the Stringency Index variable indicates that when the index increases by one unit, the sentiment, on average, decreases by around 0.1%. Thus, in the most restrictive period of the Covid-19 outbreak, where the Stringency Index reached 73, the sentiment toward WFH products reduced by approximately eight percentage points, approximately 12%.

The results indicate that the more severe the restrictions imposed by Covid-19, the more negative people reacted toward their WFH products. Specifically, the results suggest that Twitter is a good platform for applying sentimental analysis to WFH products, being in line with the results found in other research (e.g. He et al., 2017). In addition, the results suggest that the Covid-19 restrictions drove people to be more negative, which contrasts with the results in Dubey & Tripathi (2020), suggesting a more positive sentiment toward WFH. The difference might be the fact that the authors use different keywords in their study. I use product-related keywords (e.g. desk amazon) to gather tweets; meanwhile, they use more generic keywords (e.g. #WorkFromHome). However, this difference in sentiment is observed in other studies, especially regarding changing habits (Jung et al., 2021). Finally, even the sentiment toward Covid-19 varies by country; some have positive sentiment while others have a more negative sentiment (Dubey, 2020).

5.3. Covid-19 and Sentiment across Furniture Stores

Table 6 presents estimations for Sentiment specified in equation (7) in subsection 3.4. The table follows the same presentation strategy as the previous ones, displaying the coefficients for the variables Stringency Index, the interaction terms between the Stringency Index and the furniture stores, and the constant for the model.

Table 6 underlines that although the negative coefficient for the Stringency Index indicates that people posted more negative tweets toward WFH products as the Covid-19 restrictions increased, the results suggest that Target had a better reaction than other online furniture stores. In other words, the interaction term between Target and the Stringency index compensates for the negative effect from the Stringency index, which means that the sentiment towards Target's WFH products has kept quite stable. This result is in line with what I discussed in Section 4.2.

Thus, the results indicate that the restrictions imposed by covid-19 had different impacts across online furniture stores for WFH products. In other words, there are online furniture stores which the effect of Covid-19 restrictions explains the variation of sentiment, indicating that people became more negative not because of online furniture stores' products or services but because people were being restricted.

Table 6 – Fixed-Effects Estimations of Sentiment from WFH Tweets for each Online Store[a,b]

Variables	Model (3) Sentiment
Stringency Index	-0.0011***
	(0.0001)
Stringency Index * Amazon	0.0003
	(0.0008)
Stringency Index * Ikea	0.0006
	(0.0008)
Stringency Index * Target	0.0017**
	(0.0008)
Stringency Index * Walmart	0.0005
	(0.0008)
Constant	-0.4378***
	(0.0240)
Fixed Effects	Yes
Statistics	
Number of Observations	245
R^2	0.6375
F stat	45.92

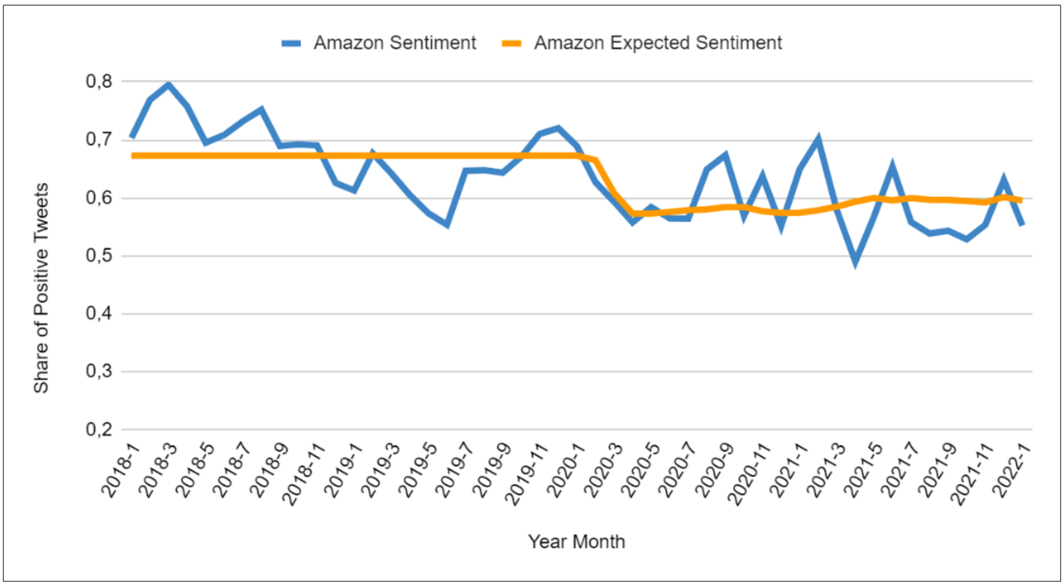
[a] Robust standard deviations in brackets
[b] *,**, and *** correspond to the 10%, 5%, and 1% significance levels, respectively.

