THE REPUBLIC OF TURKEY
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INVESTIGATING THE EFFECT OF UNBOXING VIDEOS OF CONSUMER ELECTRONICS ON CONSUMER EMOTIONS THROUGH SENTIMENT ANALYSIS OF ONLINE CUSTOMER COMMENTS

Master's Thesis

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This is to certify that we have read this thesis and we find it fully adequate in scope, quality and content, as a thesis for the degree of Master of Business Administration.

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ABSTRACT

INVESTIGATING THE EFFECT OF UNBOXING VIDEOS OF CONSUMER ELECTRONICS ON CONSUMER EMOTIONS THROUGH SENTIMENT ANALYSIS OF ONLINE CUSTOMER COMMENTS

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With the increasing use of technology and social media tools in the last decade, customers' opinions about companies have become more important for companies. With companies starting to invest in social media marketing, companies can now analyze customer reactions very quickly and even instantly.

As a social media tool, YouTube has become a popular video platform in recent years for both customers and companies to promote themselves and conduct marketing activities. From the company's point of view, it is a great place to promote their products. On the customer's side, YouTube is a free space to praise or criticize products.

Unboxing videos, which have been the trend on YouTube recently, attracted much attention from consumers. The process in these videos starts with the person unpacking the product, and then the person uses the product and gives the audience information about the product. Unboxing videos have reached about ten times the number of views compared to the official videos of the products. Especially consumer electronics and toy unboxing videos are the most watched videos on YouTube.

The main purpose of this study is to measure the emotional distribution of popular unboxing videos. The consumer electronics category was chosen for its high number of videos and reviews. Lexicon based sentiment analysis technique was used for measurement. In addition to sentiment analysis, it was also measured whether unboxing videos had a positive or negative impact on customers. In addition to these results, the comments written on the official video of the product and the comments made only by the purchasers were analyzed in order to make a more accurate analysis of the products. Finally, all these results are compared and presented.

Keywords: Unboxing on YouTube, Sentiment Analysis, Electronic Word of Mouth, Customer Reviews, Polarity.

ÖZET

DUYGU ANALİZİ YÖNTEMİ İLE ELEKTRONİK ÜRÜNLERİN KUTU AÇMA VİDEOLARININ TÜKETİCİ DUYGULARI ÜZERİNE ETKİSİNİN ARAŞTIRILMASI

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Teknoloji ve sosyal medya araçlarının kullanımının son on yılda artmasıyla birlikte, müşterilerin şirketler hakkındaki düşünceleri şirketler için daha önemli hale gelmiştir. Sosyal medya pazarlamasına yatırım yapmaya başlayan şirketler artık müşteri reaksiyonlarını çok hızlı ve hatta anında analiz edebiliyor.

Bir sosyal medya aracı olarak, YouTube, son yıllarda hem müşterilerin hem de şirketlerin kendilerini tanıtması ve pazarlama faaliyetleri yürütmesi için popüler bir video platformu haline geldi. Şirketin açısından bakıldıdğında ürünlerini tanıtmaları için harika bir platform. Müşterinin tarafından bakıldığında ise YouTube, ürünleri övmek veya eleştirmek için özgür bir alandır.

Son zamanlarda YouTube'da trend olan kutu açma videoları tüketicilerin dikkatini çekti. Bu videolardaki süreç, kişinin ürünün paketini açmasıyla başlar ve ardından ürünü kullanması ve izleyicilerine ürün hakkında bilgi vermesiyle devam eder. . Kutudan çıkarma videolarının görüntülenme sayısı, ürünlerin resmi videolarındaki görüntülenme sayısının yaklaşık on kat üzerine ulaştı. Özellikle, tüketici elektroniği ve oyuncak kutu açma videoları YouTube'daki en çok izlenen videolardır.

Bu çalışmanın temel amacı, popüler kutu videolarının insanlar üzerindeki duygu dağılımını ölçmektir. Tüketici elektroniği kategorisi, çok sayıda video ve yorum barındırdığı için seçildi. Ölçüm için sözlük tabanlı duygu analizi tekniği kullanıldı. Duygu analizine ek olarak, aynı zamanda kutudaki videoların müşteriler üzerinde olumlu veya olumsuz bir etkisi olup olmadığı da ölçüldü. Bu sonuçlara ek olarak, ürünlerin daha doğru bir analizini yapmak için ürünün resmi videosuna yazılan yorumlar ve satın alan kişiler tarafından yapılan yorumlar da analiz edildi. Son olarak, tüm bu sonuçlar karşılaştırıldı ve sunuldu.

Anahtar Kelimeler: Kutu açma, Duygu analizi, Elektronik fısıltı pazarlaması, Tüketici değerlendirmeleri, Polarite.

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ABBREVIATIONS

CRF	:	Conditional Random Fields
EWOM	:	Electronic Word-of-Mouth
GS	:	Google Shopping
IDE	:	Integrated Development Environment
IR	:	Information Retrieval
NLP	:	Natural Language Processing
OV	:	Official Video
PMI	:	Point-Wise Mutual Information
SA	:	Sentiment Analysis
UV	:	Unboxing Video
WOM	:	Word-of-mouth
YO	:	YouTube Official Video
YU	:	Youtube Unboxing Video
GSR	:	Google Shopping Reviews

1. INTRODUCTION

Today, companies try to survive in the current system by improving themselves every day due to the competitive environment. With competitive environment and global change, it is no longer possible to survive with product-centric strategies. Therefore, it is more beneficial for companies to have customer-oriented approaches instead of product-oriented approaches (Aytekin & Mayda, 2013). For these reasons, today, businesses change their management understanding and strive to provide and develop long lasting relationships with their customers. The most important way to strengthen this relationship is to understand customer requests and meet customer demands. When the digitalizing era is considered, data is very important for companies.

It is now known that companies that can process and use data with digitalization are more effective in marketing and gain critical advantages. For this reason, all data-related developments attract the attention of companies and companies continue their investments in this field.

For companies, social media is often a very powerful source of data. With the help of developing technology, companies can access this data quickly and store this data in their databases when necessary. These data, which are kept in the database, can be analyzed by experts and can be used in forward-looking forecasts. Recently, sentiment analysis is the most important method for companies to understand customers. Through sentiment analysis, the company can continuously analyze the feelings of its customers about itself and make more effective decisions in line with customer thoughts and shape its brand.

Today, people use social media channels at a high rate. Through these channels, they can share their feelings, thoughts and ideas with other people. Along with the prevalence of social media, individiuals often want to evaluate the opinions of others when they need to make a decision as consumers (Liu 2015). This applies not only to individuals but also to companies (Sammut 2017). People intend to make fewer mistakes by benefiting from the experiences of others.

One of the media that can be used for consumers to get the experiences of others is the YouTube. It is one of the strongest social media resources. It is the most visited and produced online video sharing site in the world. In recent years, unboxing videos on Youtube has attracted attention with its popularity. Unboxing videos are box opening videos, as the name suggests. The unboxing video starts with opening the product box, ends with testing and commenting on the product.

The aim of the current research is to understand the consumer emotions toward unboxing videos while comparing them with Google shopping site customer reviews and official YouTube videos of the companies. To reach the aim, online customer comments at the bottom of the unboxing videos, official YouTube videos, and customer reviews on Google shopping were analyzed with the help of lexicon based sentiment analysis.

In the first part of the study, general information about sentiment analysis and unboxing videos was given. In the following, coding tools, robotic tools and other systems to be used in the study were mentioned.

In the second part, information was given about where and how the data required for sentiment analysis was collected. In the following, manipulation techniques on data were discussed in order to make accurate analysis. The model of the results of sentiment analysis is explained

In the third part, sentiment analysis results were shared in three different platforms. In addition, analysis results and wordclouds between products and categories were described. Finally, the fourth part was the last part of the study. At this stage, the results of sentiment analysis were interpreted and discussions were made about the reasons.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 MARKETING

2.1.1 Definition of Marketing

Marketing is an activity where individuals and businesses have been working on for many years to achieve success and shaped their actions at this point (Tekin 2007). Marketing is a link between vendors and customers in order to meet the demands and expectations of consumers in daily life and includes many variables (Tekin 2007). American Marketing Association has defined marketing as the planning and implementation process of pricing, promotion and distribution of ideas, products and services in creating the changes that will achieve the personal and organizational goals (Mucuk 2010). Marketing is a system based on the exchange of goods or services between buyers and sellers who have the intention and power to buy in a real or virtual marketplace (Elden 2013). Kotler defined marketing as meeting the needs of the consumers, not as telling or selling (Kotler 1996).

Marketing by most people is thought to be only for sales and advertising (Kotler 1996). Marketing is more than just a concept that is positioned on sales and is evaluated only through sales (Kotler 1996). The concept of sales refers only to the process after the production of the product and to the presentation to the consumer, while the marketing refers to a process that involves many variables, including the pre-production and post-sales service (Kotler 1996). Marketing is a term that starts before the sales process, continues throughout the sales and covers the after-sales processes (Bilge & Göksu 2010).

Marketing is an effort for companies to reach more consumers with more positively positioned elements in the marketplace to make their communication and interaction activities more profitable with consumers (Kotler & Keller 2012). Marketing is the process of introducing, planning and promoting the development of targeted goods-services and ideas for the purpose of achieving individual and institutional goals (Altunışık et al 2002). Marketing is an exchange process to meet the needs and demands of consumers (Bilge & Göksu 2010).

Marketing is not only about supplying goods and services to consumers, but also about telescopic processes in technology (Koçak 2012). Marketing is commercial activities related to products and services for producers and consumers (Korkmaz 2004).

Economic, political, social and technological changes since the emergence of exchange systems have revealed some differences on marketing approaches (Ebren 2006). The concept of marketing, which is shaped according to the stage of development of societies, has developed by differentiating its understanding and philosophy according to the stages divided into agriculture, industry, service and information society (Ebren 2006). At this point, it is possible to summarize the phases of marketing in the historical process as follows (Ebren 2006):

i. Production Approach: The distance between producer and consumer is very close. Consumers have no chance to choose between the products produced. Manufacturers think they can easily sell what they produce. It is the philosophy that aims to make more sales and achieve maximum profits through those sales. The consumer considers the product offered to him / her enough. For this reason, it is a process in which the expectations of the consumer are not very important for the producer.
ii. Product-oriented Approach: It is the opinion that high performance products will be sufficient to achieve the desired targets by increasing the quality on the basis of the product oriented approach which is the continuation of the production approach and which has similarities in the context of general criteria. Customer demands and expectations are not taken into account.
iii. Sales Approach: In the process following the World War II, there were some problems in the competition of the products produced in the competitive environment with the emergence of similar products. This situation has revealed the sales approach that includes the actions of enterprises to provide consumer persuasion with a number of sales development tools. It is a period in which advertising works aiming at door-to-door sales and consumer towards the product are frequently encountered in marketing. It is a period of intense efforts to deceive consumers both in personal sales and in advertising.

iv. Marketing Approach: This approach, which is dominated in the process from the 1950s to the 1970s and is regarded as a modern marketing concept, is the period when the consumer participates in the process for the first time, unlike the past practices. In this approach, customers are in an important place. it is observed that some applications such as production, engineering and R & D have come to the fore to differentiate from the competitors. In this period, concepts such as customer focus and integrated marketing communication began to emerge. In addition to this, the marketing concept was carried out through the marketing departments within the company, and this period was an important factor in the emergence of modern marketing concept.

v. Social Marketing Approach: It is an approach adopted since the 1970s. It has emerged as a result of consumer awareness and diversification of expectations. According to the social marketing approach, while providing the products that respond to consumer wishes and desires, on the other hand, it gives priority to people and community welfare.

The importance of marketing communication in the marketing mix, which constitutes a critical aspect of the general marketing characteristics of enterprises, has been increasing dramatically in recent years (Keller, 2001). However, marketing communication is an important determinant of the success or failure of the company mission and vision (Keller, 2001). In this context, it is possible to say that, marketing communication which represents the voice of a brand in communicating with its target audience, aims at establishing the right dialogue channels on the road to success (Keller, 2001).

With the concept of marketing communication, it is tried to explain all the actions of marketing managers in order to guide the purchasing decisions in a positive way by recognizing the product by the consumers (Odabaşı & Oyman, 2014). The most important factor that distinguishes it from other marketing activities is the formation of a marketing communication as a convincing communication effort that involves the information and transformation of the consumer's thoughts on the product and service as a result of the information obtained by the consumer (Mucuk 2010). In this context, it is important to establish a comprehensive communication strategy that includes all components to ensure successful marketing communication (Mucuk 2010). Large and small, commercial, government, charities, education and other non-profit organizations must all communicate with stakeholders (Fill & Jamieson, 2011). Businesses need to establish a communication system in which they can understand consumers' intentions and wishes and accurately describe the goods and services they offer (Fill & Jamieson, 2011). In this respect, it is an intermediary that establishes a link between marketing communication and related parties (business-consumer), where they can better understand each other (Fill & Jamieson, 2011).

2.1.2 Definition of Digital Marketing

Due to the modernization of marketing, marketing is in a process of continuous change and transformation (Merisavo 2006). Thus, marketing processes and practices have become relevant to the current situation and conditions and are suitable for a structure that can meet changing consumer needs (Merisavo 2006). In line with these developments, the most important change in the marketing concept is to enable traditional marketing activities to adapt to the digital environment (Merisavo 2006). As a result of the integration of marketing with technology, in the digital environment, producers and consumers are become closer (Merisavo 2006).

The definition of digital marketing is to maintain commercial activities using platforms that involve interaction with the Internet instead of using traditional marketing and media tools such as television, radio or magazines. (Altındal 2013). Digital marketing is the creation of demand with the power of the Internet and the innovative way to meet demand (Stokes 2013). With technological developments and the Internet gaining a very important place in life, companies have started to take advantage of this new and technological system to reach their customers (Bulunmaz 2016). As a result of features such as instant recognition of consumers' reactions, low-cost promotions and the ability to update quickly, the Internet is the main determinant of the digital revolution (Bulunmaz 2016). With the widespread use of the Internet in the world, a group of users emerged who can communicate with each other, discuss, facilitate access to information sources, organize forums, spend some time on the Internet (Kırcova 2002). Previously, this user group used the Internet for research purposes only, but later started to use it for relaxation and entertainment shopping (Kırcova 2002). Users' interaction with digital channels ensures that information and content is spread over a wide range (Wertime & Fenwick 2008).

Digital marketing is the realization of all marketing activities and applications using digital channels in digital environment (Bulunmaz 2016). Digital marketing is a social and managerial process that makes it easier for customers and companies to meet their demands and needs (Kotler & Armstrong 1993). As an application, digital marketing forms the basis for direct marketing that requires a customer database to monitor and measure customers' business behavior (Zahay 2015). Digital marketing also includes efforts by an enterprise to reach its target audience through electronic technologies such as e-mail, mobile-based geolocation, social media, online customer communities, webinars and other video-based content (Rouse, 2015).

With their digital marketing strategies, companies can capture real-time data about what consumers are actually doing and achieve a steady growth momentum (Wertime ve Fenwick 2008). At this point, the new media channels created by the digital revolution offer significant advantages in the implementation of the systematic work of the enterprise (Wertime & Fenwick 2008).

Media tools that are transformed from traditional to digital make it easier to realize interactive, participatory and speed-oriented activities (Wertime & Fenwick 2008). As in many consumer-focused configurations, a digital transformation in marketing concept is necessary (Wertime & Fenwick 2008). Adding only a few digital events to the marketing plans is not enough to ensure marketing success in reaching the consumer (Wertime & Fenwick 2008). Instead of this approach, marketing approaches around the features of new media and digital marketing should be radically changed and reapplied (Wertime & Fenwick 2008). In this respect, while the basic and traditional marketing principles such as positioning and segmentation of marketing are continuing, it is important to reveal the dynamics of how consumers are affected by digital channels (Wertime & Fenwick 2008).

2.1.3 Definition of Social Media Marketing

Individuals live together from friendship relations to the communities they belong to and share their ideas, insights and experiences. Social media marketing is important as one of the categories of broader digital marketing. The main purpose of social media marketing is to create a company's online presence in different social media channels and to enable customers to communicate in these channels (Chaffey & Ellis-Chadwick 2012). Social media marketing refers to social media sites to appear more on the internet and to promote goods and services (Yayla 2010).

Especially in recent years, the competition on the internet has increased (Olgun 2015). For this reason, social networks used as a marketing tool and this subject has attracted the attention of researchers (Olgun 2015). Social media marketing has gained importance recently and the interest in marketing has increased (Olgun 2015). As a result, social media marketing has been a significant contributor to the revenue sources of enterprises (Olgun 2015).

Social media marketing provides many benefits (Zimmerman & Sahlin 2010). One of the most important of these benefits is the lack of cash payment (Zimmerman & Sahlin 2010). However, social media marketing has the disadvantage as well as its advantage (Zimmerman & Sahlin 2010). One of the disadvantages is that enterprises need investment to launch social media campaigns (Zimmerman & Sahlin 2010).
The benefits of social media for businesses are listed as follows (Zimmerman & Sahlin 2010):

i. Creating a Great Network with the Goal of Understanding the Target Market: Those who visit social media sites are already customers or potential customers of businesses. Businesses to understand the target market and social media to attract a large number of customers to attract a large network is required.
ii. Branding: Social media offers businesses a great advantage in terms of creating and promoting their brands. In order to maintain branding on social media effectively, it is necessary to divide target groups into sections. Thanks to this

segmentation, enterprises will be able to manage the marking process more effectively.

iii. Establishing Relationship: Businesses establish various relationships on social media. For these relationships to be effective:

a. Create a specialization area,
b. Participating in the social media environment as a “good citizen“,
c. To stay away from self-hold,
d. Silently selling,
e. They need to increase their values by establishing various links, providing resources and obtaining objective information.

iv. Business Process Development: Companies need to develop their business processes with social media and use social media actively in order to improve their business processes. Social media offers businesses the following opportunities in business development:

a. To be aware of customers' problems and complaints and to find solutions,
b. Using customer returns in new product design or product change,
c. Many people can provide technical support at the same time,
d. Ensure that the service is delivered more efficiently,
e. Finding new equipped vendors, service providers and employees with support from professional networks such as LinkedIn,
f. Collecting information about industries, competitors and markets by following social media.

v. Improved Search Engine Ranking: Another task of companies is to enable businesses to rank better in search engine ranking. To do this, businesses can benefit from tools such as Google, Yahoo and Bing.

vi. Sales when Opportunity is Obtained: The aim of developing social media is to establish long-term commitment to marketing and branding, not sales, and also through social media, businesses provide online sales to followers.

vii. Saving Money for Advertising: A company needs to be supported by social media to provide advertising at the time of its founding.

People in decision-making and advisory positions in businesses focus on how to increase the ratio of profitability with Facebook, Instagram, LinkedIn etc. platforms (Kaplan & Haenlein 2010). Social media applications that consumers use intensively are noticed by businesses and businesses focus on these applications (Kaplan & Haenlein 2010). These applications and platforms are easy to use and manage, and businesses use these applications and platforms for marketing purposes (Kaplan & Haenlein 2010).

