ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

EXAMINING THE HELPFULNESS OF ONLINE CUSTOMER REVIEWS BASED ON REVIEW RELATED FACTORS: THE MODERATING EFFECT OF PRODUCT TYPE

M.Sc. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ★ FEN BİLİMLERİ ENSTİTÜSÜ

YORUMLARA İLİŞKİN FAKTÖRLER TEMELİNDE ÇEVRİMİÇİ MÜŞTERİ YORUMLARININ YARARLILIĞINI İNCELEME: ÜRÜN TÜRÜNÜN DÜZENLEYİCİ ETKİSİ

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TEMMUZ 2020

Betül Durkaya, a M.Sc. student of ITU Graduate School of Science Engineering and Technology student ID 507171007, successfully defended the thesis/dissertation entitled "EXAMINING THE HELPFULNESS OF ONLINE CUSTOMER REVIEWS BASED ON REVIEW RELATED FACTORS: THE MODERATING EFFECT OF PRODUCT TYPE", which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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Date of Submission : 15 June 2020
Date of Defense : 14 July 2020

To my family,

FOREWORD

I would like to thank all people who contributed efforts in this thesis even if just a drop. First, I would like to thank my precious thesis advisor, Prof. Dr. Şebnem BURNAZ. I am grateful to her for all her guidance, criticism and kindness during this thesis.

Additionally, I appreciate Prof. Dr. Banu ELMADAĞ BAŞ and Assoc. Prof. Dr. Elif KARAOSMANOĞLU for their support throughtout my master studies. I would like to thank Dr. Melek DEMİRAY for her advices during my master studies. And also many thanks to Prof. Dr. Kemal Burç ÜLENGİN for his important remarks for the analysis part of this thesis.

I would also like to thank my colleagues, Res. Asst. Berker PANDIR for his valuable suggestions and encouragement and Res. Asst. Gizem KAYA for her great support on the analysis part of this thesis.

Besides, special thanks to Comp. Eng. Mert KURTCAN for his contribution in data collection and analysis in this thesis. I would like to thank him and my friends for their continuous encouragement and support during this thesis.

Finally, I am grateful to my family, and I owe my thanks to my family for their endless love and support through all my life.

June 2020 Betül DURKAYA
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ABBREVIATIONS

WOM	**:** Word of Mouth
EWOM	**:** Electronic Word of Mouth
ELM	**:** Elaboration Likelihood Model
HSM	**:** Heuristic Systematic Model
POS	**:** Part-of-Speech
NLTK	**:** Natural Language Toolkit
NRC	**:** National Research Council Canada
EmoLex	**:** Word-Emotion Association Lexicon
GALC	**:** Geneva Affect Label Coder
LIWC	**:** Linguistic Inquiry and Word Count

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EXAMINING THE HELPFULNESS OF ONLINE CUSTOMER REVIEWS BY USING REVIEW RELATED FACTORS: THE MODERATING EFFECT OF PRODUCT TYPE

SUMMARY

At the present time, the widespread use of the Internet contributes to human life in a variety of areas. Humans can benefit from Internet to acquire information about any subject. For instance, a customer can take advantage of online resources in the information search phase of buying decision process for a product. During the information search process, humans can prefer to read online customer reviews. Online customer reviews are presented by many websites such as retail websites, brand websites, review websites discussion forums and blogs. The helpfulness of online reviews to readers can also help their purchase decisions. Therefore, review helpfulness appears as an important concept to evaluate the effectiveness of online reviews.

Based on Elaboration Likelihood Model (ELM) and Heuristic Systematic Model (HSM), this thesis focuses on the factors in online reviews that can influence review helpfulness. The central route of ELM and the systematic view of HSM are represented by review related factors which are rating, length, image count, polarity, subjectivity, informativeness, and emotionality of reviews. Here, review emotionality includes Plutchik's (1980) emotion dimensions (anger, anticipation, disgust, fear, joy, sadness, surprise, and trust). Reviewer credibility represents the peripheral route of ELM and the heuristic view of HSM. This thesis aims to discover the influential factors on review helpfulness. It is also examined how the effects of these factors change according to product type (experience vs. search goods).

1,673 online customer reviews are collected from Amazon.com, and are tested with negative binomial regression analysis. Before regression analysis, this thesis implements various analyses to measure some variables of the research model. Sentiment analysis is applied to measure review polarity and review subjectivity. An existing lexicon is also utilized to evaluate review emotionality. Feature extraction operation is used to assess review informativeness in this thesis. The results show that rating, length, image count, polarity, anger, fear, joy, and trust in online reviews affect review helpfulness positively while subjectivity, informativeness, anticipation, sadness, and surprise in online reviews negatively influence review helpfulness. Furthermore, review length, image count, review subjectivity, review informativeness and sadness have greater impacts on review helpfulness for experience goods than for search goods. Disgust and joy in reviews have greater effects on review helpfulness for search goods than for experience goods.

YORUMLARA İLİŞKİN FAKTÖRLERİ KULLANARAK ÇEVRİMİÇİ MÜŞTERİ YORUMLARININ YARARLILIĞINI İNCELEME: ÜRÜN TÜRÜNÜN ILIMLI ETKİSİ

ÖZET

Günümüzde internetin yaygın kullanımı insanların hayatına çeşitli alanlarda katkı sağlamaktadır. İnsanlar herhangi bir konu hakkında bilgi sahibi olmak için internetten faydalanabilirler. Örneğin; bir müşteri, bir ürünü satın alma sürecinin bilgi arama aşamasındayken çevrimiçi kaynaklardan yararlanabilir. Bilgi arama süreci sırasında çevrimiçi müşteri yorumlarını okumayı tercih edebilir. Çünkü bu yorumlar, bu ürünü daha önce satın almış insanların ürünle ilgili deneyimlerini barındırır. Bu çevrimiçi müşteri yorumları perakendecilerin siteleri, markaların siteleri, yorum siteleri, tartışma forumları ve bloglar gibi birçok websitesi tarafından insanlara sunulur. Çevrimiçi yorumlar okuyucularına yarar sağlayabilirse, bu durum bu okuyucuların satın alma kararlarına da yardımcı olabilir.

Çevrimiçi müşteri yorumu sunan birçok websitesi okuyucularının çevrimiçi yorumları yararlılıkları açısından değerlendirebilmeleri için olanak sunar. Okuyucular, her yorum için yorumun kendileri için yararlı olup olmamasına göre oy kullanabilirler. Ayrıca kullanıcılarına oy verme imkanı sunan siteler, her yorum için o yorumu kaç kişinin yararlı bulduğunu da sunmaktadır. Yorumların kullanıcılara yardımcı olup olmaması durumu, özellikle kullanıcıların satın alma kararlarında etkili olabilir. Bu nedenle firmaların yorum yararlılığını etkileyen faktörleri anlaması, müşterilerine daha faydalı yorumlar sunmalarını sağlayabilir. Bu yüzden yorumun yararlılığı, çevrimiçi yorumların etkinliğini değerlendirmede önemli bir kavram olarak ortaya çıkar.

Çevrimiçi müşteri yorumları bağlamında sıklıkla kullanılan ve insanların bilgiyi iki ayrı yolla işlediğini savunan İkili İşlem Modelleri (Dual-Process Models) bu tezde de benimsenmiştir. Spesifik olarak Ayrıntılı İnceleme Olasılığı Modeli (Elaboration Likelihood Model) ve Sezgisel-Sistematik Bilgi İşleme Modeli'ne (Heuristic Systematic Model) dayanan bu tez, yorum yararlılığını etkileyebilecek çevrimiçi müşteri yorumları faktörlerine odaklanmaktadır. Günümüzde birçok websitesi kullanıcılarına yorum yazabilme imkanı sunduğundan, kullanıcılar ürün deneyimleriyle ilgili düşüncelerini belirterek diğer kullanıcılara bilgi verebilir ve bu deneyimle ilgili bir derecelendirme yapabilirler. Ayrıca sadece yazılı bir ifadenin yanı sıra, yorumla birlikte görsel içerikler de paylaşabilirler. Bu tezde, yüksek seviyede bilişsel çaba gerektiren Ayrıntılı İnceleme Olasılığı Modeli'nin merkezi rotası ve Sezgisel-Sistematik Bilgi İşleme Modeli'nin sistematik görüşü yorumla ilişkili faktörler tarafından temsil edilmektedir. Yorumun

derecesi, uzunluğu, resim sayısı, polaritesi, öznelliği, bilgilendiriciliği ve duygusallığı yorumla ilgili faktörleri oluşturmaktadır.

Yorumun duygusallığı kavramı Plutchik'in (1980) duygu boyutlarını (öfke, beklenti, iğrenme, korku, sevinç, üzüntü, şaşkınlık ve güven) içermektedir. Ayrıca buradaki polarite kavramı, yorumun negatif, pozitif ve nötr yargılar içermesiyle ilgili bir kavramdır. Düşük seviyede bilişsel çaba gerektiren Ayrıntılı İnceleme Olasılığı Modeli'nin çevresel rotası ve Sezgisel-Sistematik Bilgi İşleme Modeli'nin sezgisel görüşü ise yorumcunun güvenilirliği ile temsil edilmektedir. Bu tez, yorum yararlılığı üzerinde etkili faktörleri keşfetmeyi amaçlamaktadır. Yalnızca yorumda yazılanların değil, kimin yorumu yazdığının da önemli olabileceği düşünüldüğünden yorumla ilişkili faktörlerin yanı sıra yorumcuyla ilişkili bir faktöre de odaklanılmıştır. Literatürde yorumların duygusallığına ve bilgilendiriciliğine aynı anda odaklanan bir çalışmanın eksikliği olduğundan, bu tezle özellikle bu eksikliği gidermek amaçlanmaktadır. Ayrıca bu çalışmada, hem yorumla hem yorumcuyla ilişkili olan faktörlerin etkilerinin ürün türlerine (deneyimsel ve araştırma ürünleri) göre nasıl değiştiği de incelenmektedir. Bu açıdan da literatüre katkı sağlamak amaçlanmaktadır.

Bu tezde yorumun bilgilendiriciliğini değerlendirebilmek için Taylor ve arkadaşlarının (1997) bilgi işaretlerinden yararlanılmıştır. Bu işaretler, 30 adet bilgi türünü kapsamaktadır. Bu yüzden bilgi türlerinin hangilerinin insanlar için daha ön planda olduğunu anlamak adına bir ön çalışma yapılmış ve bu amaca uygun bir anket oluşturulmuştur. Amazon Mechanical Turk vasıtasıyla dağıtılan anketi 107 kişi cevaplamıştır. Bu anketin sonucunda 30 adet bilgi işaretinden 11 tanesi katılımcılar tarafından daha önemli bulundukları için seçilmiştir ve yorum bilgilendiriciliğinin hesaplanması için bu işaretlerden faydalanılmıştır. Ayrıca bu anketle çevrimiçi yorumları inceleyen insanların, hangi yorumları okumayı tercih ettiklerini öğrenmek de amaçlanmıştır. İnsanlar çevrimiçi perakende sitelerinde, çevrimiçi yorumları güncelliklerine veya popülerliklerine göre okumayı tercih edebilirler. Yine birçok websitesi insanlara bu imkanı sağlamaktadır. Bunun sonucunda ise popüler yorumlardan oluşan bir veri seti oluşturulmasında karar kılınmıştır.

Veri kaynağı olarak Amazon.com tercih edilmiştir. Ürün türü belirleme aşamasında ise Nielsen raporlarından yararlanılmıştır. Bu raporlara göre en çok satış yapılan ürün kategorileri incelenmiştir, giyim ve elektronik ürün kategorileri bunlar arasındadır. Veri kaynağı olan Amazon.com sitesinde bu kategorilerin en çok satan ürünleri incelenip; sonucunda deneyimsel ürün olarak ayakkabılar, araştırma ürünü olarak ise kulaklıklar seçilmiştir. Amazon.com aracılığıyla 1,673 çevrimiçi müşteri yorumu toplanmıştır ve bu yorumların 859 tanesi kulaklık, 814 tanesi ayakkabı kategorisinden ürün yorumlarını içermektedir. Bu yorumlar negatif binomiyal regresyon ile analiz edilmektedir. Fakat yorumcunun güvenilirliği değişkeni, veri setinde yeterli oranda değişmediğinden analize dahil edilememiştir. Ayrıca regresyon analizine geçmeden önce araştırma modelindeki bazı değişkenleri ölçebilmek için çeşitli analizler uygulanmıştır. Yorumların polaritesini ve öznelliğini ölçebilmek için duygu analizine başvurulmuştur; bir Python kütüphanesi olan TextBlob yardımıyla yorumların polarite ve öznellik değerleri hesaplanmıştır. Yorumların duygusallığını ölçmek için ise hazır bir sözlük kullanılmıştır. Bu sözlük yardımıyla her yorumun, hangi duyguları hangi oranda barındırdığı hesaplanmıştır. Son olarak yorumların bilgilendiriciliğini değerlendirmek için özellik çıkarımı işleminden yararlanılmıştır. Bu işlem sayesinde yorumlardaki ürün özellikleri belirlenmiş, ardından bu özellikler, Taylor ve arkadaşlarının bilgi işaretlerine göre sınıflandırılmıştır. Yani ürün özelliklerinin hangi bilgi türüyle eşleştiği belirlenmiştir. Bu aşamalardan sonra negatif binomiyal regresyon analizine başvurulmuştur.

Regresyon analizi sonuçlarına göre; yorumun derecesi, uzunluğu, resim sayısı, polaritesi, yorumlardaki öfke, korku, sevinç ve güven duyguları yorum yararlılığını pozitif olarak etkileyen faktörlerdir. Yorumun öznelliği, bilgilendiriciliği, yorumlardaki beklenti, üzüntü ve şaşkınlık duyguları ise yorum yararlılığını negatif olarak etkilemektedir. İğrenme duygusunun ise yorum yararlılığı üzerinde önemli derecede bir etkisine rastlanamamıştır. Ayrıca araştırma modelindeki değişkenlerin ürün türüyle etkileşimlerine bakıldığında ise yorum derecesi, yorum kutupsallığı, öfke, beklenti, korku, şaşkınlık ve güven duygularının yorumun yararlılığı üzerinde önemli bir etkileri gözlemlenememiştir. Yorum uzunluğu, resim sayısı, yorumun öznelliği, yorumun bilgilendiriciliği ve yorumlardaki üzüntü duygusu, deneyimsel ürünler için yorum yararlılığı üzerinde araştırma ürünlerine göre daha fazla etkiye sahiptir. Yorumlardaki iğrenme ve sevinç duyguları ise araştırma ürünleri için yorum yararlılığını deneyimsel ürünlere kıyasla daha fazla etkilemektedir. Ayrıca yorumcuya ilişkin belirlenen yorumcu güvenilirliği faktörü analize dahil edilemediğinden Ayrıntılı İnceleme Olasılığı Modeli'nin çevresel rotası ile Sezgisel-Sistematik Bilgi İşleme Modeli'nin sezgisel görüşünü temsil eden bu faktör değerlendirilememiştir. Fakat bu tez, Ayrıntılı İnceleme Olasılığı Modeli'nin merkezi rotası ile Sezgisel-Sistematik Bilgi İşleme Modeli'nin sistematik görüşünü temsil eden faktörleri ayrıntılı bir şekilde ele almıştır ve yorumla ilişkili olan yorum yararlılığında etkili faktörlere ışık tutmaktadır.

Araştırma sonuçlarına göre firmalar müşterilerine daha iyi bir kullanıcı deneyimi sağlamak adına websitelerinde çeşitli düzenlemeler yapabilirler. Örneğin; firmalar, müşterileri için daha yararlı olabilecek yorumları ön plana çıkarabilirler. Bir satın alma işlemi gerçekleştirmiş müşterilerini yorumları inceleyen insanlar için yararlı olacak yorumlar yazmaya teşvik edebilirler. Bu araştırma sonuçlarına göre yorum yararlılığında etkili faktörleri düşünerek onlara rehberlik edebilirler.

1. INTRODUCTION

With the developing technology, virtual environments have an important place in people life nowadays. People can meet a great number of needs through virtual platforms. They can pay the bill, buy a theatre ticket, book a hotel room, or purchase a product. While doing all these, they may benefit from other people's experiences via online customer reviews. There are a variety of companies using online platforms to sell their products. In these platforms, customers can examine products, read online reviews of other customers and purchase a product if they want. Online customer reviews are a valuable information source in the process of product evaluation and purchase, they can change the nature of the purchase decision. According to Podium's (2017) report, 93% of consumers stated that online reviews affect their purchase decision. Hence, a great number of studies about online reviews have been conducted by many scholars.

A variety of studies analyzed the effects of online customer reviews on purchase behavior (Ziegele and Weber, 2015; Reimer and Benkenstein, 2016; Weisstein et al., 2017; Kim et al., 2018; Yusuf et al., 2018). Furthermore, a number of researches have been conducted using review helpfulness to evaluate the performance of online reviews due to the fact that review helpfulness reflects other customers' opinions about whether the review is helpful or not (Mudambi and Schuff, 2010; Felbermayr and Nanopoulos, 2016; Salehan and Kim, 2016; Singh et al., 2017; Srivastava and Kalro, 2019; Sun et al., 2019; Wang et al., 2019). In terms of helpfulness, customers could both comment on their experience about products or services and vote the other reviews that they read in online platforms when they are searching for a product since many online review websites provide customers with an opportunity to comment and vote. These reviews can be read by other individuals who search for a product to buy. The content of these reviews may be influential on individuals' opinions.

When a consumer seeks for a product to purchase, his/her purchase decision might be influenced by his/her thought about perceived review helpfulness if he/she read the online reviews about the product. His/her notion on the product may alter because of online reviews. It can depend on whether reviews are perceived as helpful or not. Therefore, investigating factors that affect review helpfulness is the major purpose of this thesis. Especially, it aims to explore the effects of emotionality and informativeness of reviews on review helpfulness. Reviews that contain emotions can excite consumers and can lead to change their opinions on review helpfulness. Thus, analyzing different emotion types on review helpfulness is another goal of this thesis. Besides, online product reviews comprise customers' experiences about any product that they purchase, so they generally include a variety of information about product features. It is aimed to see how this information in online reviews influences review helpfulness. Finally, the factors related with comment content such as review rating, review length, review subjectivity, review polarity, and image count of the reviews will be examined in terms of their effect on review helpfulness. Whether the effect of the factors on review helpfulness change according to product type (experience vs. search goods) will also be analyzed. Therefore, this study proposes mainly two research questions as below:

RQ1: How do emotional and informational content of online customer reviews influence review helpfulness?

RQ2: Is there any change between factors that affect review helpfulness when different product types are considered?

