DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

A PRACTICAL IMPLEMENTATION FOR BIG DATA MINING AND SENTIMENT ANALYSIS

by
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İZMİR

A PRACTICAL IMPLEMENTATION FOR BIG DATA MINING AND SENTIMENT ANALYSIS

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M.Sc THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"A PRACTICAL IMPLEMENTATION FOR BIG DATA MINING AND SENTIMENT ANALYSIS"** completed by **CEREN ASILKEFELİ** under supervision of **ASSIT.PROF.DR. ŞEBNEM DEMİRKOL AKYOL** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Master of Science.

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A PRACTICAL IMPLEMENTATION FOR BIG DATA MINING AND SENTIMENT ANALYSIS

ABSTRACT

In recent years, there has been a massive interest in sharing various experiences and opinions about different goods and services on blogs, social media sites, and review-focused websites. Potential customers who read and consider previous buyers' feedback before purchasing a particular good or service can benefit from the customer reviews obtained from those sites. Additionally, companies may use online customer reviews to gauge how satisfied customers are with their goods or services and then incorporate this data into customer relationship management software. In this thesis, a decision support tool is developed to measure and evaluate the level of customer satisfaction with a particular product or service and to enable potential customers to rank the products/services according to this evaluation. This tool can be used by companies and potential customers. There are primarily two steps in the decision support system. The online customer reviews are first turned into customer satisfaction scores using sentiment analysis. This study is twofold. According to the performance scores achieved in the first phase, the alternatives are rated using a multi-criteria decision-making (MCDM) methodology in the second phase. The created decision support system is implemented in a case study where alternative mobile phones are ranked by the sentiment analysis results using the Fuzzy ELECTRE approach. Customer feedback regarding their experiences with mobile phones is assessed using aspect-based sentiment analysis.

Keywords: Sentiment analysis, MCDM, product ranking

BÜYÜK VERİ MADENCİLİĞİ VE DUYGU ANALİZİ UYGULAMASI

ÖZ

Son yıllarda bloglarda, sosyal medya sitelerinde ve inceleme odaklı web sitelerinde farklı ürün ve hizmetlerle ilgili çeşitli deneyim ve fikirlerin paylaşılmasına olan ilgide büyük bir artış olmuştur. Belirli bir ürün veya hizmetle ilgili satın alma kararı vermeden önce, önceki kullanıcıların geri bildirimlerini okuyup dikkate alan potansiyel müşteriler, bu sitelerden elde edilen müşteri yorumlarından yararlanabilir. Ek olarak şirketler, müşterilerin ürünlerinden veya hizmetlerinden ne kadar memnun olduklarını ölçmek için çevrimiçi müşteri incelemelerini kullanabilir ve ardından bu verileri müşteri ilişkileri yönetimi yazılımına dahil edebilir. Bu tezde, belirli bir ürün veya hizmetle ilgili müşteri memnuniyet düzeyini ölçmek, değerlendirmek ve potansiyel müşterilerin bu değerlendirmeye göre ürünleri/hizmetleri sıralamasını sağlamak için bir karar destek aracı geliştirilmiştir. Bu araç şirketler ve potansiyel müşteriler tarafından kullanılabilir. Geliştirilen karar destek sisteminde temel olarak iki adım vardır. Çevrimiçi müşteri yorumları, öncelikle duygu analizi kullanılarak müşteri memnuniyet puanlarına dönüştürülür. Birinci aşamada elde edilen performans puanlarına göre alternatifler, ikinci aşamada çok kriterli karar verme (ÇKKV) metodolojisi kullanılarak derecelendirilir. Oluşturulan karar destek sistemi, Bulanık ELECTRE yaklaşımı kullanılarak duygu analizi sonuçlarına göre alternatif cep telefonlarının sıralandığı ve cep telefonu deneyimlerine ilişkin müşteri geri bildirimlerinin hedef tabanlı duygu analizi kullanılarak değerlendirildiği bir vaka çalışması üzerinde uygulanmaktadır.

Anahtar Kelimeler: Duygu analizi, ÇKKV, ürün sıralama

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CHAPTER ONE
INTRODUCTION

In recent years, the rapid increase of digital technologies enabled people to share their opinions online. Thus, space has occurred for customers to share their reviews on the products they purchased. A massive amount of subjective reviews is being generated every day. This user-generated content not only provides a significant information source to help customers make purchasing decision, but also contributes to retailers improving their marketing strategies. As a result of the increase in internet users, e-commerce websites have seen a significant increase in both the number of purchases made through them and the number of comments left on products, making it practically impossible to thoroughly review and analyze the vast amount of feedback.

Weber Shandwick (2012) surveyed 2004 American shoppers to understand how they use online product reviews when making purchase decisions. The result of this study shows that approximately 65% of consumers are sufficiently influenced by online reviews to purchase a consumer electronics product that they do not consider. The study of Cisco Business Solutions Group (2013) shows that nearly eight in 10 consumers are digital shoppers who regularly research and purchase using the Internet. In this study respondents were asked to indicate the three most important sources of information they use for making purchasing decisions. When the 2010 and 2012 results are analyzed, it is seen that there is a great increase in reliance in online reviews on retailer websites (44% - 52%) and online reviews from expert sources (29% - 42%), while reliance in friends and family recommendations (60% - 49%) has decreased.

Clients have a wide range of options for products that are either cheaper or of higher quality in the competitive atmosphere of the modern global economy. Customers should therefore thoroughly research and assess these options before choosing the best one. It is essential to thoroughly, affordably, and accurately analyze comments and opinions on the internet and use the results in decision-making by the businesses and potential clients.

CHAPTER TWO
LITERATURE REVIEW

2.1 Background of Sentiment Analysis

Text is one of the most common forms of stored information, and emails, corporate documents, web pages, news, blogs, and social network feeds are some examples of textual data. Sentiment analysis is one of the data mining methods which deals with text formed data. This study focuses on sentiment analysis due to the rapid increase of opinionated textual data generation.