2.1.3.1 Youtube for social media marketing

Since the day humanity has existed, individuals have begun to communicate through facial expressions and later through conversation (Safko & Brake 2009). Communication with facial expressions and tones is the oldest method used by any creature (Safko & Brake 2009). In this context, the video, which essentially involves seeing and saying, makes it possible to make the audience laugh, to teach new things or to develop a relationship with them at the basic level and to have an opportunity to connect with the audience on an individual level (Sherman & Smith 2013). Because there is only one individual and the ensuing community facing the camera (Sherman & Smith 2013).

The explosion of web content has created a new media network (Manovich 2009). At the practical level, this universe has made it easier for people to share their media and easily access media produced by others through free web platforms and software tools (Manovich 2009). Online video has already existed before YouTube. However, since there is no integrated platform which is easy to use, it is very difficult to upload, manage, share and watch videos (Cheng et al 2008). New generation video sharing sites, known as user-generated content sites, have overcome these issues, where users like YouTube are participative and creative (Cheng et al 2008). Systems enable users to effortlessly upload videos, tag and upload uploaded videos with keywords, and evaluate and comment videos (Cheng et al 2008). Media sharing sites such as YouTube, as well as user-centric content sites (Van Dijck 2013), with easy-to-use digital cameras and high-speed Internet connections, have become quite popular (Zarrella 2009). This popularity and content production has led to the reshaping of the online video market (Cha et al 2007). Online payment system PayPal’s former employees Steve Chen, Chad Hurley and Jawed Karim founded Youtube in December 2005 with the idea that people can share videos (Yüksel 2017). Youtube is a social media platform that allows video sharing and is a digital application that can be accessed by desktops, tablets, smartphones and smart TVs (Cook & Ryan 2015). The platform first came into prominence with the release of Saturday Night Live's video "Lazy Sunday" and a 83 percent increase in the number of visits to YouTube was made during the week after the video was published (Prescott 2007). At the end of its first year of publication, YouTube reached 38 million visitors, representing one of the fastest growing websites in history (Miller 2011). The site was launched in 2006 by Google Inc. was purchased for 1.65 million dollars as one of the biggest investments in the company's history (Yüksel 2017).

YouTube represents the first of the services that aim to remove technical barriers to online video sharing, enabling users to watch, upload and publish videos without high technological knowledge (Burgess & Green, 2013). Mueller (2014) states that YouTube, the video hosting and sharing platform, is an archetypal example of a media platform that includes features of the web 2.0 model and participatory culture ideals.

Media that catches more viewers for advertisers is valuable (Farchy 2009). Through YouTube, both large and small businesses can continue their marketing efforts with online videos (Miller 2011). Because YouTube does not charge any fee for uploading, hosting and monitoring videos from users or brands (Miller 2011). In this context, it represents a low-budget marketing opportunity, but brands need to identify their strategy to carry out successful marketing work on YouTube (Miller 2011).

2.2 WORD-OF-MOUTH (WOM)

The most general and simple definition of word-of-mouth communication was known as referring to the opinions of people around consumers with the intention of learning about a particular brand, product or business in the past (Sarıışık & Özbay 2012). In the current marketing literature, it is stated that consumers are perceived as the most important and most reliable source of information for the decision to make a purchase (Bristor 1990) and helping to understand the service before consumption and to reduce the risk (Yaylı & Bayram 2010).

WOM communication is considered as the transfer of product information from a particular source to other consumers (Mookerjee 2001). Information that comes from a reliable source as a suggestion and communicated to other consumers by mouth to mouth communication can also be described as "Recommendation" (Mookerjee 2001). For the evaluation of the recommendation as a Word-of-mouth communication, the communicator must be independent of the manufacturer (Wee Lim & Lwin, 2015).

WOM communication can be considered as informal, person-to-person communication between a sender and recipient, not commercially perceived about a product, business or service (Arndt 1967). Word -of-mouth communication is a conversation about product information during a conversation between non-business people (Lampert and Rosenberg 1975). Word -of-mouth communication is a conversation about a business, including a brand, product, or service (Buttle 1998). Kutluk & Avcıkurt (2014) defined it as a spontaneous form of communication between individuals to reveal their preferences or subconsciously.

Consumers share their experiences after consumption of a particular product or service with those around them (Laczniak et al 2001). WOM communication can be randomly based on consumers' own experience, or it can be systematic with many consumers sharing similar experiences about product or brand defects (Wee Lim & Lwin 2015).

The main idea of word-of-mouth communication is the spread of information about goods, services, stores and operations from one consumer to another (Brown et al 2005). In its broadest sense, it involves the direct transport of any information related to the target object (such as business or brand) through some means of communication or from one person to another (Brown et al 2005). Although studies on interpersonal communication have old origins (Buttle 1998), WOM communication in marketing literature has been seen as the most effective source of information transfer since the beginning of human society (Godes & Mayzlin 2004; Maxham & Netemeyer 2002). In addition, WOM in the last 10 years has been the subject of the most research in marketing (Gheorghe 2012).

It is stated that oral communication is normally used in the definition of recommendations from other consumers (East et al. 2007). Thus, word of mouth communication can affect the opinions, ideas and decisions of others (Ahmad et al. 2014) and it is stated that consumers can be seen as an important factor in shaping the buying behaviors (Whyte 1954; East et al. 2007). Moreover, negative mouth-to-mouth communication of consumers, which may affect purchasing behavior, may cause a decrease in sales, while positive mouth-to-mouth communication may positively affect a possible increase in sales (Dye 2000). For such reasons, it is stated that word-of-mouth communication has valuable resources and can be highly valued by many marketing experts (Havaldar & Dash 2009).

In general, a satisfied customer's contact with a potential customer has been the focus of studies on word-of-mouth communication (Karaoğlu 2010). In addition, while the sense of pleasure on word-of-mouth communication had a significant effect (Ladhari 2007), it was found that the sense of satisfaction and pleasure motivated positive WOM communication (Buttle 1998). In addition, it has been stated that the satisfaction of the product or service usually results in loyalty and positive mouth-to-mouth communication (de Matos et al. 2009; Wangenheim & Bayón 2007). However, although satisfaction is stated to trigger positive mouth-to-mouth communication, dissatisfaction triggers negative mouth-to-mouth communication (Derbaix & Vanhamme 2003; Buttle 1998). In addition, the intention to communicate with the positive mouth to the mouth is positively associated with the value and quality perceived by the customer (Hartline & Jones 1996), while the intent of making negative mouth-to-mouth communication is expressed as one of the behaviors that the client has complained about in the past (Singh 1988).

2.2.1 The Importance and Characteristics of Word-of-Mouth Communication

Consumer audiences can ignore or block traditional forms of marketing and advertising efforts. However, the situation may change if a family member or friend conducts marketing online and offline conversations (Walker 2004). Word-of-mouth communication is considered an effective determinant of the consumer purchase process (Eisingerich et al. 2014). Since, word-of-mouth communication is a cost-effective and reliable method of providing information about goods and services, it plays an important role in the dissemination of knowledge and shaping the attitudes of consumers in consumer markets (Mizerski 1982). Customer satisfaction does not mean that a customer will buy or recommend more goods and services on their own (Arlı 2012). In order to increase sales in a service business, customer satisfaction alone is not enough, businesses should encourage more word-of-mouth communication (Eisingerich et al. 2014). WOM communication features as follows (Silverman 2007):

i. Most influential, effective and convincing force on the market
ii. Experience-transmission mechanism.
iii. Reliable because it is independent
iv. Becomes part of the product
v. Personalized, more relevant and complete
vi. Occurs on its own, self-nourishes, multiply, sometimes multiply by multiplying.
vii. Unlimited in speed and freedom of movement
viii. May arise from a single source or from relatively small sources.
ix. Highly dependent on the nature of the source
x. Saves a lot of time and business.
xi. In general, the negative side is in the foreground but can be considered positive in terms of its effects.
xii. Promoting, strengthening and sustaining may be less costly and easier.

2.3 ELECTRONIC WORD-OF-MOUTH (eWOM)

Word-of-mouth communication can take place in electronic environments such as telephone, chat rooms, e-mail or web sites (Buttle 1998). In addition an enterprise may offer incentives or awards to spread the Word-of-mouth communication (Buttle 1998). It is emphasized as a distinctive feature of Word-of-mouth communication to be acceptable to the recipients regardless of institutional impact (Buttle 1998). There are two important features that distinguish word-of-mouth communication from other sources of information, such as advertisements (Liu 2006). One of them is that word-of-mouth communication is generally more credible and reliable, and the other is it is more accessible through social networks (Liu 2006). With the flexibility of information and access to information that makes the Internet different from other communication tools, consumers have the opportunity to obtain information that is appropriate to their wishes and needs (Faber 2004). Another distinguishing feature of the Internet, the versatility of the word-of-mouth communication has brought a new dimension and traditional mouth-to-mouth communication allows the Internet to be transferred (Dellarocas 2003).

The effect of consumer on word-of-mouth communication, which is one of the ways of interpersonal communication, has shown more progress with the emergence of the Internet (Cheung & Thadani 2010). With the expansion of the use of the Internet, the concept of expanding word-of-mouth communication has triggered the emergence of electronic word-of-mouth communication, a new concept (Chung & Kim 2015). Jeong and Jang (2011) describe electronic word-of-mouth communications as broad Web-based, anonymous, always accessible and multi-directional; Yang (2017) has defined the electronic word-of-mouth communication as communication through various technological media. In addition to these definitions, some other definitions related to electronic oral communication are: eWOM communication is a practice action that has strong effects on others (Fu et al. 2015). Electronic word-of-mouth communication is a positive or negative expression about a product or service that is widely available on the Internet (Boo & Kim 2013). Electronic word-of-mouth communication is the exchange of information and discussions made by the network user about certain products or services via network media (Sun et al. 2006).

eWOM communication is a communication application between people who do not know each other in virtual environments, where many topics and comments can be shared through different channels and methods (Sarıışık & Özbay 2012). With the increase of these shares and the spread of comment websites, it has managed to include a wider audience (Sarıışık & Özbay 2012). The speed and ease of communication are increasing with only technological developments such as Facebook, Twitter and Messenger which are especially online communication ways (Berger 2014). At the same time, this correspondence is written on a daily basis everyone can share their thoughts with millions of users of the Internet and can be effective on different issues over others with their decisions (Duan et al. 2008; Dellarocas 2003). Especially in recent times, Internet forums have a strong influence on both their readers' preferences and other forum reader preferences by empathizing with their readers (Bickart & Schindler 2001; Dellarocas & Narayan 2006). In this way, customers are able to provide information and information to everyone about an unlimited number of products and services, wherever they are in the world as well as their acquaintances (Lee Matthew et al. 2006).

2.3.1 Electronic Word-of-Mouth Channels

Blogs

Blogs are websites that allow bloggers to log, share personal experiences and content in a given region, and interact with readers by publishing comments (Sotiriadis & Zyl 2013). Blogs have specific features and gained popularity among consumers (Labsomboonsiri 2012). There are two main types of blogs created by marketers and consumers (Labsomboonsiri 2012). Consumers can obtain useful information from blogs to facilitate purchasing decisions (Labsomboonsiri 2012). Blogs created by marketers enable companies to promote their products and brands and to engage with their customers (Carson & Schmallegger 2007). Blogs are more advantageous than other content formats with the following features (Carson & Schmallegger 2007):

i. Easy to update
ii. Structurally flexible
iii. Encouraging interaction between the author and reader

Online Consumer Reviews

Consumers can share their experiences and opinions with other users on a product or service online (Sotiriadis & Zyl 2013). Through virtual idea platforms, consumers can share their views and experiences and read the opinions and experiences of other consumers in different areas of consumption. The contributions to the idea platforms include both the information of the consumer's experience with a product and the rating of the product. In addition, while ratings can be view by other consumers, systematic monitoring of online consumer reviews can help companies to identify the weaknesses associated with their products or services and have a chance to improve the quality of their products or services (Hennig-Thurau & Walsh 2003).

Online reviews, which are an independent product-information source, gain popularity and importance (Park et al. 2007). Online consumer reviews play an important role in making a purchase decision for a product. The quality of comments has a positive effect on the consumer's intention to buy and consumers' purchasing intent increased with the number of positive comments. (Park et al. 2007).

Social Network Websites

Social networking sites are websites where people create personal profiles, connect with other users, communicate and improve their relationships. Facebook as a social network, professional network as a LinkedIn example can be given (Sotiriadis & Zyl, 2013). Social networking sites are online communities that allow users to connect and communicate with each other, as well as to create a personal network for sharing personal content (Akar 2010). Users make suggestions and share ideas on social networking sites (Akar 2010). When consumers think about buying goods and services, it is seen that they are investigating the ideas of others (Akar 2010). The ideas of others are seen more objectively than companies' own marketing messages (Akar 2010). Consumers use online resources that include social networks to learn the ideas of others (Akar 2010).

Increasing the use of reliable sources of communication technologies for consumers to obtain information, product or service understanding, and other consumers' opinions shows that web communication and social networking services increasingly affect brand perceptions and purchasing decisions (Jansen et al. 2009). This situation offers new opportunities for establishing brand relationships between potential customers and electronic mouth-to-mouth communication platforms (Jansen et al. 2009).

Discussion Forums

Discussion forums, such as message boards, internet forums and chat rooms, allow consumers to share their experiences, thoughts and information on specific topics with other consumers (Chiou & Cheng 2003). The messages contained in the discussion forums are believed to be stronger in terms of affecting consumer attitudes than marketing-related messages (Chiou & Cheng 2003). Because the consumer messages contained in the discussion forums do not have a commercial purpose and are considered as reliable by consumers (Chiou & Cheng 2003). Moreover, negative messages in discussion forums significantly reduce the attitudes of consumers to the brand (Chiou & Cheng 2003).

2.3.2 Reasons to provide eWOM

The fact that it is a social dimension that increases value can be shown as an important reason for providing eWOM (Amblee & Bui 2008). With eWOM, it is stated that the person gains a sense of worthiness (Han 2008).

When people write comments about products, they feel within a social group (Han 2008). Therefore, the desire for social communication is also shown as the reason for providing eWom (Amblee & Bui 2008).
The desire to help people can also be cited as the reason for providing eWom (Amblee & Bui 2008).

People can provide eWOM to support the manufacturer when they are satisfied with a product, or to harm the manufacturer if they are not satisfied with the product (Han 2008).

Finally, people can provide economic advantages by providing eWOM. By making agreements with companies, they can provide eWom with an economic response (Han 2008).

2.4 UNBOXING AND UNBOXING VIDEOS ON YOUTUBE

An interesting phenomenon has emerged on the Internet lately: people document the process of opening the package, interpret and share their emotions, it is called the phenomenon of unboxing. Unboxing is self-photographing or recording while opening a new product from the original packaging to show the buyer's first impression of the product and its contents.

The moment of withdrawal from the box is critical because it arouses emotion and raises certain expectations for internal products (Google n.d.; Pantin-Sohier 2009). Box opening determines the initial impression of the product (Merieux 2015; Roger 2014), so it is recommended that companies make impressive and catchy designs (Google, n.d.; Merieux 2015; Roger 2014). In addition to a pleasant experience, it may also have an impact on brand experience (Google n.d.; Merieux 2015). Therefore, improved and well-designed packages can make products more understandable, give users a fun experience and leave positive brand image in their minds (Google n.d.; Merieux 2015). People express their emotions about the product as consumer comments on YouTube just below the unboxing video.

The first example of unboxing phenomenon is that in 2006, Aradius Media Network has released a video about unpacking the box of the Nokia E61, a new mobile phone. More than 120 million results are available today when unboxing video is searched in YouTube. Unboxing is an important item in the YouTube economy and the producers of most popular videos started earn very significant revenues with these videos (Li 2015). In 2014, the highest-income Youtube Channel with $4.8 million was the DisneyCollector, which released videos about unboxing toys (Ferenstein 2015). According to Techbotinc.com's report in 2016, Lewis Hilsenteger, the owner of the “Unbox Therapy” channel, has estimated $ 1.9 million in revenue.

2.4.1 Emotional Experience

People feel a sense of emotion during the interaction between themselves and an object (Desmet 2007). This experience is called emotional experience (Desmet 2007). Emotional feelings and emotional reactions of people to certain stimuli are related to survival instinct and need (Arnold 1960). People have an instinctive reflex for the horrors of safe life-threatening things (Desmet 2002). In other words, the negative or unpleasant feeling will be affected by a dangerous or harmful situation, and a positive and affective reaction will be obtained for the beneficial works (Desmet 2002). From a product experience perspective, emotions affect the rationality of what to buy, consumer satisfaction, product loyalty and overall well-being (Desmet & Schifferstein 2012). The communication of positive emotions can be triggered by product qualities, and the meaning of the product that enables communication with users on an emotional level can be meaningful (Demirbilek & Sener 2013).

2.4.2 Unboxing as Emotion Lever

Opening the box is a critical moment that evokes a strong feeling when a person is about to unpack and use the product for the first time (Dazarola 2012). It is particularly intense regarding the emotions aroused in consumers (Dazarola 2012). In order to trigger personalized emotional responses, packaging products are as important as transmitting relevant information about product (Patrick 2014). Brand owners and service providers are expected to find new ways to use packets and labels as emotional leverage (Patrick 2014).

2.5 SENTIMENT ANALYSIS AS CONSUMERS' EMOTIONAL MEASURE

Nowadays, sensitivity analysis is an important technology that used to determine people's reactions to all developments especially in social media (Liu 2012). Sentiment analysis is the study area that analyzes the opinions, feelings, evaluations, attitudes and feelings of the people about the products, services, organizations, individuals, activities, subjects and their characteristics (Liu 2012). Another definition of sentiment analysis is opinion mining (Liu 2012).

Sentiment analysis is the classification and definition of the feelings of the opinion holder by using statistical models and software on a specific subject (Jade 2013). Sentiment analysis is an idea mining that analyzes the thoughts of individuals as well as their feelings towards quality like company and product (Tripathy et al. 2016). There are 3 different classification approaches in sentiment analysis:

i. Sentiment analysis at document level: All document extracted from the emotional state. Only one emotion pole formed for a document. It is determined from which perspective the opinion expressed on the document.
ii. Sentiment analysis at the sentence level: There is a separate emotion pole for each sentence. Generally used in complaint management and social media messages.
iii. Sentiment analysis at property level: a specific property selected, usually used for product reviews. The product name is determined as a feature and its sentiment is calculated.

In the internet with the increase of content created by users, there has been a desire to use emotion analysis in order to extract healthy information for corporations and companies (Pang and Lee 2008). The first studies on this subject are the studies about a product (Pang and Lee 2008). While the text processing method tries to determine the class that a text expresses emotionally called sentiment analysis, the method of revealing the content in a social media message semantically called opinion mining (Şeker 2016).