In order to reach these objectives, literature review has been conducted in a comprehensive manner, based on the relevant studies on word of mouth (WOM) impact and online consumer reviews. Moreover, the academic studies on the evaluation of online consumer reviews performance are examined. Then, a preliminary study was conducted with consumers who purchase online before going for the overall research study. Secondary data analysis has been conducted, and amazon.com was the main data source. Shoes as experience goods and headphones as search goods were selected, and online consumer reviews on these products were collected through amazon.com. Information extraction, sentiment analysis, emotion analysis and negative binomial regression operations were applied to 1,673 online consumer reviews gathered in total.

The thesis consists of four major sections. After the introduction, the literature review part points out various research studies on WOM and online consumer reviews. Research design and methodology section includes research objectives and hypothesized model as elements of research design and methodology. Also, preliminary study, data, analyses, and results are comprehensively explained in this section. Lastly, the thesis was concluded and information about limitations of the thesis and future research directions are given in the part of conclusion.

2. LITERATURE REVIEW

With the development of the Internet, personal channels have also taken their place in electronic media. Word of mouth (WOM) impact on consumers emerges in the form of online customer reviews in electronic media. The antecedents and consequences of WOM have been investigated from past to present. With the increasing use of electronic media, online customer reviews have constituted a new research area. The evaluation of the performance of these reviews in terms of purchase decision of customers takes also important part in the literature. Examining the factors affecting the performance of online customer reviews is the main focus of this thesis.

In this section, the role of WOM is emphasized in the context of marketing, and the differences between WOM and electronic word of mouth (EWOM) are discussed. Online consumer reviews make up a large portion of EWOM, so how these online reviews can be used and how their performance can be measured are other important considerations for this section. Also, factors that may influence online review performance are explained in depth. The elaboration likelihood model (ELM) and the heuristic systematic model (HSM) as dual-process models are used to explain these factors, and detailed explanations are presented about these models.

2.1 Word-of-Mouth Impact in Marketing

Word of mouth (WOM) means person to person communication about a product or a service experience (Sen and Lerman, 2007). People can guide their acquaintances by talking about their experience with a product or a service through their purchase journey. People's ideas about the product or the service may cause their relatives to change their opinions about that product or service. From marketing point of view, WOM may have positive or negative valence (Buttle, 1998). While recommendations connected to agreeable experiences are examples of positive WOM, complaints and vilifications relevant to disagreeable experiences are instances of negative WOM (Anderson, 1998). Positive WOM might make a favorable impression on individuals while negative WOM might make an unfavorable impression on individuals.

Previous researches demonstrated that WOM may affect judgments about products (Herr et al., 1991; Bone, 1995). Hence, it is thought to have an impact on the purchase decision of consumers. Arndt (1967) found a relationship between WOM and purchase probability. Bansal and Voyer (2000) researched WOM processes for service purchase decisions, and found that if WOM information is actively sought by the receiver, it will have a higher effect on purchase decision than if it is not actively sought. Also, they showed that the expertise of the WOM sender is significantly and positively related with purchase decision of the receiver. Basri et al. (2016) investigated the impacts of WOM attributes on consumers' purchase decision in Malay upscale restaurants, these attributes were service quality, food quality, physical environment, and price. Their results demonstrated that service quality, physical environment, and price are significant indicators on purchase decision. Furthermore, whether WOM is positive or negative could have an impact on purchase decision. Wang (2011) declared that purchase intention and the perception on service quality are more positive if there are more positive WOM events. WOM has continued to be effective in consumer decisions for so long.

Electronic word of mouth (EWOM) turns out to be more remarkable owing to its easy accessibility in recent decades. There are various tools providing information flow between consumers about products or services. Brand websites, retail websites, review websites, discussion forums, weblogs and social networking sites are some of the platforms carrying these flows. Enlargement of personal interaction to the cyberspace via these tools indicates EWOM (Goldsmith and Horowitz, 2006). EWOM can possess positive or negative meanings. Park and Lee found that the effect of EWOM is bigger for negative EWOM than for positive EWOM.

There are not only some similarities but also some differences between WOM and EWOM. The reach of the impact of reviews and the speed of interactivity constitutes the basic distinction between WOM and EWOM (Cantallops and Salvi, 2014). The amount of WOM information in online platforms is higher than the amount of WOM information obtained in traditional ways; moreover, online WOM involves a number of positive and negative information simultaneously from multiple sources (Chatterjee, 2001). Further, Cheung and Lee (2012) stated that EWOM is more measurable than traditional WOM thanks to EWOM's appearance form, amount and permanence. Cheung and Thadani (2012) also declared that there are three unique differences which distinguish EWOM from traditional WOM. These differences arise from the fact that EWOM is more persistent and accessible, and more measurable than traditional WOM. Moreover, EWOM has an extraordinary scalability and diffuses fast unlike traditional WOM.

2.2 Electronic Word of Mouth and Online Consumer Reviews

It is obvious that Internet is a substantial tool in people's life, people search to obtain information about anything. They can benefit from Internet to make decisions like purchase a product, or they can give information about their purchase experiences via Internet. While doing this, they can be exposed to EWOM. Reviews in online platforms generate an important part of EWOM. Consumers can take advantage of online reviews especially for information search of buying decision process. People can tell about their product experiences by writing online reviews, so this can lead readers of these reviews to change their attitudes on the products.

Unlike traditional sellers, online sellers can offer two types of product information, either seller-created product information or consumer-created product information (Park et al., 2007). The information created by consumers leads to online WOM. Online WOM information is found to be more credible than marketer-generated information (Bickart and Schindler, 2001). Nevertheless, consumers may be suspicious of marketer-generated websites. Since information can be changed, supplemented or removed by the owner of the website (Lee and Youn, 2009), customers might not be sure about the credibility of these websites. Hence, humans could head towards consumer-generated product information.

In the literature, a variety of studies exist about antecedents and consequences of EWOM (Hennig-Thurau et al., 2003; Goldsmith and Horowitz, 2006; Sun et al., 2006; Lee and

Youn, 2009). Sun et al. (2006) specified that opinion leadership and opinion seeking are the basic dimensions of EWOM and found the determinants of these dimensions. Hennig-Thurau and Walsh (2003) remarked that customer reviews in online platforms affect consumer decision-making. Various studies were conducted to understand the impacts of EWOM on purchase intention (Chan and Ngai, 2011; See-To and Ho, 2014; Erkan and Evans, 2016). Erkan and Evans (2016) offered a new model, that is called information acceptance model (IACM), to clarify the factors of EWOM information which affect purchase intentions of customers. Bataineh (2015) revealed that EWOM credibility, EWOM quality and EWOM quantity are determinants which affect purchase intention positively. Pitta and Fowler (2005) stated that buyers can search for online information about a product or a service to help their purchase decisions. Thus, online reviews can play an important role in the purchase decision process of individuals.

Online reviews can have an important power on consumers' decisions; hence, many scholars have researched on the effectiveness of online reviews. Companies can acquire clues about how to manage WOM in online platforms. Companies might improve their strategies on the management of online websites by gaining insight into online reviews. Managing online reviews correctly could be a critical asset to companies' success. Besides, online retailers could offer their customers better experiences on their websites by coping with information overload because of countless online reviews. It may be possible that companies get more customers and more sales due to well-designed and user-friendly websites.

2.3 Online Review Performance

Online review performance is measured with a variety of ways by different scholars. Purchase intention, purchase probability, volume of sales, review helpfulness, or review usefulness were utilized to measure the performance of the online reviews. The researches, based on surveys or experimental designs, generally used purchase intention to evaluate the performance (Reimer and Benkenstein, 2016; Weisstein et al., 2017; Yusuf et al., 2018). However, Bulut and Karabulut (2018) utilized online repurchase intention and stated that not only the quality but also the quantity of EWOM have a strong influence on online repurchase intention.

Some researchers interpreted online review performance by using online reviews as secondary data (Cheng and Ho, 2015; Felbermayr and Nanopoulo, 2016; Hlee et al., 2019; Sun et al., 2019). While Kim et al. (2018) employed purchase probability, Zhang et al. (2013) examined sales volume of cameras and found that average review rating and the number of online reviews affect camera sales significantly. Ye et al. (2009) studied on the effective factors on hotel room sales by using the number of bookings as a dependent variable, and they explored that positive online reviews positively influences bookings count of a hotel.

Besides, the studies that are adopted review usefulness or review helpfulness are available in the literature (Salehan and Kim, 2016; Li et al., 2017; Singh et al., 2017; Srivastava and Kalro, 2019; Wang et al., 2019). Chatterjee (in press) examined the determinants of review helpfulness and found that overall rating has a positive impact on review helpfulness in his study on online hotel reviews. Here, review helpfulness is relative to the perception of the review as helpful by people, and review usefulness is related with the perception of the review as useful by people. The reason why the concepts were named this way is related with the approach of the website where the reviews were gathered. While some of online retailers prefer to use the term “usefulness” so that customers can vote, some of them prefer the term “helpfulness” in their websites. In this studies, review helpfulness was calculated by the number of helpful votes (Li et al., 2017; Srivastava and Kalro, 2019; Wang et al., 2019) or the ratio of helpful votes to total votes (Chua and Banarjee, 2014; Salehan and Kim, 2016; Singh et al., 2017).

In this thesis, review helpfulness is adopted to assess online review performance mainly based on the information accessibility. Many online retail websites present information about whether reviews in their websites are helpful or not. To illustrate, amazon.com allows readers to vote for the helpfulness of each review and presents the most helpful reviews as top reviews. On account of the fact that this situation makes the website more user-friendly, it leads to get more customers (Singh et al., 2017). Amazon's sales have risen by 2.7 billion dollars annually owing to promoting the most helpful reviews (Spool, 2009).

Furthermore, Schuckert et al. (2015) stated that review helpfulness is one of the most critical elements to help customers to make decisions. Chen et al. (2008) revealed that helpful reviews have stronger impact on purchase decisions of customers than other reviews have. Review helpfulness also provides an inference about whether customers read the comment or not. If a customer voted for a review, it can be said that he/she did that after he/she read the review. For these reasons, review helpfulness is a considerable context to measure the performance of customer reviews.

In addition to review helpfulness, factors that may have an impact on review helpfulness have an important position in this thesis. These factors are related to how customers process information in reviews; thus, understanding the way of information processing when handling an online review is crucial in order to evaluate the effectiveness of that review appropriately.

2.4 Dual-Process Models Focus on Online Customer Reviews

Dual-process models assert that people process information in two distinct methods. One is effortless processing method that entails well-learned former associations. The other is effortful processing method that entails on rule-based implications. (Smith and DeCoster, 2000) Dual-process models have been the most influential models in the area of persuasion and change of attitude (Smith and DeCoster, 2000). These models considerably contributed to comprehend information judgment of consumers and information processing strategies, so they have been strong in persuasion and the change of attitude (Jun and Vogt, 2013). Several researchers adopted dual-process models such as Elaboration Likelihood Model (ELM) (Petty and Cacioppo, 1986a) or Heuristic Systematic Model (HSM) (Chaiken, 1980) to explain persuasive influences of online customer reviews (Cheng and Ho, 2015; Kim et al., 2018; Li et al., 2017; Hlee et al., 2018; Srivastava and Kalro, 2019). Both models assert that there are two different ways to process information (Kim et al., 2018). One of them is an effortful processing, and the other is an effortless processing (Jun and Vogt, 2013).

According to HSM, individuals can handle messages in a heuristic or systematic way. Heuristic processing requires low level cognitive effort while systematic processing requires high level cognitive effort (Chaiken et al., 1989). In other words, a systematic view of HSM necessitates to process information in detail, while a heuristic view of HSM does not (Chaiken, 1980). On the other hand, ELM offers two main routes that are the central route and the peripheral route to persuasion. The level of elaboration is high for the central route, while it is low for the peripheral route (Srivastava and Kalro, 2019). Here, it can be noticed that these two models have similarities owing to the fact that systematic processing is parallel to central route, and heuristic processing is parallel to peripheral route.

As can be seen from Figure 2.1 that shows the routes of ELM, central route requires motivation and ability for cognitive processing while peripheral route does not. ELM is a very suitable model for the context of online reviews since online consumer reviews can create persuasive communication and at the end attitude change which also predicts behavioral decision. In Figure 2.1, Petty and Cacioppo (1986b) defined attitude individuals' general assessments towards themselves, other individuals, objects or subjects. When a consumer is subjected to a review about a product, this review may affect the customer's attitude towards the product. In this way, it can make a change in the purchase decision of the consumer. Two routes which are recommended by ELM could reinforce the improvement of consumer behavior (Yusuf et al., 2018). Therefore, ELM is used commonly in the EWOM context, and it is also adopted in this thesis.

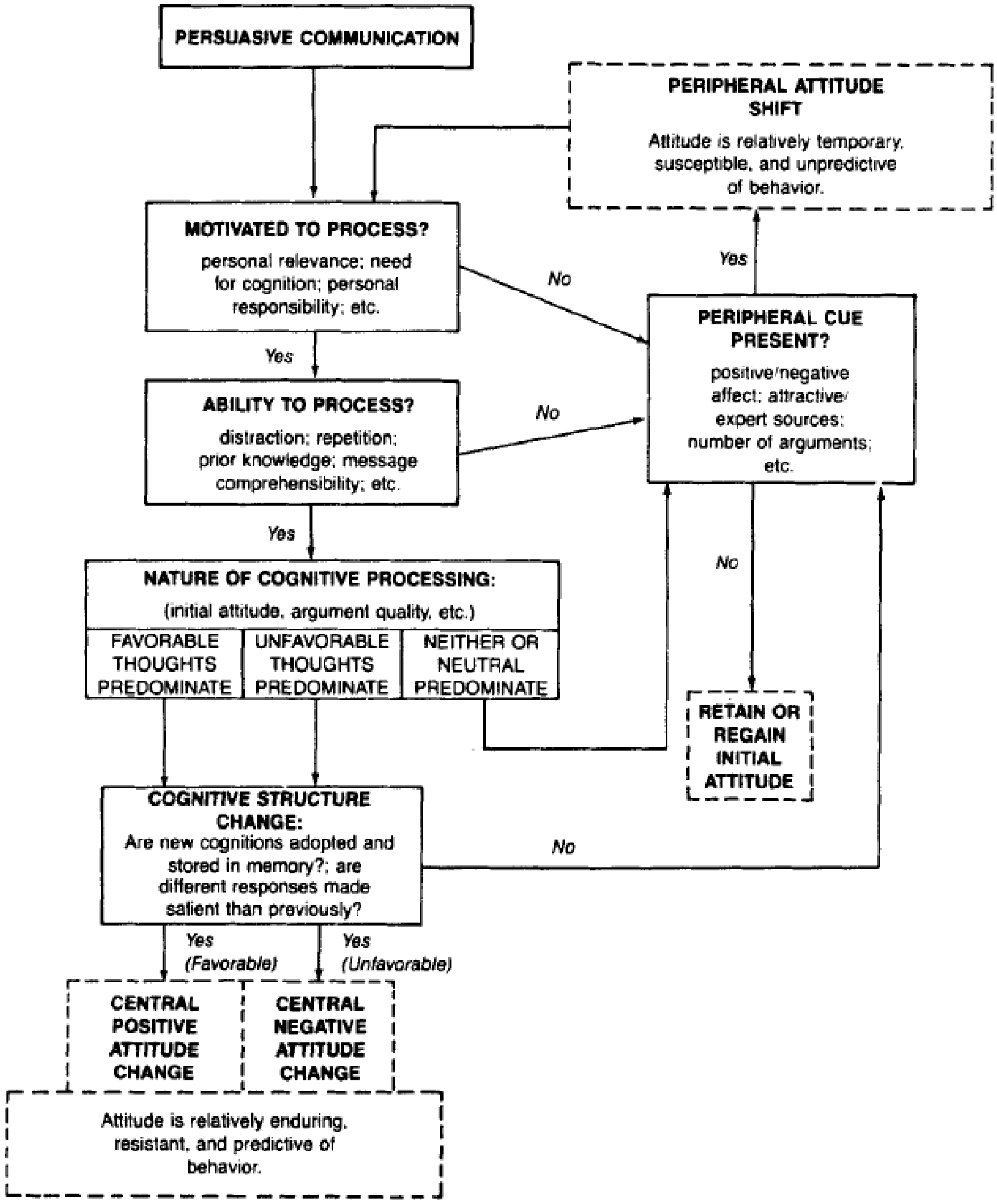

Figure 2.1 : Central and peripheral routes to persuasion.

Source: Petty, R.E., & Cacioppo, J.T. (1986b). The elaboration likelihood model of persuasion. *Advances in Experimental Social Psychology,* 19, 123-205.

In EWOM literature, the central route of ELM represents the factors associated with review content, and the peripheral route represents the factors associated with reviewers. The processing ways of HSM have been used likewise owing to the similarities of the dual-process models. The essential difference among these models originates from the connection between information processes which include two different ways. While systematic processing and heuristic processing are independent from each other and can concurrently take place in HSM, central route and peripheral route are in a reverse relation in ELM. Namely, when one increases, the other decreases (Larson, 2013). Zhang et al. (2014) emphasized that co-occurrence of systematic and heuristic processing in HSM is a crucial theoretical expansion that distinguishes it from ELM. Consumers can employ both processes in HSM simultaneously, so it is possible to see the simultaneous effects of heuristic processing and systematic processing. HSM can also explain more extensive information processing activities such as it can be applied to a broad context of validity-seeking (Chaiken et al., 1989). Due to the use of HSM in various information processing activities and some theoretical extensions of HSM, Zhang and Watts (2008) utilized HSM instead of ELM to explain the determinants on information adoption.

HSM defines three motivations for the processing of information which are accuracy, defense, and impression. Defense motivation is concerned about confirmation of the validity of attitudinal positions while impression motivation is concerned about assessment of the social acceptability of attitudinal positions (Chaiken et al., 1989). Accuracy motivation clarifies the assessment of the validity of the attitude related information (Chaiken et al., 1989). It explains validity-seeking concept; for instance, consumers can seek for accurate online reviews (Zhang et al., 2014). The accuracy is the most appropriate motivation for the concept of online customer reviews (Kim et al., 2018). Heuristic and systematic information processing views support accurate motivation (Chaiken et al., 1989) since both information processing views of HSM explain assessment of the validity of the arguments by the recipients (Chaiken, 1980). HSM is embraced in this thesis considering its appropriateness to the EWOM context. It offers a useful framework to understand features of online customer reviews.

Table 2.1 exhibits the list of studies on online customer reviews utilizing dual-processing models. There are limited number of studies that adopted HSM to explain how online customer reviews function. It was aimed to contribute to the literature by showing that HSM can be used within the context of online customer reviews. Consequently, relying on the suitability on online reviews context, this thesis adopts both ELM and HSM by focusing on both aspects of these models. In other words, it concentrates on both the factors related to review content and reviewer related factors.