The table presents regression estimates for Equation (7) presented in Chapter 3.4. Heteroskedasticity-consistent standard errors are presented in parentheses.

Despite these results, there are periods when restrictions fail to explain the variation in sentiment. Figures 5 to 7 plot the sentiment evolution for Amazon, Ikea and Walmart, the online furniture stores which sentiment towards WFH products changed. The blue line indicates the variation of sentiment for that online furniture store. The orange line shows the evolution in sentiment that can be explained by the Stringency Index. In other words, when the orange line overlaps the blue line, it indicates that the variation is fully explained by the imposed restrictions, suggesting that the customers are being influenced by this external factor.

Figure 5 suggests that, at the time of the first lockdown, where restrictions were severe, the drop in sentiment toward Amazon happened because people were unhappy with the restrictions imposed. However, from July 2020 to March 2021, the results suggest that Amazon took actions which circumvented the negative covid-19 effect. In March 2021, the results indicate that general sentiment has fallen again, no longer explained by covid-19 restrictions.

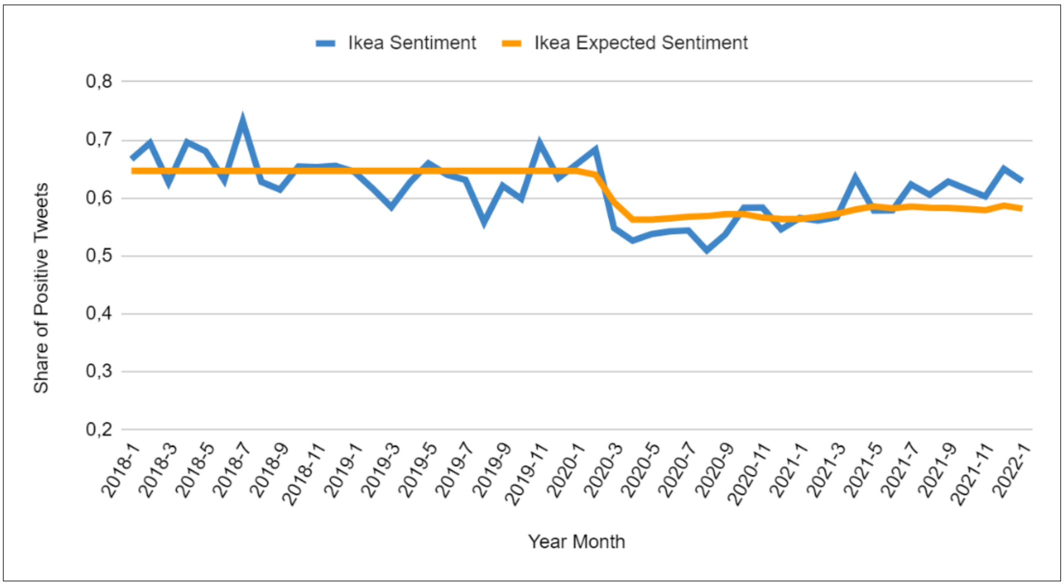
Figure 5 – Sentiment toward Amazon and Covid-19 Restrictions



The graph presents a comparison between Amazon Sentiment and Amazon Expected Sentiment. The blue line plots the evolution along time of Amazon Sentiment. Orange line plots the expected Sentiment due the restrictions. Source: developed by the author.

Figure 6 suggests that, in the first lockdown, the drop in sentiment toward Ikea is not only explained by Covid-19 restrictions. This result indicates that other reasons may have motivated consumers to go to Twitter and make negative comments. Despite this challenging situation, Ikea seems to have overcome it because, from June 2021, there was an increase in sentiment towards Ikea, suggesting that Ikea took actions, which may have contributed to this increase in sentiment.

Figure 6 – Sentiment toward Ikea and Covid-19 Restrictions



The graph presents a comparison between Ikea Sentiment and Ikea Expected Sentiment. The blue line plots the evolution along time of Ikea Sentiment. Orange line plots the expected Sentiment due the restrictions. Source: developed by the author.

Figure 7 suggests that Walmart was the online furniture store that suffered the most in the first semester of 2020. Shortly after the first lockdown, the results suggest that restrictions can explain the drop in sentiment. However, in April 2020, the sentiment dropped significantly, reaching the mark of 23.88% of positive comments compared to the remaining negative ones. Shortly after this period, the results indicate that Walmart bypassed this period, reaching sentiment values like the time before Covid-19.