Generally indicated that there are two types of approaches for sentiment analysis (Yadav 2015). The first one is lexicon-based-approach, which is used in this research. The other is the machine learning approach (Yadav 2015).

2.5.1 Lexicon-based Approach

In this approach, the sentiment lexicon is the main source of the sentiment analysis. In fact, the lexicon-based methods divided into two categories: dictionary based and corpus based (Serrano-Guerrero 2015). Dictionary-based methods based on meaningful dictionaries, which often include common terms of opinion. SentiWordNet (Baccianella, Esuli & Sebastiani 2010) is a good example and this research used this dictionary. Although this is a reliable approach, there may be some limitations when dealing with different areas. In the same context, corpus-based methods also based on dictionaries, but these dictionaries contain the relevant terms or stages of related fields (Serrano-Guerrero 2015).

Turnley has produced an algorithm that distinguishes customer reviews as recommended or not recommended (Turney 2002). Point-Wise Mutual Information (PMI) and Information Retrieval (IR) are two main methods for calculating semantic orientation and measuring reference words that mean "good" or "bad" (Turney 2002). When 410 comments in different fields examined, 84% success achieved in automobile datasets and 66% success achieved in film datasets (Liu 2012). Because of the urgent need of industrial applications, many researchers prioritized product reviews for sentiment analysis (Liu 2012). In order to determine the potential product characteristics, with the opinion summarization system, they aimed to identify product characteristics and to identify common words used for opinion guidance (Liu 2012). In the process of defining the features of the product, firstly, with part-of-speech tagging which is a technique of natural language processing (NLP), the speech of each word was determined (Liu 2012). This method resulted in a high success rate (Liu 2012).

To determine the semantic orientations of opinion words, relaxation-labeling method, which is more advanced method based on extraction method used (Popescu 2007).

It deduced that traditional feature extraction was not fully effective and different approaches emerged. AutoSlog, which is a different extraction method, recommended by Riloff as a principle (Riloff 1996). In addition to this alternative approach, there was a study called Conditional Random Fields (CRF) (Lafferty et al 2001), which identifies sources as a sequence-tagging task proposed by Lafferty. A hybrid approach combined these two approaches (Choi et al. 2005). In this approach, AutoSlog focused on pattern extraction task, while CRFs focused on the tagging task (Choi et al. 2005). This hybrid study was more successful than the previous two studies (Choi et al. 2005).

A new approach for identifying appraisal groups in order to accommodate a dictionary list emerged (Whitelaw et al. 2005). Sentiment analysis with 1329 appraisal groups resulted in high performance (Whitelaw et al. 2005). The process in this approach is as follows:

i. Appraisal group includes an adjective with a predefined attitude type
ii. Each one refers to the transformation of one or more assessment qualities of the head
iii. An optional list of previous valuation modifiers

“Not so good” and “So bad” are two examples of the appraisal group.

2.5.1.1 WordNet-Affect

A lexicon of words that indicate the presence of a particular emotion (Strapparava & Valitutti 2004). Wordnet-affect contains six emotion categories, which are composed of six word lists (Strapparava & Valitutti 2004). In the following table 2.1, the number of words according to emotions is as follows:

Table 2.1: Distribution of labels in the WordNet-Affect lexicon

Happiness	Sadness	Anger	Disgust	Surprise	Fear	Total
398	201	252	53	71	141	1116

2.5.1.2 The Prior-Polarity Lexicon

Prior-polarity lexicon contains clues on subjectivity collected from more than 8000 sources (Wilson et al. 2009). In this method, in addition to the clues of subjectivity previously issued by Riloff (2003), a list of synonyms and a list of positive and negative words collected from general inquirer added. Words are grouped into strong subjective and weak subjective clues; the following table 2.1 shows the distribution of words (Wilson et al. 2009):

Table 2.2: Distribution of words of positive negative, netural and both

Neutral	Negative	Positive	Both
6.9%	59.7%	31.1%	0.3%

2.5.1.3 NRC Emotion Lexicon

This lexicon is a list of words and their associations with eight emotions as following (Mohammad & Turney 2010):

i. Anger
ii. Fear
iii. Anticipation
iv. Trust
v. Surprise
vi. Sadness
vii. Joy
viii. Disgust

This lexicon also includes two sentiments named positive and negative. This manual annotation constructed with the crowd-sourcing method of Mechanical Turk, a product of Amazon (Mohammad & Turney 2010). At least three annotators used for each word-emotion pair. Following Figure shows the distribution of words as emotion and polarity:

Table 2.3: Distribution of labels in the NRC-emotion lexicon

Joy	Sadness	Anger	Disgust	Surprise	Fear	Trust	Anticipation	Pos.	Neg.
689	1191	1247	1058	534	1476	1231	839	2312	3324

In this research, NRC Emotion Lexicon used because of the high number of words and diffraction of emotions.

Based on previous research on this subject, the following research questions had been proposed:

RQ1: How do unboxing videos create a distribution of sentiment on customers?

RQ2: Is unboxing video a more effective method when compared to official video?

RQ3: Is there a direct relationship between the eight sentiments and the polarity ratio?

RQ4: When comparing effectiveness of unboxing videos, official videos and Google Shopping reviews in terms of customer sentiments through opinions of customers, which one does create the most positive result?

RQ5: Does the difference in emotion analysis results by platform vary by product category?

RQ6: Does the unboxing video have the same effect for competing products in the same product category?

2.5.2 Machine Learning Approach

Machine learning, which is a part of artificial intelligence, evaluated in two main categories: supervised learning and unsupervised learning (Serrano-Guerrero 2015). The issue of extracting the properties of the dataset is effective in machine learning (Serrano-Guerrero 2015). The success rate of machine learning related with extraction of sentiment features with Natural Language Processing (NLP) techniques.

2.6 AUTOMATION AND ARTIFICAL INTELLIGENCE

Artificial Intelligence is an approach which a machine or software can generate intelligence actions such as speech, image or text recognition (Gil 2017). Robotic Process Automation is a robotic method for modeling and automating back-end IT processes of software without human actions (UiPath 2018). The most important benefits of using Automation and AI are (Cameron 2018):

i. Cost decreases
ii. Productivity increases
iii. Error rate decreases
iv. Performance increases
v. Availability of time increases

Learning is based on methods that try to simulate human brain neuron networks that allow computers to recognize objects at the scene (Ostdick 2016).

2.6.1 Robotic Process Automation (RPA)

RPA is a useful tool for automating the business processes and flows that maintained manually in companies (Gil 2017). Enabling companies to use their workforce more effectively, RPA gives both the company and employees the opportunity to think about how to improve their existing processes (Gil 2017).

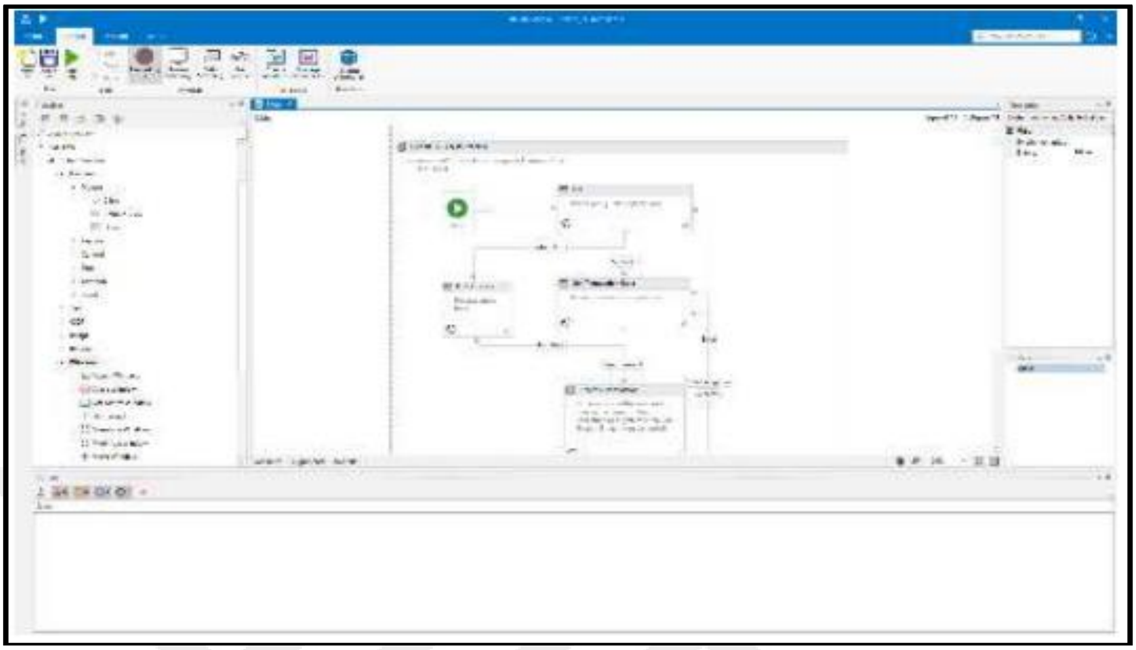
In addition to enabling companies to reevaluate their workflows and processes, RPA also enables companies to reevaluate processes more carefully, to eliminate potential bottlenecks and to make processes simple. RPA saves time and money by accelerating operations and simplifying workflows, as well as saving resources with 7/24 operating robots.

UiPath as a RPA tool

UiPath is a software company that builds and runs robots on the companies' software platforms (UiPath 2018). The mission of the company is to make repetitive processes wise by using software automation (UiPath 2018).

After using a visual and intuitive method to model processes, processes modeled in Studio, using two-dimensional process modeling based on actions that users will perform in the user interface (UiPath 2018). In addition to having drag-and-drop activities to help model the processes, the most important advantage of Studio is that it is one of the best Citrix automation methods that uses fast and intelligent automation facilities and computer vision to detect the screen. (UiPath 2018). Figure 2.1 below shows UiPath Studio, which is used to model business processes (UiPath 2018).

Figure 2.1: General view of UiPath screen



2.7 PYTHON AND LIBRARIES

Python is a interpreter programming language created by Guido Van Rossum in 1989, which supports open source, object-oriented programming and functional programming.

TextBlob on Python

In general, positive or negative reviews are called polarity of sentiment analysis (Bhayani et al. 2009). TextBlob is a library on Python that uses NLP) techniques to measure the polarity of each comment, regardless of other comments (TextBlob 2019). TextBlob is the best sentiment analysis tool by combining Pattern Analyzer (based on pattern library) and Naïve Bayes Analyzer (an NLTK nclassifier trained on a movie reviews corpus) (Toolkit 2014). The naive bayes based implementation is part of NLTK and comes complete with a prelabeled dataset for easy training of the model (Bird & Edward 2006). TextBlob generates polarity scores in the range of (−1, 1). For each review it returns the probability that it is positive and the probability that it is negative. TextBlob can translate between languages with using Google Translate API as infrastructure.

LBSA on Python - Lexicon-based Sentiment Analysis

LBSA is a library on python is for sentiment analysis. LBSA allows sentiment analysis by using the NRC Emotion Lexicon. Exports eight different emotion and polarity results of the analysis. In this study, TextBlob was preferred for the polarity calculation because it produces more computable results.

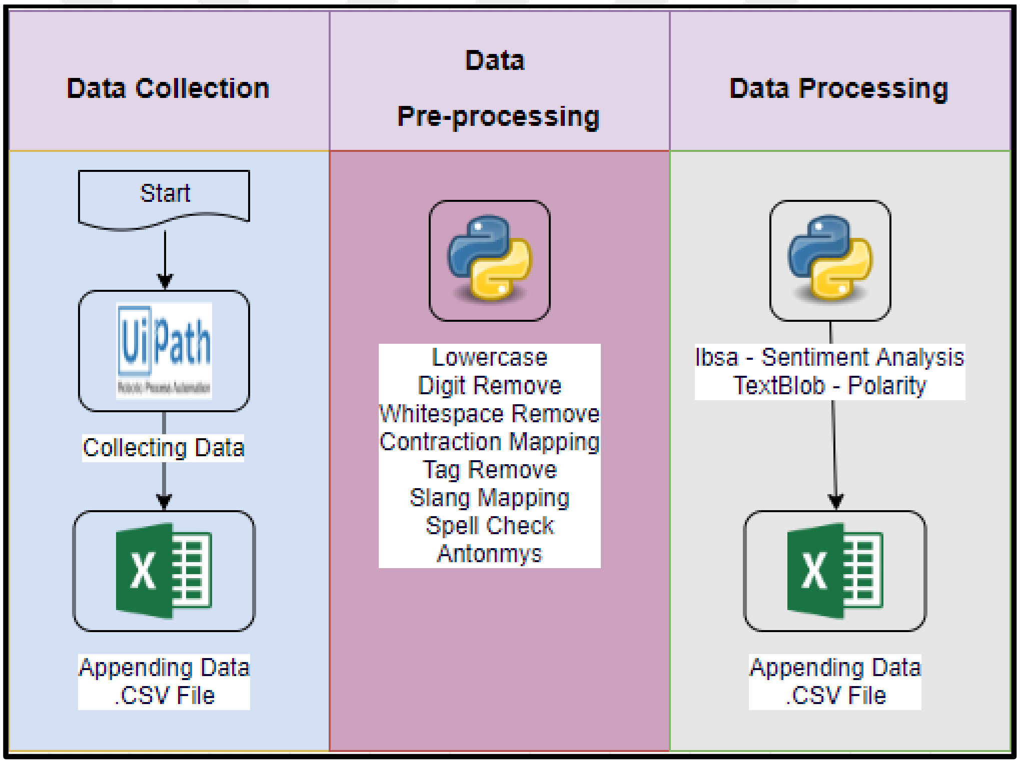
Langdetect on Python

Langdetect is a library on python ported from Google’s language-detection. Langdetect supports 55 different languages. Language detection algorithm is non-deterministic, which means that if you try to run it on a text which is either too short or too ambiguous, you might get different results everytime you run it.

3. METHODOLOGY AND DATA COLLECTION

The methodology part of this study started with the installation of the relevant tools on the system and continued with data collection. The collect data was subjected to a number of pretreatments to give accurate results from the analysis. After these procedures, data were collected regularly in excel environment before analysis. Then, both sentiment analysis and polarity analysis of the data were performed using python infrastructure. After the analysis, all of the inputs and outputs were kept in a new excel file. The flow chart of the data-related operations is as in Figure 3.1 below.

Figure 3.1: General Process of Methodology



3.1 INSTALLATION PROCESS OF UIPATH, PYTHON AND LIBRARIES

In this study, first step was to download the RPA tool UiPath which was used to collect the data. The download of UiPath Community Verision is provided through the official UiPath website (UiPath 2019).

PyCharm is preferred for an interface where to run Python codes. As with UiPath, the PyCharm Community Edition is downloaded via the Official website (PyCharm 2019).

The download process for Python is provided via the official website. 3.7.3 was preferred as the version (Python 2019).

After python installation, library installations started. The installed libraries are as follows: nltk, lbsa, langdetect and textblob. The installation method is the same for all libraries. First, cmd prompt application in windows operating system is started. In the next step, the "pip install" command with the library name is written. An example is shown in the following Figure 3.2:

Figure 3.2: Command Prompt Screen

After the installation process, the system became available for data collection.

3.2 PRODUCT SELECTION AND DETERMINATION

At product selection phase, a study was conducted across the unboxing videos on YouTube. As a result of this study, the categories with the highest number of unboxing videos were observed as consumer electronics and children's toys. In order to choose from these two categories, it was checked whether there is official video of the same products exist. Due to the high number of official videos in the consumer electronics category, products in the children's toys category were excluded.

Consumer electronics category was divided into five different categories in terms of the number of videos and comments. The categories are as follows:

i. Video Game Consoles
ii. Smart Phones
iii. Action Cameras

iv. Smart Home
v. Audio

To avoid brand influence, products of two different brands were selected from five different categories. In other words, a total of ten different products were selected. The product list is as follows:

i. PlayStation 4 & Xbox One
ii. Huawei P20 & Samsung Galaxy S8
iii. DJI Osmo Action & GoPro Hero 7
iv. Amazon Echo & Google Home
v. Sony WF-1000XM3 & Beats By Dre Powerbeats Pro.

3.3 DATA COLLECTION

In this study, UiPath, which is a robotic process automation tool (RPA) used in data collection process. This study conducted for ten different products. Two different processes for receiving data from two different platforms designed on UiPath. The first process is to collect data on *Google Shopping* web page. The process proceeds as follows:

i. The link of the webpage of the relevant product is taken from the user as an input
ii. Automation finds the decisive link on the screen. This link contains texts “View all” and “reviews”. This link navigates to the page with user comments.
iii. UiPath tool prompts the user to address only one comment on the web page. Thus, the program itself can identify all other comments on the web page.
iv. However, since not all comments are on a single page, the program prompts the user to address the “next page” button.
v. The program automates the process until to the last page and writes the results to an .xls file

The second process is to collect data from *YouTube*. This process is similar to the first process in general. In this process, automation expected from user to provide two different links for a product. One of them is the official video link and the other one is the unboxing video link. Unlike the *Google Shopping* website on the *YouTube* website, the "next page" button is not available. The process for each type of video proceeds as follows:

i. The link of the webpage of the relevant product is taken from the user as input
ii. Automation runs the scroll down command until all the comments are listed on the webpage
iii. UiPath tool prompts the user to address only one comment on the web page. Thus, the program itself can identify all other comments on the web page.
iv. The program automates the process until there is no more data to collect and writes the results to an .xls file

The process described above continues for up to ten different products.

3.4 DATA MODEL

In order to create a dataset, all the online comments published about ten different products were collected from two different platforms named *YouTube* and *Google Shopping*. Two different video comments collected from *YouTube* on a single product basis. One of them is the product unboxing video while the other is the product official video. The number of data received from each platform is limited to one thousand after data pre-processing in order to stabilize data quality. A key named Index defined for each comment. Sample input data for a single product formed as following table 3.1:

Table 3.1: Collected data with index

Index	ProductName	YouTubeOfficial	YouTubeUnboxing	GoogleShopping
1	Samsung Galaxy Note 8	Looks Great☺ Happyyy	Looks Amazingg	Hard to use!
2	Samsung Galaxy S8	Not bad?	Not like expected!	Costly☹
….	…	…	…	..
1000	Samsung Galaxy S8	Not good☹	Unproffesional!!!	Disgussedd!!

The sample input table view for all dataset (10 products) is as following table 3.2:

Table 3.2: Input data table

Index	Product Name	YouTube Official	YouTube Unboxing	Google Shopping
1	Samsung Galaxy S8	Looks Great☺ Happyyy	Looks Amazingg	Hard to use!
2	Samsung Galaxy S8	Not bad?	Not like expected!	Costly☹
…	…	…	…	…
1001	Huawei P20 Pro	Gonna buy it now?	Watching this on My Note 9	The battery life drom my experience is a total of 12 or more hours depending on if i'm playing games or not
…	…	…	…	…
89999	XBOX ONE	I wish I could have one lol	I love your videos but was a bit disappointed in this one	Overacting...
…	…	…	…	…
99999	PlayStation4	The price is so crazy!	Still worth buying?	Few days later it blows up
10000	PlayStation4	Great video. Can’t wait to sett	Superb.. Lovely voice & good comentry..	Getting mines Friday!!!?!!