The central cues or systematic factors on review helpfulness have been evaluated by image count and word count in the literature (Cheng and Ho, 2015; Kim et al., 2018; Hlee et al., 2019; Srivastava and Kalro, 2019); also, Srivastava and Kalro (2019) utilized review rating as a central cue for review helpfulness. Nonetheless, there may be more factors related to the online reviews that affect review helpfulness. Thus, there is a deficit of an extensive approach to the central cues. It is aimed to fill this deficit in the literature by examining the central cues comprehensively. In this thesis, informativeness, emotionality, rating, image count, word count, polarity, and subjectivity of reviews are determined as the factors associated with central route of ELM and systematic information processing of HSM in terms of online customer reviews. In addition to central process of ELM and systematic process of HSM, reviewer related factors which refer to peripheral process of ELM and heuristic process of HSM are considered in this thesis. It is thought that besides what is said in the reviews, it may also matter who says it. Various scholars used source credibility as a peripheral or a heuristic cue on review helpfulness or usefulness (Zhu et al., 2014; Cheng and Ho, 2015; Hlee et al., 2019). In this thesis, reviewer credibility which indicates source credibility is utilized as a peripheral and a heuristic factor on review helpfulness. These factors and their effects according to product type are explained in detail in the next sections.

Table 2.1 : Studies on online customer reviews based on dual-processing models in literature.

Author(s)	Theory	Input(s)	Moderator(s) or Mediator(s)	Output(s)	Method	Findings
Cheng and Ho (2015)	ELM	Reviewer's number of followers, Reviewer's level of expertise, Image count, Word count		Usefulness of the review	Secondary data analysis of online reviews	Consumers perceive more usefulness to source credibility than argument quality. Reviewer's level of expertise is positively and significantly related with the usefulness of the review.
Filieri (2015)	Dual-process theory	Information quality, Information quantity, Overall product rankings, Consumer ratings	Perceived source credibility	Perceived information diagnosticity	Survey	The most important antecedent of information diagnosticity in EWOM is information quality. Not only overall product rankings but also consumer ratings are critical factors of information diagnosticity.
Hlee et al. (2019)	ELM	Content richness (Number of words, Number of images), Source credibility (Number of friends, Elite badge)	Restaurant type	Useful votes, Funny votes	Secondary data analysis of online reviews	Consumers think that a review is more useful and funny when the review has more images. Elite badge is more effective than the number of friends on peer evaluations (useful and funny votes).
Kim et al. (2018)	HSM	Review length, Review valence, Review sidedness, Source credibility, Reviewer recommendation	Review helpfulness	Purchase probability	Secondary data analysis of online reviews	Source credibility and reviewer recommendation are important factors that affect purchase probability.
Li et al. (2017)	ELM	Review sentiment, The size of reviewer’s social network, The composition of reviewer’s social network	Reviewer social identity	Perceived funny, Perceived, usefulness, Perceived coolness	Secondary data analysis of online reviews	Not only the size of the reviewer’s social network but also the composition of the reviewer’s social network has an influence on peer evaluations (perceived funny, usefulness, and coolness).

Table 2.1 (continued) : Studies on online customer reviews based on dual-processing models in literature.

Author(s)	Theory	Input(s)	Moderator(s) or Mediator(s)	Output(s)	Method	Findings
Park et al. (2007)	ELM	The quality of online consumer reviews, The quantity of online consumer reviews	Involvement	Purchase intention	Experiment	The quality and the quantity of online consumer reviews positively affect consumer purchase intention. While low-involvement consumers are influenced by review quantity, high-involvement consumers are influenced both by review quantity and by review quality.
Srivastava and Kalro (2019)	ELM	Reviewer related factors, Review rating, Review length, Image count, Comprehensiveness, Review clarity, Review readability		Review helpfulness	Secondary data analysis of online reviews	If a review is comprehensive or easily readable ,then it is perceived as more helpful.
Yusuf et al. (2018)	ELM	Information quality, Information credibility, Website quality, Consumer innovativeness, Social support, Attitude toward EWOM	EWOM engagement	Purchase intention	Survey	Influential factors of EWOM engagement, which has an effect on purchase intention, are attitude toward EWOM, information credibility, innovativeness, and website quality.
Zhang and Watts (2008)	HSM	Argument quality, Source credibility	Disconfirming information, Focused search	Information adoption	Survey	Information adoption is affected by argument quality and source credibility.
Zhang et al. (2014)	HSM	Argument quality, Source credibility, Perceived quantity of reviews		Behavioral intention	Survey	Behavioral intention is importantly influenced by argument quality, source credibility, and perceived quantity of reviews.

2.4.1 Factors related to online reviews

To assess the messages, recipients need to use cognitive effort dramatically in a systematic view of HSM (Chaiken, 1980). In the context of online reviews, factors that are related to the systematic view of HSM or central route of ELM are considered. Argument quality is one of the most common factor which has been used by many scholars. It was measured by using perceived informativeness and perceived persuasiveness in the research of Zhang et al. (2014). However, Cheng and Ho (2015) measured argument quality with image count and word count. Hlee et al. (2019) also utilized word count and image count to evaluate content richness of reviews. Srivastava and Kalro (2019) used review rating as a central factor to review helpfulness. Furthermore, review sidedness and review valence referring to the existence of positive and negative statements in a review, has been used as systematic factors (Kim et al., 2018). Consequently, review informativeness, review emotionality, review sentiment, review subjectivity, review rating, review length and image count of the review are accepted as review related factors in this thesis.

2.4.1.1 Review informativeness

One of the important reasons why people read reviews is that they would like to have information about the product or the service that they consider purchasing. They can acquire information about the product or the service based on the experiences of previous consumers by reading the reviews. Therefore, information residing in the reviews is used as a central cue for the purposes of this study. It is under consideration that how much information a review contains may be an important element affecting review helpfulness.

Informativeness refers a statement to be perceived as informative by customers. As informativeness eliminates the uncertainty about a product, it has a great importance especially in advertising. Advertisements offering information about products or services can contribute to information search step of buying decision process for customers. Several studies exist on the information content of advertisements in the literature (Resnik and Stern, 1977; Abernethy and Franke, 1996; Taylor et al., 1997; Franke et al., 2004). While Resnik and Stern (1977) measured informativeness of television advertising through 14 items, Taylor et al. (1997) utilized 30 items to describe information cues in television commercials. Price or value, quality, performance, components or contents, availability, special offers, taste, packaging or shape, guarantees or warrantees, safety, nutrition, independent research, company/sponsored research and new ideas constitute Resnik and Stern's (1977) informational cues. Taylor et al. (1997) added variety of the product, value, size, economy/savings, supply, quantity available, or limitation, method of payment, dependability/reliability/durability, sensory information (other than taste), research from unidentified source, user's satisfaction/loyalty, superiority claim, convenience in use, new product or new and improved features, use occasion, characteristics or image of users and company information to these informational cues.

Based on the research of Gao and Koufaris (2006), it is explored that perceived informativeness, perceived entertainment and perceived irritation are significantly associated with user attitude towards a commercial site. They demonstrated that perceived informativeness and perceived entertainment affect attitude positively while perceived irritation affects it negatively. Likewise, Ducoffe (1995) indicated that not only informativeness but also entertainment has a significant relationship with the value of advertisements. Also, Taylor et al. (2011) stated that entertainment and informativeness are the two most influential variables on attitude toward social networking advertising, entertainment being four times more effective than knowledge. The common characteristic of these studies is that they used primary data based on survey method and evaluated the informativeness with 3 items.

In some studies, credibility or quality of the reviews have been used to assess informative content (Cheng and Ho, 2015; Filieri, 2015; Yusuf et al., 2018). Filieri (2015) employed information quantity, quality and credibility, and he developed a scale consisting of 5 items to measure information quality. Yusuf et al. (2018) used information quality and credibility to evaluate information content. The research of Cheng and Ho (2015) is another study using source credibility and argument quality to interpret the credibility and quality of information, they utilized reviewer's number of followers and level of expertise for source credibility, they used image count and word count for argument quality. It is clear that the researchers did not find sufficient to measure only image count and word count in order to assess information content of reviews.

Sun et al. (2019) evaluated review informativeness with the help of the number of product attributes and platform attributes, and they found that review informativeness has a significant impact on review helpfulness. Here, platform attributes comprise information about shipping and packaging. They applied to an existing Chinese lexicon to find both product and platform attributes, and this lexicon contained specific terms that reflect product related words based on product using guides. On the other hand, other information than product attributes could be significant in customer reviews. To illustrate, customers could give information about their experiences of consuming the product or their satisfaction after the consumption about the product. That is why the information cues of Taylor et al. (1997) are adopted for the purpose of this thesis as they are more comprehensive (See Appendix A). There is no previous study that examines the informativeness of online customer reviews in detail by integrating additional criteria.

However, it is tough to extract information from online reviews because there can be countless reviews about a single product. To extract product information of online reviews, some researches focused on feature or aspect extraction from the reviews. (Dave et al., 2003; Hu and Liu, 2004; Popescu and Etzioni, 2007; Cruz et al., 2010; Poria et al., 2014). For instance, a rule-based approach was introduced by Poria et al. (2014) that utilized common-sense knowledge and sentence dependency trees to determine explicit and implicit aspects of reviews. Popescu and Etzioni (2007) created the OPINE information extraction system to designate product features and opinions relating to the features; providing to find the polarity of opinions and to rank in order opinions according to their strength. Hu and Liu (2004) presented some techniques for summarization of reviews of a certain product, and this summarization included identifying product features and opinions expressed in reviews.

Thanks to the process of feature extraction or aspect extraction, prominent product attributes could be found in a raw review dataset. Information of product features in reviews could be stated explicitly or implicitly. Explicit aspects are overtly expressed in a sentence, but implicit aspects are not (Poria et al., 2014). For example, a sentence like “The size is too big” informs about the aspect of size, but the sentence of “it lasted about six months” does not give clear information despite the fact that it is associated with the aspect of durability. Product aspects or features are related to the informational cues of Taylor et al. (1997) due to the fact that these cues hold product related information. Hence, feature extraction process is adopted in this study, with the aim of using this process to explore which information cues a review contains.

2.4.1.2 Review emotions and sentiments

As a result of a product experience of an individual, his/her emotions and thoughts about that product may alter. It might be inevitable that he/she reflects his/her emotions about that product, if he/she writes a review about that experience. Hence, the emotional content in the reviews is also added as a systematic factor to be explored in this thesis. It is further probable that the reviews include positive or negative judgments about products. Customers' product experiences may cause positive or negative thoughts, so sentiments in the reviews that reflect positive or negative opinions are also examined.

There are a great number of definitions of emotion in the literature. Emotional state has been defined as "a function of a state of physiological arousal and of a cognition appropriate to this state of arousal" by Schachter and Singer (1962). According to Cabanac (2002), “emotion is any mental experience with high intensity and high hedonic content”. Emotions are associated with sentiments as the power of a sentiment is connected with the intensity of emotions, but emotion and sentiment are certainly not equal concepts (Liu, 2012). A sentiment is an opinion component that is positive, negative or neutral. Nevertheless, emotions are frequently intensive states of feeling, they are aimed at someone or some situation, and they go on for just a couple of minutes (Colquitt et al., 2015).

There are disagreements among researchers on classifying fundamental emotions. To illustrate, Ekman (1992) divided emotions into six groups: anger, disgust, fear, happiness, sadness, and surprise. Izard (1977) pointed out the existence of 10 major emotions that are interest, joy, surprise, sadness, anger, disgust, contempt, fear, shame, and guilt. Plutchik (1980) specified emotion dimensions as anger, disgust, sadness, surprise, fear, trust, joy, and anticipation, which can be seen in the Figure 2.2. In this figure, these dimensions constitute first layer of the wheel, and the inner layer comprises of rage, loathing, grief, amazement, terror, admiration, ecstasy, and vigilance. The outer layer of the wheel contains annoyance, boredom, pensiveness, distraction, apprehension, acceptance, serenity, and interest. The feelings of the inner layer trigger the emotion dimensions of the first layer. Moreover, the feelings in the inner layer are the most intensive ones, and their intensity diminishes towards the outer layer. If the emotions in the first layer combine, it causes integrated emotion dimensions (Felbermayr and Nanopoulos, 2016). For instance, remorse appears when a person feels disgust and sadness.

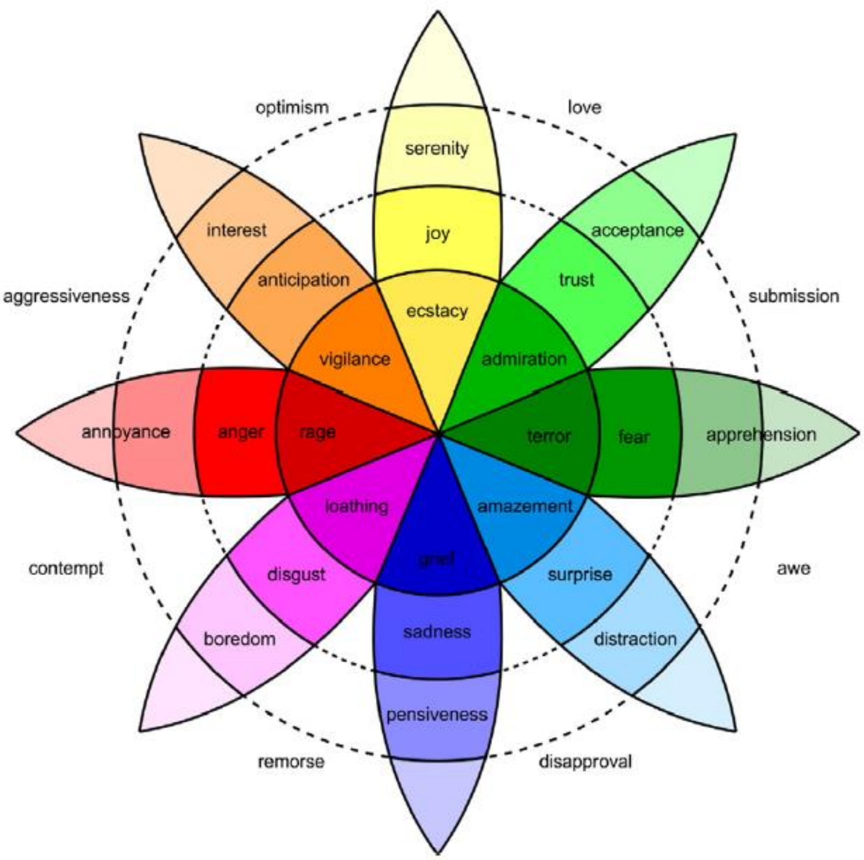

Figure 2.2 : Wheel of emotions based on Plutchik (1980).

Source: Felbermayr, A. & Nanopoulos, A. (2016). The role of emotions for the perceived usefulness in online customer reviews. *Journal of Interactive Marketing*, 36, 60-76.

Emotions and sentiments can have effects on a variety of marketing outcomes. In their study on the role of emotions in marketing, Bagozzi et al. (1999) emphasized that emotional state of an individual can have effects on different facets of information processing. Besides, Menon and Dube (2000) showed that positive emotions induce to higher customer satisfaction than do negative emotions. Bloemer and Ruyter (1999) indicated that positive emotions positively affects service loyalty for high and low involvement services. DeWitt et al. (2008) demonstrated that not only positive but also negative emotions partially mediate the effect of perceived justice on customer loyalty. A few researchers conducted studies by using pleasure and arousal dimensions of emotion (Ladhari, 2007; Walsh et al., 2011). Walsh et al. (2011) revealed that pleasure affects not only store satisfaction but also store loyalty. Ladhari (2007) discovered that both arousal and pleasure have positive influence on satisfaction and pleasure influences WOM positively. Septianto and Chiew (2018) carried out an investigation on the effects of 9 distinct positive emotions on EWOM, and detected that acceptance of EWOM is significantly and positively affected by the emotions of joy, hope, and love.

Several products or brands were subject to research about the impact of sentiments. Mostafa (2013) assessed sentiments of consumers toward some reputable brands by using tweets in Twitter where he found that consumer sentiments were usually positive toward those well-known brands. Liang et al. (2015) conducted a research to discover the effects of textual reviews on mobile app sales, and they developed a sentiment analysis approach to measure sentiment scores from the viewpoint of product quality and service quality. They found service quality related reviews had greater influence on sales rankings than product quality related reviews did. Chong et al. (2016) carried out a study to forecast online product sale and checked the interactions among sentiments, online reviews and online promotion strategies. They found that sentiments significantly interacted with online review volume, this interaction having a significant effect on predicting product sales. Apart from these studies, only a few studies researched the effect of sentiments on review helpfulness. Singh et al. (2017) declared that polarity which is an indicator of sentiment is the second most important variable that affects helpfulness, and rating is the most important one. Chatterjee (in press) found that review polarity negatively influences review helpfulness, but Siering and Muntermann (2013) stated that positive polarity leads to raise review helpfulness. In addition, Li et al. (2017) explored that review sentiment which refers to positive or negative meaning of a review negatively affects votes for usefulness.

A few study carried out to see the outcomes of emotions in online customer reviews (Felbermayr and Nanopoulos, 2016; Ullah et al., 2016; Wang et al., 2019), some of them adapted Plutchik's (1980) emotion dimensions (Felbermayr and Nanopoulos, 2016; Wang et al., 2019). In the study of Kim and Gupta (2012), it was mentioned that perceived informativeness of a review and negative influence on product evaluations diminish by negative emotions of a single review, but they raise by convergent negative emotions of multiple reviews. Ullah et al. (2016) searched to find out the distribution of emotions in online reviews, and they revealed that online reviews have shorter lengths if they contain more emotional words. Felbermayr and Nanopoulos (2016) stated that trust, joy, and anticipation are the most outstanding dimensions of emotions in the reviews. Wang et al. (2019) revealed that emotions which have positive effects on review helpfulness are anger, disgust and fear while joy, sadness and trust have negative effects on review helpfulness. Moreover, Yin et al, (2014) implied that reviews including anxiety are perceived more helpful than reviews including anger, and perceived cognitive effort of reviewers brings about this distinctness. Ismagilova et al. (2020) determined that review helpfulness is positively influenced by emotion of regret even though helpfulness is negatively influenced by emotion of frustration. Ahmad and Lorache (2015) explored that happiness and disgust in the review positively affect review helpfulness while anxiety has negative impact on review helpfulness.

It is found no study examining the influences of both emotion and sentiment together on review helpfulness. This study aims to fill this gap since sentiments and emotions are not identical notions. Sentiments are negative or positive expressions. Emotions can also be positive or negative, but they indicate certain emotion types. Therefore, the effects of sentiment and the effects of emotion on review helpfulness could differ from each other. In addition, there is lack of a study focusing on informativeness and emotionality in the reviews at the same time. Thus, another objective of this study is to examine the effects of these concepts in terms of different product types.