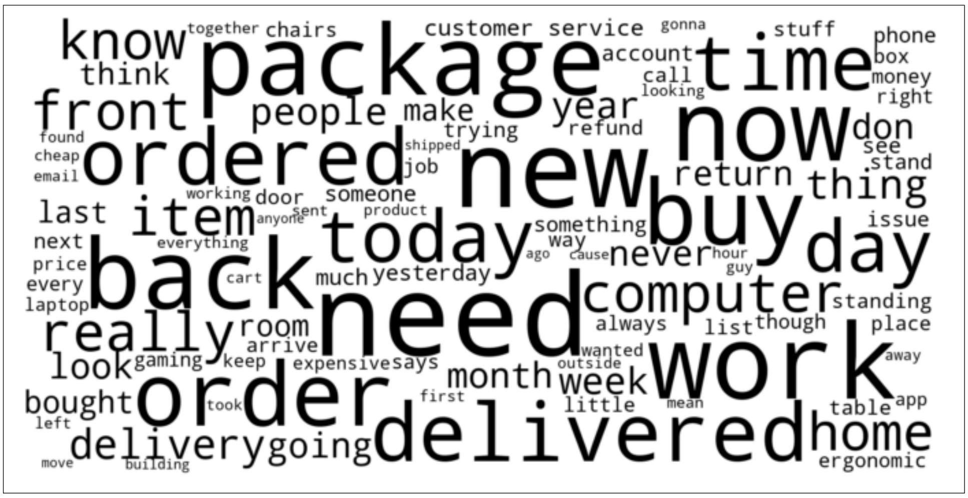
Figure 7 - Sentiment toward Walmart and Covid-19 Restrictions

The graph presents a comparison between Walmart Sentiment and Walmart Expected Sentiment. The blue line plots the evolution along time of Walmart Sentiment. Orange line plots the expected Sentiment due the restrictions. Source: developed by the author.

In order to understand the motivations of consumer comments that Covid-19 restrictions cannot explain, Figures 8 to 10 present world clouds from tweets for each online furniture store. More specifically, these word clouds analyze tweets from the moments when Covid-19 restrictions cannot explain the negative sentiment toward each online furniture store. In all cases, the words with the largest font indicate the most frequent words used by Twitter users. To understand the reasons behind those negative sentiments and for a better visualization, I remove adjectives from the word clouds.

Figure 8 presents the word cloud for negative tweets mentioning Amazon WFH products from July 2021 until December 2021, the most turbulent period for Amazon. From this figure, the words “delivered”, “package”, and “order” are highlighted, suggesting that users may have had some negative experiences and expressed their displeasure with the packaging/logistics service.

Figure 8 - Amazon World cloud for Negatives Tweet from 07/2021 to 12/2021

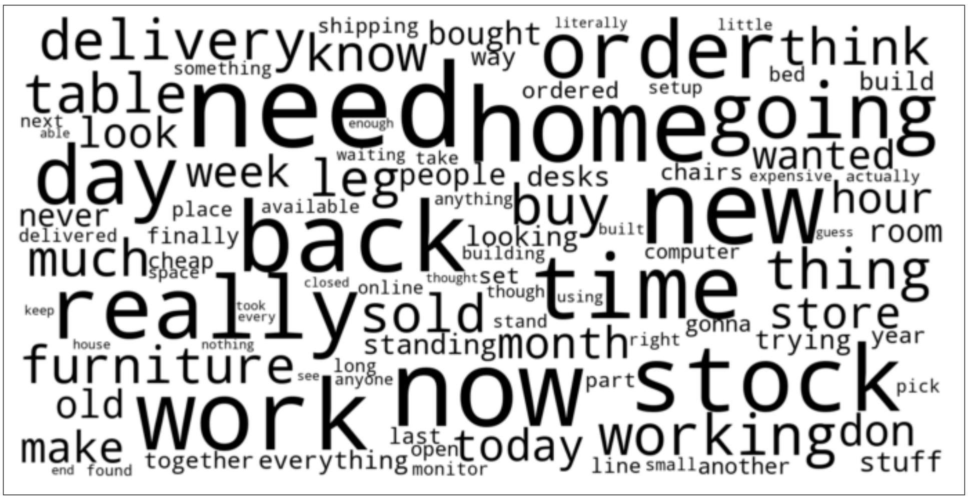


This figure presents the word cloud from tweets from Amazon. Words with the largest font indicate the most frequent words used by Twitter users. Source: Developed by the author.

Figure 9 presents the word cloud for negative tweets mentioning Ikea WFH products from March until October 2020, the most turbulent period for Ikea. This figure highlights the words "time", "stock", and "order", suggesting that consumers had some negative experiences when trying to place an order or even regarding the delivery time of the products. In fact, Ikea had several problems during the Covid-19, such as being out of stock in several products, reports of delays in delivery and high shipping costs (Wilson, 2020). The results are in line with the existing literature, as consumers use social media to complain about products and services, and social media is a reliable source to manage customer complaints (Einwiller & Steilen, 2015).