2.1.1 Big Data

Big data is used to capture, store, manage, analyze and process complex and large amounts of data. It can be seen in Figure 2.1 that how the term "big data" became popular gradually over time. With the increase in its usage, big data definitions developed rapidly and this caused some confusion. Figure 2.2 shows how big data definitions differed based on an online survey of 154 global executives in April 2012. De Mauro et. al (2015) identified four key themes that big data refers to: Information, Technologies, Methods and Impact. Considering these keys, they propose the following definition:

"Big Data represents the Information assets characterized by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value." (De Mauro et al., 2015)

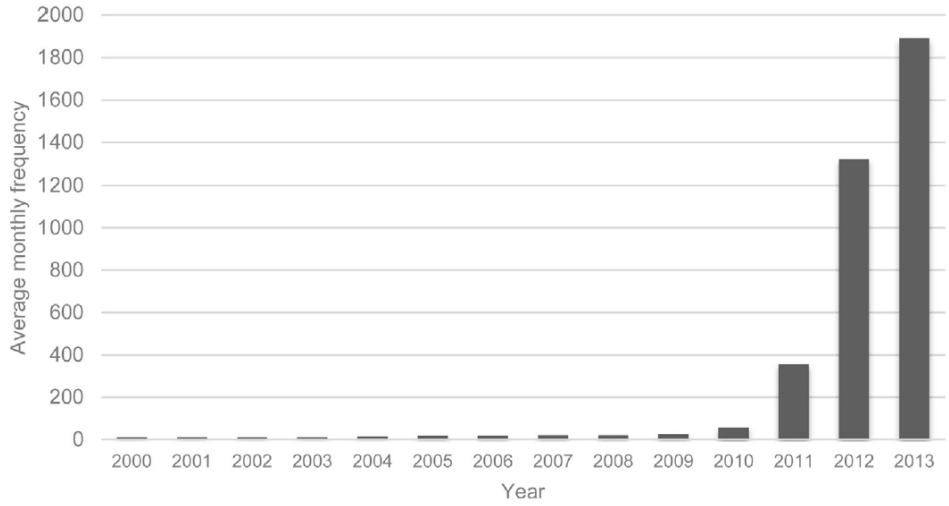


Figure 2.1 Frequency distribution of document containing the term "big data" (Gandomi & Haider, 2015)

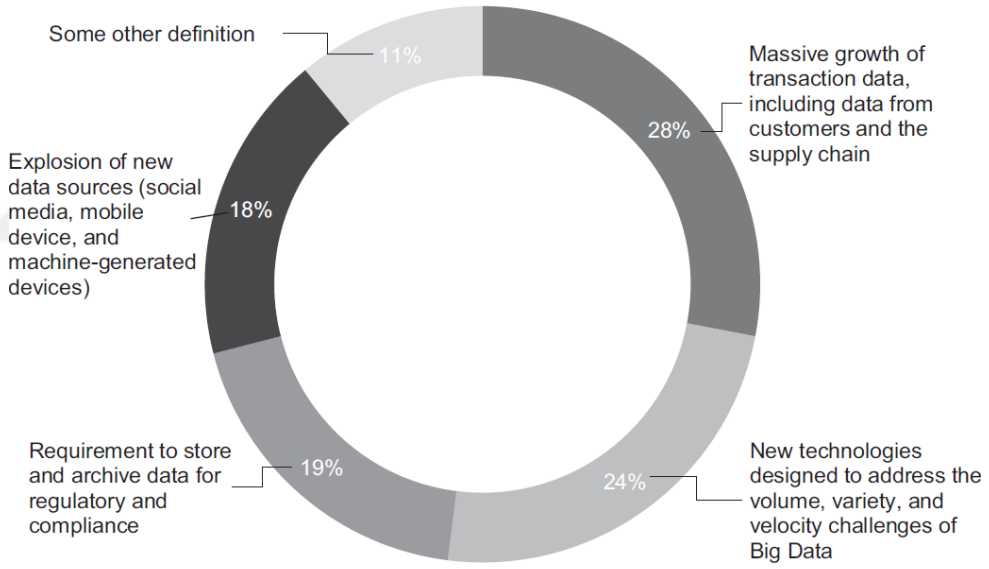


Figure 2.2 Big data definitions based on an online survey (Gandomi & Haider, 2015)

There are three difficulty dimensions in data management: volume, variety and velocity (Laney, 2001). In addition, other dimensions of big data are mentioned in the literature. The dimensions of big data can be explained as follows:

- Volume: Volume represents the magnitude of data. Big data sizes could be reported in terabytes or petabytes. Beaver et. al (2010) reported that users upload one billion new photos which are about 60 terabytes every week. Definitions of big data

volumes can vary depending on factors such as time and data type. In addition, two sets of data of the same size may require different data management technologies depending on the type.

- Variety: Variety corresponds to different types of data structures. Today, thanks to technological developments, various types of structured, semi-structured, and unstructured data can be used. Structured data come in a standard format of numbers and words such as tabular data. Structured data accounts for only %5 of all available data (Cukier, 2010). The rest are semi-structured and unstructured data including photos, texts, videos, audios etc.

- Velocity: Velocity refers to the data generation rate. The proliferation of digital devices, such as smartphones, has led to an unprecedented data generation rate. Every day 5 billion users browse, tweet, upload and send both multimedia and standard data (Tanwar et al., 2020). This fast data flow requires new efficient data analysis and management tools.

- Value: Value means the attribute of big data and is one of the most critical elements of big data. It is good to have access to big data, but it is useless unless we can convert it into value. Value implies the use and retrieval of valuable information from large volumes and diversity of data (Tanwar et al., 2020).

- Veracity: Veracity is used to define unreliability and messiness in some data sources (Marr, 2014). It is difficult to control quality and accuracy in many big data formats. For example, customer emotions on social media are uncertain because they require human reasoning. However, they still contain valuable information. The need to deal with this imprecise data, requires the development of methods and tools for the management and mining of uncertain data.

2.1.2 Sentiment Analysis

Sentiment analysis is a text mining method. Text mining refers to techniques that extract useful information from text data. It is an interdisciplinary field that includes information retrieval, machine learning, statistics, computational linguistics and especially data mining. Most text analytics systems are based on text representation and natural language processing (NLP). NLP techniques allow computers to analyze, understand, and even compose text by improving existing knowledge of text terms (Hu et al., 2014).

Sentiment analysis has become a popular subject of research, with the rise of machine learning methods in natural language processing and information retrieval, and the realization of commercial applications that the area offers. Sentiment analysis or opinion mining techniques analyze opinionated text that contains people's opinions for specific entities and enables computers to recognize and express emotions (Pang & Lee, 2009).

Sentiment Analysis task is considered a sentiment classification problem. The first step to the sentiment classification problem is to extract and select text features. Sentiment classification techniques can be roughly divided into machine learning approach, lexicon-based approach, and other hybrid approaches (Medhat et al., 2014).