2.4.1.3 Other review related factors

In this thesis, other factors that represent central cues for systematic information processing are considered besides review informativeness and review emotionality, one of them is review rating. Many studies that were relevant to the effects of rating on various dependent variables have been conducted (Chua and Banerjee, 2014; Liu and Park, 2015). Chua and Banerjee (2014) revealed that review rating has a negative relation with review helpfulness for the reviews including low number of word count. Singh et al. (2017) found that review rating has the most impact on review helpfulness for book category where they used datasets of books, baby products and electronic products. Mudambi and Schuff (2010) stated that rating has a nonlinear relation with helpfulness for experience goods; that is, reviews with extreme ratings have less helpfulness than the ones with moderate ratings for experience goods. Therefore, Srivastava and Kalro (2019) dealt with rating squared, and discovered a significant relation between rating squared and review helpfulness. Also, it was explored that rating is not significantly associated with helpfulness for search goods despite the fact that rating square is (Mudambi and Schuff, 2010). As a result, review rating is considered as a systematic factor in this study since it is thought that review rating might have an effect on review helpfulness.

Another systematic factor studied in this thesis is review length. Salehan and Kim (2016) detected that review length has a significant relationship with helpfulness. In a few studies, length was measured by word count in the review (Mudambi and Schuff, 2010; Baek et al., 2012; Zhu et al., 2014; Cheng and Ho, 2015; Huang et al., 2015; Hlee et al., 2019). Word count was found significantly related with online review helpfulness (Huang et al, 2015). Also, Cheng and Ho (2015) specified that the relationship with word count and perceived review usefulness is both significant and positive; both Liu and Park (2015) and Hlee et al. (2019) further reached the same result. Also, Mudambi and Schuff (2010) and Chua and Banerjee (2014) utilized word count in the reviews to measure review depth, and they demonstrated that review depth is significantly and positively related to review helpfulness. However, Chatterjee (in press) found a negative relation between length and review helpfulness in his research with hotel reviews. Pan and Zhang (2011) demonstrated that review length is positively related to review helpfulness, but they measured review length by character count in the review. As a consequence, review length is associated with review helpfulness and is designated by word count of the review in this thesis.

Image count in the review is one of the factors that is used with respect to the central route of ELM. Many websites offer people the opportunity to share images when creating reviews. People who read the online reviews can have an idea about products by examining the images in the reviews. Cheng and Ho (2015) found both significant and positive relation between image count and usefulness of review, which is supported by Hlee et al. (2019) study. Srivastava and Kalro (2019) also specified a significant effect of image count on review helpfulness. Thus, image count was considered as a systematic factor that could have an impact on review helpfulness in this study.

Review subjectivity is the last factor to be handled by this study. If a review contains objective or subjective judgments about a product, it may be effective determinant of review helpfulness. Subjectivity is among the significant variables that affect helpfulness (Singh et al., 2017). Ghose and Ipeirotis (2006) made a research by analyzing reviews of audio and video equipments, digital cameras, and computers, and they indicated that review subjectivity significantly influences on perceived review helpfulness.

2.4.2 Factors related to online reviewers

In a heuristic view of HSM, recipients use less cognitive effort to assess the messages in contrast with the systematic view (Chaiken, 1980). In general, consumers process information heuristically before they process information systematically by examining carefully (Hlee et al., 2018). Instead of processing the review itself, they can be interested in information that is easy to access (Chaiken, 1980). In the context of online reviews, factors that are related to the heuristic view of HSM or peripheral route of ELM comprise of reviewer related factors.

Source credibility was utilized in some studies since it is thought it affects review helpfulness or usefulness (Cheng and Ho, 2015; Weathers et al., 2015; Hlee et al., 2019), and it is used as a heuristic and a peripheral factor in this thesis. Cheng and Ho (2015) used source credibility as peripheral factor and argument quality as a central factor, and found that source credibility has a greater impact on review usefulness than argument quality. Hlee et al. (2019) showed that source credibility significantly influences review usefulness. Kim et al. (2018) described source credibility as whether a buyer has been verified or not by the online retailer; furthermore, they revealed that it is positively associated with purchase probability. In some online retailers' websites, it can be seen that the reviewer purchased that product or not via these websites; this may alter reader's perceptions on the review. Therefore, source credibility refers to reviewer credibility in this thesis, reviewer credibility could have an impact on review helpfulness.

2.4.3 Product type

The factors explained above will be examined with respect to product types because there may be differentiating determinants that people pay attention to according to different product types. Product type has been chosen as a moderator in a few studies; besides, product type has been treated as experience or search goods (Mudambi and Schuff, 2010; Weathers et al., 2015; Ullah et al., 2016; Sun et al., 2019). Search goods have the product attributes which can be known precisely before purchasing. Nonetheless, exact product attributes cannot be known for experience goods until purchasing or using of the product. The product becomes an experience good if searching for it is costlier (Klein, 1998).

Mudambi and Schuff (2010) revealed that word count has a higher positive impact on review helpfulness for search goods than for experience goods. Baek et al. (2012) further unveiled that word count is more effective on review helpfulness for search goods than for experience goods. In addition, Siering and Muntermann (2013) stated that product type moderates the effect of review sentiment on review helpfulness. In spite of the fact that positive review sentiment has a positive relation with review helpfulness for search goods, this situation is the opposite for experience goods. In other words, negative review sentiment has a positive relation with review helpfulness for experience goods (Siering and Muntermann, 2013). Ghose and Ipeirotis (2011) research based on the reviews of products in audio and video, digital cameras, and DVDs product categories, revealed a significant relationship between review subjectivity and review helpfulness for these product categories. Felbermayr and Nanopoulos (2016) utilized text-mining methods to see the impacts of emotion dimensions on perceived usefulness for diverse product categories. There exist limited researches taking into account different product types while exploring the impacts of several factors on review helpfulness.

3. RESEARCH DESIGN AND METHODOLOGY

This section presents the research objectives along with the research model, and research hypotheses developed according to this model. Subsequently, the preliminary study that was carried out before data collection is explained. Then, data collection method and variables of the research are given. Lastly, conducted analyses are described in depth, and the results are discussed.

3.1 Research Objectives

The main objective of this thesis is to explore factors that influence review helpfulness in online platforms–where review helpfulness is considered as a significant indicator of review performance. It is aimed to find out how the content of the reviews affects review helpfulness. Especially, emotions and sentiments in the reviews are crucial factors in this thesis. This thesis intends to research which emotion types are effective in review helpfulness and how the effects of these emotion types differentiate when considering the product type.

Information content of reviews is another important factor that can have impact on review helpfulness. The effects of review informativeness on review helpfulness is seen as under investigated field in the literature, but there are limited availability of studies on this topic. Information in the reviews was evaluated in various ways such as information credibility and information quality. However, information of the reviews is approached from a different perspective in this thesis. This perspective is related with the evaluation of how much information the reviews contain. Therefore, another objective of the thesis is to explore how the informative content of the reviews affects review helpfulness. In addition, this thesis analyzes the effects of other review related factors such as rating, length, image count and subjectivity of the reviews on review helpfulness in terms of different product types.

3.2 Research Model

The literature has been comprehensively reviewed, and factors affecting review helpfulness have been identified in accordance with research purposes. After this extensive literature review process, a conceptual model is developed as in the Figure 3.1.

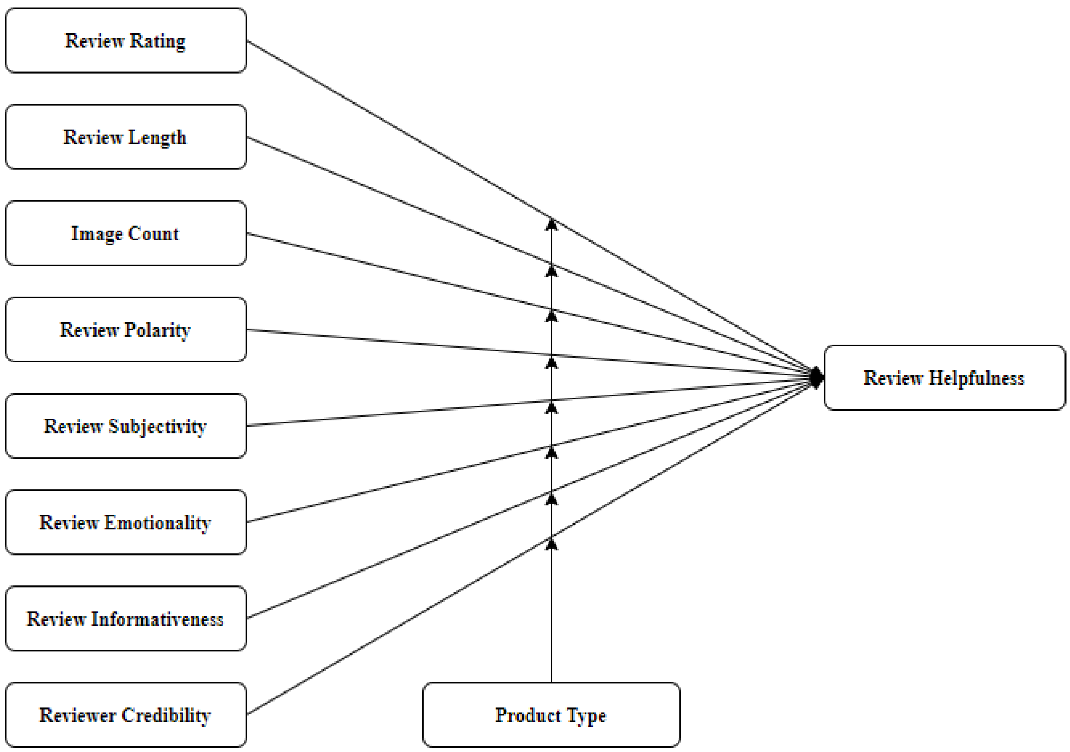

Figure 3.1 : The research model.

H_1: Review rating has a significant effect on review helpfulness.

H_2: Review length has a significant impact on review helpfulness.

H_3: Image count significantly influences review helpfulness.

H_4: Review polarity affects review helpfulness significantly.

H_5: Review subjectivity influences review helpfulness significantly.

H_6: Review emotionality significantly affects review helpfulness.

H_{6a}: If a review contains ‘anger’, it has a significant effect on review helpfulness.

H_{6b}: If a review contains ‘anticipation’, it has a significant effect on review helpfulness.

H_{6c}: If a review contains ‘disgust’, it has a significant effect on review helpfulness.

H_{6d}: If a review contains ‘fear’, it has a significant impact on review helpfulness.

H_{6e}: If a review contains ‘joy’, it has a significant impact on review helpfulness.

H_{6f}: If a review contains ‘sadness’, it has a significant impact on review helpfulness.

H_{6g}: If a review contains ‘surprise’, it has a significant impact on review helpfulness.

H_{6h}: If a review contains ‘trust’, it has a significant effect on review helpfulness.

H_{7}: Review informativeness significantly influences review helpfulness.

H_{8}: Reviewer credibility has a significant influence on review helpfulness.

H_{9}: Product type moderates the effect of review star rating on review helpfulness. Review star rating has a greater impact on review helpfulness for experience goods than for search goods.

H_{10}: Product type moderates the impact of review length on review helpfulness. Review length has a bigger influence on review helpfulness for search goods than for experience goods.

H_{11}: Product type moderates the impact of image count on review helpfulness. Image count has a greater effect on review helpfulness for experience goods than for search goods.

H_{12}: Product type moderates the impact of review polarity on review helpfulness. Review polarity has a greater impact on review helpfulness for experience goods than for search goods.

H_{13}: Product type moderates the impact of review subjectivity on review helpfulness. Review subjectivity has a bigger effect on review helpfulness for experience goods than for search goods.

H_{14a}: Product type moderates the effect of ‘anger’ in a review on review helpfulness. If a review contains ‘anger’, it has a has a greater impact on review helpfulness for experience goods than for search goods.

H_{14b}: Product type moderates the effect of 'anticipation' in a review on review helpfulness. If a review contains 'anticipation', it has a has a greater impact on review helpfulness for search goods than for experience goods.

H_{14c}: Product type moderates the effect of 'disgust' in a review on review helpfulness. If a review contains 'disgust', it has a has a greater impact on review helpfulness for search goods than for experience goods.

H_{14d}: Product type moderates the effect of 'fear' in a review on review helpfulness. If a review contains 'fear', it has a has a greater impact on review helpfulness for experience goods than for search goods.

H_{14e}: Product type moderates the effect of 'joy' in a review on review helpfulness. If a review contains 'joy', it has a has a greater impact on review helpfulness for search goods than for experience goods.

H_{14f}: Product type moderates the effect of 'sadness' in a review on review helpfulness. If a review contains 'sadness', it has a has a greater impact on review helpfulness for experience goods than for search goods.

H_{14g}: Product type moderates the effect of 'surprise' in a review on review helpfulness. If a review contains 'surprise', it has a has a greater impact on review helpfulness for experience goods than for search goods.

H_{14h}: Product type moderates the effect of 'trust' in a review on review helpfulness. If a review contains 'trust', it has a has a greater impact on review helpfulness for experience goods than for search goods.

H_{15}: Product type moderates the effect of review informativeness on review helpfulness. Review informativeness has a greater effect on review helpfulness for experience goods than for search goods.

H_{16}: Product type moderates the effect of reviewer credibility on review helpfulness. Reviewer credibility has a greater effect on review helpfulness for experience goods than for search goods.

3.3 Preliminary Study

The major aim of the preliminary study is to select criteria which customers give more importance among thirty informational cues offered by Taylor et al. (1997); for this reason, a survey was conducted via Amazon Mechanical Turk (See Appendix B). Moreover, it is obvious that people does not read all product reviews for getting information when they buy a product online. There are numerous reviews about each product; hence, determining the optimum number of reviews customers read is other goal of the preliminary study.

The survey of the preliminary study used filtering questions in order to exclude consumers who do not buy products online. In addition, buyers who specified that they do not read online reviews were removed. To determine the most important cues among thirty information cues, it was asked to choose only 10, and the participants who chose less than 4 cues were eliminated.

122 respondents answered the questionnaire, but 107 respondents remained after the necessary elimination. Table 3.1 shows the distribution of the respondents' online buying frequency; accordingly, consumers who purchase online once or twice a month and about once a week constitute 74% of the respondents.

Table 3.1 : Respondents based on Online Buying Frequency.

Online Buying Frequency	Count	Percentage
Less than once a month	8	7.5
Once or twice a month	37	34.6
About once a week	37	34.6
A few times a week	23	21.5
Almost every day	2	1.9
Total	107	100

The frequency distribution of how many review page respondents read can be seen in Table 3.2, it is assumed that a page consists of 10 reviews. This is because Amazon.com is used as data source in this study, and each review page of Amazon includes 10 reviews. It is seen that 40.2% of the respondents prefer to read 1 or 2 review pages. In addition, 44.9% of the respondents expressed that they read not only most popular reviews, but also most recent ones (See Table 3.3). Based on these results, it was decided that both 2 pages from most popular reviews and 2 pages from most recent ones will be used for the process of data collection of the main study.

Table 3.2 : Respondents based on the Number of Pages They Read.

The Number of Review Pages	Count	Percentage
1 or 2	43	40.2
3 or 4	38	35.5
5 or 6	17	15.9
7+	9	8.4
Total	107	100

Table 3.3 : Respondents based on the Review Type They Prefer to Read.

Review Preference	Count	Percentage
Most popular reviews	19	17.8
Most recent reviews	40	37.4
Both	48	44.9
Total	107	100

Table 3.4 shows how many respondents chose each information cue as important. Accordingly, the most important cue which respondents selected is price since 91.6% of respondents specified it. Quality is in the second rank with 76.6%, value and availability fall within the third place with 64.5%. The cues chosen by at least one of three participants were identified as prominent cues, these cues are taken into consideration regarding the informativeness of the reviews. These cues are price, quality, value, availability, performance, results of using, dependability/reliability/durability, safety, economy/savings, method of payment, user’s satisfaction/loyalty, and size respectively.

Table 3.4 : Informational Cues Most Preferred by the Respondents.

Information Cues	**Count**	**Percentage**
Price	98	91.6
Variety of the product	22	20.6
Value	69	64.5
Quality	82	76.6
Size	39	36.4
Economy/savings	45	42.1
Supply, quantity available, or limitation	11	10.3
Method of payment	40	37.4
Dependability/reliability/durability	52	48.6
Nutrition/health	20	18.7
Taste	28	26.2
Sensory information	6	5.6
Components/contents/ingredients	22	20.6
Availability	69	64.5
Packaging or shape	13	12.1
Guarantees/warranty	36	33.6
Safety	46	43.0
Independent research results	14	13.1
Company research results	4	3.7
Research from unidentified source	2	1.9
New ideas, new uses	16	15.0
Performance, results of using	58	54.2

Table 3.4 (continued) : Informational Cues Most Preferred by the Respondents.

Information Cues	Count	Percentage
User's satisfaction/loyalty	40	37.4
Superiority claim	7	6.5
Convenience in use	33	30.8
Special offer or event	21	19.6
New product or new and improved features	6	5.6
Use occasion	14	13.1
Characteristics or image of users	4	3.7
Company information	15	14.0

As a result of this study with the aim of filtering out of 30 informational cues of Taylor et al. (1997), 11 cues are selected as outstanding informational cues according to the respondents' preferences. These cues will be investigated when evaluating the information content of data. The selection and decision processes about the online reviews are given in the following section.

3.4 Sampling and Data Collection

Online customer reviews from Amazon.com are selected as the dataset in order to explore the effects of online customer reviews on review helpfulness. The reason of selection Amazon.com as data source is that it is a significant global retailer which represents a wide information source along with visits of people all around the world. According to Forbes' Global 2000 list which was created based on the scores consisting of a combination of revenues, profits, assets, and market values, Amazon is the largest retailer in the world although Walmart overtaken Amazon in terms of revenues and assets (Debter, 2019). In May 2020, Amazon reached over 2.5 billion online visitors via desktop and mobile devices according to Statista (Clement, 2020).

In the stage of product selection, the best-seller products have been searched; accordingly, Nielsen reports have contributed. According to Nielsen's Connected Commerce Report (2018), top product categories of online purchase in global are listed in Table 3.5 below.

Table 3.5 : Top Selling Categories in Global.

Product Categories	**% Global Consumers Claimed Purchasing**
Fashion	61
Travel	59
Books & Music	49
IT & Mobile	47
Event Tickets	45

Source: Nielsen. (2018). *Connected Commerce Report*

Purchasing percentages of fashion-related products, IT and mobile and consumer electronics categories were 55%, 40% and 37% respectively, in the last quarter of 2015 (Nielsen, 2016). Based on these information, fashion and electronics have been chosen due to the fact that they represent top selling product categories.