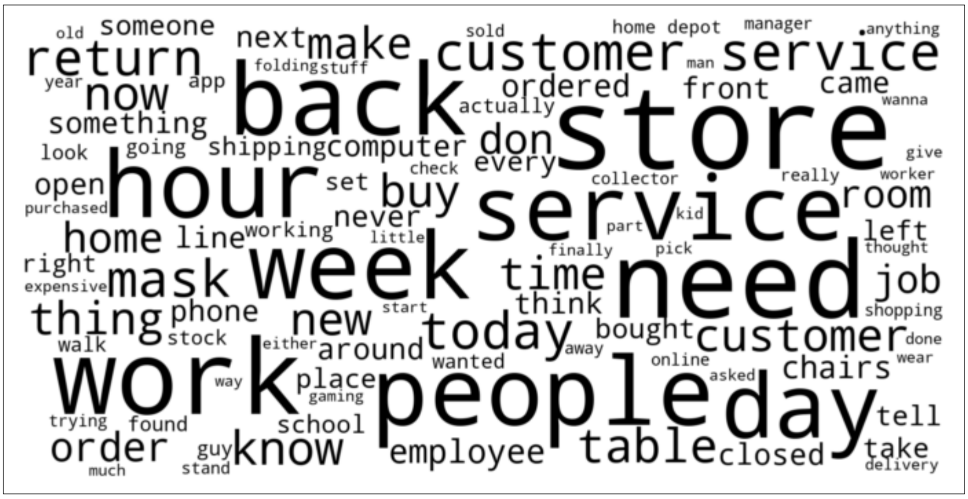
Finally, Figure 10 presents the word cloud for negative tweets mentioning Walmart WFH products from April until August 2020, the most turbulent period for Walmart. From this figure, the words "store", "service", and "customer service" appear highlighted, suggesting that the problem faced by Walmart may be related to customer service, and customers may have experienced a negative experience in the stores.

Figure 9 - Ikea World cloud for Negatives Tweet from 03/2020 to 10/2020



This figure presents the word cloud from tweets for Ikea. Words with the largest font indicate the most frequent words used by Twitter users. Source: Developed by the author.

Figure 10 - Walmart World cloud for Negatives Tweet from 04/2020 to 08/2020



This figure presents the word cloud from tweets for Walmart. Words with the largest font indicate the most frequent words used by Twitter users. Source: Developed by the author.

6. CONCLUSION

As mentioned throughout the study, Covid-19 led several people to change their habits, influencing people's daily lives personally and professionally (Sheth, 2020). This study aimed to understand the effect of the Covid-19 outbreak on consumers' sentiment toward the biggest online furniture stores in the United States, delving deeper into the discussion on WFH products and how these stores reacted to Covid-19 restrictions.

The results are as follows. First, I identify a significant increase in the Number of Tweets related to WFH products due to the restrictions applied to control the Covid-19 pandemic. The results suggest that Twitter is a good platform for extracting user-generated content about WFH products, collaborating with the literature that points to Twitter as a valid platform for studying customer sentiment. Second, the results indicate that the Covid-19 restrictions gave people more negative sentiments, implying that their feelings were affected by external elements, which caused negativity towards the products purchased. Third, the results show that this negative reaction was different across the online furniture stores, suggesting that although people have become more negative due to covid-19 restrictions, actions taken by companies can accentuate, both positively and negatively, consumer sentiment.

The results presented in this study have important marketing implications. First, even with the increase in the use of other social networks by consumers and companies, Twitter remains a good alternative for carrying out sentimental analysis. Thus, the marketer needs to keep tracking Twitter's content. Second, sentimental analysis is a valid tool to understand customers' perception of the product's pros and cons, helping the company to have an efficient service recovery. Third, Twitter may help companies better understand their competitors, making more assertive analyses and taking better decisions that differentiate their products or services from others, which make the company more competitive in the long run. Fourth, knowing that consumers may be more negative due to external factors allows the company to take actions focused on this external effect, connecting more naturally with its customers and increasing eWOM associated with its store. Fifth, the study provides a model for measuring sentimental analysis with Twitter data and shows how practitioners can analyze the information. Finally, by using machine learning and textual analysis techniques, this study showed the potential created by combining IT and Marketing, which companies can follow in the future. Indeed, several companies are already looking for professionals with expertise in both areas (Rossum, 2019).

Finally, this work has some limitations. As much as textual analysis techniques are advancing exponentially, it is still necessary to perform several corrections in the raw database. A suggestion for future work would be to apply more recent techniques for the treatment of bots, which was one of the main difficulties of this study. Another limitation is the fact that only one social network is used to measure consumers' sentiment. Consumers can use other social networks to express their opinions about products or services. Therefore, future work should include more social networks and test if there is any significant difference in sentiment depending on the social network.

7. REFERENCES

Agarwal, A., Xie, B., Vovsha, I., Rambow, O., & Passonneau, R. (2011). Sentiment Analysis of Twitter Data. *Proceedings of the Workshop on Languages in Social Media*, 30–38. Portland, Oregon: Association for Computational Linguistics.