Eight export parameters of sentiment analysis and polarity results were used in the output data structure. Output data structure examined in three stages based on platform where data was collected. Results for each key were evaluated in three different categories.
The meaning of the first two characters of the column names defines the platform. The definitions of these first two characters are as follows:

i. YO: YouTube Official Video
ii. YU: YouTube Unboxing Video
iii. GS: Google Shopping Reviews

Last character of the column names defines the sentiment analysis categories and polarity. The definitions of the last characters are as follows:

i. 1: Anger
ii. 2: Anticipation
iii. 3: Disgust
iv. 4: Fear
v. 5: Joy
vi. 6: Sadness
vii. 7: Surprise
viii. 8: Trust
ix. P: Polarity Rate

For example, the YO5 column addresses the Joy value in YouTube Offical Video. The following table 3.3 lists the results for YouTube Official Video index 1:

Table 3.3: Youtube official video data index1

Index	YO1	YO2	YO3	YO4	YO5	YO6	YO7	YO8	YOP
1	0	1	0	0	1	0	0	1	1

The following table 3.4 lists the results for YouTube Unboxing Video index 1:

Table 3.4: Youtube unboxing video data index1

Index	YU1	YU2	YU3	YU4	YU5	YU6	YU7	YU8	YUP
1	0	0	0	0	1	0	0	0	1

The following table 3.5 lists the results for Google Shopping index 1:

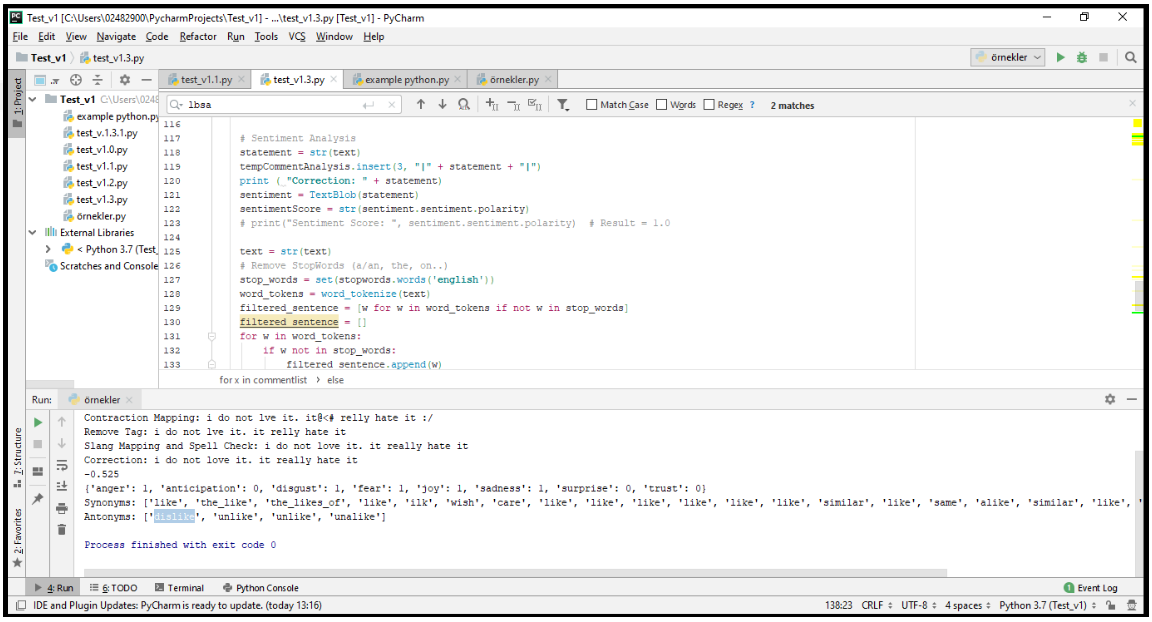
Table 3.5: Youtube unboxing video data index1

Index	GS1	GS2	GS3	GS4	GS5	GS6	GS7	GS8	GSP
1	1	0	0	0	0	1	0	0	-1

3.5 DATA PRE-PROCESSING

In order to preprocess the data imported into the .xls file with UiPath, a platform, which we can use python language is required. For this purpose, PyCharm was preferred. PyCharm is an integrated development environment (IDE) used in computer programming, specifically for the Python language. Following Figure 3.3 is the interface representation of PyCharm.

Figure 3. 3: PyCharm screen



Data pre-processing process was applied separately for each comment in the dataset. This step is a necessary process to do the sentiment analysis. Usually, in the comments or reviews, attention is not paid to grammar and correct writing. For this reason, there are many words, which do not make sense in terms of sentiment analysis in these unstructured reviews. When the noise rate in the dataset exceeds 40 percent, it creates confusion in machine learning algorithms (Fayyad, 2013). Unfortunately, abbreviations, punctuation marks and slang words used for emotion expressions frequently encountered in product reviews. For all these reasons, the initial review text must be processed and made meaningful before sentiment analysis. This process allows the development of data quality and more accurate results.

Sentiment analysis requires that the language of the data be English. Therefore, a study conducted to determine the language of all interpretations through the langdetect library on the Python. The following code block describes the language detection method for a given text:

```
import langdetect
LangDetect = langdetect.detect_langs(text)
```

Since the language detection algorithm was not deterministic, the comments that could not be detected were deleted from the list. All comments in langdetect return in English have been deemed sufficient for the next steps. For non-English comments, the translate method of the TextBlob library was used. Later, however, it was found that the translation process did not work effectively in some languages. Therefore, only the comments in English, which have the return of "EN” from run command were kept for analysis.

After the text in xls file transferring process to txt file manually, text was read line by line with open command in Python. The text before the corrections were as follows:

I don't lke   it. It@<# relly looks Ba12d :/
Really love it!! It Looks fantastic. Strongly recommend!
Honesly, this is not like I expcte2d. Firm must be Crazzzzyyy!!
132i don't know what to   say!!

Lowercase

All letters were converted to lowercase letters at this step with standard python library.

```
text = text.lower()
```

Lowercase Output:

i don't lke   it. it@<# relly looks ba12d :/
really love it!! looks fantastic. strongly recommend!
honesly, ths isn't like i expcte2d. firm must be ####crazzyy!!
132i don't know what to   say!!

Digit Remove

All numbers in the text were deleted in this step with standard python library.

```
text = ''.join([i for i in text if not i.isdigit()])
```

Removing Digits Output:

i don't lke   it. it@<# relly looks bad :/
really love it!! looks fantastic. strongly recommend!
honesly, ths isn't like i expcted. firm must be ####crazzyy!!
i don't know what to   say!!

White space remove

At this step, all of the unnecessary and meaningless spaces in the middle and end of the sentence were deleted with standard python library.

```
text = text.strip()
text = text.lstrip()
text = text.rstrip()
text = re.sub(' +', ' ',text)
```

Removing Whitespace Output:

i don't lke it. it@<# relly looks bad :/
really loved it!! looks fantastic. strongly recommend!
honesly, ths isn't like i expcted. firm must be ####crazzyy!!
i don't know what to say!!

Contraction Mapping

At this step, contraction words were corrected according to the dictionary in the article of “Yet Another Twitter Sentiment Analysis” 2018. This step was crucial for more accurate results.

```
for word in text.split():
    if word.lower() in contractions:
        text = text.replace(word, contractions[word.lower()])
```

Contraction Mapping Output:

i do not lke it. it@<# relly looks bad :/
really loved it!! looks fantastic. strongly recommend!
honesly, ths is not like i expcted. firm must be ####crazzyy!!
i do not know what to say!!

Tag Remove

At this step, the special characters used in the text cleared.

```
text = re.sub(r"[-()\"#/@<>{}`+=~|,]", "", text)
```

Removing Tags Output:

i do not lke it. it relly looks bad
really love it!! looks fantastic. strongly recommend!
honesly ths is not like i expcted. firm must be crazzyy!!
i do not know what to say!!

Slang Mapping and Spell Check

This step contained the correction of the slang words. For this process, the suggestion method in the python enchant library was used. For example, correcting "thk" as "thank". Textblob library of Python was used for this process

```
text = TextBlob(text)
text = text.correct()
text = str(text)
```

Slang Mapping and Spell Check Output:

i do not like it. it really looks bad
really loved it!! looks fantastic. strongly recommend!
honestly this is not like i expected. firm must be crazy!!
i do not know what to say!!

Antonmys

This step was only for sentences containing contraction. Antonmy meaning of the next word was taken into consideration. NLTK library of Python was used for this purpose. To obtain more accurate results sentiment analysis was the benefit of this study.

Antonmys output:

i hate it. it really looks bad
really loved it!! looks fantastic. strongly recommend!
honestly this dislike i expected. firm must be crazy!!
i ignore what to say!!

After all these steps, data was ready for processing.

3.6 DATA PROCESSING AND OUTPUT

After data pre-processing, data has become more meaningful and suitable for analysis. Corrected data was included in two different processes. The first was sentiment analysis and the other is polarity analysis. In both operations, Python commans were applied.

At the first step for sentiment analysis, lbsa, a python library was used. The words and their emotional responses in the lbsa library, NRC Emotion Lexicon, were collected. Then, the text which sentiment analysis was requested, given as an input to lbsa's 'get_lexicon' method. The analysis result and text were combined on a key. The purpose of this key was to follow both sentiment analysis and polarity results. In order to be more descriptive, the texts after the data-preprocessing process were given as examples.

i hate it. it really looks bad
really love it!! looks fantastic. strongly recommend!
honestly this dislike i expected. firm must be crazy!!
i ignore what to say!!

The method returns a result after the sentiment analysis as in the following table 3.6:

Table 3.6: Sentiment analysis return output structre

Key	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust
1	2	0	2	2	0	2	0	0
2	0	0	0	0	1	0	0	1
3	2	1	1	1	0	1	0	0
4	0	0	0	0	0	0	0	0

In the text analyzed according to table 3.6, key one, contained feelings such as anger, fear, disgust and sadness, but did not contain feelings such as anticipation, joy, surprise and trust. This analysis was expected to have a negative trend. In order to support the accuracy of these analyzes, polarity results were followed on the same key. The second key, unlike the first, included positive sentiments like joy and trust. As a result of the analysis, no meaningful conclusions could be drawn. Therefore, if the polarities of such reviews are also zero, neutral, it is decided not to evaluate. This review was excluded from the data set.

Polarity analysis was applied as the second step of data processing. Like the analysis of sentiment, polarity analysis was implemented through Python, but different libraries were used. This step the textblob library was used via Python. As a result of the polarity analysis, as in sentiment analysis, the polarity of the whole review was calculated. In other words, the system calculated the polarity of all the sentences in the comment. The polarity analysis resulted in a value between -1 and 1. Approaching -1 indicated the degree of being negative, whereas approaching +1 indicates positive. The value to be queried here as zero. Theoretically, the meaning of zero is neutral, but when the system could not calculate polarity, it returned zero. In order to control this situation, emotion analysis and polarity results were evaluated together. If the result of the emotion analysis was empty, this review was not processed and dropped from the dataset. The polarity results of the comments in table 3.5 are as follows in table 3.7:

Table 3.7: Polarity results of example data

Key	Polarity
1	-0.43
2	0.64
3	-0.15
4	0.0

Table 3.7 shows that polarity of the key 1 with 0.43 was in the negative direction, key 2 with 0.64 in the positive direction and the key 3 with 0.15 in the negative direction. According to table 3.4.2 and table 3.4.3, the polarity and the sentiment analysis of key 4 is empty. Therefore, key 4 was removed from the list and was not included in the process. After the polarization analysis, polarity results and sentiment analysis results were combined on a key basis. The following table 3.8 shows the results:

Table 3.8: Output data after sentiment and polarity analysis

Key	Anger	Anticiption	Disgust	Fear	Joy	Sadness	Suprise	Trust	Pol.
1	2	0	2	2	0	2	0	0	-0.43
2	0	0	0	0	1	0	0	1	0.63
3	2	1	1	1	0	1	0	0	-0.15

4. FINDINGS

At this stage, the results of the analysis of 30000 comments from three different platforms for ten different products were found. The results of sentiment analysis and polarity analysis for each review were shared below.

4.1 OVERALL ANALYSIS OF ALL REVIEWS

At this stage, results of sentiment analysis and polarity were obtained for ten products in a total of five different categories. Three thousand comments were read for each product from three different platforms. In total, 30000 comments were analyzed. According to this analysis:

i. 85,849 emotion words were found in the comments.
ii. 23,052 of emotion words were in official videos, 22,405 of emotion words in unboxing videos and 40,392 of emotion words in Google Shopping reviews.
iii. 6,227 indicated *Anger*, 17,386 indicated *Anticipation*, 3,929 indicated *Disgust*, 6,198 indicated *Fear*, 17,127 indicated *Joy*, 8,325 indicated *Sadness*, 8,622 indicated *Suprise* and 18,035 indicated *Trust*.

The number of words indicating emotion in the 30,000 comments was shown in the following table 4.1.

Table 4.1: The number of words indicating emotion according to the platform

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Total
OV	1858	4598	1455	2016	4120	2392	2272	4341	**23052**
UV	1971	4182	1398	2142	3778	2239	2068	4627	**22405**
GS	2398	8606	1076	2040	9229	3694	4282	9067	**40392**
	6227	**17386**	**3929**	**6198**	**17127**	**8325**	**8622**	**18035**	**85849**

The polarity of the 30,000 comments was also measured relative to the platform. While the polarity rate was 19.05% in official videos, the rate was 18.51% in unboxing videos and 34.87% in *Google Shopping* reviews. The polarity of all comments on a platform basis was in the following table 4.2:

Table 4.2 : Polarity rate results

	Polarity
OV	19.05%
UV	18.51%
GS	34.87%

4.2 ANALYSIS OF ALL REVIEWS ON A PLATFORM BASIS

On the platform basis, the sentiments expressed by the reviews were calculated as a percentage. In *Official Videos, Anger* was 8.06 percent, *Anticipation* was 19.95 percent, *Disgust* was 6.31 percent, *Fear* was 8.75 percent, *Joy* was 17.87 percent, *Sadness* was 10.38 percent, *Suprise* was 9.86 percent and *Trust* was 18.83 percent. In *Unboxing Videos, Anger* was 8.80 percent, *Anticipation* was 18.67 percent, *Disgust* was 6.24 percent, *Fear* was 9.56 percent, *Joy* was 16.86 percent, *Sadness* was 9.99 percent, *Suprise* was 9.23 percent and *Trust* was 20.65 percent. In *Google Shopping, Anger* was 5.94 percent, *Anticipation* was 21.31 percent, *Disgust* was 2.66 percent, *Fear* was 5.05 percent, *Joy* was 22.85 percent, *Sadness* was 9.15 percent, *Suprise* was 10.6 percent and *Trust* was 22.45 percent. Table 4.3 shows the number and percentage distribution of all emotions. Figure 4.1 shows the platform based percentage distribution of sentiments and polarity of all interpretations. Figure 4.2 shows the number of words platfrom based indicates emotion for eight different sentiment.

Table 4. 3: Platform based sentiment and polarity analysis results

	Anger		Anticipation		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	1858	8.06	4598	19.95	1455	6.31	2016	8.75	4120	17.87	2392	10.38	2272	9.86	4341	18.83	19.05
UV	1971	8.80	4182	18.67	1398	6.24	2142	9.56	3778	16.86	2239	9.99	2068	9.23	4627	20.65	18.51
GS	2398	5.94	8606	21.31	1076	2.66	2040	5.05	9229	22.85	3694	9.15	4282	10.60	9067	22.45	34.87

Figure 4.1: Platform based sentiment and polarity analysis results (%)

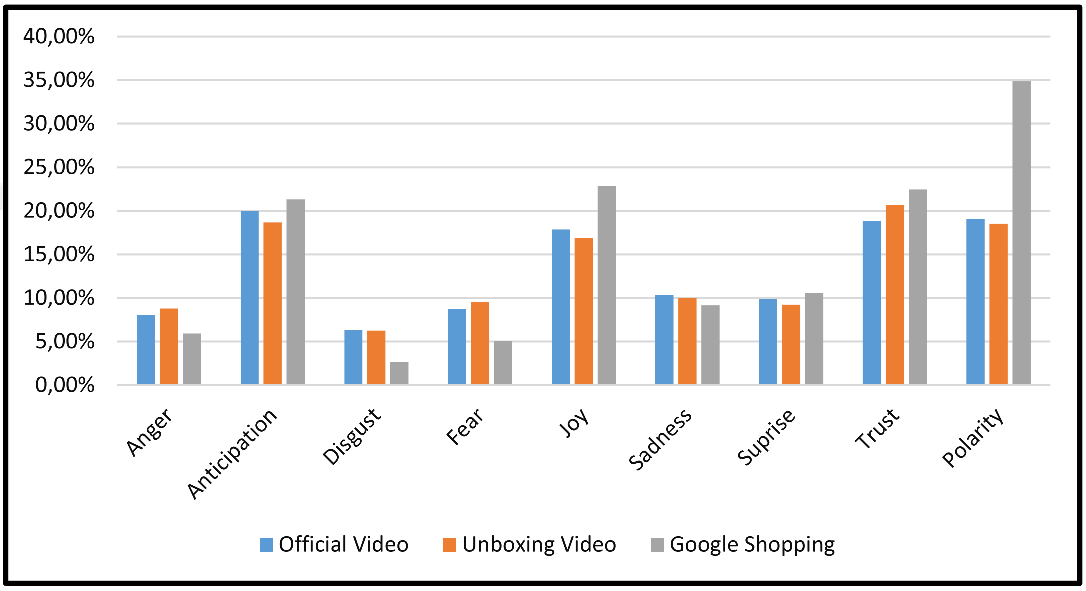
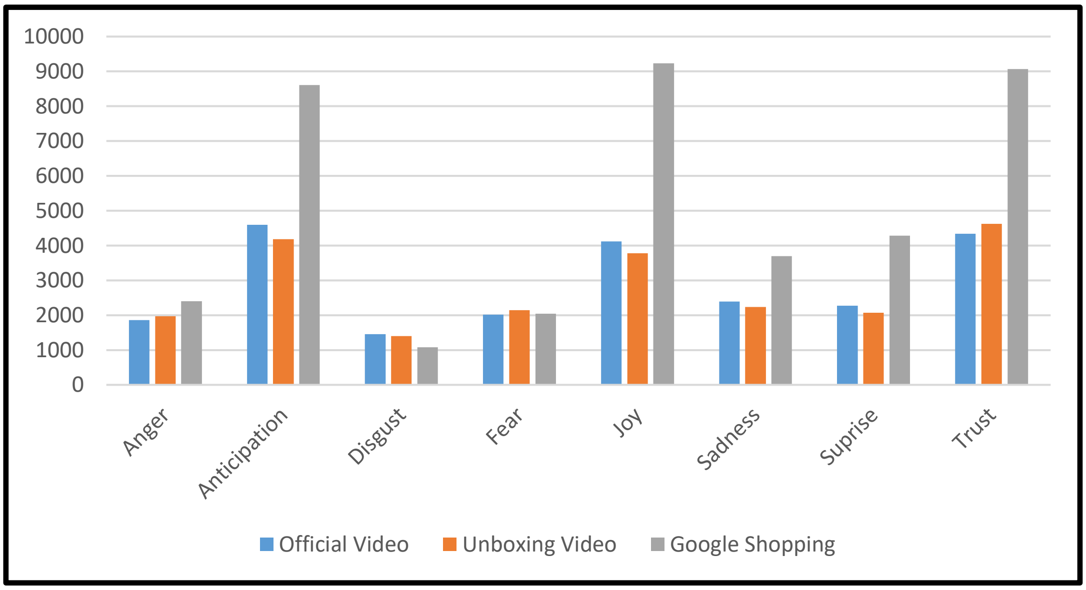