Then, reviews in these categories have been examined in Amazon.com, as the data source of the thesis. Shoes have been chosen from fashion product category, and headphones have been from electronics category. Besides the availability of considerable varieties of shoes and headphones in Amazon's best sellers list, they were found suitable for the purpose of this study as shoes represent experience goods, and headphones, search goods.

After the determination of product category, the best sellers list of Amazon was controlled for these product categories to pick specific products. Sport shoes were top in shoes category so, the other types of shoes like sandals, which were in the minority, were eliminated. Also, both sleep headphones and work headphones used in offices were removed from headphones category since they were among less sellers. Thus, 44 sport shoe models and 47 headphone models were elected for the analysis.

For both sport shoes and headphones, it was decided to collect customer reviews at the first 2 pages of not only most popular but also most recent reviews based on the results of the preliminary study. Nonetheless, when most recent reviews were checked, it was seen that nobody had voted for reviews to evaluate the helpfulness of reviews. Hence, it was abandoned the collection of most recent reviews for analysis as people might not have read those reviews yet. Only 2 page reviews in most popular reviews of each product model were gathered, and each page consisted of 10 reviews. Thus, 1,820 reviews were acquired in total, 880 reviews of them were from sport shoes category and the remaining 940 were from headphones category.

Duplicate reviews were eliminated from the raw dataset, so 60 reviews were excluded from the headphones category, and 880 reviews remained from this category. Shoes category had no duplicate reviews, 880 reviews were considered in this category. Likewise, the reviews which had no helpfulness vote from readers were removed from the review dataset, so 1,673 reviews remained in total; 859 were from headphones category, and the remaining 814 from shoes category.

3.5 Variables

The dependent variable of this thesis is review helpfulness which refers to how many customers perceive the review as helpful. In Amazon.com, people who have read a review can vote by clicking the helpful button if they think the review is helpful. The number of helpful votes of the review represents the degree of review helpfulness.

The independent variables are review rating, review length, image count, review polarity, review subjectivity, review emotionality, review informativeness, and reviewer credibility. Review rating is related with how the reviewer rates the product; it ranges between 1 and 5. Review length refers to the word count of the review; image count refers to the number of images that the review contains. Review polarity refers to the sentiment of the review; it is associated with whether the review has negative or positive meaning.

Review subjectivity is related to whether the review has subjective or objective judgement. Sentiment analysis was applied to measure review polarity and review subjectivity; measurement of these variables is explained in sentiment analysis section. Emotions in the reviews refers to how much emotions the review holds, and review informativeness refers to how much information the review contains. The measurement of review emotions is reported in emotion analysis section, review informativeness measurement in the section of information extraction. Reviewer credibility refers to whether a reviewer’s purchase is verified by Amazon.com or not. Besides, product type is the moderator variable in this thesis; it refers to whether the product is search good or experience good. Headphones that are search goods were coded as 0, and shoes that are experience goods were coded as 1. Table 3.6 below informs about the variables of the research study.

Table 3.6 : Description of the variables.

Variable	Description	Value	Method
Review rating	The star rating of the review	An integer between 1 and 5	Collected directly from Amazon
Review length	The number of words in the review	An integer between 1 and 1,096	Calculated with Python
Image count	The number of images in the review	An integer between 0 and 14	Collected directly from Amazon
Review polarity	Whether the review has positive, neutral, or negative opinion	A decimal between -1 and 1	TextBlob** Python library
Review subjectivity	Whether the review is subjective or objective	A decimal between 0 and 1	TextBlob** Python library
Anger	How much anger emotion the review involves	A decimal between 0 and 1	NRC lexicon*
Anticipation	How much anticipation emotion the review involves	A decimal between 0 and 1	NRC lexicon*
Disgust	How much disgust emotion the review involves	A decimal between 0 and 1	NRC lexicon*

Notes: NRC lexicon: A lexicon which is used for the classification of emotion dimensions; TextBlob: A Python library which is used for natural language processing

Table 3.6 (continued) : Description of the variables.

Variable	Description	Value	Method
Fear	How much fear emotion the review involves	A decimal between 0 and 1	NRC lexicon*
Joy	How much joy emotion the review involves	A decimal between 0 and 1	NRC lexicon*
Sadness	How much sadness emotion the review involves	A decimal between 0 and 1	NRC lexicon*
Surprise	How much surprise emotion the review involves	A decimal between 0 and 1	NRC lexicon*
Trust	How much trust emotion the review involves	A decimal between 0 and 1	NRC lexicon*
Review informativeness	How much information the review involves	An integer between 1 and 7	Feature extraction
Reviewer credibility	Whether the purchase of the reviewer is verified or not	0 for not verified purchase and 1 for verified purchase	Collected directly from Amazon
Product type	Whether the product is search good or experience good	0 for headphones and 1 for shoes	
Review helpfulness	The number of helpful vote in the review	An integer between 1 and 7,523	Collected directly from Amazon

Note: NRC lexicon: A lexicon which is used for the classification of emotion dimensions.

3.6 Analyses

Negative binomial regression analysis was used to assess hypotheses in this thesis because it is an appropriate analysis method for discrete data. Nonetheless, first a few methods were used such as feature extraction, sentiment analysis, and emotion analysis in order to measure a few variables of the research model. Lastly, the detailed explanations about negative binomial regression can be found in the section of regression analysis.

3.6.1 Information extraction

This thesis adopted information extraction process to discover which information cues are contained in each review. The reviews were also manually read by two people to classify them according to the information cues, and a consensus was reached to evaluate the accuracy of the information extraction process. All steps of information extraction process are presented in the Appendix C.

For extraction process, noun and noun groups were examined in the dataset to identify product features as in Hu and Liu's (2004) study. Because product features generally comprise of noun or noun groups in reviews (Hu and Liu, 2004), part-of-speech tagging (POS tagging) was utilized for the process of identification of noun or noun groups. POS tagging provides to classify words as nouns, verbs, adjectives, and adverbs. POS tagger in the natural language toolkit (NLTK) was used to tag the words in the dataset. NLTK is an open source program that allows many text processes such as classification, tokenization, parsing, and tagging (Loper and Bird, 2002). Before POS tagging process, tokenization process with NLTK was applied to split reviews into sentences and then to split sentences into words. To do this, sentence tokenizer and word tokenizer functions of NLTK were utilized. Then, tags for each word were created after the stop words in the reviews were removed. Stop words are frequently used words such as the, a, an, for, can, on etc. Using stop words are meaningless to find product features; in consequence, stop words were cleared away via stop words corpus of NLTK. This process was fulfilled by checking whether a sentence includes a stop word in the corpus or not. After these processes, the output of POS tagging was as in the examples below in Table 3.7. Here, the tag of "NN" means noun, the tag of "VB" refers to verb, "JJ" tag indicates adjective, and "RB" tag expresses adverb.

Table 3.7 : Exemplary POS Tagging by Natural Language Toolkit.

Sentence	**Word**	**POS tag output**
I wore these around the house for a day and decided they were too big	wore	VBP
	around	RB
	house	NN
	day	NN
	decided	VBD
	big	JJ
They charge really fast as well	charge	NN
	really	RB
	fast	RB
	well	RB

After POS tag of each word was examined for each sentence, the frequencies of the noun words were found to discover the most common product features. It is calculated how many times each noun word was used in the total dataset, and the count of all noun words in the total dataset was also found for the calculation of the frequencies. The frequency of a noun word was found by dividing this noun word count by all noun words count. Moreover, noun words were lemmatized before the frequency calculations. Lemmatization process provides to return a word to its basic form, and this form is called lemma. If this action was not taken, separate frequencies would have been created for not only singulars but also plurals of the same noun words. In spite of the fact that Hu and Liu (2004) considered the noun words with the frequencies higher than 0.01 as the product feature candidates, the noun words with the frequencies greater than 0.001 are accepted as the candidates for product features. It is aimed not to overlook any product features.

In addition, APriori algorithm (Agrawal and Srikant, 1994) of association rule mining (Agrawal et al., 1993) was applied to find associations between noun words. Association rule mining is a machine learning method that is also used in market basket analysis. By controlling words' coexistence in sentences, it provides to establish relations between words in this thesis. APriori algorithm examines each word individually and checks its relationships with other words. The minimum frequency of associations was defined as 0.001 for this process, too. This process is regarded as necessary because word groups can sometimes form product features. To illustrate, “life” word is not meaningful product feature alone, but “battery life” word group is useful to consider as a product feature (Hu and Liu, 2004).

After all product feature candidates were identified, it was inspected that whether the sentences that have at least one product feature contain any adjective that describes the features or not. This was because any sentence containing any product feature may not give information about product. For a sentence to be informative, it needs to specify an opinion. The existence of adjectives in a sentence is helpful for estimation whether the sentence states an opinion or not (Hu and Liu, 2004). It was accepted that a sentence includes a feature if the sentence has both a feature candidate and an adjective.

After features with their adjectives were found, the synonyms and antonyms of these adjectives were checked by the help of WordNet (Miller et al., 1990). WordNet is an online lexical database, and it is freely available. It comprises nouns, verbs, adjectives, and adverbs; words are categorized with their synonyms. Thus, for each feature, all adjectives that describe these features were defined. Table 3.8 includes the examples of feature-adjective associations. Sound quality was mentioned in the first sentence, and its excellence was emphasized. The reviewer described the price of the product as reasonable in the second sentence, and in the third one, the reviewer highlighted that the battery life is unprecedented. Furthermore, sound quality and battery life were found as features thanks to association rule mining.

Table 3.8 : Exemplary explicit features.

Sentence	**Feature**	**Adjective**
The sound quality is excellent	Sound quality	Excellent
Not to mention the price is reasonable too	Price	Reasonable
The battery life on these is unprecedented	Durability	Unprecedented

If a sentence had a feature and an adjective associated with that feature, it was assumed that the sentence was related to that feature. However, features were not always explicitly expressed by the reviewers as in Table 3.9 below. In the first sentence, the reviewer gave information about the size of the product, but the word of "size" did not appear in the sentence. In the second sentence, the reviewer mentioned about durability feature, but it was not pronounced explicitly. In the last sentence, the reviewer stated his/her satisfaction. As seen in the examples below, people can sometimes inform implicitly and specify their opinions by using just adjectives.

Table 3.9 : Exemplary implicit features.

Sentence	**Feature**	**Adjective**
They are narrow	Size	Narrow
I could tell they weren't as durable	Durability	Durable
All in all, I'm satisfied with my purchase	Customer satisfaction	Satisfied

Therefore, the frequencies of adjectives were inspected as applied to nouns, and the adjectives with frequencies greater than 0.001 were examined. Among these adjectives, those which really describe a feature were detected. To do this, the predetermined features were utilized, and the adjectives associated with these features were examined. It was seen that some adjectives that describe these features can be used without features in the sentences. These adjectives were obvious to notice. For example, "expensive" as an adjective qualifies price while "sturdy" as an adjective qualifies durability. The other obvious adjectives were determined, and it was accepted that the sentences including these adjectives carried product information.

Lastly, the frequencies of all other words were also checked to see if there might have been overlooked features. Two words that may refer to product information were designated for both product categories with this way: “fit” and “last”. Based on the study of Hu and Liu (2004), it can be said that “fit” as a verb qualifies size. It can also be said that “last” as a verb qualifies durability based on the study of Poria et al (2014). The examples of the use of these words are seen in Table 3.10 below.

Table 3.10 : Exemplary other implicit features.

Sentence	Feature	Verb
It fits perfectly into my ears, no complaints	Size	Fit
They lasted only 9 months	Durability	Last

After all the words describing any feature were determined separately according to the product type, it was checked which sentences include these words. The relationships of each sentence with each feature were controlled. If there was a relation, it was coded as 1. If there was no relation, it was coded as 0. Then, sentences were combined into reviews again, and the relationships of the reviews with features emerged. Additionally, the relationships of the reviews with the information cues appeared after the features were matched with the information cues.

For performance and results of using among information cues, all reviews were coded as 1 since it was assumed that all reviews are related with performance and results of using. The reason is that all reviews involve reviewer’ experiences with the product use based on Taylor et al.'s (1996) remarks about that cue. Also, reviews about availability, safety, economy/savings, and method of payment were not found in the feature extraction process. After examining the review dataset also manually for these cues, no related reviews were found, therefore these cues were removed from the information cues list. The remained information cues were price, quality, value, performance and results of using, dependability/reliability/durability, size, and user’s satisfaction/loyalty.

All reviews were read manually to reassure the accuracy of the extraction process as explicit and implicit features can be easily noticeable. Nevertheless, assessment by only one person may be subjective, so the evaluation process was done with the consensus of two people. One of them is the researcher herself, and the other is a computer engineer. Accordingly, the accuracy values for shoes category can be seen in Table 3.11, and for headphones category in Table 3.12. Average of F1 score was 0.8024 for shoes category while this score was 0.8061 for headphones category, and the overall F1 score is 0.8043 as seen in Table 3.13. Accuracy, precision, recall and F1 score are performance metrics for binary classification. Accuracy is the ratio of correctly predicted cases to all cases. Precision indicates how often the positive predictions are actually correct while recall indicates how often actual positive cases are predicted correctly. F1 score is the harmonic mean of precision and recall values, and it becomes 0.5 if the cases are randomly predicted. It can be said that as F1 scores are higher than 0.5, information extraction method outperforms random prediction.

Table 3.11 : Accuracy values of the extraction process for shoes category.

Information Cues	Accuracy	Precision	Recall	F1 Score
Price	0.9170	0.7018	0.6723	0.6867
Quality	0.8909	0.9647	0.8632	0.9111
Value	0.9659	0.7636	0.7119	0.7368
Durability	0.8727	0.6550	0.8197	0.7282
Size	0.9068	0.9316	0.9103	0.9208
Satisfaction	0.8625	0.8414	0.8204	0.8308
Average:	0.9027	0.8097	0.7996	0.8024

Table 3.12 : Accuracy values of the extraction process for headphones category.

Information Cues	Accuracy	Precision	Recall	F1 Score
Price	0.8250	0.8296	0.7187	0.7701
Quality	0.8795	0.9739	0.8692	0.9186
Value	0.8500	0.8416	0.6572	0.7381
Durability	0.8341	0.8102	0.8595	0.8341
Size	0.8466	0.8636	0.7201	0.7854
Satisfaction	0.7989	0.7557	0.8288	0.7905
Average:	0.8390	0.8458	0.7756	0.8061

Table 3.13 : The overall accuracy values of the extraction process.

Product Category	Accuracy	Precision	Recall	F1 Score
Shoes	0. 9027	0. 8097	0. 7996	0. 8024
Headphones	0. 8390	0. 8458	0. 7756	0. 8061
Average:	0.8708	0.8277	0.7876	0.8043

In Table 3.14 below, it can be seen how many reviews were associated with each information cue according to extraction process results. Also, it was calculated how many information cues each review contains in total. As a result of this process, information scores were formed for each review. These scores refer to review informativeness, and it is an integer ranging from 1 to 7. Table 3.15 shows that the distribution of information scores for each product category.

Table 3.14 : Information cues according to the product category.

Information Cues	Shoes		Headphones	
	0*	**1****	**0***	**1****
Price	710	104	556	303
Quality	346	468	260	599
Value	762	52	643	216
Performance	0	814	0	859
Durability	602	212	419	440
Size	341	473	579	280
Satisfaction	485	329	428	431

Notes: 0: The review does not contain the specified information cue for the specified product; 1: The review contains the specified information cue for the specified product

Table 3.15 : The frequency distribution of overall information scores in the product categories.

Overall Information Score	Shoes	Headphones	All Products
1	67	93	160
2	212	134	346
3	278	188	466
4	176	172	348
5	65	151	216
6	14	87	101
7	2	34	36
Total	814	859	1673

Table 3.15 above presents the distribution of review informativeness in the total dataset. As a result of the operations performed, scores between 1 and 7 were assigned to informativeness of each review. If informativeness score of a review equals to 1, it indicates that the review contains a small amount of information. If review

informativeness score equals to 7, it refers to containment of high information. In other words, the higher the informativeness score of a review is, the more information is held by the review.

3.6.2 Sentiment analysis

Review polarity and subjectivity were measured by means of TextBlob that is a Python library for natural language operations, and it is freely available natural language processing tool. It was used to conduct sentiment analysis in this thesis as Micu et al. (2017) indicated that it is an efficient tool for sentiment analysis. The results of polarity and subjectivity can be obtained easily.

According to TextBlob, polarity has a value in the range of [-1.0, 1.0], while subjectivity has a range of [0.0, 1.0]. If the subjectivity value of a text is close to 0, it means the text is objective. If its value is close to 1, then it means that the text is subjective (Loria, 2020). Higher subjectivity values refer to more subjective judgements. Likewise, higher polarity values refer to more positive sentiments. While the text reflects positive sentiment if the polarity value is positive, the text states negative sentiment if the polarity score is negative. And if the polarity score is 0, then the text states neutral sentiment.

TextBlob contains polarity and subjectivity values of a great number of words which are adjectives in majority. For sentiment analysis, TextBlob applies preprocessing to the reviews; it removes stop words and punctuations from the reviews. Then, it checks the polarity and subjectivity scores of the words in each review, and it calculates the overall polarity and subjectivity scores for each review. After sentiment analysis with TextBlob was applied to the review dataset, the sentiments for each product category were reported (See Table 3.16). Neutral sentiments constituted the minority for both product categories; positive sentiments have been much more than the negative ones for both categories. For shoes category, 85% of the reviews have positive sentiment while 14% of the reviews have negative sentiment. For headphones category, positive reviews constituted 90% of the total reviews while negative ones 9%.

Table 3.16 : The frequency distribution of sentiments in the product categories.

Sentiment	Shoes	Headphones
Positive	693	774
Neutral	11	9
Negative	110	76
Total	814	859

The polarity in all review dataset can be seen in Figure 3.2, and the subjectivity was shown in Figure 3.3 in terms of frequency distribution.

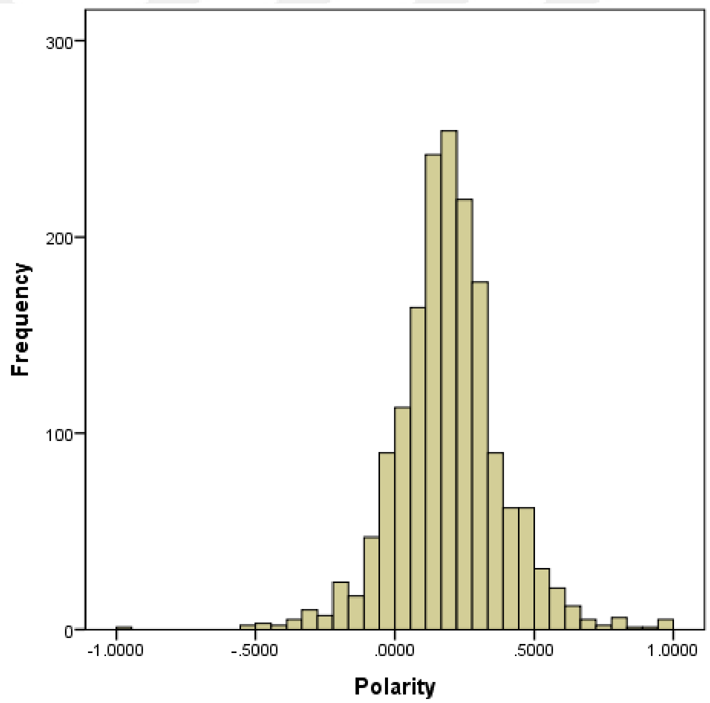

Figure 3.2 : The frequency distribution of polarity in all dataset.