Aggarwal, C. C., & Zhai, C. (2012). *Mining text data* (1st ed.). New York, NY: Springer. https://doi.org/10.1007/978-1-4614-3223-4

Aggarwal, S., Nawn, S., & Dugar, A. (2021). What caused global stock market meltdown during the COVID pandemic–Lockdown stringency or investor panic? *Finance Research Letters*, *38*, 101827. https://doi.org/https://doi.org/10.1016/j.frl.2020.101827

Akana, T. (2021). Changing US consumer payment habits during the COVID-19 crisis. *Journal of Payments Strategy & Systems*, *15*(3), 234–243. Retrieved from https://search.ebscohost.com/login.aspx?direct=true&db=bth&AN=153066899&site=eds-live

Alalwan, A. A., Rana, N. P., Dwivedi, Y. K., & Algharabat, R. (2017). Social media in marketing: A review and analysis of the existing literature. *Telematics and Informatics*, *34*(7), 1177–1190. https://doi.org/10.1016/j.tele.2017.05.008

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. *Management Science*, *57*(8), 1485–1509. https://doi.org/10.1287/mnsc.1110.1370

Aristeidou, M., & Cross, S. (2021). Disrupted distance learning: the impact of Covid-19 on study habits of distance learning university students. *Open Learning*, *36*(3), 263–282. https://doi.org/10.1080/02680513.2021.1973400

Bhatti, A., Akram, H., Basit, M., Khan, A., Mahwish, S., Naqvi, R., & Bilal, M. (2020). E-commerce trends during COVID-19 Pandemic. *International Journal of Future Generation Communication and Networking*, *13*(2), 1449–1452. Retrieved from https://www.researchgate.net/publication/342736799_E-commerce_trends_during_COVID-19_Pandemic

Bloom, N. (2014). To raise productivity, let more employees work from home. *Harvard Business Review.*

Brem, A., Viardot, E., & Nylund, P. A. (2021). Implications of the coronavirus (COVID-19) outbreak for innovation: Which technologies will improve our lives? *Technological Forecasting and Social Change*, *163*, 120451. https://doi.org/10.1016/j.techfore.2020.120451

Broniatowski, D. A., Jamison, A. M., Qi, S., AlKulaib, L., Chen, T., Benton, A., … Dredze, M. (2018). Weaponized health communication: Twitter bots and Russian trolls amplify the vaccine debate. *American Journal of Public Health*, *108*(10), 1378–1384. https://doi.org/10.2105/AJPH.2018.304567

Budiharto, W., & Meiliana, M. (2018). Prediction and analysis of Indonesia Presidential election from Twitter using sentiment analysis. *Journal of Big Data*, *5*(1), 1–10.

Chamlertwat, W., Bhattarakosol, P., Rungkasiri, T., & Haruechaiyasak, C. (2012). Discovering Consumer Insight from Twitter via Sentiment Analysis. *J. Univers. Comput. Sci.*, *18*(8), 973–992.

Chaturvedi, S., Mishra, V., & Mishra, N. (2017). Sentiment analysis using machine learning for business intelligence. *IEEE International Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI)*, 2162–2166. Chennai, India: IEEE. https://doi.org/10.1109/ICPCSI.2017.8392100

Chen, F., Deng, P., Wan, J., Zhang, D., Vasilakos, A. v, & Rong, X. (2015). Data Mining for the Internet of Things: Literature Review and Challenges. *International Journal of Distributed Sensor Networks*, *11*(8), 431047. https://doi.org/10.1155/2015/431047

Chen, W. K., Riantama, D., & Chen, L. S. (2021). Using a text mining approach to hear voices of customers from social media toward the fast-food restaurant industry. *Sustainability (Switzerland)*, *13*(1), 1–17. https://doi.org/10.3390/su13010268

Chintalapudi, N., Battineni, G., & Amenta, F. (2021). Sentimental Analysis of COVID-19 Tweets Using Deep Learning Models. *Infectious Disease Reports*, *13*(2), 329–339. https://doi.org/10.3390/idr13020032

Choy, M., Cheong, M., Laik, M. N., & Shung, K. P. (2012). *US presidential election 2012 prediction using census corrected Twitter model.* arXiv. https://doi.org/10.48550/arXiv.1211.0938

Dadgar, S. M. H., Araghi, M. S., & Farahani, M. M. (2016). A novel text mining approach based on TF-IDF and Support Vector Machine for news classification. *IEEE International Conference on Engineering and Technology (ICETECH)*, 112–116. Coimbatore, India: IEEE. https://doi.org/10.1109/ICETECH.2016.7569223

Domingos, P., & Pazzani, M. (1996). Beyond independence: Conditions for the optimality of the simple Bayesian classifier. In L. Saitta (Ed.), *Proceedings of the Thirteenth International Conference on Machine Learning* (pp. 105–112). San Francisco, CA: Morgan Kaufmann. Retrieved from https://www.ics.uci.edu/~pazzani/Publications/mlc96-pedro.pdf