Figure 4.2: Distribution of the number of emotion words containing platform based



4.3 SENTIMENT ANALYSIS DISTRIBUTION OF ALL PRODUCT REVIEWS

Sentiment and polarity analysis was performed for each product without platform separation. According to the results of polarity analysis, the *PS4* was 18.85 percent, while the *Xbox* was 18.34 percent, the *S8* was 26.85 percent, the *P20* was 27.34 percent, the *GoPro* was 26.76 percent, the *Osmo* was 21.05 percent, the *Google Home* was 26 percent, the *Amazon Echo* was 26.09 percent, *Beats* was 25.70 percent and Sony was 24.38 percent. The following Table 4.4 shows the results of sentiment and polarity analysis on product basis:

Table 4. 4: Sentiment and polarity analysis results on product basis

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
PS4	6.28%	21.43%	5.40%	7.29%	19.44%	10.94%	9.14%	20.08%	18.85%
Xbox	7.69%	19.69%	6.37%	7.69%	16.91%	12.94%	8.27%	20.44%	18.34%
S8	8.89%	19.58%	5.69%	7.66%	21.24%	8.02%	8.59%	20.33%	26.85%
P20	9.19%	17.82%	4.49%	7.46%	18.99%	8.50%	9.62%	23.93%	27.34%
GoPro	7.65%	21.51%	4.22%	6.62%	19.85%	7.04%	12.56%	20.53%	26.76%
Osmo	8.32%	19.95%	5.15%	9.12%	16.89%	9.01%	10.96%	20.61%	21.05%
Home	5.81%	19.58%	5.19%	6.85%	21.78%	9.95%	9.63%	21.21%	26.07%
Echo	5.44%	18.07%	4.22%	6.31%	23.87%	8.82%	11.37%	21.90%	26.09%
Beats	8.02%	21.65%	5.49%	8.61%	18.15%	10.26%	9.04%	18.78%	25.70%
Sony	8.91%	19.66%	4.66%	9.69%	17.05%	11.28%	9.70%	19.06%	24.38%

4.4 DISTRIBUTION OF SENTIMENT ANALYSIS BY PRODUCT CATEGORY

Sentiment and polarity analysis was also made according to product categories. According to the results of this analysis, the polarity rate of *Game Consoles* was 18.85 percent, 27.10 percent of *Smart Phones*, 23,90 percent of *Action Cameras*, 26.08 percent of *Smart Houses* and 25.04 percent of *Audio*. The following table 4.5 shows the sentiment and polarity analysis results of the products by category.

Table 4. 5: Sentiment and polarity analysis results of the products by category

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
Game Console	6.99%	20.56%	5.88%	7.49%	18.18%	11.94%	8.70%	20.26%	18.59%
Smart Phones	9.04%	18.70%	5.09%	7.56%	20.12%	8.26%	9.11%	22.13%	27.10%
Action Cameras	7.99%	20.73%	4.68%	7.87%	18.37%	8.03%	11.76%	20.57%	23.90%
Smart Home	5.63%	18.82%	4.70%	6.58%	22.83%	9.38%	10.50%	21.56%	26.08%
Audio	8.46%	20.65%	5.08%	9.15%	17.60%	10.77%	9.37%	18.92%	25.04%

As a result of the analysis, the percentage and polarity of all emotions were calculated. According to the results of all analysis, *Anger,* 7.62 percent, *Anticipation* 19.89 percent, *Disgust* 5.09 percent, *Fear* 7.73 percent, *Joy* 19.42 percent, *Sadness* 9.67 percent, *Suprise* 9.89 percent and 20.69 percent of the *Trust* is distributed. The polarity of all comments was 24.14 percent.

4.5 SENTIMENT ANALYSIS ON PRODUCT AND PLATFORM BASIS

Sony PlayStation 4

The distribution of sentiment analysis in PS4 comments was as follows: 6.28 percent *Anger*, 21.43 percent *Anticipation*, 5.40 percent *Disgust*, 7.29 percent *Fear*, 19.44 percent *Joy*, 10.94 *Sadness* per day, 91.4 percent *Suprise*, and 20.08 percent *Trust*. The polarity of PS4 reviews was 18.85 percent. Table 4.6 shows the emotion analysis and polarity percentage of PS4.

Table 4. 6: Sentiment Analysis of PlayStation 4

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
PS4	6.28%	21.43%	5.40%	7.29%	19.44%	10.94%	9.14%	20.08%	18.85%

The sentiment analysis distribution and polarity rate by platform for PS4 is as in Table 4.7 below. The line OV shows the sentiment analysis results and polarity rate for PS4 in the official video, while the UV line shows the results in the unboxing video and the GS line shows the results in Google Shopping.

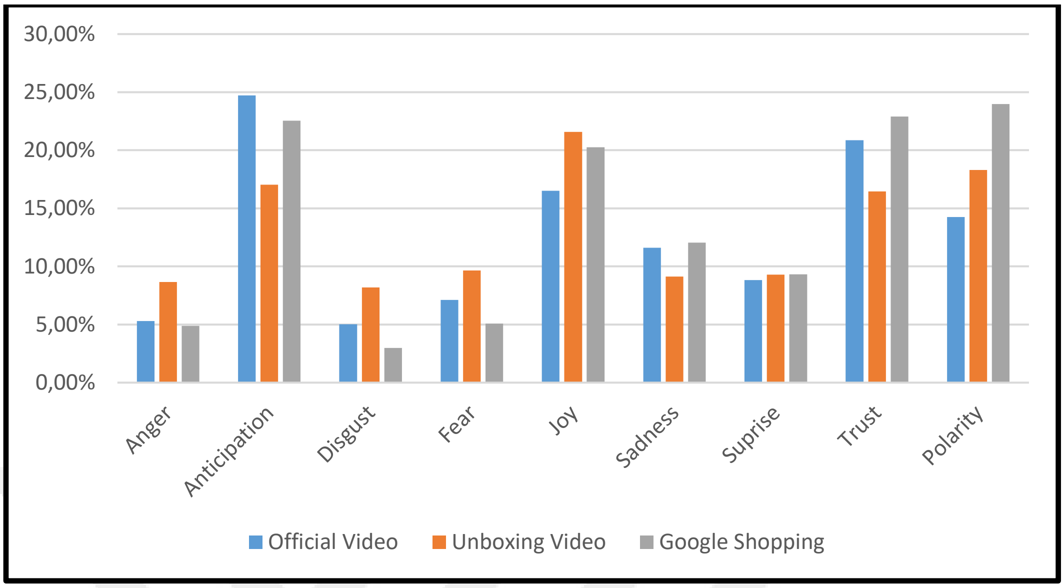
The number of *Anger* words in official videos is 114, 532 with *Anticipation*, 108 with *Disgust*, 153 with *Fear*, 355 with *Joy*, 250 with *Sadness*, 190 with Suprise and *449* with Trust. The number of *Anger* words in unboxing videos is 181, 356 with *Anticipation*, 171 with *Disgust*, 202 with *Fear*, 451 with *Joy*, 191 with *Sadness*, 194 with Suprise and *344* with Trust. The number of *Anger* words in Google Shopping is 306, 1411 with *Anticipation*, 187 with *Disgust*, 318 with *Fear*, 1268 with *Joy*, 755 with *Sadness*, 583 with Suprise and *1434* with Trust.

While the *Polarity Rate* in PS4 official video is 14.25 percent, the rate in unboxing video is 18.31 percent and the rate in Google Shopping is 23.99 percent. The distribution of sentiment analysis in the PS4 official video is as follows: 5.30 percent *Anger*, 24.73 percent *Anticipation*, 5.02 percent *Disgust*, 7.11 percent *Fear*, 16.50 percent *Joy*, 11.62 percent *Sadness*, 8.83 percent *Suprise* and 20.87 percent *Trust*. The distribution of sentiment analysis in the PS4 unboxing video is as follows: 8.66 percent *Anger*, 17.03 percent *Anticipation*, 8.18 percent *Disgust*, 9.67 percent *Fear*, 21.58 percent *Joy*, 9.14 percent *Sadness*, 9.28 percent *Suprise* and 16.46 percent *Trust*. The distribution of sentiment analysis in the PS4 Google Shopping is as follows: 4.89 percent *Anger*, 22.53 percent *Anticipation*, 2.99 percent *Disgust*, 5.08 percent *Fear*, 20.25 percent *Joy*, 12.06 percent *Sadness*, 9.31 percent *Suprise* and 22.90 percent *Trust*.

Table 4. 7: PS4 platform based sentiment and polarity analysis results

	Anger		Anticipation		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	114	5.30	532	24.73	108	5.02	153	7.11	355	16.50	250	11.62	190	8.83	449	20.87	14.25
UV	181	8.66	356	17.03	171	8.18	202	9.67	451	21.58	191	9.14	194	9.28	344	16.46	18.31
GS	306	4.89	1411	22.53	187	2.99	318	5.08	1268	20.25	755	12.06	583	9.31	1434	22.90	23.99

Figure 4. 3: Platform based sentiment analysis distribution and polarity rate for PS4



Microsoft Xbox

The analysis results of Microsoft Xbob which is in the same category as the PlayStation 4, were shown in the Table 4.8 below. According to the analysis results, sentiment of *Trust* had the highest distribution with 20.44 percent, while *Disgust* had the lowest rate with 6.37 percent. Polarity rate was calculated as 18.34 percent.

Table 4. 8: Sentiment Analysis of Microsoft Xbox

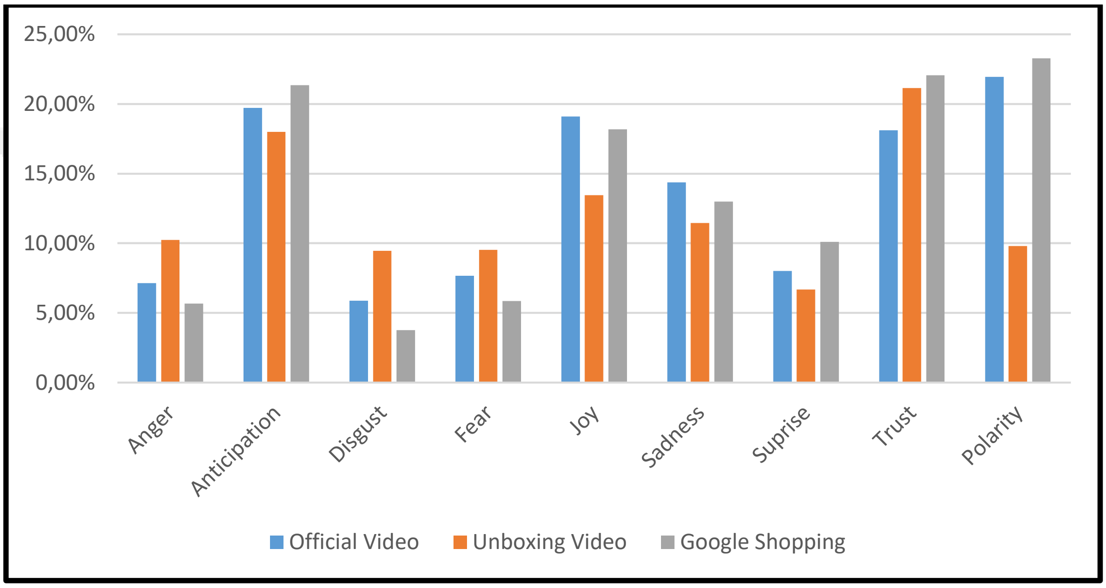
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
Xbox	7.69%	19.69%	6.37%	7.69%	16.91%	12.94%	8.27%	20.44%	18.34%

The platform-based results of the Xbox product were shown in Table 4.9 and Figure 4.4 below. According to these results, Official Video had the highest rate of *Joy* with 19.09 percent and *Sadness* with 14.36 percent. In Unboxing Video, *Anger* with 10.25 percent, *Disgust* with 9.47 percent and *Fear* with 9.54 percent had the highest distribution. According to the results in Google Shopping, Anticipation with 21.34 percent, Suprise with 10.09 percent and Trust with 22.07 percent have the highest distribution.

Table 4. 9: Xbox platform based sentiment and polarity analysis results

	Anger		Anticipation		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	124	7.15	342	19.72	102	5.88	133	7.67	331	19.09	249	14.36	139	8.02	314	18.11	21.94
UV	144	10.25	253	18.01	133	9.47	134	9.54	189	13.45	161	11.46	94	6.69	297	21.14	9.80
GS	367	5.67	1381	21.34	244	3.77	379	5.86	1177	18.19	841	13.00	653	10.09	1428	22.07	23.28

Figure 4. 4: Platform based sentiment analysis distribution and polarity rate for Xbox



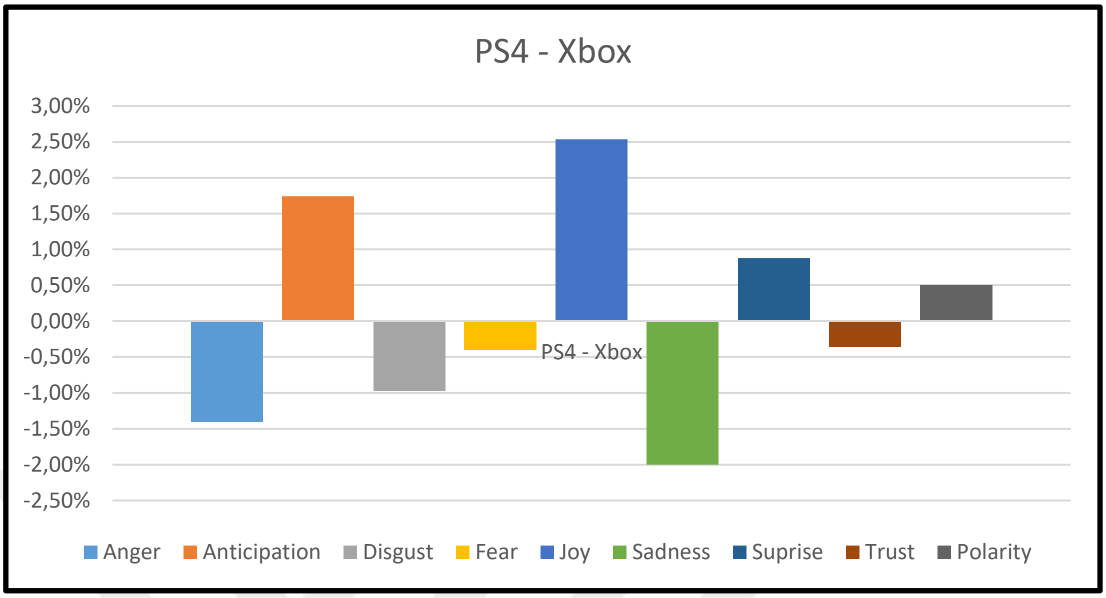
PS4 vs Xbox

PS4 and Xbox are rated in the same product category. The emotional analysis and polarity differences of these two products in the same category were shown in the following table 4.10 and Figure 4.5. *Trust* distribution difference is 0.36 percent higher on the Xbox side. The highest difference is on PS4 with 2.53 percent in *Joy*.

Table 4. 10: Differences in sentimental distribution and polarity between PS4 and Xbox

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
PS4 - Xbox	-1.41%	1.74%	-0.98%	-0.40%	2.53%	-2.00%	0.88%	-0.36%	0.51%

Figure 4. 5: Differences in sentimental distribution and polarity between PS4 and Xbox



Huawei P20

Huawei P20 was the first product analyzed in the mobile phones category. In terms of sentiment analysis, *Trust* has the highest rate of 23.93 percent. *Disgust* has the lowest distribution rate with 4.49 percent. However, the polarity rate was 27.34 percent. Details of the extensive sentiment analysis for P20 were in the following Table 4.11.

Table 4. 11: Sentiment Analysis of Huawei P20

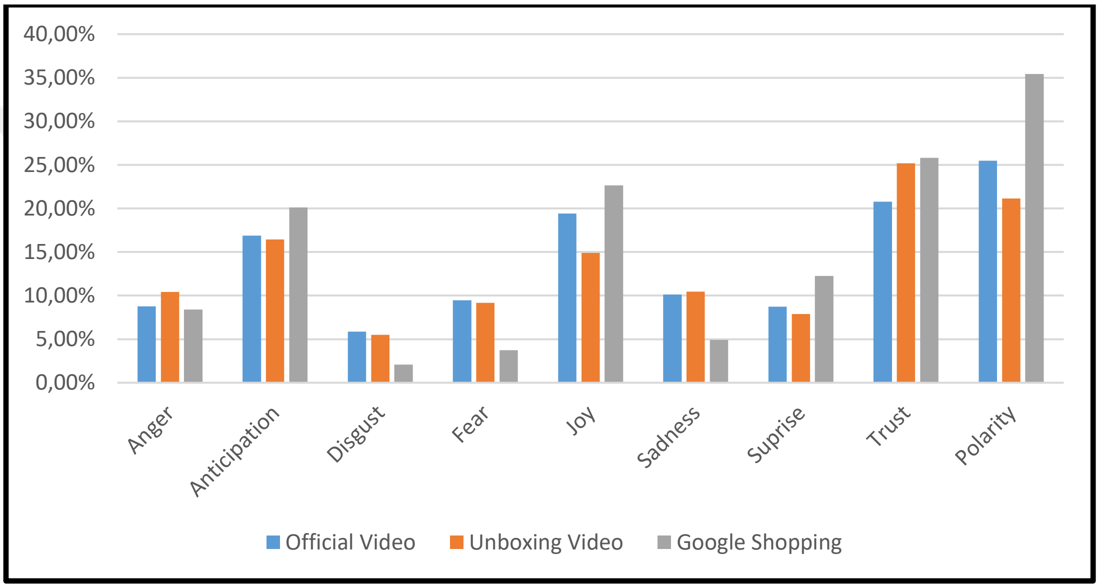
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
P20	9.19%	17.82%	4.49%	7.46%	18.99%	8.50%	9.62%	23.93%	27.34%

Huawei P20's platform-based sentiment and polarity analysis were shown in Table 4.12 and Figure 4.6 below. The highest polarity rate was 35.42 percent on the Google Shopping platform. The highest distribution rate is *Trust* feeling with 25.82 percent on the Google Shopping platform, while the lowest distribution rate is *Disgust* feeling on the Google Shopping platform with 3.72 percent.