Sentiment analysis techniques are also divided into three subgroups: document-level, sentence-level and aspect-based. Document-level techniques determine whether the entire document will express a negative or positive emotion and it is assumed that the document contains an opinion about a single object expressed by the author. Sentence level techniques try to determine the polarity of a single sentiment about a known entity expressed in a single sentence. Aspect-based techniques recognize all sentiments in a document and define the aspects of the entity that each emotion refers to (Feldman, 2013).

For example, customer product reviews often contain opinions about different aspects (or features) of a product. Using aspect-based techniques, the seller can obtain valuable information about the different characteristics of the product, which will be overlooked if the sentiment is classified only in terms of polarity.

2.1.3 A Literature Review on Sentiment Analysis

Sentiment analysis applications in the literature are examined in this section. This technique is most applied to product reviews, but it can also be applied to exchanges, news articles, or political debates.

In one of the first studies that deals with opinions from product reviews, Nasukawa and Yi (2003) illustrated a sentence level sentiment analysis approach for extracting sentiments associated with the polarity of positive or negative for specific subjects from a document, instead of classifying the whole document as positive or negative. They performed subject favorability determination by creating a sentiment lexicon of 3513 sentiment terms. Experiments were conducted on camera reviews. Xue Bai (2011), proposed a heuristic search-enhanced Markov blanket model, an approach based on machine learning, and made computational studies using aspect level sentiment analysis on online movie reviews and online news. Cruz et. al (2013), defined a set of domain-specific resources to extract the opinion words. They utilized dictionary based approach for sentiment classification. The lexicon was expanded using a random walk algorithm. Penalver-Martinez et al. (2014) performed a methodology to perform aspect level sentiment analysis on movie reviews. To extract the movie features from the reviews, they utilized a domain ontology. Qi et. al (2016) constructed a method based on conjoint analysis and sentiment analysis to filter out the online reviews that are helpful to product designers. They implemented the method on reviews of cell phones.

In this study, sentiment analysis method is applied to product reviews for the purpose of ranking product. Researchers have recently become interested in this research area. However, there aren't many papers that are directly related to it. Yang

et al. (2021), proposed a decision-making algorithm that uses a combination of aspect-based sentiment analysis and intuitionistic fuzzy VIKOR. The algorithm uses a Bi-LSTM and attention mechanism model to predict multiple attributes of a hotel from online review texts, and then applies the intuitionistic fuzzy VIKOR method to create an overall ranking of the hotels based on multiple attributes. The proposed algorithm is tested using online hotel reviews from three different online travel platforms. Qin and Zeng (2022), proposed an integrated method for product ranking based on online reviews using evidential reasoning theory and stochastic dominance rules. The method first uses sentiment analysis to analyze the sentiment orientation of online reviews, then applies the SMAA-PROMETHEE method to rank the products based on MCDM. A case study is provided to illustrate the effectiveness of the proposed method using online reviews of computers. Tayal et al. (2022), presented a novel approach for personalized ranking of products based on customer preferences and aspect-based sentiment analysis. The approach uses a MCDM framework that incorporates linguistic uncertainties in online reviews using plithogenic sets. It is shown to outperform existing methods such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and the Weighted Sum Model (WSM), as well as some state-of-the-art methods. They implemented the proposed method on hotel recommendations based on different customers' preferences.

Table 2.1 shows some of the studies that use sentiment analysis method in order to rank products. Kang and Park (2014) evaluated customer satisfaction in mobile service using a combination of sentiment analysis and VIKOR approaches. A dictionary-based approach was used to calculate the sentiment score. VIKOR multi-criteria decision making method was used in the ranking of different mobile services. Preethi et al. (2015) developed a recommender system to rank the products based on user feedback that uses AHP and TOPSIS methods for ranking. They implemented this system on mobile phone reviews. Najmi et. al (2015) proposed a product ranking system CAPRA that is a combination of sentiment analysis, product aspect analyzer, product brand ranks and review usefulness analysis. They experimented on TV and camera reviews. Alrababah et. al (2017), used sentiment analysis for aspect ranking. They formulated the product aspect ranking problem as a decision making process and

used three extraction criteria jointly to rank the extracted product aspects: frequent-based, opinion-based, and aspect relevancy. They constructed MCDM decision matrix based on these criteria and used TOPSIS and VIKOR methods to rank aspects. In order to facilitate customer purchasing decisions taking into account dynamic information preferences, Yang et al. (2019) suggested a method based on sentiment analysis approach and discrete dynamic intuitionistic fuzzy information aggregation operator. Çalı and Balaman (2019) proposed a decision support system that integrates multi criteria decision making (MCDM) and aspect level sentiment analysis techniques for product ranking problems. Intuitionistic fuzzy sets (IFSs) are used to effectively represent the customer reviews including hesitant statements in the decision matrix. C. Zhang et al. (2020) proposed a method based on prospect theory, sentiment analysis and VIKOR to calculate sentiment scores and ranking products. Kumar and Parimala (2020), combined AHP and TOPSIS methods to evaluate the best smartphones from a list of five alternatives analyzing customer reviews. D. Zhang et al. (2020), proposed an extended TODIM (an acronym in Portuguese for Iterative Multi-criteria Decision Making) method to rank products based on online reviews. They used intuitionistic fuzzy sets to describe sentiment orientations and emotional intensity. Yang et al. (2021), proposed a model based on bidirectional long short-term memory (Bi-LSTM) and attention mechanisms to predict various product attributes from online review texts. They developed an online hotel attribute evaluation and purchase decision model using the intuitionistic fuzzy set theory and VIKOR approach. Yang et al. (2021), proposed a decision-making algorithm that uses a combination of aspect-based sentiment analysis and intuitionistic fuzzy VIKOR. The algorithm uses a Bi-LSTM and attention mechanism model to predict multiple attributes of a hotel from online review texts, and then applies the intuitionistic fuzzy VIKOR method to create an overall ranking of the hotels based on multiple attributes. The proposed algorithm is tested using online hotel reviews from three different online travel platforms. Qin and Zeng (2022), proposed an integrated method for product ranking based on online reviews using evidential reasoning theory and stochastic dominance rules. The method first uses sentiment analysis to analyze the sentiment orientation of online reviews, then applies the SMAA-PROMETHEE method to rank the products based on MCDM. A case study is provided to illustrate the effectiveness of the proposed method using

online reviews of computers. Tayal et al. (2022), presented a novel approach for personalized ranking of products based on customer preferences and aspect-based sentiment analysis. The approach uses a MCDM framework that incorporates linguistic uncertainties in online reviews using plithogenic sets. It is shown to outperform existing methods such as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and the Weighted Sum Model (WSM), as well as some state-of-the-art methods. They implemented the proposed method on hotel recommendations based on different customers' preferences.