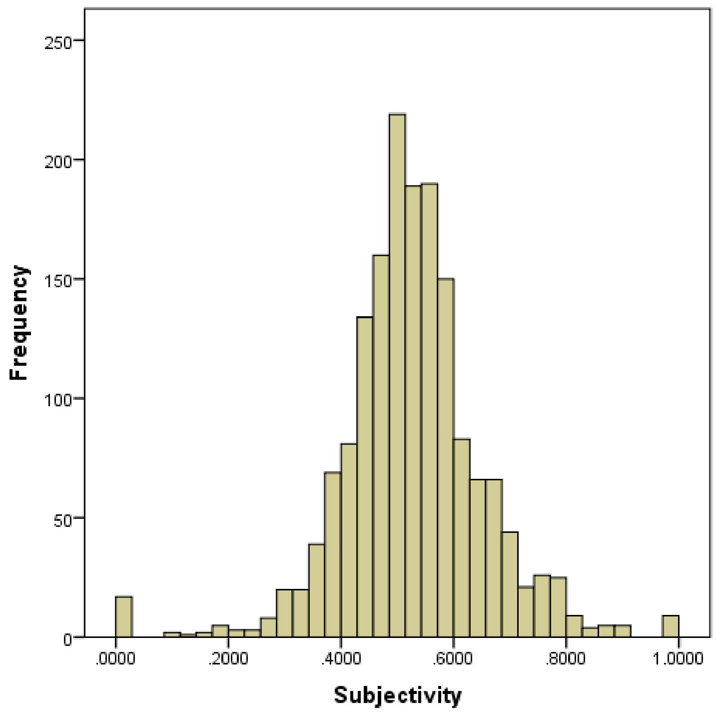

Figure 3.3 : The frequency distribution of subjectivity in all dataset.

In Figure 3.2, it can be observed that the polarity values of the reviews were piled between 0 and 0.5. Accordingly, it can be said that reviews, which have positive meaning, are majority in the data set. In Figure 3.3, it can be seen that the subjectivity values of the reviews were distributed around 0.5. It may be deduced that the majority of reviews in the dataset contain neither too subjective nor too objective judgments.

3.6.3 Emotion analysis

Various emotion lexicons were investigated to conduct an emotion analysis. One of them was WordNet-Affect which is a lexicon developed by Strapparava and Valitutti (2004). It includes 1,903 mental terms, and some of the terms reflect emotions. Furthermore, Yin et al. utilized LIWC (Linguistic Inquiry and Word Count) to measure emotion dimensions such as hope, happiness, anxiety, and anger. LIWC is a computer software created by Pennebaker et al. (2007), and it covers a dictionary containing roughly 4,500 words to classify emotion dimensions. National Research Council Canada (NRC) Word-Emotion Association Lexicon (EmoLex) (Mohammad and Turney 2010, 2013) is a large emotion lexicon which includes more than 14,000 words. EmoLex was preferred for emotion analysis because of its comprehensiveness. It comprises more words associated with emotions than other lexicons. In addition, Felbermayr and Nanopoulos (2016) compared EmoLex with another dictionary which is called GALC (Geneva Affect Label Coder) (Scherer, 2005), and the study results showed that EmoLex performs better with higher precision and F1 scores. Namely, EmoLex achieved more accurate results in detection of helpful reviews.

EmoLex adopted emotion dimensions of Plutchik (1980), and it classified English words with 8 emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) and 2 sentiments (positive and negative). Emolex demonstrates associations between senses and words (Mohammad and Turney, 2010), and any word in EmoLex can involve more than one sense. In the lexicon, if there is a connection between a word and a category (an emotion or a sentiment), the result of the association is coded as 1; otherwise, it becomes 0. Some of the words associated with emotions were given in Table 3.17. Also, emotion analysis steps are given in Appendix E.

Table 3.17 : The examples of words reflecting emotions based on EmoLex.

Emotions	**Examples**
Anger	abolish, collusion, complaint, harassing, pirate, shoplifting, shun
Anticipation	ambition, foresee, gambler, luck, mediate, probability, wishful
Disgust	deceitful, garbage, insulting, irritating, ridiculous, scum, sick
Fear	cautious, delay, escape, injury, mortality, robbery, victim
Joy	beautiful, festival, kiss, music, outstanding, rising, welcomed
Sadness	apologize, darkness, hopeless, misfortune, rainy, sadly, weep
Surprise	brighten, greatness, incident, quote, rapid, unpredictable, wild
Trust	economy, father, green, lord, recommend, seniority, title

For the process of emotion analysis, it was searched that whether the words in EmoLex match with the words in each review of the dataset. If there was a match, the relationship between the word and the emotion was proven. In other words, it was investigated whether each word of the reviews exist in EmoLex. If a word existed in EmoLex, it was checked which emotion dimensions the word is associated with. The emotion dimensions which are associated with the word were coded as 1. Then, the next word in the review was checked. If this word was related to the emotion dimensions which were assigned as 1, the values that were assigned to these emotion dimensions were increased by one. This process was repeated for each word in the review, and accumulated values were created for each emotion dimension of the review. As a result of examining of all reviews in the dataset, the values of 8 emotion dimensions were formed for each review. These values were also divided by total word count of the reviews. The reason is that all reviews did not have the same length; thus, normalization process needed to be performed. This task was conducted for each review in the dataset, and the value of each emotion dimension ranged between 0 and 1 for each review. The frequency distributions for each emotion dimension can be seen in Figure 3.4, 3.5, 3.6, 3.7, 3.8, 3.9, 3.10, and 3.11.

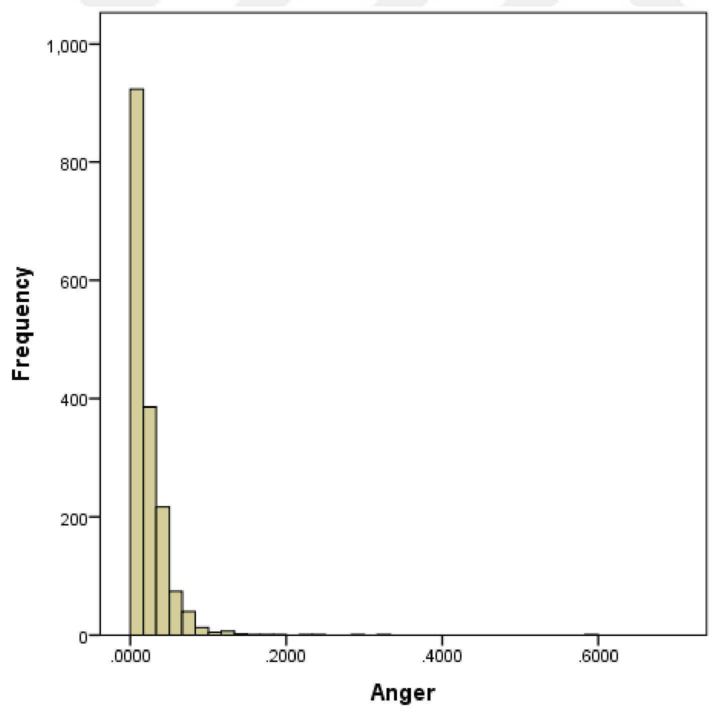

Figure 3.4 : The frequency distribution of anger in all dataset.

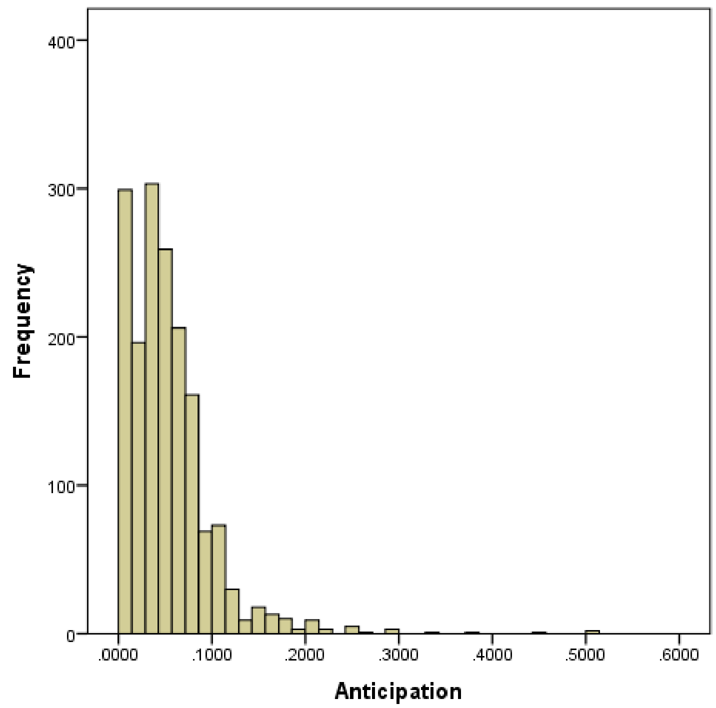

Figure 3.5 : The frequency distribution of anticipation in all dataset.

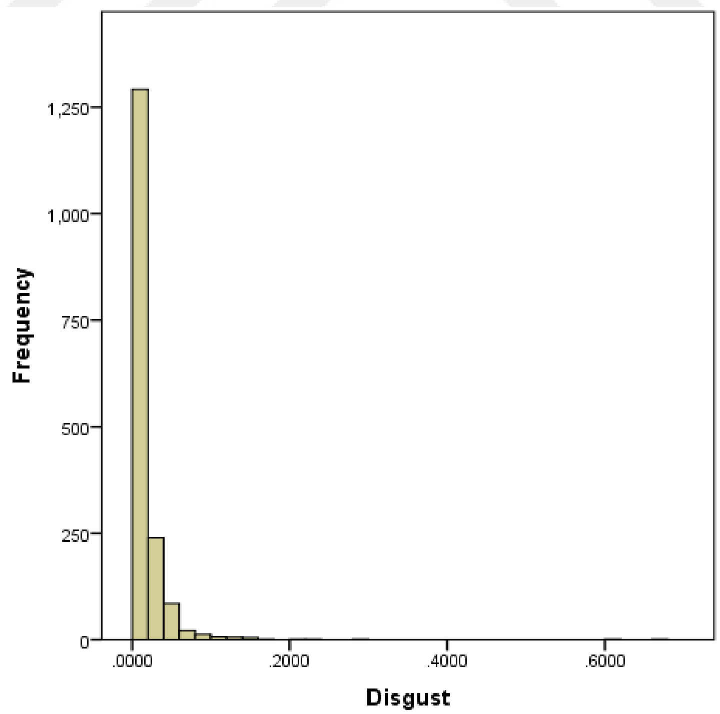

Figure 3.6 : The frequency distribution of disgust in all dataset.

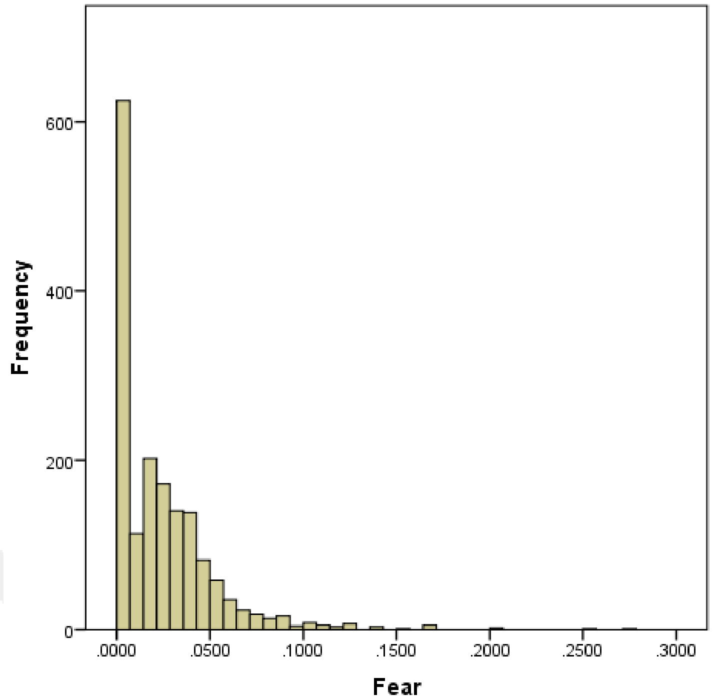

Figure 3.7 : The frequency distribution of fear in all dataset.

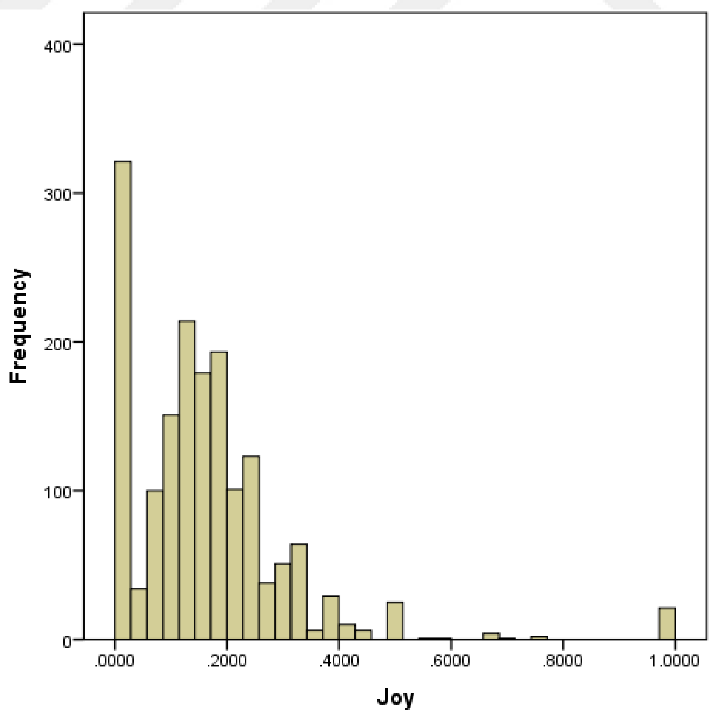

Figure 3.8 : The frequency distribution of joy in all dataset.

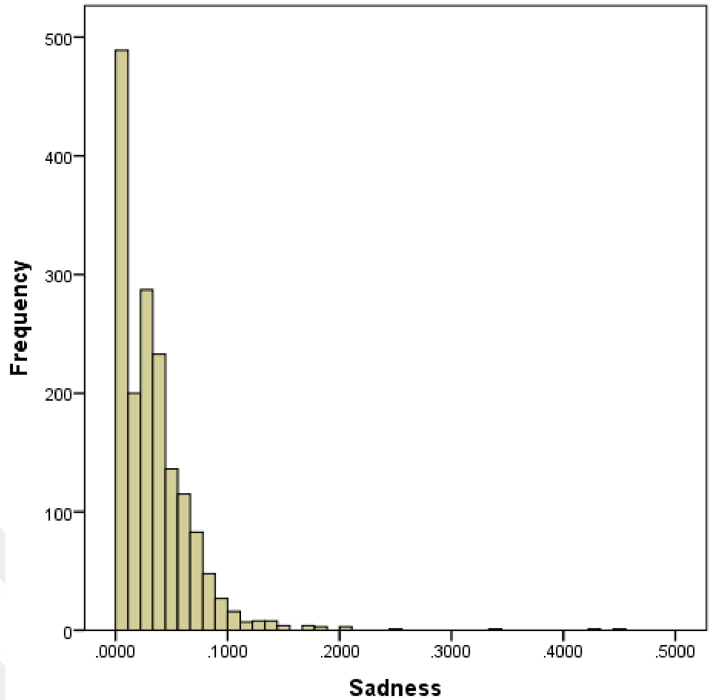

Figure 3.9 : The frequency distribution of sadness in all dataset.

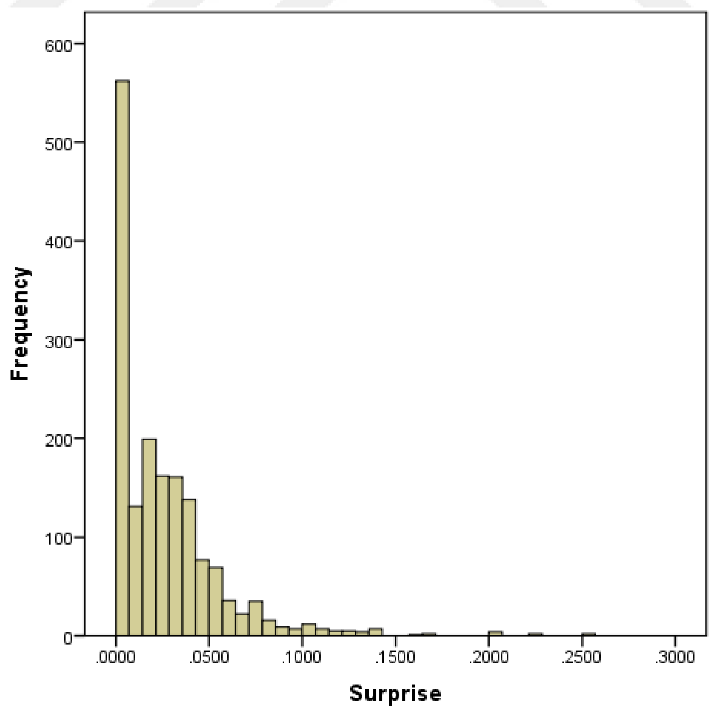

Figure 3.10 : The frequency distribution of surprise in all dataset.