Table 4. 12: P20 platform based sentiment and polarity analysis results

	Anger		Anticipation		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	211	8.76	407	16.89	141	5.85	228	9.46	468	19.42	244	10.12	210	8.71	501	20.79	25.47
UV	255	10.41	403	16.46	135	5.51	225	9.19	365	14.90	256	10.45	193	7.88	617	25.19	21.13
GS	289	8.40	692	20.12	72	2.09	128	3.72	779	22.65	169	4.91	422	12.27	888	25.82	35.42

Figure 4. 6: Platform based sentiment analysis distribution and polarity rate for P20



Samsung Galaxy S8

Galaxy S8 is the second product in the mobile phones category. Platform independent detailed information about emotion and polarity analysis of the product according to 3000 reviews is in the following Table 4.13. The highest distribution rate was *Joy* with 21.24 percent and the lowest distribution rate was 5.69 percent with *Disgust*. Polarity ratio was 26.85 percent.

Table 4. 13: Sentiment Analysis of Galaxy S8

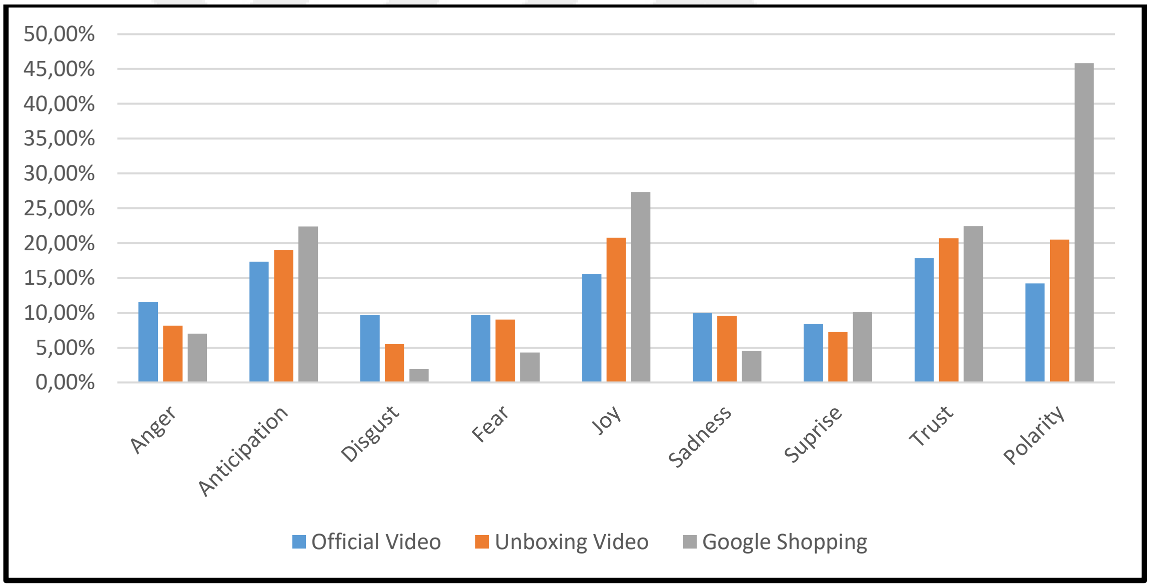
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
S8	8.89%	19.58%	5.69%	7.66%	21.24%	8.02%	8.59%	20.33%	26.85%

Platform-based distribution details were given in Table 4.14 and Figure 4.7 below. In Offical video, *Anger* has the highest distribution with 11.54 percent and *Disgust* with 9.67 percent, while Google Shopping has the lowest distribution rate of 4.28 percent with *Fear* and 1.90 percent with *Disgust*.

Table 4. 14: S8 platform based sentiment and polarity analysis results

	Anger		Anticipation		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	228	11.54	342	17.32	191	9.67	191	9.67	308	15.59	197	9.97	166	8.41	352	17.82	14.20
UV	200	8.14	468	19.04	135	5.49	222	9.03	511	20.79	235	9.56	178	7.24	509	20.71	20.49
GS	206	7.00	659	22.38	56	1.90	126	4.28	805	27.34	133	4.52	298	10.12	661	22.45	45.87

Figure 4. 7: Platform based sentiment analysis distribution and polarity rate for S8



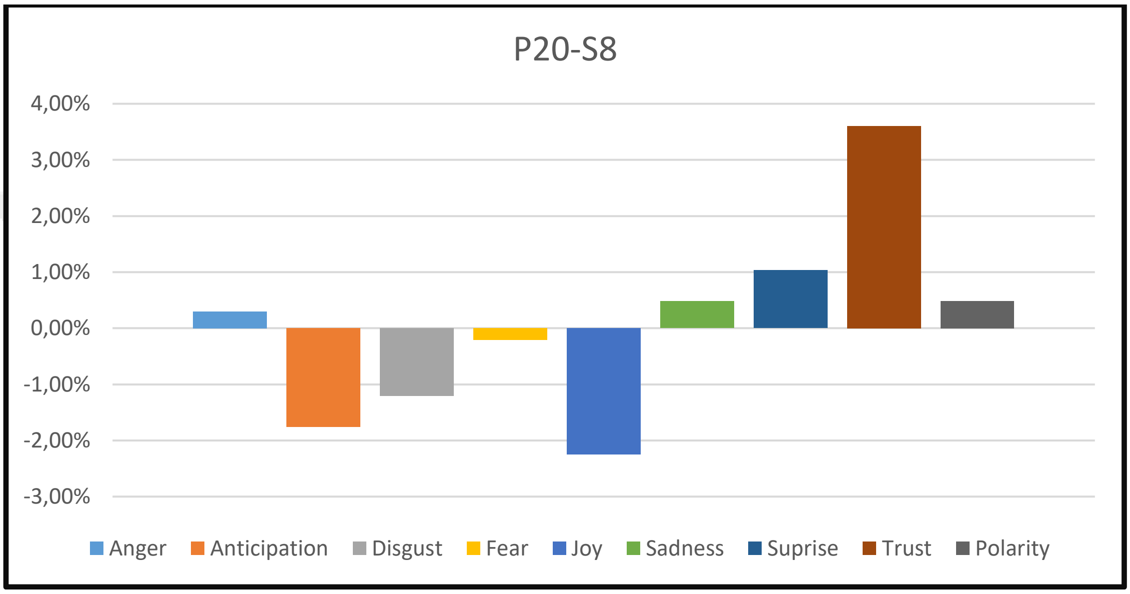
P20 vs S8

P20 and S8 are the products of two different brands examined under the mobile phones category. The table 4.15 and Figure 4.8 below shows the differences in sentiment and polarity analysis of the platform-independent 6000 reviews. While the highest difference was 3.61 percent in *Trust* for P20, the lowest difference was 0.2 percent in *Fear* in favor of S8.

Table 4. 15: Differences in sentimental distribution and polarity between P20 and S8

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
P20 - S8	0.30%	-1.76%	-1.20%	-0.20%	-2.25%	0.48%	1.03%	3.61%	0.49%

Figure 4. 8: Differences in sentimental distribution and polarity between P20 and S8



DJI Osmo Action

According to the results of platform independent DJI Osmo analysis, *Trust* had the highest dispersion ratio with 20.61 percent, while *Disgust* had the lowest dispersion ratio with 5.15 percent. Polarity rate was measured as 21.05 percent. Öore detailed description is in the following table 4.16:

Table 4. 16: Sentiment analysis of DJI Osmo Action

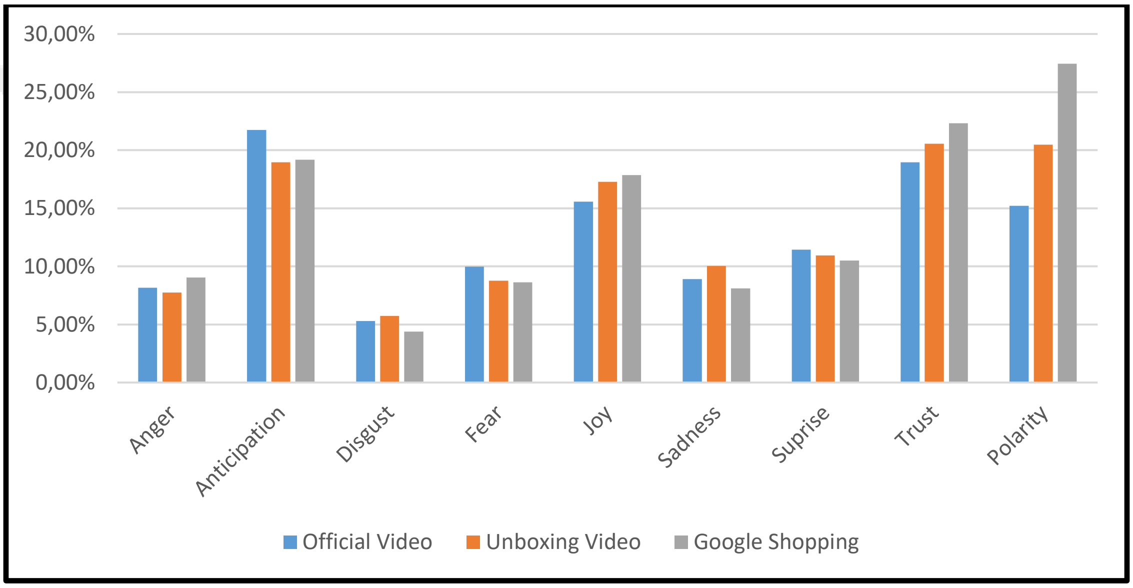
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
DJI	8.32%	19.95%	5.15%	9.12%	16.89%	9.01%	10.96%	20.61%	21.05%

Disgust had the lowest distribution rate in Google shopping platform with 4.40 percent and the highest distribution rate was *Trust* with 22.33 percent in google shopping platform. More detailed analysis is available in table 4.17 and Figure 4.9 below.

Table 4. 17: DJI Osmo Action platform based sentiment and polarity analysis results

	Anger		Anticipatio		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	197	8.15	525	21.73	128	5.30	241	9.98	376	15.56	215	8.90	276	11.42	458	18.96	15.22
UV	213	7.75	521	18.95	158	5.75	241	8.76	475	17.27	276	10.04	301	10.95	565	20.55	20.48
GS	313	9.05	663	19.17	152	4.40	298	8.62	617	17.84	280	8.10	363	10.50	772	22.33	27.44

Figure 4. 9: Platform based sentiment analysis distribution and polarity rate for DJI



GoPro7 Hero

GoPro 7 was analyzed as DJI Osmo's competitor. According to GoPro7 analysis, the polarity ratio was calculated as 26.76 percent. *Disgust* had the lowest share with 4.22 percent and *Trust* had the highest load with 20.53 percent. More detailed analysis information is available in table 4.18 below.

Table 4. 18: Sentiment analysis of DJI Osmo Action

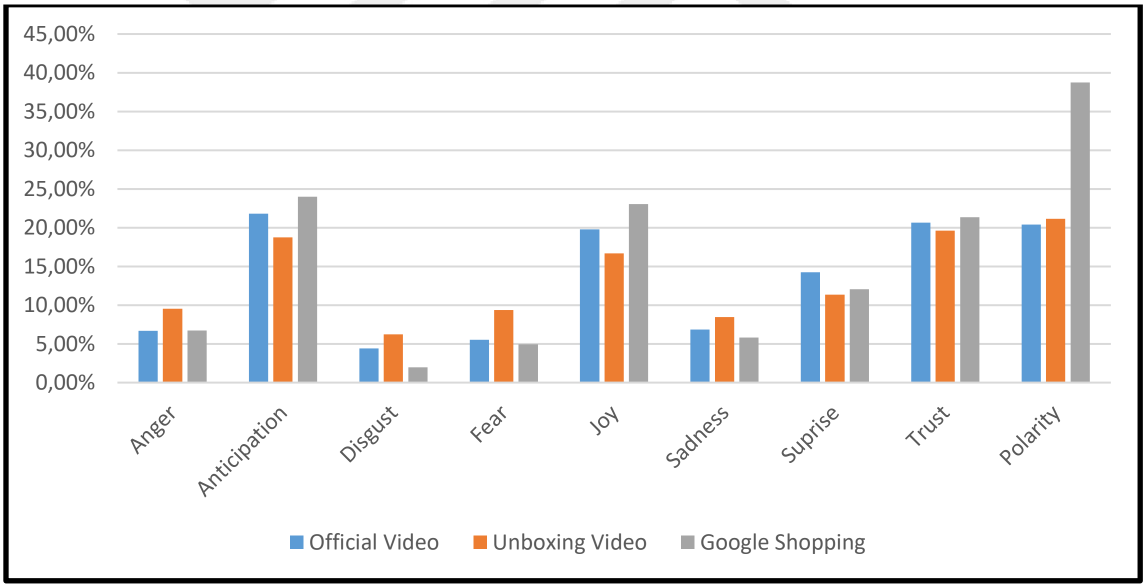
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
GoPro	7.65%	21.51%	4.22%	6.62%	19.85%	7.04%	12.56%	20.53%	26.76%

According to platform analysis, Google Shopping had the highest polarity rate with 38.73 percent, while *Anger* had the highest share with 9.54 percent in Unboxing Video. The highest *Suprise* rate was official video with 14.25 percent. The following table 4.19 and Figure 4.10 show further details.

Table 4. 19: DJI Osmo Action platform based sentiment and polarity analysis results

	Anger		Anticipation		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	191	6.70	621	21.80	126	4.42	158	5.55	564	19.80	195	6.84	406	14.25	588	20.64	20.41
UV	281	9.54	552	18.73	184	6.24	276	9.37	492	16.69	249	8.45	335	11.37	578	19.61	21.13
GS	240	6.72	857	24.01	71	1.99	177	4.96	823	23.06	208	5.83	431	12.08	762	21.35	38.73

Figure 4. 10: Platform based sentiment analysis distribution and polarity rate for DJI



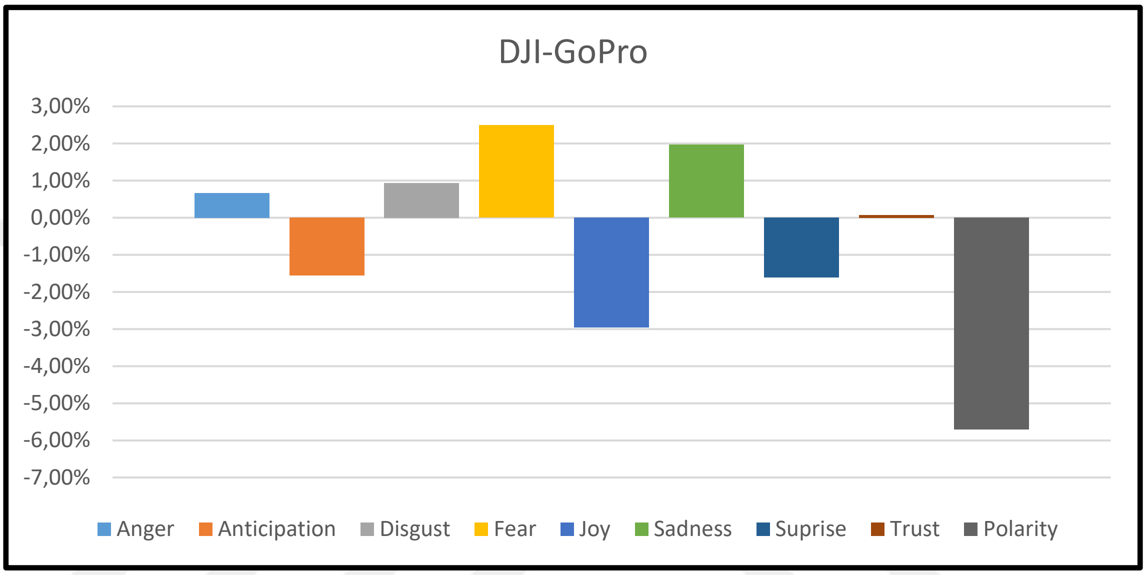
DJI vs GoPro

DJI and GoPro are two similar but competing products in the category of action cameras. The polarity difference between the two products is 5.71 percent in favor of DJI. The highest difference is in favor of DJI with 2.96 percent in the sentiment of *Sadness*. Besides, the lowest difference is *Trust* with 0.07 percent in favor of DJI. See Table 4.20 and Figure 4.11 for more detailed information.

Table 4. 20: Differences in sentimental distribution and polarity between DJI and GoPro

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
DJI-GoPro	0.66%	-1.56%	0.93%	2.50%	-2.96%	1.97%	-1.61%	0.07%	-5.71%

Figure 4. 11: Differences in sentimental distribution and polarity between DJI and GoPro



Amazon Echo

Amazon Echo is the first product in the smart home category. Platform independent detailed information about emotion and polarity analysis of the product according to 3000 reviews is in the following Table 4.21. The highest distribution rate was *Joy* with 23.87 percent and the lowest distribution rate was 5.44 percent with *Anger*. Polarity ratio was 26.09 percent.

Table 4. 21: Sentiment analysis of Amazon Echo

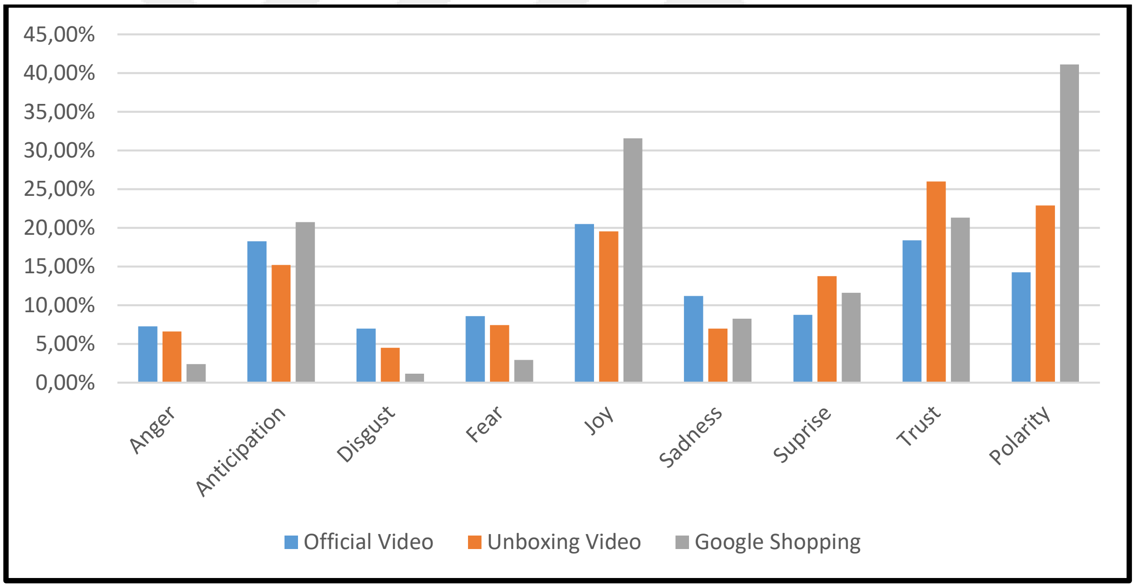
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
Echo	5.44%	18.07%	4.22%	6.31%	23.87%	8.82%	11.37%	21.90%	26.09%

Platform-based distribution details were given in Table 4.22 and Figure 4.12 below. In Offical video, *Anger* has the highest distribution with 7.29 percent and *Disgust* with 7.00 percent, while Google Shopping has the lowest distribution rate of 2.92 percent with *Fear* and 1.15 percent with *Disgust*.