Dubey, A. D. (2020). Twitter Sentiment Analysis during COVID-19 Outbreak. *SSRN*, p. 9. https://doi.org/10.2139/ssrn.3572023

Dubey, A. D., & Tripathi, S. (2020). Analysing the sentiments towards work-from-home experience during covid-19 pandemic. *Journal of Innovation Management*, *8*(1), 13–19. https://doi.org/10.24840/2183-0606_008.001_0003

eCommerceDB. (2022). eCommerce insights for your needs. Retrieved May 18, 2022, from E-commerce Revenue Analytics website: https://ecommercedb.com/

Einwiller, S. A., & Steilen, S. (2015). Handling complaints on social network sites – An analysis of complaints and complaint responses on Facebook and Twitter pages of large US companies. *Public Relations Review*, *41*(2), 195–204. https://doi.org/10.1016/j.pubrev.2014.11.012

Enberg, J. (2021). Social Media Update Q3 2021. Retrieved December 1, 2021, from https://www.emarketer.com/content/social-media-update-q3-2021

Estelami, H. (1999). The Profit Impact of Consumer Complaint Solicitation Across Market Conditions. *Journal of Professional Services Marketing*, *20*(1), 165–195. https://doi.org/10.1300/J090v20n01_12

Fayyad, U., Piatetsky-Shapiro, G., & Smyth, P. (1996). Knowledge Discovery and Data Mining: Towards a Unifying Framework. *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining (KDD96)*, 82–89. Portland, OR: AAAI Press. Retrieved from https://www.aaai.org/Papers/KDD/1996/KDD96-014.pdf

Go, A., Bhayani, R., & Huang, L. (2009). Twitter sentiment classification using distant supervision. *CS224N Project Report*, pp. 1–12. Stanford University. Retrieved from https://www-cs.stanford.edu/people/alecmgo/papers/TwitterDistantSupervision09.pdf

Guyon, I., Gunn, S., Nikravesh, M., & Zadeh, L. A. (2006). *Feature Extraction: Foundations and Applications* (1st ed.). Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-540-35488-8

He, W., Wang, F.-K., & Akula, V. (2017). Managing extracted knowledge from big social media data for business decision making. *Journal of Knowledge Management*, *21*(2), 275–294. https://doi.org/10.1108/JKM-07-2015-0296

He, W., Zha, S., & Li, L. (2013). Social media competitive analysis and text mining: A case study in the pizza industry. *International Journal of Information Management*, *33*(3), 464–472.

Hotho, A., Nürnberger, A., & Paaß, G. (2005). A Brief Survey of Text Mining. *LDV Forum - GLDV Journal for Computational Linguistics and Language Technology*, *20*(1), 19–62. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.447.4161&rep=rep1&type=pdf

Ibrahim, N. F., Wang, X., & Bourne, H. (2017). Exploring the effect of user engagement in online brand communities: Evidence from Twitter. *Computers in Human Behavior*, *72*, 321–338. https://doi.org/10.1016/j.chb.2017.03.005

Internet Live Stats. (2021). Twitter Usage Statistics. Retrieved November 23, 2021, from https://www.internetlivestats.com/twitter-statistics/#trend

Jansen, B. J., Zhang, M., Sobel, K., & Chowdury, A. (2009). Twitter power: Tweets as electronic word of mouth. *Journal of the American Society for Information Science and Technology*, *60*(11), 2169–2188. https://doi.org/10.1002/asi.21149

Janssen, M., Chang, B. P. I., Hristov, H., Pravst, I., Profeta, A., & Millard, J. (2021). Changes in Food Consumption During the COVID-19 Pandemic: Analysis of Consumer Survey Data From the First Lockdown Period in Denmark, Germany, and Slovenia. *Frontiers in Nutrition*, *8*(March). https://doi.org/10.3389/fnut.2021.635859

Jia, S. (2021). Analyzing Restaurant Customers' Evolution of Dining Patterns and Satisfaction during COVID-19 for Sustainable Business Insights. *Sustainability*, *13*(9), 4981. https://doi.org/10.3390/su13094981

Jung, H.-S., Yoon, H.-H., & Song, M.-K. (2021). A Study on Dining-Out Trends Using Big Data: Focusing on Changes since COVID-19. *Sustainability*, *13*(20), 11480. https://doi.org/10.3390/su132011480

Kaplan, A. M., & Haenlein, M. (2011). The early bird catches the news: Nine things you should know about micro-blogging. *Business Horizons*, *54*(2), 105–113. https://doi.org/10.1016/j.bushor.2010.09.004

Kapoor, K., Tamilmani, K., Rana, N., Patil, P., Dwivedi, Y., & Nerur, S. (2018). Advances in Social Media Research: Past, Present and Future. *Information Systems Frontiers*, *20*. https://doi.org/10.1007/s10796-017-9810-y