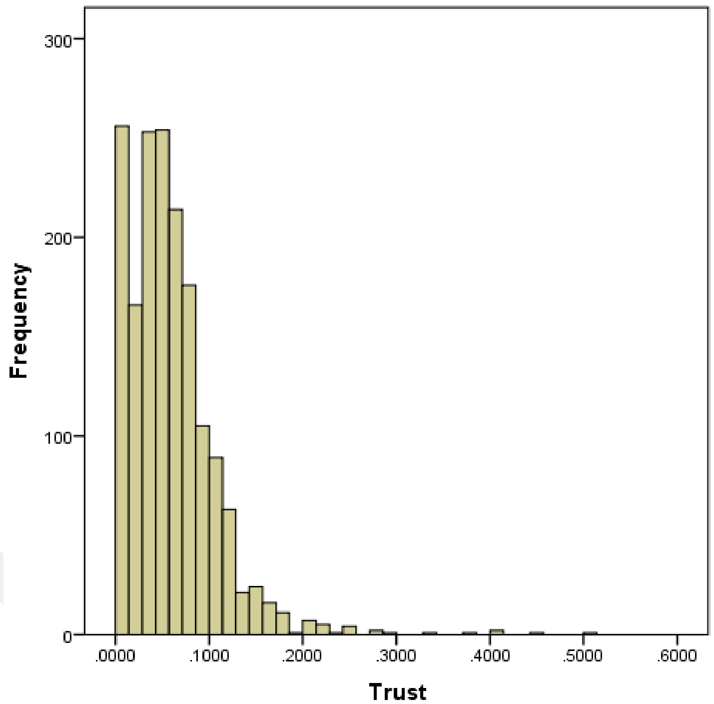

Figure 3.11 : The frequency distribution of trust in all dataset.

In the above figures that shows the distributions of the scores of each emotion, each emotion dimension has a right-skewed distribution. That is to say, the reviews in the dataset generally hold low level of emotion scores.

3.6.4 Regression analysis

Negative binomial regression analysis was applied to see the effects of independent variables on the review helpfulness as the dependent variable. The reason for this, the dependent variable is not a categorical variable and has discrete values. Therefore, the dependent variable of the model is a count variable. A count variable is a discrete variable that indicates the number of times an event occurs within a given time period, and it can have a positive value or zero value (Coxe et al., 2009). Poisson regression is the most straightforward model to analyze count data; nonetheless, it may generate misleading results if the assumptions of the model are violated (Gardner et al., 1995). One of the assumptions of Poisson regression model is the equivalence of the mean and the variance of the dependent variable. If the data is over dispersed, it causes a greater variance and skewness (Hougaard et al., 1997). When this situation occurs, negative binomial regression is used. The dependent variable of the thesis research model has right-skewed distribution (See Figure 3.12). In the context of online reviews, negative binomial regression has been used in other studies (Salehan and Kim, 2016; Li et al., 2017; Wang et al., 2019). Wang et al. (2019) also decided that negative binomial regression is more suitable way to analyze as review helpfulness had right-skewed distributed data. They further stated that negative binomial regression performs more precisely than Poisson regression for over dispersed count data where the mean and variance are not equal. Thus, it is decided to use negative binomial regression model in the context of online reviews.

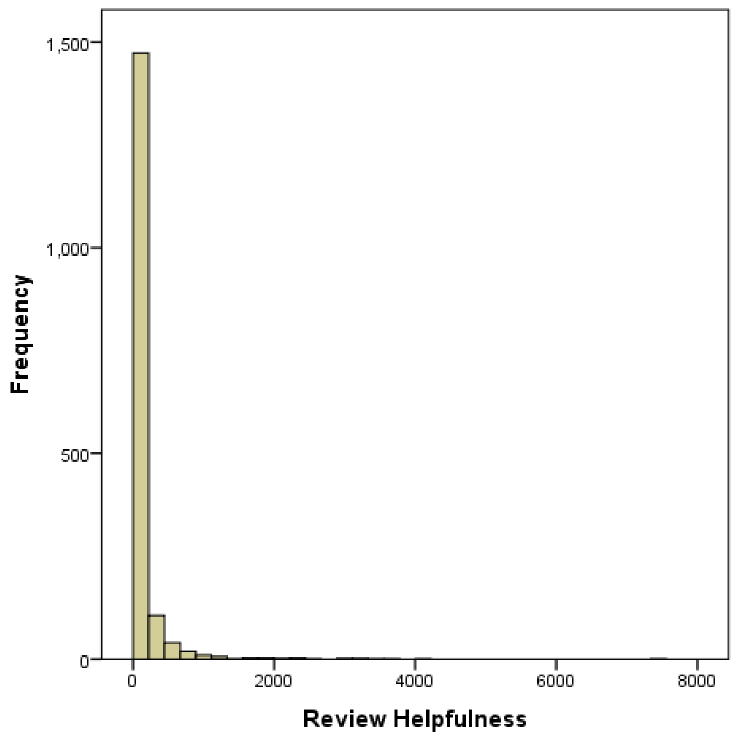

Figure 3.12 : The frequency distribution of review helpfulness in all dataset.

The regression analysis was performed in IBM SPSS application. Table 3.18 shows the descriptive statistics of the variables. The value of reviewer credibility variable was 1 for the majority of the dataset; hence, it was not included regression analysis. If the value of reviewer credibility equals to 1, the reviewer made the purchase via amazon.com. In a word, Amazon.com verified the reviewer's purchase. Considering that the dataset comprises of popular reviews, it can be easily said that the majority of popular reviews consist of verified purchases. As the value of reviewer credibility did not change, it is not possible to say that reviewer credibility can have an impact on review helpfulness. Actually, it is not feasible to assert reviewer credibility as a variable. Also, product type is the moderator variable of the model; it was coded as 1 if the product is an experience good, and 0 if it is a search good.

Table 3.18 : Descriptive statistics of the variables.

Variable	N	Minimum	Maximum	Mean	Standard Deviation
Review rating	1673	1	5	3.76	1.642
Review length	1673	1	1096	74.91	81.868
Image count	1673	0	14	.70	1.583
Review polarity	1673	0	1	0.195	0.189
Review subjectivity	1673	-1	1	0.532	0.127
Review informativeness	1673	1	7	3.33	1.448
Anger	1673	0	0.6	0.019	0.030
Anticipation	1673	0	0.5	0.052	0.047
Disgust	1673	0	0.67	0.013	0.031
Fear	1673	0	0.27	0.023	0.028
Joy	1673	0	1	0.049	0.060
Sadness	1673	0	0.44	0.033	0.035
Surprise	1673	0	0.25	0.026	0.030
Trust	1673	0	0.5	0.058	0.048
Reviewer credibility	1673	0	1	0.99	0.1
Product type	1673	0	1	0.49	0.500
Review helpfulness	1673	1	7523	119.39	363.531

The regression equation of the model can be seen in the equation 3.1. Since negative binomial regression uses logarithmic function, the equation can be written as in the equation 3.2. The variables except the dependent variable were standardized for the analysis to prevent multicollinearity.

$$\log(\text{Helpfulness}) = \beta_0 + \beta_1\text{Rating} + \beta_2\text{Length} + \beta_3\text{Image count} + \beta_4\text{Polarity} + \beta_5\text{Subjectivity} + \beta_6\text{Informativeness} + \beta_7\text{Anger} + \beta_8\text{Anticipation} + \beta_9\text{Disgust} + \beta_{10}\text{Fear} + \beta_{11}\text{Joy} + \beta_{12}\text{Sadness} + \beta_{13}\text{Surprise} + \beta_{14}\text{Trust} + \beta_{16}(\text{Rating} * \text{Product}) + \beta_{17}(\text{Length} * \text{Product}) + \beta_{18}(\text{Image count} * \text{Product}) + \beta_{19}(\text{Polarity} * \text{Product}) + \beta_{20}(\text{Subjectivity} * \text{Product}) + \beta_{21}(\text{Informativeness} * \text{Product}) + \beta_{22}(\text{Anger} * \text{Product}) + \beta_{23}(\text{Anticipation} * \text{Product}) + \beta_{24}(\text{Disgust} * \text{Product}) + \beta_{25}(\text{Fear} * \text{Product}) + \beta_{26}(\text{Joy} * \text{Product}) + \beta_{27}(\text{Sadness} * \text{Product}) + \beta_{28}(\text{Surprise} * \text{Product}) + \beta_{29}(\text{Trust} * \text{Product}) \quad (3.1)$$

$$\text{Helpfulness} = \exp(\beta_0) * \exp(\beta_1\text{Rating}) * \exp(\beta_2\text{Length}) * \exp(\beta_3\text{Image count}) * \exp(\beta_4\text{Polarity}) * \exp(\beta_5\text{Subjectivity}) * \exp(\beta_6\text{Informativeness}) * \exp(\beta_7\text{Anger}) * \exp(\beta_8\text{Anticipation}) * \exp(\beta_9\text{Disgust}) * \exp(\beta_{10}\text{Fear}) * \exp(\beta_{11}\text{Joy}) * \exp(\beta_{12}\text{Sadness}) * \exp(\beta_{13}\text{Surprise}) * \exp(\beta_{14}\text{Trust}) * \exp\big(\beta_{16}(\text{Rating} * \text{Product})\big) * \exp\big(\beta_{17}(\text{Length} * \text{Product})\big) * \exp\big(\beta_{18}(\text{Image count} * \text{Product})\big) * \exp\big(\beta_{19}(\text{Polarity} * \text{Product})\big) * \exp\big(\beta_{20}(\text{Subjectivity} * \text{Product})\big) * \exp\big(\beta_{21}(\text{Informativeness} * \text{Product})\big) * \exp\big(\beta_{22}(\text{Anger} * \text{Product})\big) * \exp\big(\beta_{23}(\text{Anticipation} * \text{Product})\big) * \exp\big(\beta_{24}(\text{Disgust} * \text{Product})\big) * \exp\big(\beta_{25}(\text{Fear} * \text{Product})\big) * \exp\big(\beta_{26}(\text{Joy} * \text{Product})\big) * \exp\big(\beta_{27}(\text{Sadness} * \text{Product})\big) * \exp\big(\beta_{28}(\text{Surprise} * \text{Product})\big) * \exp\big(\beta_{29}(\text{Trust} * \text{Product})\big) \quad (3.2)$$

After the negative binomial regression analysis was carried out, it was seen that the goodness of fit was 4.123 which means the proposed model fits data well. According to the results of omnibus test which is a likelihood ratio chi-square test, the proposed model is significant since the p value < 0.05. Omnibus test compares the proposed model with the initial model where only the constant term is included. It tests the null hypothesis which states that there is no difference between the proposed model and the initial model. Other results of regression analysis can be examined if there is a significant difference between the models according to the result of omnibus test. Outcomes regarding the effects of predictors on review helpfulness are given in Table 3.19.

Table 3.19 : Results of the negative binomial regression analysis.

Variables	B	Standard Error	P-value	Exp(B)
(Intercept)	4.687	0.0299	0.000	108.578
Rating	0.116	0.0319	0.000	1.123
Image count	0.233	0.0454	0.000	1.263
Length	1.088	0.0528	0.000	2.967
Polarity	0.139	0.0353	0.000	1.149
Subjectivity	-0.061	0.0288	0.035	0.941
Informativeness	-0.263	0.0354	0.000	0.768
Anger	0.108	0.0389	0.006	1.114
Anticipation	-0.118	0.0336	0.000	0.889
Disgust	0.018	0.0349	0.606	1.018
Fear	0.166	0.0333	0.000	1.181
Joy	0.146	0.0397	0.000	1.157
Sadness	-0.171	0.0323	0.000	0.843
Surprise	-0.077	0.0292	0.008	0.926
Trust	0.114	0.0330	0.001	1.121
Rating x Product	0.017	0.0322	0.591	1.017
Image count x Product	0.095	0.0466	0.041	1.100
Length x Product	0.604	0.0564	0.000	1.829
Polarity x Product	0.029	0.0356	0.423	1.029
Subjectivity x Product	0.144	0.0288	0.000	1.155
Informativeness x Product	0.075	0.0359	0.037	1.078
Anger x Product	-0.067	0.0395	0.090	0.935

Table 3.19 (continued) : Results of the negative binomial regression analysis.

Variables	B	Standard Error	P-value	Exp(B)
Anticipation x Product	0.001	0.0333	0.976	1.001
Disgust x Product	-0.088	0.0354	0.013	0.916
Fear x Product	0.34	0.0333	0.306	1.035
Joy x Product	-0.158	0.0393	0.000	0.854
Sadness x Product	0.115	0.0320	0.000	1.122
Surprise x Product	0.037	0.0293	0.205	1.038
Trust x Product	0.004	0.0330	0.908	1.004

In Table 3.19 above, the values of B column refer to β values of the regression equation. The values of Exp(B) column represent the values of Exp(β) in the equation 3.2. P-value column gives information about whether β values of the variables are significant or not. The β values are significant if $p < 0.05$. Also, variable x product in variables column refer to the interaction effects of the independent variables with product type. The impacts of the moderator variable were checked by this way.

3.7 Results

According to p-values in Table 3.19, disgust, rating x product, polarity x product, anger x product, anticipation x product, fear x product, surprise x product and trust x product are nonsignificant variables (p-value > 0.05); hence, these variables do not have significant effects on review helpfulness. However, remaining variables influence review helpfulness significantly (p-value < 0.05). By checking the values in B column of Table 3.19, it can be interpreted that whether these influences are positive or negative. Also, by looking at the values in Exp(B) column of Table 3.19, it can be seen how every unit increase in a predictor variable will affect the dependent variable. According to this table, it can be said that review length has the greatest effect on review helpfulness among these independent variables, review informativeness has the second greatest effect, and image count follows.

While review length and image count have positive effect, review informativeness has a negative effect on review helpfulness. In terms of review length, this thesis supports the study results of Mudambi and Schuff (2010). Contrary to this thesis results, Chatterjee (in press) found that review length negatively influences review helpfulness. In this thesis, the study results of Srivastava and Kalro (2019) and Sun et al. (2019) are also supported in terms of the impact of image count on review helpfulness. The results of this thesis with regard to review informativeness contradict with the study results of Sun et al. (2019). They utilized product and platform attributes in order to measure review informativeness, and they found that review informativeness has a positive effect on review helpfulness.

Table 3.20 shows the hypothesis testing results based on regression analysis results. Review rating (β_1 = 0.116, p-value = 0.000) affects review helpfulness positively, so H1 is supported. One-unit increase in review rating leads to 12.3% increase in review helpfulness. Image count (β_3 = 0.233, p-value = 0.000) also influences review helpfulness positively, and one-unit increase in this predictor increases helpfulness by 26.3%. One-unit increase of review length causes 196% increase of review helpfulness, in short it has a positive effect on review helpfulness (β_2 = 1.088, p-value = 0.000). Review helpfulness is positively affected by review polarity (β_4 = 0139, p-value = 0.000), and every one-unit increase in polarity produces 14.9% increase in helpfulness. Nevertheless, review subjectivity (β_5 = -0.061, p-value = 0.035) has a negative impact on review helpfulness, one-unit increase of this predictor leads to 5.9% decrease in helpfulness. In addition, review informativeness (β_6 = -0.263, p-value = 0.000) is one of the predictors that affects review helpfulness negatively, and one-unit increase of informativeness decreases helpfulness by 23.2%.

Table 3.20 : Hypothesis results.

Hypothesis	Relationship	Result
H1	Review rating → Review helpfulness	Supported
H2	Review length → Review helpfulness	Supported
H3	Image count → Review helpfulness	Supported
H4	Review polarity → Review helpfulness	Supported
H5	Review subjectivity → Review helpfulness	Supported
H6a	Anger → Review helpfulness	Supported
H6b	Anticipation → Review helpfulness	Supported
H6c	Disgust → Review helpfulness	Not supported
H6d	Fear → Review helpfulness	Supported
H6e	Joy → Review helpfulness	Supported
H6f	Sadness → Review helpfulness	Supported
H6g	Surprise → Review helpfulness	Supported
H6h	Trust → Review helpfulness	Supported
H7	Review informativeness → Review helpfulness	Supported

Table 3.20 (continued) : Hypothesis results.

Hypothesis	Relationship	Result
H9	Review rating x Product → Review helpfulness	Not supported
H10	Review length x Product → Review helpfulness	Supported
H11	Image count x Product → Review helpfulness	Supported
H12	Review polarity x Product → Review helpfulness	Not supported
H13	Review subjectivity x Product → Review helpfulness	Supported
H14a	Anger x Product → Review helpfulness	Not supported
H14b	Anticipation x Product → Review helpfulness	Not supported
H14c	Disgust x Product → Review helpfulness	Supported
H14d	Fear x Product → Review helpfulness	Not supported
H14e	Joy x Product → Review helpfulness	Supported
H14f	Sadness x Product → Review helpfulness	Supported
H14g	Surprise x Product → Review helpfulness	Not supported
H14h	Trust x Product → Review helpfulness	Not supported
H15	Review informativeness x Product → Review helpfulness	Supported

The hypothesis that defines the relation between disgust and review helpfulness could not be supported. The remaining seven emotions showed significant effects on review helpfulness. The results showed that not only anticipation (β_8 = -0.118, p-value = 0.000) but also surprise (β_{13} = -0.077, p-value = 0.008) has a negative influence on review helpfulness. One-unit increase in surprise diminishes helpfulness by 7.4%. Eleven percent decrease in review helpfulness happens if anticipation increases one-unit. Further, sadness (β_{12} = -0.171, p-value = 0.000) influences helpfulness negatively, but anger (β_7 = 0.108, p-value = 0.006) and fear (β_{10} = 0.166, p-value = 0.000) positively affect review helpfulness. When there is a one-unit increase in anger, helpfulness boosts by 11.4%. Every one-unit increase in fear increases review helpfulness by 18.1% while one-unit increase in sadness decreases review helpfulness by 15.7%. Joy (β_{11} = 0.146, p-value = 0.000) and trust (β_{14} = 0.114, p-value = 0.001) show positive effects on review helpfulness. If one-unit increase in joy occurs, it results in 15.7% rise on review helpfulness. Helpfulness goes up by 12.1% when one-unit increase takes place in trust.

In addition, interaction effects of each independent variable with product type were also examined in this thesis. Review rating x Product, Review polarity x Product, Anger x Product, Anticipation x Product, Fear x Product, Surprise x Product, and Trust x Product interactions did not show significant relations with review helpfulness (See Table 3.19); therefore, H9, H12, H14a, H14b, H14d, H14g, and H14h are rejected (See Table 3.20). For this reason, it is not possible to comment on the effects of these interactions on review helpfulness since they are non-significant. Nonetheless, the remaining interactions significantly affect review helpfulness. The interaction between image count and product type (β_{18} = 0.095, p-value = 0.041) demonstrated a significant and positive influence on review helpfulness, so H10 is supported. Image count has a greater effect on review helpfulness for experience goods than for search goods. Review length x Product interaction (β_{17} = 0.604, p-value = 0.000) also has a positive impact on review helpfulness, it refers that review length has a higher influence on helpfulness for experience goods than for search goods, so H10 is supported. H13 is also supported because Subjectivity x Product interaction (β_{20} = 0.144, p-value = 0.000) affects review helpfulness significantly and positively. That is to say, review subjectivity has a larger impact on helpfulness for experience goods than for search goods. Informativeness x Product interaction (β_{21} = 0.075, p-value = 0.037) also has a positive influence on helpfulness, review informativeness has a greater impact on review helpfulness for experience goods than for search goods. The last interaction that affects review helpfulness positively is Sadness x Product (β_{27} = 0.115, p-value = 0.000), and sadness has a bigger effect on helpfulness for experience goods than for search goods. Disgust x Product interaction (β_{24} = -0.088, p-value = 0.013) and Joy x Product interaction (β_{26} = -0.158, p-value = 0.000) influence review helpfulness negatively. Therefore, both disgust and joy have a lower impact on review helpfulness for experience goods than for search goods. It is not possible to refer about the effects of other interactions on review helpfulness since the other interactions are non-significant.