Table 4. 22: Amazon Echo platform based sentiment and polarity analysis results

	Anger		Anticipatio		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	199	7.29	498	18.24	191	7.00	235	8.61	560	20.51	306	11.21	239	8.75	502	18.39	14.25
UV	109	6.63	250	15.21	74	4.50	122	7.42	321	19.53	115	7.00	226	13.75	427	25.97	22.89
GS	83	2.40	719	20.76	40	1.15	101	2.92	1094	31.58	286	8.26	402	11.61	739	21.33	41.12

Figure 4. 12: Platform based sentiment analysis distribution and polarity rate for Amazon Echo



Google Home

The analysis results of Google Home which is in the same category as the Amazon Echo, were shown in the Table 4.23 below. According to the analysis results, sentiment of *Joy* had the highest distribution with 21.78 percent, while *Disgust* had the lowest rate with 5.19 percent. Polarity rate was calculated as 26.07 percent.

Table 4. 23 Sentiment Analysis of Google Home

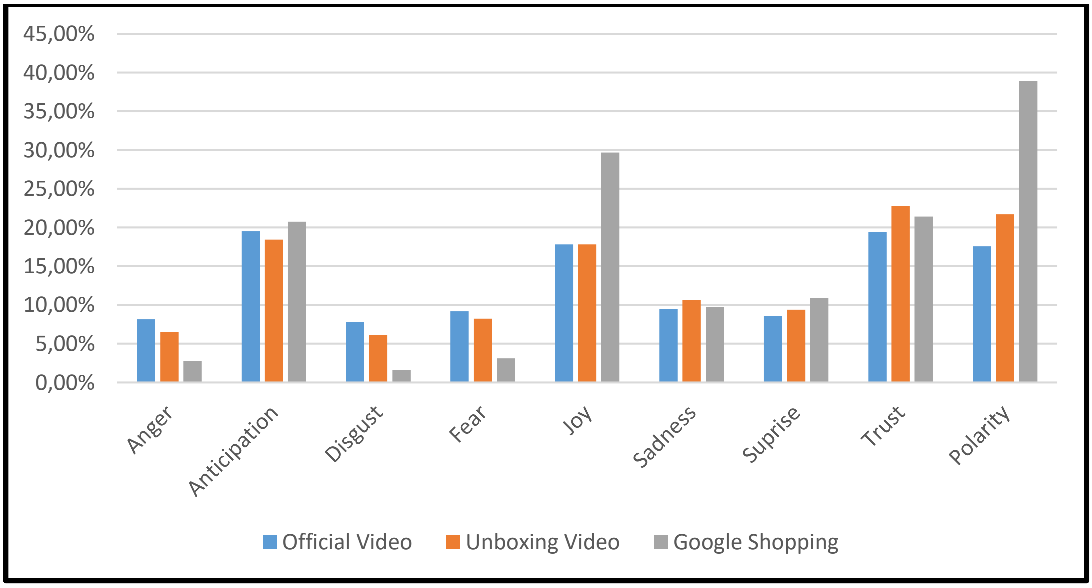
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
Home	5.81%	19.58%	5.19%	6.85%	21.78%	9.95%	9.63%	21.21%	26.07%

The platform-based results of the Home product were shown in Table 4.24 and Figure 4.13 below. According to these results, Google Shopping had the highest rate of *Joy*. with 29.69 percent and *Trust* with 21.44 percent. In Unboxing Video, *Anticipation* with 18.75 percent, *Disgust* with 6.11 percent and *Trust* with 22.79 percent had the highest distribution. According to the results in Official Video, Anticipation with 19.51 percent, Suprise with 8.61 percent and Trust with 19.41 percent have the highest distribution.

Table 4. 24: Amazon Echo platform based sentiment and polarity analysis results

	Anger		Anticipation		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	178	8.15	426	19.51	171	7.83	201	9.20	389	17.81	207	9.48	188	8.61	424	19.41	17.59
UV	118	6.56	332	18.45	110	6.11	148	8.23	321	17.84	191	10.62	169	9.39	410	22.79	21.71
GS	91	2.73	693	20.78	54	1.62	104	3.12	990	29.69	325	9.75	363	10.88	715	21.44	38.91

Figure 4. 13: Platform based sentiment analysis distribution and polarity rate for Google Home



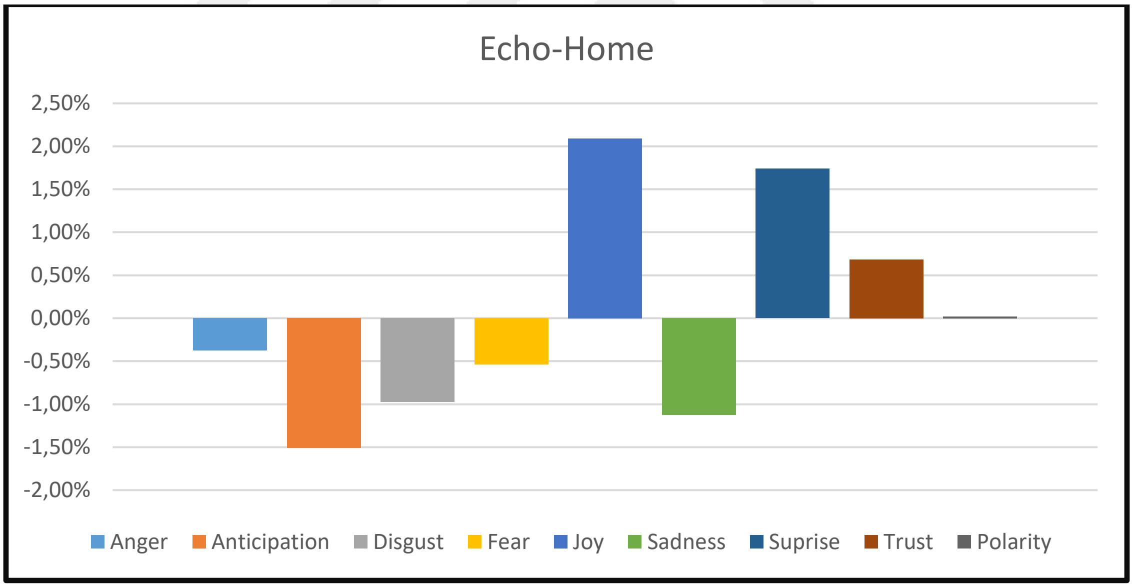
Echo vs Home

Amazon Echo and Google Home are rated in the same product category. The sentiment analysis and polarity differences of these two products in the same category were shown in the following table 4.25 and Figure 4.14. *Suprise* distribution difference is 1.74 percent higher on the Amazon Echo side. The highest difference is on Google Home with 1.51 percent in Joy.

Table 4. 25: Differences in sentimental distribution and polarity between Amazon Echo and Google Home

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
Echo-Home	-0.37%	-1.51%	-0.97%	-0.53%	2.09%	-1.13%	1.74%	0.68%	0.02%

Figure 4. 14: Differences in sentimental distribution and polarity between Amazon Echo and Google Home



Sony Earphones

Sony WF-1000XM3 was the first product analyzed in the earphones category. In terms of sentiment analysis, *Anticipation* has the highest rate of 19.66 percent. *Disgust* has the lowest distribution rate with 4.66 percent. However, the polarity rate was 24.38 percent. Details of the extensive sentiment analysis for Sony were in the following Table 4.26.

Table 4. 26: Sentiment Analysis of Sony WF-1000XM3

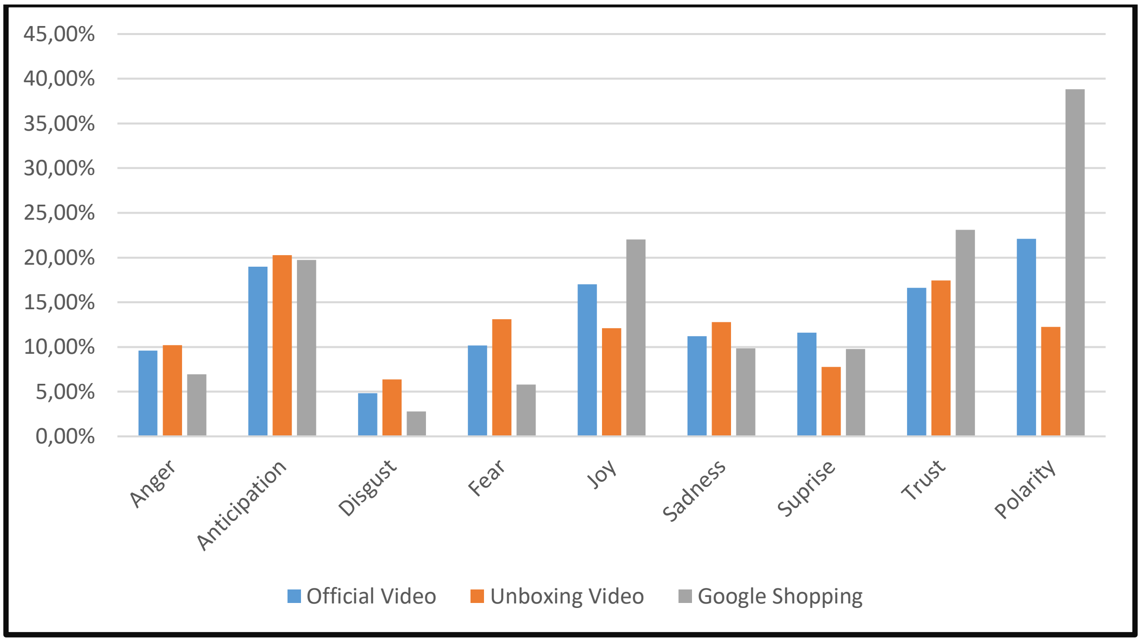
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
Sony	8.91%	19.66%	4.66%	9.69%	17.05%	11.28%	9.70%	19.06%	24.38%

Platform-based distribution details were given in Table 4.27 and Figure 4.15 below. In unboxing video, *Anger* has the highest distribution with 10.19 percent and *Disgust* with 6.36 percent, while Google Shopping has the lowest distribution rate of 5.81 percent with *Fear* and 2.78 percent with *Disgust*.

Table 4. 27: Sony WF-1000XM3 platform based sentiment and polarity analysis results

	Anger		Anticipatio		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	220	9.59	435	18.97	111	4.84	233	10.16	390	17.01	257	11.21	266	11.60	381	16.62	22.09
UV	263	10.19	523	20.27	164	6.36	338	13.10	312	12.09	330	12.79	200	7.75	450	17.44	12.24
GS	297	6.93	845	19.73	119	2.78	249	5.81	944	22.04	421	9.83	418	9.76	990	23.11	38.83

Figure 4. 15: Platform based sentiment analysis distribution and polarity rate for Sony WF-1000XM3



Beats By Dre Powerbeats Pro.

Beats By Dre Powerbeats Pro. is the second product in the earphones phones category. Platform independent detailed information about emotion and polarity analysis of the product according to 3000 reviews is in the following Table 4.28. The highest distribution rate was *Anticipation* with 21.65 percent and the lowest distribution rate was 5.49 percent with *Disgust*. Polarity ratio was 25.70 percent.

Table 4. 28: Sentiment analysis of Beats By Dre Powerbeats Pro.

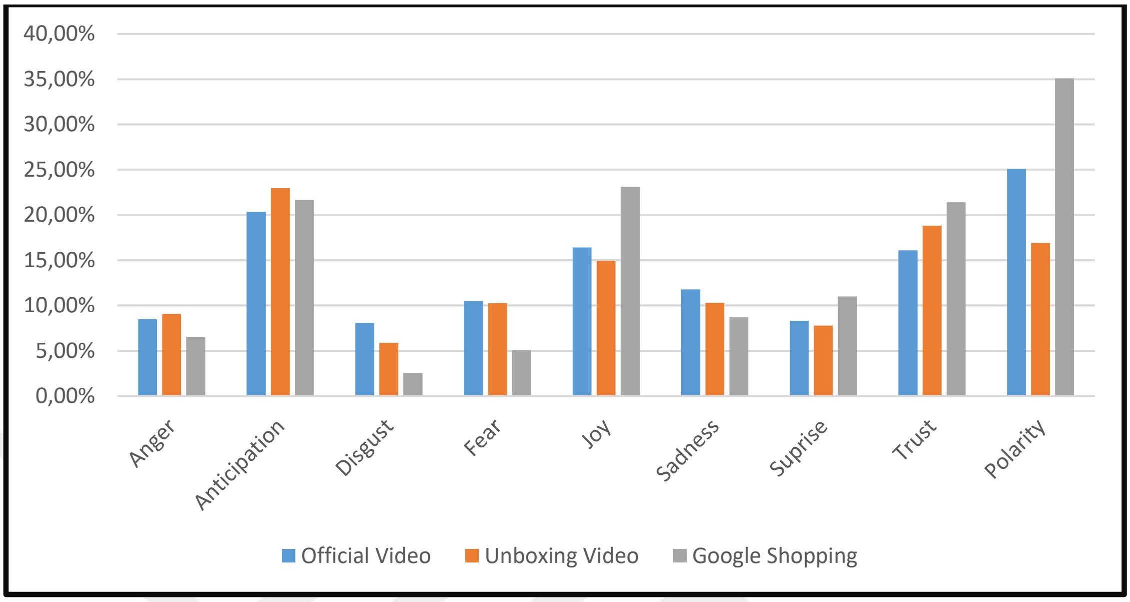
	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
Beats	8.02%	21.65%	5.49%	8.61%	18.15%	10.26%	9.04%	18.78%	25.70%

Beats By Dre Powerbeats Pro.'s platform-based sentiment and polarity analysis were shown in Table 4.29 and Figure 4.16 below. The highest polarity rate was 35.08 percent on the Google Shopping platform. The highest distribution rate is *Anticipation* sentiment with 22.95 percent on the unboxing video platform, while the lowest distribution rate is *Disgust* feeling on the Google Shopping platform with 2.56 percent.

Table 4. 29: Beats By Dre Powerbeats Pro. platform based sentiment and polarity analysis results

	Anger		Anticipatio		Disgust		Fear		Joy		Sadness		Suprise		Trust		Pol.
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	%
OV	196	8.48	470	20.35	186	8.05	243	10.52	379	16.41	272	11.77	192	8.31	372	16.10	25.09
UV	207	9.07	524	22.95	134	5.87	234	10.25	341	14.94	235	10.29	178	7.80	430	18.83	16.92
GS	206	6.50	686	21.65	81	2.56	160	5.05	732	23.11	276	8.71	349	11.02	678	21.40	35.08

Figure 4. 16: Platform based sentiment analysis distribution and polarity rate for Beats By Dre Powerbeats Pro.



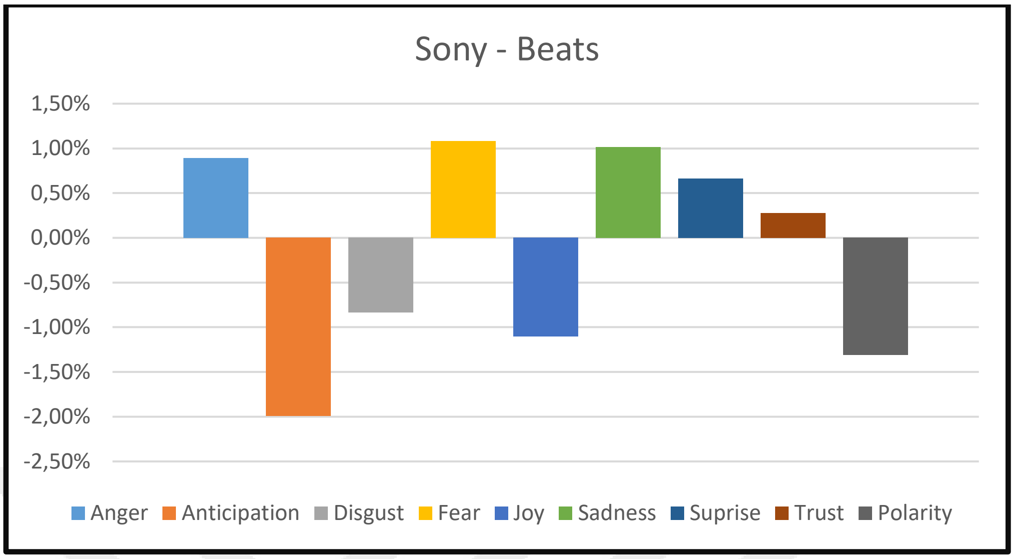
Sony vs Beats

Sony and Beats are the products of two different brands examined under the earphones category. The table 4.30 and Figure 4.17 below shows the differences in sentiment and polarity analysis of the platform-independent 6000 reviews. While the highest difference was 1.99 percent in *Anticipation* for Beats, the lowest difference was 0.28 percent in *Fear* in favor of Sony.

Table 4. 30: Differences in sentimental distribution and polarity between Sony WF-1000XM3 and Beats By Dre Powerbeats Pro.

	Anger	Anticipation	Disgust	Fear	Joy	Sadness	Suprise	Trust	Polarity
Sony-Beats	0.89%	-1.99%	-0.83%	1.09%	-1.10%	1.02%	0.66%	0.28%	-1.31%

Figure 4. 17: Differences in sentimental distribution and polarity between Sony WF-1000XM3 and Beats By Dre Powerbeats Pro.



Sentiment analysis and polarity differences on product and platform basis

The following table (Table 4.31) lists the differences in the sentiment scores and polarity rates between the official video and unboxing video of each product. The polarity ratio is in favor of the unboxing video with 4.06 percent of the PS4 product. In other words, in PS4 customer comments are 4.06 percent more positive in the unboxing video than in official video. In contrast, the *Joy* distribution ratio of the p20 product in official video is 4.52 percent more than the distribution rate in unboxing video.