Table 2.1 Reviews of studies that conduct product ranking using sentiment analysis

Author	Year	Ranking method	Data used in case study
Kang, D., & Park, Y.	2014	VIKOR	Mobile service reviews
Preethi et al.	2015	TOPSIS	Mobile phone reviews
Najmi et al.	2015	CAPRA's brand rating process	TV and camera reviews
Alrababah et al.	2017	TOPSIS and VIKOR	Two digital cameras, one cell phone and one mp3 player
Yang et al.	2019	Intuitive fuzzy score and vertical projection distance	Mobile phone reviews
Çalı and Balaman	2019	IF-ELECTRE and VIKOR	Hotel reviews
C. Zhang et al.	2020	VIKOR	Automobile reviews
Kumar and Parimala	2020	TOPSIS	Mobile phone reviews
D. Zhang et al.	2020	TODIM	Mobile phone reviews
Yang et al.	2021	VIKOR	Hotel reviews
Qin and Zeng	2022	SMAA-PROMETHEE	Computer reviews
Tayal et al.	2022	TOPSIS	Hotel reviews

CHAPTER THREE
THE PROPOSED DECISION SUPPORT SYSTEM

The main objective of this study is to develop a decision support system for prospective buyers who frequently check product reviews from experienced customers before making a purchase and for businesses assess the level of consumer satisfaction with their product(s) and/or service(s) and adjust their operational procedures or marketing strategies in response to the results. The suggested system is made to quickly extract the information that is useful from a website that has a lot of data as reading through each review in detail takes a lot of time and is almost impossible for DMs.

The developed decision support system includes two main phases: aspect level sentiment analysis and multi-criteria decision making (MCDM). Sentiment analysis phase is explained in section 3.1 and MCDM phase is explained in sections 0 and 3.3. Figure 3.1 illustrates the whole system briefly.

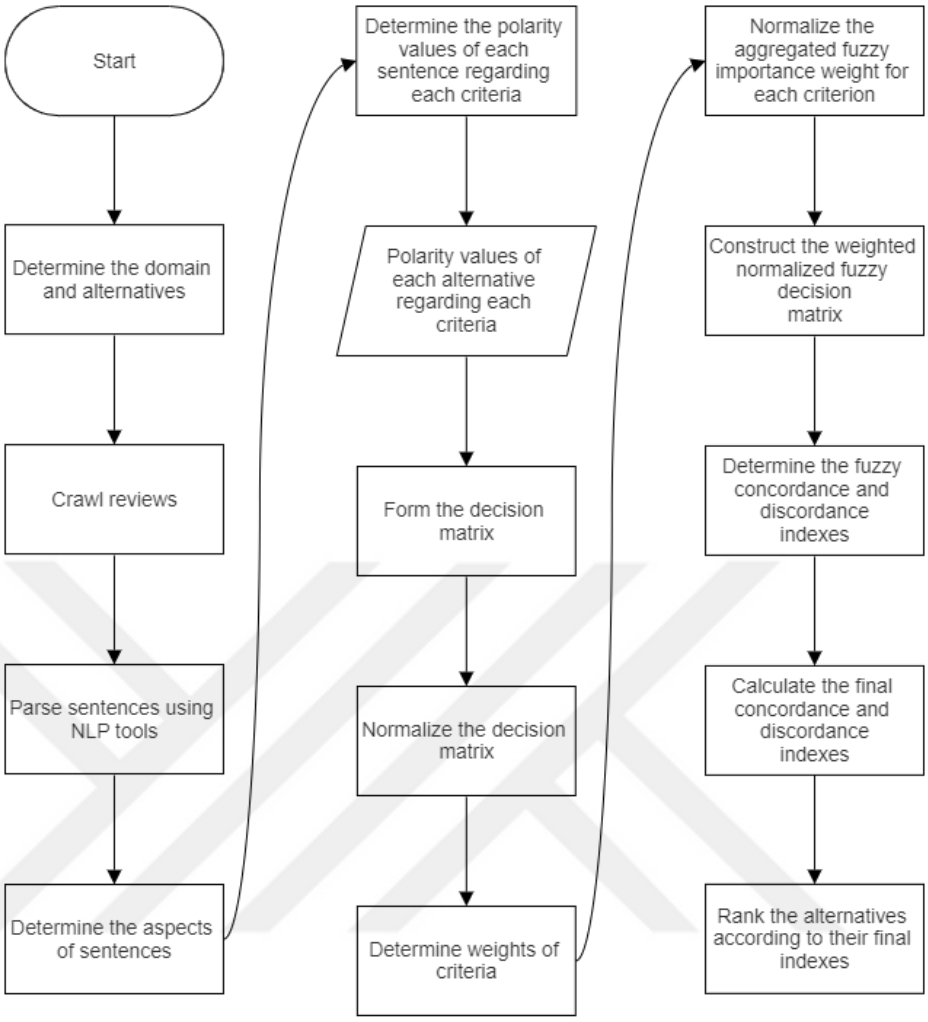


Figure 3.1 The developed system

3.1 Sentiment Analysis

The goal of sentiment analysis phase is to evaluate the customer satisfaction corresponding to alternative products. In this study, cell phone reviews have been used.

Online reviews from customers are raw data that have been gathered from the relevant website. Due to the lack of classification to extract the required information, these data can be referred to as unstructured data. In the first step, unstructured data is transformed into structured data using text mining techniques. Sentiment analysis is done by two phases which are explained in detail in the following sub-sections. Figure 3.2 shows the algorithm for sentiment analysis phase.

```
1 For every review
2       Search for sentence splitters
3       Split the review into sentences
4 end for
5 For every sentence
6       Polarity = 0
7       For every word in the sentence do
8               If word is an aspect word then
9                       Set related criterion positive for the sentence
10              end if
11              If word is a negativity word then
12                      Negativity = -1
13              end if
14              Find polarity of the word from STN dictionary
15              Polarity += polarity of the word
16      end for
17 end for
18      Add Polarity*Negativity to positive criteria
```

Figure 3.2 Algorithm for sentiment analysis

3.1.1 Data Crawling and Pre-Processing

In the first step of sentiment analysis, reviews crawled from websites are parsed using ITU Turkish NLP web service (Eryiğit, 2014). Numerous NLP tools, including tokenization, normalization, spelling checks, morphological analysis, and dependency parsing, are available through the ITU Turkish NLP Web Service. The text is divided into the smallest units by tokenization tools such as words, punctuation marks, and numbers. These smallest parts are called tokens and are analyzed grammatically with the ITU NLP tools. ITU NLP tools give roots, major and minor part of speech (POS) tags, affixes, and the mission of the token as a result. In this study root and POS tags are used. Table 3.1 shows the results of parsing a sentence. The Smallest units of the sentence are shown in the first row as tokens, and their root are shown in the second

row. Then the part of speech tags are defined. Major POS represents the POS tag of the word (token) and minor POS represents the POS tag of the root.