Karaçalı, B., Ramanath, R., & Snyder, W. E. (2004). A comparative analysis of structural risk minimization by support vector machines and nearest neighbor rule. *Pattern Recognition Letters*, *25*(1), 63–71. https://doi.org/10.1016/j.patrec.2003.09.002

Kim, E., Sung, Y., & Kang, H. (2014). Brand followers' retweeting behavior on Twitter: How brand relationships influence brand electronic word-of-mouth. *Computers in Human Behavior*, *37*, 18–25. https://doi.org/10.1016/j.chb.2014.04.020

Kwak, H., Lee, C., Park, H., & Moon, S. (2010). What is Twitter, a Social Network or a News Media? *Proceedings of the 19th International World Wide Web Conference*, 591–600. Raleigh, NC: Association for Computing Machinery, New York, NY, United States. https://doi.org/10.1145/1772690.1772751

Litvin, S. W., Goldsmith, R. E., & Pan, B. (2008). Electronic word-of-mouth in hospitality and tourism management. *Tourism Management*, *29*(3), 458–468.

Liu, B. (2012). Sentiment analysis and opinion mining. In *Synthesis lectures on human language technologies* (Vol. 5). Morgan & Claypool Publishers. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.244.9480&rep=rep1&type=pdf

Liu, M., Choo, W.-C., & Lee, C.-C. (2020). The Response of the Stock Market to the Announcement of Global Pandemic. *Emerging Markets Finance and Trade*, *56*(15), 3562–3577. https://doi.org/10.1080/1540496X.2020.1850441

Manguri, K. H., Ramadhan, R. N., & Amin, P. R. M. (2020). Twitter sentiment analysis on worldwide COVID-19 outbreaks. *Kurdistan Journal of Applied Research*, *1*(Special Issue on Coronavirus (COVID-19)), 54–65. https://doi.org/10.24017/covid.8

Mansoor, M., Gurumurthy, K., Anantharam, R. U., & Prasad, V. R. B. (2020). Global Sentiment Analysis Of COVID-19 Tweets Over Time. *CoRR*. https://doi.org/10.48550/arXiv.2010.14234

McCallum, A., & Nigam, K. (1998). A comparison of event models for naive bayes text classification. *AAAI-98 Workshop on Learning for Text Categorization*, 41–48. Menlo Park, CA: AAAI Press.

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113.

Mønsted, B., Sapieżyński, P., Ferrara, E., & Lehmann, S. (2017). Evidence of complex contagion of information in social media: An experiment using Twitter bots. *PloS One*, *12*(9), e0184148. https://doi.org/10.1371/journal.pone.0184148

Mościcka, P., Chróst, N., Terlikowski, R., Przylipiak, M., Wołosik, K., & Przylipiak, A. (2020). Hygienic and cosmetic care habits in polish women during COVID-19 pandemic. *Journal of Cosmetic Dermatology*, *19*(8), 1840–1845. https://doi.org/10.1111/jocd.13539

Mukhopadhyay, A., Maulik, U., Bandyopadhyay, S., & Coello, C. A. C. (2014). A Survey of Multiobjective Evolutionary Algorithms for Data Mining: Part I. *IEEE Transactions on Evolutionary Computation*, *18*(1), 4–19. https://doi.org/10.1109/TEVC.2013.2290086

Netzer, O., Feldman, R., Goldenberg, J., & Fresko, M. (2012). Mine your own business: Market-structure surveillance through text mining. *Marketing Science*, *31*(3), 521–543.

Pokharel, B. P. (2020). Twitter sentiment analysis during covid-19 outbreak in nepal. *Available at SSRN 3624719*.

Purwanto, A., Asbari, M., Fahlevi, M., Mufid, A., Agistiawati, E., Cahyono, Y., & Suryani, P. (2020). Impact of work from home (WFH) on Indonesian teachers performance during the Covid-19 pandemic: An exploratory study. *International Journal of Advanced Science and Technology*, *29*(5), 6235–6244. Retrieved from http://sersc.org/journals/index.php/IJAST/article/view/15627

Ramos, J. (2003). Using tf-idf to determine word relevance in document queries. *Proceedings of the First Instructional Conference on Machine Learning*, *242*(1), 29–48.