Table 4. 31: Sentiment and polarity percentage difference between official video and unboxing video on product basis

OV-UV	PS4	Xbox	P20	S8	DJI	GoPro	Echo	Home	Sony	Beats
Polarity	-4.06%	12.14%	4.34%	-6.28%	-5.27%	-0.72%	-8.64%	-4.11%	9.85%	8.16%
Anger	-3.36%	-3.10%	-1.66%	3.41%	0.41%	-2.83%	0.66%	1.59%	-0.60%	-0.58%
Anticipation	7.70%	1.72%	0.43%	-1.72%	2.78%	3.07%	3.03%	1.05%	-1.30%	-2.61%
Disgust	-3.16%	-3.58%	0.34%	4.18%	-0.45%	-1.82%	2.50%	1.72%	-1.52%	2.18%
Fear	-2.55%	-1.87%	0.27%	0.64%	1.21%	-3.82%	1.19%	0.98%	-2.94%	0.27%
Joy	-5.07%	5.64%	4.52%	-5.19%	-1.71%	3.10%	0.99%	-0.03%	4.92%	1.47%
Sadness	2.48%	2.90%	-0.33%	0.41%	-1.14%	-1.60%	4.21%	-1.14%	-1.58%	1.48%
Suprise	-0.45%	1.33%	0.83%	1.16%	0.48%	2.88%	-4.99%	-0.79%	3.85%	0.51%
Trust	4.41%	-3.03%	-4.41%	-2.89%	-1.59%	1.03%	-7.58%	-3.38%	-0.83%	-2.73%

The table showing the ratio of the differences in the sentiment analysis distribution between OV and UV with polarity differences is given below (Table 4.32). A value of PS4 of *Anger* indicates that the percentage of polarity decreases while the percentage of anger decreases. In contrast, the *Disgust* value on Xbox is zero because the percentage of polarity increases while the percentage of disgust decreases. According to this table, the sense of *Joy* and polarity ratio is directly proportional to 80 percent. According to another finding, *Anger* is directly proportional to the polarity rate of 20 percent. In other words, it is inversely proportional to the polarity ratio of 80 percent.

Table 4. 32: Table of the relationship between polarity and difference of emotion distribution between OV and UV

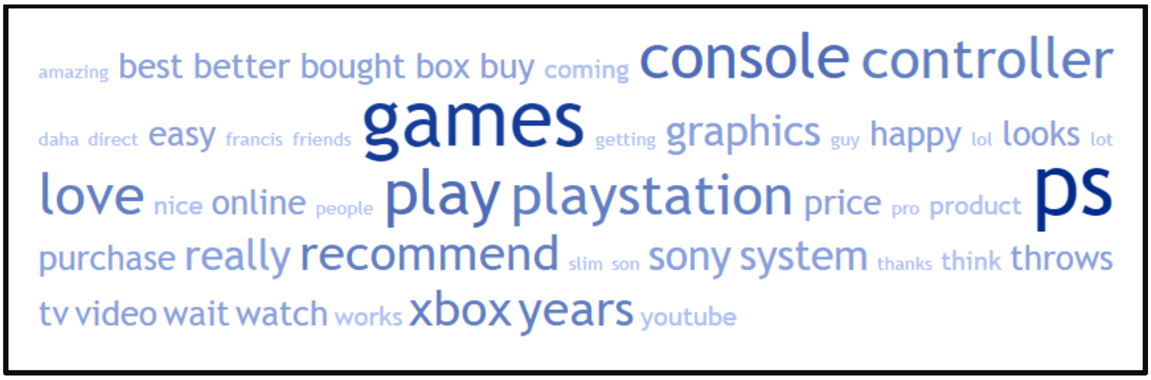
OV-UV DP	PS4	Xbox	P20	S8	DJI	GoPro	Echo	Home	Sony	Beats	Perc.
Anger	1	0	0	0	0	1	0	0	0	0	20.00%
Anticipation	0	1	1	1	0	0	0	0	0	0	30.00%
Disgust	1	0	1	0	1	1	0	0	0	1	50.00%
Fear	1	0	1	0	0	1	0	0	0	1	40.00%
Joy	1	1	1	1	1	0	0	1	1	1	80.00%
Sadness	0	1	0	0	1	1	0	1	0	1	50.00%
Suprise	1	1	1	0	0	0	1	1	1	1	70.00%
Trust	0	0	0	1	1	0	1	1	0	0	40.00%

4.6 WORDCLOUDS FOR ALL PRODUCTS

The word cloud analysis for the products are based on the the mostly repeated words in the customer comments.

The following Figure 4.18 created for PlayStation 4 had the following words mostly repeated in the customer comments: *ps*, *games*, *console*, *love* and *xbox*.

Figure 4. 18: Wordcloud for PS4 reviews



The following Figure 4.19 created for Xbox contains the following words most: *play*, *games*, *console*, *xbox* and *love*.

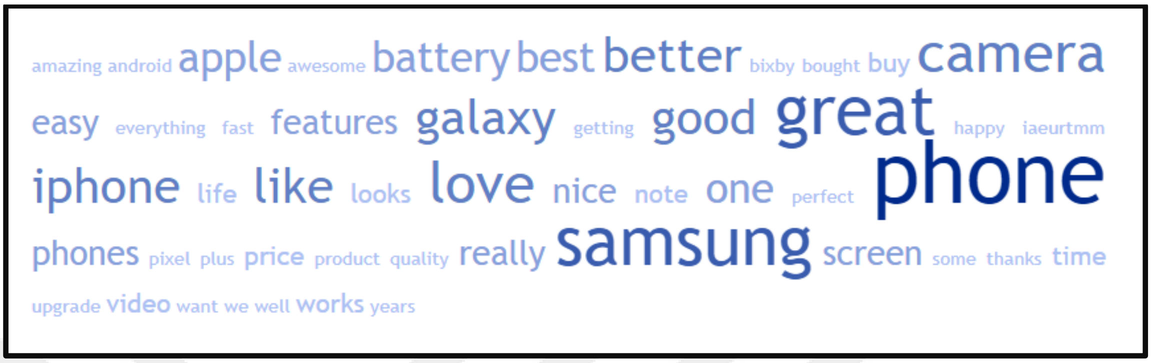
Figure 4. 19: Wordcloud for Xbox reviews

The following Figure 4.20 created for P20 contains the following words most: *phone*, *huawei*, *camera*, *battery* and *iphone*.

Figure 4. 20: Wordcloud for P20 reviews

The following Figure 4.21 created for S8 contains the following words most: *phone*, *samsung*, *great*, *love* and *iphone*.

Figure 4. 21: Wordcloud for S8 reviews



The following Figure 4.22 created for DJI Osmo Action contains the following words most: *gopro*, *dji*, *osmo*, *camera* and *video*.

Figure 4. 22: Wordcloud for DJI reviews

The following Figure 4.23 created for GoPro Hero 7 Action contains the following words most: *gopro*, *hero*, *camera*, *video* and *buy*.

Figure 4. 23: Wordcloud for GoPro reviews

The following Figure 4.24 created for Amazon Echo Action contains the following words most: *alexa*, *great*, *music*, *love* and *sound*.

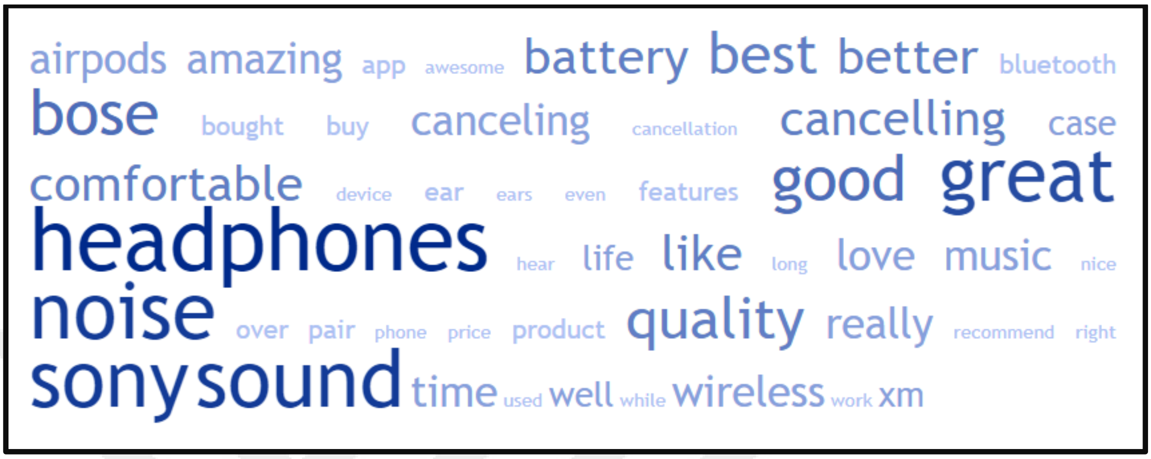
Figure 4. 24: Wordcloud for Amazon Echo reviews

The following Figure 4.25 created for Google Home Action contains the following words most: *google*, *gome*, *great*, *easy* and *music*. At a low rate, competing product Echo is mentioned in comments.

Figure 4. 25: Wordcloud for Google Home reviews

The following Figure 4.26 created for Sony contains the following words most: *headphones*, *great*, *noise*, *sonysound* and *bose*. In reviews, Sony's rival *Bose* is mentioned at a high rate of the other rival *Apple Airpods* also based on a considerable proportion.

Figure 4. 26: Wordcloud for Sony reviews



The following Figure 4.27 created for Beats contains the following words most: *great*, *good*, *sound*, *headphones* and *beats*. At a low rate, competing product *Apple Airpods* is mentioned in comments.

Figure 4. 27: Wordcloud for Beats reviews

The implications of all these analysis were discussed in the following section.

5. DISCUSSION AND MANAGERIAL IMPLICATIONS

In the last 10 years, unboxing videos have become one of the most popular videos on YouTube (e.g. Li 2015, Ferenstein 2015) and there are limited studies on this subject in the literature. During the study, the average view of unboxing videos was found to be about 5 times higher than the official videos. The aim of this study was to analyze the unboxing videos in sentimental way and to measure the polarity ratio positively and negatively. In other words, the aim of the study was to show in detail how people emotionally react to unboxing videos.

Within the scope of the study, the effects of unboxing videos on customers were measured. The *first research question* about the distribution of sentiments on consumers about unboxing videos was answered as follows: In total, Anger was 8.80%, Anticipation was 18.67%, Disgust was 6.24%, Fear was 9.56%, Joy was 16.86%, Sadness was 9.99%, Suprise was 9.23% and Trust was 20.65%. Thus, it can be concluded that mostly the positive sentiments are expressed in the comments of unboxing videos.

In order to achieve a meaningful result, not only unboxing videos, but also official videos and comments on Google Shopping website were also examined. In this study, apart from individual platform analysis, cross-platform comparison technique was also used to understand the effects of unboxing videos.

At data collection stage, it was observed that the reviews on Google Shopping website were much more detailed and longer than the reviews on YouTube. The reason for this difference was thought to be related to motivation to provide eWOM. Consumers create eWOM with different motivations. Sometimes the motivation is the altruistic –people's need to help others-, and for some it may be self-enhancement -desire to enhance the personal image in the eye of others- (Çadırcı Ozansoy & Sağkaya Güngör 2015). When people are satisfied with a product, they want to do something for the benefit of the company by providing positive eWOM (Han 2008). Conversely, if the product does not meet people's expectations, they can provide the eWOM with a negative impact to the company (Han 2008). With a parallel perspective of the literature, this was thought to be the result of the fact that, unlike YouTube, only people who purchased or experienced the product could comment on Google Shopping. As supportive information, the customer does not have to purchase the product to comment on YouTube.

In terms of polarity, the reviews on the Google Shopping website were nearly 15% more positive than the reviews on the unboxing video and official video. This could be explained by the fact that Google Shopping website has the comments of the actual users of product. Besides, as an answer to *research question four* on comparing the effectiveness of unboxing videos, official videos and Google Shopping reviews it had been seen that the Google Shopping web page produces the most positive result. While the polarity rate was 19.05% in official videos, the rate was 18.51% in unboxing videos and 34.87% in Google Shopping reviews. The result may still stem from the fact that the Google shopping reviews are written by the consumers who actually purchased the product, used the product and, then, wrote their comments about the product.

It was seen that the polarity of unboxing videos was very close to the official video polarity. In terms of polarity and in response to *second research question* (Is unboxing video a more effective method when compared to official video?), it can be said that unboxing videos and official videos have been created similar sentiments on people. More generally, although unboxing videos have been very popular lately (Li 2015), they don't have a different impact on customers than official videos. On the other hand, if official videos are considered very effective, it can be said that unboxing videos are as at least effective as official videos.

When analyzed by sentiment analysis, eight different emotions can be evaluated in three categories as positive, negative and bidirectional. Polarity and sentiment change proportions can be cited as the basis of this distinction. To support this comment, *Anger*, *Surprise* and *Disgust* sentiments can be examined. The polarity ratio and *Anger* sentiment distribution are inversely proportional to 80%. In other words, when the polarity ratio increases, Anger distribution ratio decreases by 80%. In contrast, the distribution rate of *Surprise* and the polarity ratio are directly proportional to 70%. Unlike *Anger* and

Surprise, no relationship was found between *Disgust* sense and polarity rate. In fact, the proportion between them is 50%. In other words, if the sentiment of *Disgust* rate increases, the polarity rate increases in% or decreases by 50%. For this reason, Disgust was evaluated bilaterally. In summary, while *Surprise* and *Joy* were evaluated as positive emotions, *Anger* and *Anticipation* could be evaluated as negative. Apart from these, *Trust*, *Fear*, *Disgust* and *Sadness* can be evaluated as bi-directional. In response to *research question three*; investigating the relationship between the eight sentiments and the polarity ratio; *Surprise*, *Joy, Anger* and *Anticipation* have a direct relationship with polarity, while a direct relationship to *Disgust* and *Sadness* could not be observed.

According to the results of the sentiment analysis, differences between YouTube and Google Shopping, sentiment of *Anger* is the highest in the unboxing videos with 8.8% rate. This means that when people watch unboxing videos, they reflect more anger than they do in official video and Google Shopping in their comments. This result may be caused by the release date of the other videos. People usually watch the official video first because the release date is early. People meet the product here and their expectations are set by official videos. The high level of *Anticipation* rate with 19.95% in the official video also supports this situation. When they watch the unboxing video, they can't find what they expect and in parallel the *Anticipation* rate is also decreases to 18.67%. This may also be the reason for the increase in the *Anger* ratio from 8.06% to 8.80%. In support of these results, it can be shown that the *Trust* sentiment ratio in unboxing video is higher than the ratio in the official video. It can be said that the detailed display of the product on unboxing video gives people more confidence than the presentation in the official video. This discussion can be concluded by presenting the superiority of unboxing videos over official videos in creating positive consumer emotions.

Based on the results of the analysis, it can be concluded that all those three channels are very effective for consumers to express especially their trust level. Therefore, while analyzing the consumer sentiments within the comments of the consumers, marketers must carefully seek the words that are the indicators of trust.

When looking at the differences between official video and unboxing video on product basis, it was observed that the official video of Xbox, Sony and Beats in official video had a much higher polarity ratio than the unboxing video. In contrast, the unboxing video of the Amazon Echo was found to be much more effective.

For marketers, unboxing videos can reach to wider audiences with the increasing popularity of YouTube. The product can be marketed to a wider audience by supporting unboxing videos but marketers need to be careful because unboxing videos contain anger and sadness to a considerable extent outside of positive emotions. In terms of product promotion, the official videos can be preferred because the content can be determined entirely by the product owner. On the other hand, it is a handicap that the company cannot intervene in the unboxing video content. Google Shopping can be chosen as a more accurate address if you want to create a more positive impact on the customer. Google Shopping can also be selected because only people who have actually used the product can write a comment and have a high degree of confidence in the comments. As a result, publishing an official video in unboxing videos format based on analysis results of Google Shopping reviews may be a different method for marketers to try.

When sentiment analysis results were examined by product category, the difference in the distribution of emotion analysis on the basis of platform varies between 1% and 4% in product categories. In other words, it was seen that the change between the product categories on the basis of platform is not very noticeable. This discussion answers the *research question five* on investigating whether the emotion analysis results by platform vary by product category.

From a company point of view, unboxing videos are an area that needs attention due to its popularity. Unboxing videos are usually created by YouTubers who are considered as celebrities of the age. There is a risk for companies here because people who have already used the product make more positive evaluations, while an independent YouTuber may be marketing your product negatively. In order to prevent this, the comments in Google Shopping should be carefully analyzed and followed. Then analyses should be compared with unboxing video. If the product is shown below the value it deserves in the unboxing video, company may publish its own unboxing video and turn the situation into a positive side in terms of product.

Another implication for the marketers lies in the polarity rates. The highest polarity rate is in Google product reviews. This means that people are more eager to express both positive and negative emotions freely on Google product reviews more than any other platform. The comments on Google product reviews should be followed by the marketers to get a real idea about what emotions consumer electronics create on consumers.
When the products were examined one by one without video type comparison and the products in the same category were compared, interesting results were found. In general and response to *sixth research question* on the effect of unboxing videos for competing products in the same product category, the polarity ratio and sentiment analysis results of products in the same category was very close to each other, but only the polarity between DJI Osmo and GoPro is remarkable. For this reason, the *wordclouds* of these two products were examined and it was found that one of the most common words in DJI Osmo product comments, which have low polarity ratio, was the name of the competitor. It has been observed that the name of the competitor product is frequently found in the comments has a negative effect on the polarity ratio.

When the summary sentiment analysis in the product categories was analyzed, it is noteworthy that the distribution of *Fear* in the *Audio* category was 9.15%. This can be attributed to the unpredictability of people's sense of hearing. In general, the *Joy* distribution in the *Smart Home* category was highest. *Disgust* sentiment in the action cameras category has the lowest dispersion ratio. In terms of polarity rates, the *Smartphone* category has the highest value of 27.10% while the *Game Console* category has the lowest polarity rate of 18.59%.

As any other study, the findings of this thesis should be approached carefully with its limitations. Every limitation is an opportunity for further studies. Selecting only consumer electronics as a product category was considered as a limitation. The results could be different if a different product category was chosen. From the point of view of methodology, the ironies in the comments could not be detected technically. Therefore, the inverse result in the analysis was considered a limitation. Emoticons are also used frequently in reviews, but sentiment analysis responses have not been evaluated as they are not yet known. Emoticons can be analyzed with a different method in the future studies. The inability to evaluate emoticons was also considered as a limitation. Another limitation of the study is gathering data from only two platforms. Today, Twitter is also a powerful data source, so Twitter data can be used in a future study.

6. CONCLUSION

The aim of this study was to analyze the emotional impact of unboxing videos on customers. Although the popularity of unboxing videos has increased noticeably in recent years, no detailed research has been conducted on the impact on customers. The results of this study will help marketers to re-shape social media and video marketing strategies by providing more specific and unexpected details about unboxing videos that are becoming more popular every day.

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APPENDICES