Table 3.1 Result of parsing a sentence

Token	Root	Major POS	Minor POS
Yılbaşı	yılbaşı	Noun	Noun
Öncesi	önce	Noun	Noun
Hediye	hediye	Noun	Noun
Olarak	olarak	Postp	PCNom
Gayet	gayet	Adverb	Adverb
İyi	iyi	Adj	Adj
Bir	bir	Adj	Num
Fiyata	fiyat	Noun	Noun
Ürünü	ürün	Noun	Noun
Aldım	al	Verb	Verb
.	.	Punc	Punc

3.1.2 Aspect Extraction

The next step is to find aspects of sentences based on predefined aspect words. In this study cell phones are examined based on six criteria which are function, battery, price, screen, appearance, and camera. The most used words of the reviews of iPhone 11 are examined to choose the aspect words as iPhone 11 is the product that has the greatest number of reviews. After examining these words, aspect words which are shown in Table 3.2 are specified corresponding to al criteria.

Before starting sentiment analysis, every review is split into sentences using sentence splitters. Sentence splitters are dot and negative conjunctions such as “ama”, “ancak” (but). The tokens that have noun as a major POS tag are considered to determine the aspects of sentences while analyzing the sentences. However, some adjectives are usually used for specific features of the product. Noun aspect words are called explicit aspect words and have no polarity. On the contrary, adjectives that

indicate aspects have a polarity and they are called implicit aspects. For example, “pahalı” (expensive) corresponds to the price criteria and it has a negative meaning.

Table 3.2 Aspect words

Criteria	Explicit Aspect Words	Implicit Aspect Words
Function	kullanım (usage) performans (performance) işlemci (processor) kalite (quality) sistem (sytem)	yavaş (slow)
Battery	şarj (charge) batarya (battery)	
Price	fiyat (price) para (money) kampanya (campaign) indirim (discount)	pahalı (expensive) uygun (reasonable) ucuz (cheap)
Screen	ekran (screen)	
Appearance	renk (color) aksesuar (accessories) tasarım (design) görünüş (appearance)	hafif (light) şık (stylish) ağır (heavy) ince (thin) kalın (thick)
Camera	kamera (camera) fotoğraf (photograph) video (video)	

3.1.3 Sentiment Lexicon and Evaluating Values

In this step, sentiment values of the words are defined using a dictionary-based methodology. After finding aspects of sentences, all words are analyzed using SentiTurkNet dictionary (Dehkharghani et al., 2016). Dictionary has been downloaded from http://myweb.sabanciuniv.edu/rdehkharghani/sentiturknet-3/. Words are considered as positive or negative based on the dictionary.

For example, “kaliteli” (quality) from the sentence “Kamera ve ekran görüntüsü kaliteli.” (Camera and screen are of good quality.) has a positive value which is 1. As the aspect words correspond to camera and screen criteria, the value of camera and screen increase by 1 point. This result can be seen in the Table 3.5, row 7 (sixth sentence, fifth review).

3.1.4 Illustrative Example

There is an illustrative example based on 10 reviews from online reviews of Samsung Galaxy S21.

1. “Yılbaşı öncesi hediye olarak gayet iyi bir fiyata ürünü beğenerek aldım.” (I bought this product for a very good price as a gift before Christmas.)
2. “Ürünün tasarımı güzel ama gereksiz pahalı.” (The design of the product is beautiful but it is unnecessarily expensive.)
3. “Kamera modülü köşede ve dışa doğru çıkık olduğu için düz bir zemin üzerine koyulup kullanıldığında bir köşesi havada kalıyor ve bu sebeple diğer köşelerden sürekli darbe alıyor.” (Since the camera module is in the corner and protrudes outward, one corner stays high when placed on a flat surface and therefore the other corners are constantly hit.)
4. “Ürünün işlemcisi çok iyi dizayn edilmiş.” (The processor of the product is very well designed.)
5. “Kamera ve ekran görüntüsü kaliteli.” (Camera and screen are of good quality.)
6. “Ürün hızla elime ulaştı, beyaz renk gayet güzel duruyor.” (The product arrived quickly, the white color looks very nice.)
7. “Muadillerine göre fiyat ve performans olarak açık ara en iyisi” (The price and performance are by far the best compared to their counterparts.)
8. “Ekran ile köşeler arasında boşluk sorunu var.” (There is a gap problem between the screen and the corners.)
9. “Bu telefon gerçekten çok iyi. Şarjı da gayet güzel gidiyor.” (This phone is really good. The charge also lasts a long time.)

10. “Her şeyini beğendim ama batarya kesinlikle iyi değildi.” (I liked everything but the battery was definitely not good.).

In the first step, sentences are parsed by ITU NLP tools. Results are shown in Table 3.3. Then the sentences are examined in order. When examining the sentence, system finds aspect words and sentiment words (Table 3.4). Afterwards, total score of the related criteria increases or decreases based on the polarity value of the sentiment word.

The first review has one sentence. This sentence includes one aspect word which is “fiyat” (price) and one aspect expression which is “iyi” (good). The aspect word corresponds to the Price criteria and the aspect expression is positive. Therefore, the total score of Price increases based on the value of “iyi” (good) from STN dictionary.

The decision support system evaluates the second review as two separate sentences: before and after the negative conjunction “ama” (but). In the first part, “tasarım” (design) is the aspect expression for Appearance and beautiful is a positive adjective. Therefore, the total score of Appearance increases based on the value of “güzel” (beautiful) from STN dictionary.

The last review is examined in two sentences as the second review because of the negative conjunction “ama” (but). The first part which is the twelfth sentence of all reviews has no aspect words. For this reason, total scores are not changed as seen in Table 3.5. The second part includes the aspect word “batarya” (battery) which corresponds to the Battery criteria and the aspect expression “iyi” (good) which is a positive adjective. However, there is the negativity word “değil” (not). Therefore, the system decreases the total score of the Battery by the value of “iyi”.