Ranjan, S., Sood, S., & Verma, V. (2019). Twitter Sentiment Analysis of Real-Time Customer Experience Feedback for Predicting Growth of Indian Telecom Companies. *Proceedings - 4th International Conference on Computing Sciences, ICCS 2018*, 166–174. IEEE. https://doi.org/10.1109/ICCS.2018.00035

Ravi, K., & Ravi, V. (2015). A survey on opinion mining and sentiment analysis: Tasks, approaches and applications. *Knowledge-Based Systems*, *89*, 14–46. https://doi.org/10.1016/j.knosys.2015.06.015

Ritchie, H., Mathieu, E., Rodés-Guirao, L., Appel, C., Giattino, C., Ortiz-Ospina, E., … Max, R. (2020). Coronavirus Pandemic (COVID-19). Retrieved July 1, 2022, from Our World in Data website: https://ourworldindata.org/covid-stringency-index

Rosen, A. (2017, November 7). Tweeting Made Easier. Retrieved June 4, 2022, from blog.twitter.com website: https://blog.twitter.com/official/en_us/topics/product/2017/tweetingmadeeasier.html

Rossum, B. van. (2019, September 17). 5 Evolving Marketing Jobs That Will Be in High Demand in 2020 [Infographic]. Retrieved June 28, 2022, from www.business2community.com website: https://www.business2community.com/marketing/5-evolving-marketing-jobs-that-will-be-in-high-demand-in-2020-infographic-02241268

Sheth, J. (2020). Impact of Covid-19 on consumer behavior: Will the old habits return or die? *Journal of Business Research*, *117*, 280–283. https://doi.org/10.1016/j.jbusres.2020.05.059

Shirdastian, H., Laroche, M., & Richard, M.-O. (2019). Using big data analytics to study brand authenticity sentiments: The case of Starbucks on Twitter. *International Journal of Information Management*, *48*, 291–307. https://doi.org/10.1016/j.ijinfomgt.2017.09.007

Shukri, S. E., Yaghi, R. I., Aljarah, I., & Alsawalqah, H. (2015). Twitter sentiment analysis: A case study in the automotive industry. *2015 IEEE Jordan Conference on Applied Electrical Engineering and Computing Technologies (AEECT)*. Amman, Jordan: IEEE. https://doi.org/10.1109/AEECT.2015.7360594

Sotiriadis, M. D., & van Zyl, C. (2013). Electronic word-of-mouth and online reviews in tourism services: the use of twitter by tourists. *Electronic Commerce Research*, *13*(1), 103–124.

Stone, T., & Choi, S.-K. (2013). Extracting Consumer Preference From User-Generated Content Sources Using Classification. *ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference. Volume 3A: 39th Design Automation Conference*. Portland, Oregon: ASME. https://doi.org/10.1115/DETC2013-13228

Teng, S., Khong, K. W., Chong, A., & Lin, B. (2016). Persuasive Electronic Word-of-Mouth Messages in Social Media. *Journal of Computer Information Systems*, *57*, 1–13. https://doi.org/10.1080/08874417.2016.1181501

Tumasjan, A., Sprenger, T., Sandner, P., & Welpe, I. (2010). Predicting elections with twitter: What 140 characters reveal about political sentiment. *Proceedings of the International AAAI Conference on Web and Social Media*, *4*(1).

Valle-Cruz, D., Fernandez-Cortez, V., López-Chau, A., & Sandoval-Almazán, R. (2022). Does Twitter Affect Stock Market Decisions? Financial Sentiment Analysis During Pandemics: A Comparative Study of the H1N1 and the COVID-19 Periods. *Cognitive Computation*, *14*(1), 372–387. https://doi.org/10.1007/s12559-021-09819-8

Verma, S., & Yadav, N. (2021). Past, present, and future of electronic word of mouth (EWOM). *Journal of Interactive Marketing*, *53*, 111–128.

Vermeulen, I. E., & Seegers, D. (2009). Tried and tested: The impact of online hotel reviews on consumer consideration. *Tourism Management*, *30*(1), 123–127. https://doi.org/https://doi.org/10.1016/j.tourman.2008.04.008

Viglia, G., Minazzi, R., & Buhalis, D. (2016). The influence of e-word-of-mouth on hotel occupancy rate. *International Journal of Contemporary Hospitality Management*, *28*, 2035–2051. https://doi.org/10.1108/IJCHM-05-2015-0238

Wilson, M. (2020, September 8). Ikea's e-commerce was already pretty bad. During COVID-19, it absolutely fell apart. Retrieved June 22, 2022, from Fast Company website: https://www.fastcompany.com/90547486/ikeas-e-commerce-was-already-pretty-bad-during-covid-19-it-absolutely-fell-apart

Ye, Q., Law, R., & Gu, B. (2009). The impact of online user reviews on hotel room sales. *International Journal of Hospitality Management*, *28*(1), 180–182.

Zhang, W., Yoshida, T., & Tang, X. (2011). A comparative study of TF*IDF, LSI and multi-words for text classification. *Expert Systems with Applications*, *38*(3), 2758–2765. https://doi.org/10.1016/j.eswa.2010.08.066

Zhang, Z., Ye, Q., Law, R., & Li, Y. (2010). The impact of e-word-of-mouth on the online popularity of restaurants: A comparison of consumer reviews and editor reviews. *International Journal of Hospitality Management*, *29*(4), 694–700. https://doi.org/10.1016/j.ijhm.2010.02.002