4. CONCLUSION

Internet has been critical in facilitating humans' lives in a variety of ways. People use Internet to obtain information about plenty of topics. In this stage, they can also benefit from it to get an idea when they consider about purchasing a product. Nowadays, retailers can reach customers via Internet, and online retailer websites provide customers with product information. Through these websites, customers can both access this information and place orders for the products they want. In addition to the product information procured by the seller, online customer reviews are offered in several websites. These reviews can further give customers an insight with respect to products since they comprise of the product evaluations of customers who have already purchased and experienced the products. 60% of consumers trust online customer reviews as an information source for products and services (Deloitte, 2014). Therefore, online customer reviews bring about a valuable source in the sense of holding a view about products and their performance.

Online customer reviews were emphasized in this thesis, and the factors affecting review helpfulness were examined. After an extensive literature review, a conceptual model was created. Afterwards, factors were measured by varied methods, and the relations in the research model were tested by means of regression analysis. In this section, the thesis is concluded, and its contributions to the literature are mentioned. Recommendations are also given for online retailers. Finally, the limitations of the thesis and future research directions are explained.

4.1 Conclusions and Recommendations

The factors in online customer reviews that affect review helpfulness were investigated in this thesis. Review helpfulness was considered as central to the research question, being an indicator of online review performance. Rating, length, image count, polarity, subjectivity, emotion types, and informativeness were the factors related with online customer reviews. A total of 1,673 online customer reviews were collected from Amazon.com, and regression analysis was applied to this dataset.

The regression results demonstrate that review rating, review length, image count, and review polarity are factors that affect review helpfulness significantly and positively. As in the results of this study, Chua and Banerjee (2014) and Huang et al. (2015) discovered a significant relation between review rating and review helpfulness. Chua and Banerjee (2014) stated that rating has a negative relation with review helpfulness. However, the thesis results show that rating has a positive influence on review helpfulness. This means that the reviews with high rating are more likely to be perceived as helpful by the readers. The reviews with high rating scores probably include more favorable comments about product experiences. According to BrightLocal report, 91% of consumers stated that they are more likely to use a business when they are exposed to positive reviews (Murphy, 2019). Thus, it can be reasonable that high rated reviews are perceived as more helpful by customers. Kim (2019) found a positive relationship between review length and helpfulness, and this thesis supports that relation. Chua and Banerjee (2014) also discovered that review length has a positive impact on review helpfulness. Despite the fact that Chatterjee (in press) expected a positive relation between review length and review helpfulness, he found that review length is negatively related to review helpfulness. According to this thesis results, longer reviews are perceived as more helpful by customers. Readers might expect that longer reviews contain more detailed information about products; hence, they could perceive longer reviews as helpful. In the literature, Sun et al. (2019) revealed that image count positively affects review helpfulness. This thesis confirms this finding. If the readers see product images in the reviews, this can give them more opinions on the products. Accordingly, these reviews may be more helpful for the readers. As the study results of Siering and Muntermann (2013) showed, this study also shows that review polarity has a positive effect on review helpfulness. This result differs from the research result of Chatterjee (in press), where stated that polarity negatively affects review helpfulness. According to the results of this thesis, high polarity scores in the reviews cause the readers to perceive the reviews as more helpful. The reviews with high polarity have positive opinions about the experiences of the reviewers. As in the case of review rating, it may be sensible that these reviews are perceived as helpful by the readers.

Review subjectivity and review informativeness have negative impacts on review helpfulness according to the results of this thesis. Previous research of Singh et al. (2017) showed that review subjectivity influences review helpfulness significantly. It means that if a review includes objective judgments, the review is perceived as more helpful. This may be reasonable because the readers might consider that impartial reviews may be more accurate or trustworthy. Sun et al. (2019) indicated that review informativeness is a significant predictor of review helpfulness. They measured review informativeness by the help of product and platform attributes. Nevertheless, review informativeness was measured in this thesis by using feature extraction process, and the results shows that review informativeness has a significant effect on review helpfulness. People can obtain information about products by reading online reviews related to customers' product experiences. The information regarding product experiences in these reviews can help people for their purchase decisions. Thus, it is comprehensible for review informativeness to be an important predictor of review helpfulness.

According to the study results, it was seen that emotion types except disgust have significant influence on review helpfulness. Although the previous researches demonstrated that disgust positively affects review helpfulness (Ahmad and Laroche, 2015; Wang et al., 2019; Chatterjee, in press), this study could not find a significant relation between disgust and review helpfulness. As in the study results of Wang et al. (2019), anger and fear influence review helpfulness positively. Nonetheless, Chatterjee (in press) showed that fear has a negative influence on review helpfulness. The appearance of fear in the reviews can be realistic to the readers; thus, this emotion could increase the helpfulness of the reviews. Anger may occur when failing situations arises as a result of the product experiences. This emotion may lead to increase the persuasiveness of the reviewers' experiences. Hence, this may cause the reviews to be perceived as more helpful by the readers. Wang et al. (2019) revealed that sadness has a negative impact on review helpfulness, and this study confirms that result. If a review contains the emotion of sadness, the readers might not find the review convincing. They might think that the review is exaggerative. This situation can negatively affect the helpfulness of the review. Wang et al. (2019) also stated that joy and trust negatively influence helpfulness; however, this thesis results indicated that joy and trust has positive effect on review helpfulness. The reviews including joy could be perceived as sincere by the readers, and this may lead to improve review helpfulness. When the reviews contain trust, the readers may trust these reviews by showing empathy towards the reviewers of these reviews. Therefore, the reviews containing trust can positively influence review helpfulness. Further, the results of this study demonstrated that anticipation and surprise negatively affect review helpfulness. In the literature, there is no study that indicated that these emotions are related to review helpfulness. Surprise in the reviews could bring about uncertainty for the readers, and this could have a negative impact on review helpfulness. Also, the reviews with anticipation which is the counterpart of surprise may reduce review helpfulness. This thesis revealed that all emotion types except disgust significantly influence review helpfulness. Emotional reviews can appeal to people's emotions, so these reviews may be more effective on the decisions of people whose emotions are triggered.

Moreover, the effects of the interaction of these factors with the product type were examined considering search versus experience goods. Review length, image count, review subjectivity, review informativeness, emotions such as disgust, joy, and sadness significantly affect review helpfulness in their interactions with product type. Nonetheless, the interactions of other factors with product type could not be found to have a significant impact on review helpfulness. Review length, image count, review subjectivity, review informativeness and sadness were found to have a positive effect on review helpfulness in their interactions with product type. This means that these factors have a greater impact on review helpfulness for experience goods than for search goods. These results are contrary to the research results of Baek et al. (2012) because they stated that central cues are more effective on review helpfulness for search goods. However, it may be usual for experience goods to have a greater impact on review helpfulness since people can need to do more research to buy an experience good. Even though firms provide information about products, it is important to examine online customer reviews for experience goods because they reflect information about customer experiences. It was further observed that the interactions of emotions such as disgust and joy with product type have negative effect on review helpfulness. It means that these emotions have a higher impact on review helpfulness for search goods than for experience goods. Emotion dimensions such as disgust and joy in the reviews are more prominent factors for search goods.

The results of this thesis provide various theoretical and managerial insights. In this thesis, a theoretical framework was provided for online customer reviews by adopting ELM (Petty and Cacioppo, 1986a) and HSM (Chaiken, 1980). Central processing of ELM and systematic view of HSM were applied to understand review related factors. By this means, this thesis sheds light on a better understanding of the diverse online review characteristics which influence review helpfulness. Besides, review informativeness was approached differently than other studies (Gao and Koufaris, 2006; Filieri, 2015; Yusuf et al., 2018) in the literature and measured mainly by using and adjusting Taylor et al.'s (1997) cues. The main contribution is seen as presenting a new perspective to review informativeness. This new perspective involves the use of feature extraction process for review informativeness in this thesis, which adopts the information cues of Taylor et al. (1997). In addition, types of emotions effective on review helpfulness were integrated to this study. Another contribution of the thesis is including the examination of how these effects differentiate by product type and the use of product type to see the changes in the effects of all factors on review helpfulness. Review related attributes were comprehensively approached, and it was also evaluated how these attributes affect review helpfulness by product type. Finally, the thesis brings about information extraction process as a methodological contribution.

The results of this thesis can contribute to marketers in many ways. Online retailers could arrange their websites building on more useful tools for customers. They can edit review pages in their websites and present them in a suitable form based on the findings of this research study. Taking into account the effective factors on review helpfulness, they can predict which reviews might be more helpful for customers. It can be more appropriate to provide salient positions for reviews that can benefit customers more. For instance, Amazon presents the most positive and the most negative reviews at the top of the review page. Presenting the reviews, which can be perceived more useful by customers, at the top of the page can provide more user-friendly website for customers. Thus, customers may notice a helpful review more easily. Considering the factors affecting the review helpfulness, website designers can distinctly locate helpful reviews on review pages of the website. In this way, online retailers can highlight the reviews that could be perceived more helpful by customers because these reviews have a substantial place in customers' decisions.

Besides, online retailers may encourage customers, who make a purchase, to write reviews. To illustrate, some online retailers encourages people to write positive reviews about their experiences by offering gift cards. They can also encourage consumers to write helpful reviews. While doing this, they can guide the reviewers to write. They may support the reviewers by considering about the factors that affect review helpfulness. In accordance with the results of this thesis, they can guide to write reviews by viewing which factors drive review helpfulness. Online retailers can provide a guideline to review, and they can lead their customers to write more helpful reviews through the instructions of the guideline. For example, customers can be encouraged to share product reviews with images via a reviewing guideline. By this way, more helpful reviews may be created for the readers. Also, online retailers can move consumers in different ways depending on the product purchased. They can help their customers by giving a detailed guide which includes a great variety of instructions that will serve to write helpful reviews.

4.2 Limitations and Future Research Directions

The thesis is not free of some limitations. Although ELM and HSM were adopted in this thesis, two information processing ways of both models could not be applicable because reviewer credibility which represents the peripheral route of ELM and heuristic view of HSM could not be included to the regression analysis. Hence, this thesis explains only review related factors, which reflect central route of ELM and systematic view of HSM, on review helpfulness.

Reviewer related attributes in a review may change reader’s perceptions on the review. For further studies, other reviewer related attributes may also be used besides reviewer credibility. For instance, reviewer expertise could be an important predictor on review helpfulness. Thus, future research can include reviewer related factors to understand the impact of heuristic factors on review helpfulness. Both aspects of ELM and HSM could be implemented, so a more comprehensive perspective can be obtained.

The effects of image count on review helpfulness were analyzed in the context of this thesis. Nevertheless, other factors connected with images can also affect review helpfulness. For instance, the content of the image can be an important determinant of review helpfulness. Apparently, a review with images not including the product cannot be so helpful to acquire information about the product. As for the reviews with images containing the product, investigating which components of the image are effective on review helpfulness might be an issue of the further research. Moreover, this thesis focused on the factors related with review content; nevertheless, the titles of the reviews might influence the readers' decisions. Besides review content, focusing on the factors related to review titles on review helpfulness may be another further research direction.

Also, the factors that influence review helpfulness were examined owing to the fact that they can lead to change in consumer attitudes towards products. Various researchers utilized review helpfulness to assess the effectiveness of online reviews (Baek et al., 2012; Singh et al., 2017; Srivastava and Kalro, 2019), but using review helpfulness is not an only approach for the evaluation of the effectiveness of online reviews. Online customer reviews might cause changes in product-related decisions, such as purchasing, being the most critical one. Hence, it can be conducted a research to check the impacts of online customer reviews on purchase probability or product sales for a specific time period. Taylor et al.'s (1997) informational cues are adjusted by summarizing into 7 informational cues, but all thirty cues might be examined, and the role of each information cue can be investigated separately as well, in future research.

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APPENDICES

APPENDIX A: Taylor et al.'s Informational Cues (Taylor et al, 1997)

Table A.1 : Taylor et al.'s (1997) Informational Cues.

Cues	**Description**
Price	Refers to the amount the consumer must pay for the product or service; may be in absolute terms, like a suggested retail price, or relative terms, like a 10-percent-off sale.
Variety of the product	Refers to claiming for or featuring more than one type of product.
Value	Refers to some combination of price and quality or quantity, as in better quality at a low price or best value for the dollar.
Quality	Refers to how good the product or service is; may refer to craftsmanship and/or attention during manufacture, use of quality (i.e., better, best) ingredients or components, length of time to produce the product.
Size	Refers to the physical size or capacity of the product, how long, tall, wide, heavy, capacity to do particular size tasks.
Economy / savings	Refers to saving money or time either in the original purchase or in the use of the product relative to other products in the category.
Supply, quantity available, or limitation	Refers to how much or how many items are available and directly or indirectly the need to act before the supply is exhausted.

Table A.1 (continued) : Taylor et al.'s (1997) informational cues.

Cues	Description
Method of	Information on preferred method to pay; for example, by credit card
Dependability / reliability / durability	Information concerning how long the product will last without repair, service records, and other related items.
Nutrition/health	Information concerning the nutritional or health-related characteristics of a product; for example, "fortified with vitamin D," "the formula doctors recommend," "relieves iron-poor blood."
Taste	Primarily for food, drink, or personal care products.
Sensory information (other than taste)	Information (such as fragrance, touch, comfort, styling, or sound) concerning a sensory experience, appearance, classic beauty, beautiful sound, etc., associated with the product either when purchased or when prepared in final form.
Components / contents / ingredients	What went into the making or manufacture of the product; for example, "contains iron," "made with pudding."
Availability	Any information concerning the place(s) where the consumer may purchase or otherwise obtain the product; for example, "available in supermarkets."
Packaging or shape	Information about the packaging of the product; for example, "the package is reusable," "in one convenient serving package."
Guarantees / warranty	Refers to any information concerning the presence of a guarantee or warranty.

Table A.1 (continued) : Taylor et al.’s (1997) informational cues.

Cues	Description
Safety	Information concerning the safety of the product; for example, "has a built-in cut-off switch," "won't harm delicate hair," "nontoxic."
Independent research results	Information about tests of the product or of its users that were carried out by an identified individual or organization other than the company manufacturing the product.
Company research results	Information about tests of the product or its users that were carried out by the company manufacturing the product.
Research from unidentified source	Information about tests of the product or users of the product when the source of the test results is not identified.
New ideas, new uses	Refers to any information about a new way to use an established product.
Performance, results of using	Any information concerning the outcomes associated with the use of a product. Performance deals with whether the product accomplishes a consumer purpose.
User's satisfaction/loyalty	Refers to any information concerning users' satisfaction, dedication, preference for the brand, or length of time a consumer has used the advertised product.
Superiority claim	Information that claims the advertised product is better than competitive products or better than an older version of the advertised product in some particular ways.

Table A.1 (continued) : Taylor et al.'s (1997) informational cues.

Cues	**Description**
Convenience in use	Information concerning the ease in which the product may be obtained, prepared, used, or disposed of.
Special offer or event	Information concerning special events such as sales, contests, two-for-one deals, premiums, or rebates that occur for a specified period of time.
New product or new and improved features	Refers to any information concerning a new product introduction, or new components, ingredients, or features of an existing product.
Use occasion	Information that clearly suggests an appropriate use occasion or situation for the product; for example, "buy film for the Christmas season," "enjoy Jello at a birthday party."
Characteristics or image of users	Refers to any information concerning the type(s) of individual(s) who might use the advertised product.
Company information	Refers to any information (e.g., size or number of years in business) about the image or reputation of the company that manufactures or distributes the product.

APPENDIX B: Conducted Survey

A survey about online purchase

Hi,

You are about to take part in a survey about purchasing online. It takes just a couple of minutes.

Thanks for your participation.

How often do you purchase online? *

- ☐ Never
- ☐ Once or twice a year
- ☐ A few times a year
- ☐ Once or twice a month
- ☐ Once or twice a week
- ☐ More than twice a week
- ☐ Almost every day

How many review pages do you read when you are looking for a product to buy online? *

Assume that each review page has 10 reviews.

- ☐ 0
- ☐ 1-2
- ☐ 3-4
- ☐ 5-6
- ☐ 7+

Which of the following do you prefer to read mostly?

☐ Most popular reviews

☐ Most recent reviews

☐ Both

When buying a product online, which information do you think is more important about the product? Please choose only 10 options from the list given below. *

If you think there is another type of information, please state it below.

☐ Price	☐ Taste	☐ New ideas, new uses
☐ Variety of the product	☐ Sensory information	☐ Performance, results of using
☐ Value	☐ Components / contents / ingredients	☐ User's satisfaction / loyalty
☐ Quality	☐ Availability	☐ Superiority claim
☐ Size	☐ Packaging or shape	☐ Convenience in use
☐ Economy / savings	☐ Guarantees/warranty	☐ Special offer or event
☐ Supply, quantity available, or limitation	☐ Safety	☐ New product or new and improved features
☐ Method of payment	☐ Independent research results	☐ Use occasion
☐ Dependability / reliability / durability	☐ Company research results	☐ Characteristics or image of users
☐ Nutrition/health	☐ Research from unidentified source	☐ Company information

APPENDIX C: The Steps of Information Extraction Process

- Tokenization to split reviews into words
- Removing stop words
- POS tagging to classify words
- Lemmatization of noun words
- Frequencies of noun words
- Association rule mining to find noun groups
- Identification of product feature candidates
- Identification of opinions for each product feature candidate
- Identification of synonyms and antonyms for opinions
- Identification of explicit product features
- Frequencies of opinion words
- Identification of implicit product features
- Identification of reviews that are associated with the identified features
- Matching product features with information cues
- Manual evaluation of the reviews in terms of information cues
- Accuracy evaluation of the proposed method

APPENDIX D: Sentiment Analysis Steps

- Removing stop words and punctuations by TextBlob
- Checking polarity and subjectivity scores of the words for each review by Textblob
- Calculation of overall polarity and subjectivity scores for each review by Textblob

APPENDIX E: Emotion Analysis Steps

- Tokenization to split reviews into words
- Removing stop words
- Checking if the words in the reviews exist in EmoLex
- If no, adding 0 to emotion dimensions
- If yes, checking which emotion dimensions the existing word represents
- Assigning 1 to the represented emotion dimensions by the existing word
- Repeating this process for each word in the reviews
- Summing 1s which are assigned to emotion dimensions by the existing words for each review
- Normalization process for each review

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