Table 3.3 NLP results

Token	Root	Major POS	Minor POS
Yılbaşı	yılbaşı	Noun	Noun
Öncesi	önce	Noun	Noun
Hediye	hediye	Noun	Noun
Olarak	olarak	Postp	PCNom
Gayet	gayet	Adverb	Adverb
İyi	iyi	Adj	Adj
Bir	bir	Adj	Num
Fiyata	fiyat	Noun	Noun
Ürünü	ürün	Noun	Noun
Aldım	al	Verb	Verb
.	.	Punc	Punc
Ürünün	ürün	Noun	Noun
Tasarımı	tasarım	Noun	Noun
Güzel	güzel	Adj	Adj
Ama	ama	Conj	Conj
Gereksiz	gereksiz	Adj	Adj
Pahalı	pahalı	Adj	Adj
.	.	Punc	Punc
Kamera	kamera	Noun	Noun
Modülü	modül	Noun	Noun
Köşede	köşe	Noun	Noun
Ve	ve	Conj	Conj
Dışa	dış	Noun	NAdj
Doğru	doğru	Adj	Adj
Çıkık	çıkık	Adj	Adj
_	ol	Verb	Verb
Olduğu	_	Adj	PastPart
İçin	için	Postp	PCNom
Düz	düz	Adj	Adj
Bir	bir	Adj	Num
Zemin	zemin	Noun	Noun
Üzerine	üzer	Noun	Noun
_	koy	Verb	Verb
Koyup	_	Adverb	AfterDoingSo
_	kullan	Verb	Verb
Kullanıldığında	_	Noun	PastPart
Bir	bir	Adj	Num

Table 3.3 Continues

Token	**Root**	**Major POS**	**Minor POS**
Köşesi	köşe	Noun	Noun
Havada	hava	Noun	Noun
Kalıyor	kal	Verb	Verb
Ve	ve	Conj	Conj
Bu	bu	Det	Det
Sayede	saye	Noun	Noun
Diğer	diğer	Adj	Adj
Köşelerden	köşe	Noun	Noun
Sürekli	sürekli	Adverb	Adverb
Darbe	darbe	Noun	Noun
Alıyor	al	Verb	Verb
.	.	Punc	Punc
Ürünün	ürün	Noun	Noun
İşlemcisi	işlemci	Noun	Noun
Çok	çok	Adverb	Adverb
İyi	iyi	Adj	Adj
Dizayn	dizayn	Noun	Noun
Edilmiş	et	Verb	Verb
.	.	Punc	Punc
Kamera	kamera	Noun	Noun
Ve	ve	Conj	Conj
Ekran	ekran	Noun	Noun
Görüntüsü	görüntü	Noun	Noun
Kaliteli	kaliteli	Adj	Adj
.	.	Punc	Punc
Ürün	ürün	Noun	Noun
Hızla	hız	Noun	Noun
Elime	el	Noun	Noun
Ulaştı	ulaş	Verb	Verb
,	,	Punc	Punc
Beyaz	beyaz	Adj	Adj
Renk	renk	Noun	Noun
Gayet	gayet	Adverb	Adverb
Güzel	güzel	Adj	Adj
Duruyor	dur	Verb	Verb
.	.	Punc	Punc
Muadillerine	muadil	Noun	NAdj
Göre	göre	Postp	PCDat
Fiyat	fiyat	Noun	Noun
Ve	ve	Conj	Conj
Performans	performans	Noun	Noun
Açık	açık	Adj	Adj

Table 3.3 Continues

Token	**Root**	**Major POS**	**Minor POS**
Ara	ara	Noun	NAdj
En	en	Adverb	Adverb
İyisi	iyi	Noun	NAdj
.	.	Punc	Punc
Ekran	ekran	Noun	Noun
İle	ile	Conj	Conj
Köşeler	köşe	Noun	Noun
Arasında	ara	Noun	NAdj
Boşluk	boşluk	Noun	Noun
Sorunu	sorun	Noun	Noun
Var	var	Adj	Adj
.	.	Punc	Punc
Bu	bu	Det	Det
Telefon	telefon	Noun	Noun
Gerçekten	gerçekten	Adverb	Adverb
Çok	çok	Adverb	Adverb
İyi	iyi	Adj	Adj
.	.	Punc	Punc
Şarjı	şarj	Noun	Noun
Da	da	Conj	Conj
Gayet	gayet	Adverb	Adverb
Güzel	güzel	Adj	Adj
Gidiyor	git	Verb	Verb
.	.	Punc	Punc
Her	her	Det	Det
Şeyini	şey	Noun	Noun
Beğendim	beğen	Verb	Verb
Ama	ama	Conj	Conj
Batarya	batarya	Noun	Noun
Kesinlikle	kesinlik	Noun	Noun
İyi	iyi	Adj	Adj
Değildi	değil	Postp	Neg
.	.	Punc	Punc

Table 3.4 Aspect and sentiment words

Review	Sentence	Aspect Expression	Related Criteria	Sentiment Word	Polarity
1	1	fiyat (price)	Price	iyi (good)	positive
2	2	tasarım (design)	Appearance	güzel (beautiful)	positive
	3	pahalı (expensive)	Price	pahalı (expensive)	negative
3	4	kamera (camera)	Camera	darbe (hit)	negative
4	5	işlemci (processor)	Function	iyi (good)	positive
5	6	kamera (camera)	Camera	kaliteli (quality)	positive
		ekran (screen)	Screen	kaliteli (quality)	positive
6	7	renk (color)	Appearance	güzel (beautiful)	positive
7	8	fiyat (price)	Price	iyi (good)	positive
		performance (performance)	Function	iyi (good)	positive
8	9	ekran (screen)	Screen	sorun (problem)	negative
9	11	şarj (charge)	Battery	güzel (beautiful)	positive
10	13	batarya (battery)	Battery	iyi değil (not good)	negative

Table 3.5 Sentiment analysis results

Review	Sentence	Function	Battery	Price	Screen	Appearance	Camera
0	0	0.00	0.00	0.00	0.00	0.00	0.00
1	1	0.00	0.00	1.75	0.00	0.00	0.00
2	2	0.00	0.00	1.75	0.00	1.00	0.00
	3	0.00	0.00	0.02	0.00	1.00	0.00
3	4	0.00	0.00	0.02	0.00	1.00	-0.96
4	5	1.00	0.00	0.02	0.00	1.00	-0.96
5	6	1.00	0.00	0.02	1.00	1.00	0.04
6	7	1.00	0.00	0.02	1.00	2.00	0.04
7	8	1.50	0.00	0.53	1.00	2.00	0.04
8	9	1.50	0.00	0.53	0.53	2.00	0.04
9	10	1.50	0.00	0.53	0.53	2.00	0.04
	11	1.50	1.00	0.53	0.53	2.00	0.04
10	12	1.50	1.00	0.53	0.53	2.00	0.04
	13	1.50	0.00	0.53	0.53	2.00	0.04

3.2 ELECTRE Method

Multi criteria decision making (MCDM) aims to structure and solve problems involving numerous criteria in planning and decision-making. It has been widely applied in many areas such as engineering, management and environmental sciences. Multiple Attribute Decision-Making (MADM) and Multiple Objective Decision-Making (MODM) are the two primary categories used to classify MCDM (Triantaphyllou, 2000). MODM models that assume continuous solution spaces (and so rely on continuous mathematics) seek to identify the best possible compromise solutions and typically assume that the issue at hand can be represented as a mathematical programming problem. MADM concentrates on issues with discrete decision spaces, i.e. with a limited number of alternatives, and mostly use discrete mathematics techniques that are not as elegant theoretically as the former. The term MCDM is widely used for MADM problems.

The ELECTRE method for choosing the best alternative(s) from a given set of alternatives was developed in 1965, and was later referred to as ELECTRE I (Roy, 1968). ELECTRE is an abbreviation for: ELimination Et Choix Traduisant la REalite´ (ELimination and Choice Expressing the REality). After that, various versions of ELECTRE methods were developed: ELECTRE II (Roy et al., 1971), ELECTRE III (Roy, 1978), ELECTRE IV (Roy & Hugonnard, 1982), ELECTRE TRI (Roy & Bouyssou, 1993; Yu, 1992), and ELECTRE IS(Roy & Bouyssou, 1993).

The ELECTRE method can be defined as follows (Sevkli, 2010):

Suppose a MCDM problem has m alternatives (A_1, A_2, …, A_m), and n criteria/attributes (C_1, C_2, ..., C_n). Regarding the n criteria/attributes, each alternative is scored. A decision matrix is comprised of all the ratings for the alternatives in relation to each criterion denoted by $X=(x_{ij})_{mxn}$. Let $W=(w_1, w_2, \ldots, w_n)$ be the relative weight vector criteria, satisfying $\sum_{j=1}^{n} w_j = 1$. Then the steps proceed as follows:

Step 1: Normalize the decision matrix X by calculating r_{ij}, which donates the normalized criteria rating.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \text{where } i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n \tag{3.1}$$

Step 2: Calculate the weighted normalized decision matrix $V = (v_{ij})_{mxn}$

$$v_{ij} = r_{ij} \,.\, w_{ij} \quad \text{where } i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n, \tag{3.2}$$

where w_j is the relative weight of the jth criterion and $\sum_{j=1}^{n} w_j = 1$.

Step 3: Determine the concordance and discordance sets. For each pair of alternatives A_p and A_q ($p, q = 1, 2, \ldots, m$ and $p \neq q$) the set of criteria is divided into two separate subsets. If alternative A_p is preferred to alternative A_q for all criteria, the concordance set is created. This can be shown as:

$$C(p,q) = \{j | vpj > vqj\}, \tag{3.3}$$

where v_{pj} is the weighted normalized rating of alternative A_p with according to the jth criterion. To put it another way, $C(p, q)$ is the set of attributes where A_p is better than or equal to A_q. All criteria for which A_p is worse than A_q are contained in the complement of $C(p, q)$, also known as the discordance set. This can be shown as:

$$D(p,q) = \{j | vpj > vqj\} \tag{3.4}$$

Step 4: Calculate the concordance and discordance indexes. The following formula denotes the concordance index of $C(p, q)$:

$$C_{pq} = \sum_{j^*} w_{j^*}, \tag{3.5}$$

where j^* refers to attributes contained in the concordance set *C(p, q)*. The degree of disagreement in $(A_p \rightarrow A_q)$ is represented by the discordance index *D(p, q)*, which is defined as:

$$D_{pq} = \frac{\sum_{j^+} |v_{pj^+} - v_{qj^+}|}{\sum_j |v_{pj} - v_{qj}|} \tag{3.6}$$

where v_{ij} is the weighted normalized evaluation of alternatives *i* on criterion *j* and j^+ are attributes contained in the discordance set *D(p, q)*.

Step 5: Outranking relationship. When $C_{pq} \geq \bar{C}$ and $D_{pq} \leq \bar{D}$, where $\bar{C}$ and $\bar{C}$ are the averages of C_{pq} and D_{pq}, respectively, the method indicates that A_p outranks A_q.

3.3 Fuzzy ELECTRE Method

The weights of the criteria and the ratings of the alternatives for each criterion are accurately known in traditional ELECTRE methods, and crisp values are utilized in the evaluation process. Exact or precise facts, however, are frequently insufficient to accurately predict actual circumstances.

3.3.1 Fuzzy Triangular Numbers

Depending on the circumstance, many fuzzy numbers can be used. Due to their computational simplicity, triangular fuzzy numbers (TFNs) are valuable in applications because they facilitate representation and information processing in a fuzzy environment. In this study, fuzzy triangular numbers are used when describing the aggregated fuzzy importance weights.

Triangular fuzzy numbers can be described as a triplet with the parameters a, b, and c denoting the lowest, most promising, and largest possible values that can be used to

characterize a fuzzy event, respectively. In Figure 3.3, a triangular fuzzy number depicted.

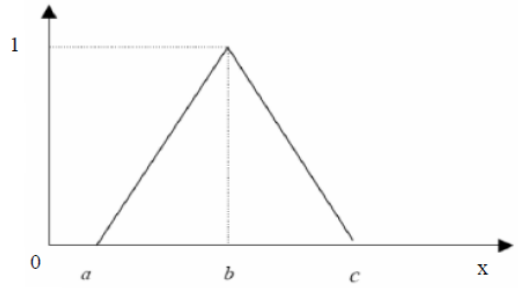


Figure 3.3 An example of a triangular membership function

3.3.2 Steps of Fuzzy ELECTRE Method

Step 1: In the first step, a panel of decision-makers (DMs) is established. The group has K decision makers (D_1, D_2, …, D_k) determines the importance each criterion (C_1, C_2, …, C_n) using linguistic variables Table 3.6. Then, the aggregated fuzzy importance weigh for each criterion can be described as fuzzy triangular numbers $\widetilde{w} = (l_j, m_j, u_j)$ for k=1,2, …, K and j=1,2, …, n. The aggregated fuzzy importance weight can be determined as follows:

$$l_{jk} = min_k\{y_{jk}\}\text{c} \qquad m_{jk} = \frac{1}{k}\sum_{k=1}^{k} y_{jk} \qquad u_{jk} = max_k\{y_{jk}\} \tag{3.7}$$

Table 3.6 Linguistic variables for the weight of each criterion (Chen, 2000)

Importance	Fuzzy triangular numbers
Very Low (VL)	(0, 0, 0.1)
Low (L)	(0, 0.1, 0.3)
Medium Low (ML)	(0.1, 0.3, 0.5)
Medium (M)	(0.3, 0.5, 0.7)
Medium High (MH)	(0.5, 0.7, 0.9)
High (H)	(0.7, 0.9, 1.0)
Very High (VH)	(0.9, 1.0, 1.0)

Then, the aggregated fuzzy importance weight for each criterion is normalized as $\widetilde{w} = (w_j^1, w_j^2, w_j^3)$, where

$$w_{j1} = \frac{1/l_j}{\sum_{j=1}^{n} 1/l_j} \qquad w_{j2} = \frac{1/m_j}{\sum_{j=1}^{n} 1/m_j} \qquad w_{j3} = \frac{1/u_j}{\sum_{j=1}^{n} 1/u_j} \tag{3.8}$$

Then the normalized aggregated fuzzy importance weight matrix is constructed as $\widetilde{W} = [\widetilde{w}_1, \widetilde{w}_2, \widetilde{w}_3]$.

Step 2: A decision matrix is created:

$$X = \begin{bmatrix} X_{11} & X_{12} & \cdots & X_{1m} \\ X_{21} & X_{22} & \cdots & X_{2m} \\ \vdots & & & \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix} \tag{3.9}$$

Step 3: After creating the decision matrix, normalization is applied. In order to conduct the calculation, formulas (3.1) and (3.2) are used. The normalized decision matrix is then obtained as follows:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \vdots & & & \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{3.10}$$

Step 4: The weighted normalized decision matrix is calculated by multiplying the values in the normalized decision matrix by the importance weight of the assessment criteria, taking into account the various weights of each criterion. For each criterion, the weighted normalized decision matrix V is defined as

$\tilde{V} = \left[\breve{v}_{ij}\right]_{m\times n}$ for i = 1, 2, … , m and j =1, 2, … , n, where $\tilde{v}_{ij} = r_{ij} \times \tilde{w}_j$, (3.11)

and

$$V^1 = \begin{bmatrix} v_{11}^1 & v_{12}^1 & \cdots & v_{1m}^1 \\ v_{21}^1 & v_{22}^1 & \cdots & v_{2m}^1 \\ \vdots & & & \\ v_{m1}^1 & v_{m2}^1 & \cdots & v_{mn}^1 \end{bmatrix}, V^2 = \begin{bmatrix} v_{11}^2 & v_{12}^2 & \cdots & v_{1m}^2 \\ v_{21}^2 & v_{22}^2 & \cdots & v_{2m}^2 \\ \vdots & & & \\ v_{m1}^2 & v_{m2}^2 & \cdots & v_{mn}^2 \end{bmatrix}, \quad (3.12)$$

$$V^3 = \begin{bmatrix} v_{11}^3 & v_{12}^3 & \cdots & v_{1m}^3 \\ v_{21}^3 & v_{22}^3 & \cdots & v_{2m}^3 \\ \vdots & & & \\ v_{m1}^3 & v_{m2}^3 & \cdots & v_{mn}^3 \end{bmatrix}.$$

Here $\breve{v}_{ij}$ denotes normalized positive triangular fuzzy numbers.

Step 5: Different weights of each criterion (w_{j1}, w_{j2}, w_{j3}) are used to calculate the concordance and discordance indexes. The level of confidence in pairwise judgments ($A_p \rightarrow A_q$) is represented by the concordance index C_{pq}. For the suggested model, the concordance index C_{pq} is defined as

$$C_{pq}^1 = \sum_{j^*} w_{j1},\ C_{pq}^2 = \sum_{j^*} w_{j2},\ C_{pq}^3 = \sum_{j^*} w_{j3}, \quad (3.13)$$

Where j^* are attributes contained in the concordance set *C(p, q)*.

Step 6: On the other hand, the discordance index evaluates the power of *D(p, q)*. The degree of disagreement in ($A_p \rightarrow A_q$) is represented by the discordance index *D(p, q)*, which can be defined as

$$D_{pq}^{1} = \frac{\sum_{j+}\left|v_{pj+}^{1} - v_{qj+}^{1}\right|}{\sum_{j}\left|v_{pj}^{1} - v_{qj}^{1}\right|}, \quad D_{pq}^{2} = \frac{\sum_{j+}\left|v_{pj+}^{2} - v_{qj+}^{2}\right|}{\sum_{j}\left|v_{pj}^{2} - v_{qj}^{2}\right|}, \quad D_{pq}^{3} = \frac{\sum_{j+}\left|v_{pj+}^{3} - v_{qj+}^{3}\right|}{\sum_{j}\left|v_{pj}^{3} - v_{qj}^{3}\right|}, \tag{3.14}$$

Where j^{+} are attributes that discordance set *D(p, q)* contains and v_{ij} is the weighted normalized calculation of alternatives *i* on criterion *j*.

Step 7: The following formula is used to determine the final concordance and discordance indexes:

$$C_{pq}^{*} = \sqrt[z]{\prod_{z=1}^{Z} C_{pq}^{z}}, \; D_{pq}^{*} = \sqrt[z]{\prod_{z=1}^{Z} D_{pq}^{z}}, \text{ where } Z = 3. \tag{3.15}$$

Step 8: Ranking process is obtained by sorting final values of alternatives in descending order. Final value of alternative *p* is calculated using formula

$$\boldsymbol{F_p = \sum_{q} C_{pq}^{*} - D_{pq}^{*}} \tag{3.16}$$

CHAPTER FOUR
CASE STUDY

The decision support system developed in this study is used in a case study focusing on mobile phone reviews to choose the best mobile phone from a selection of alternatives using aspect level sentiment analysis and the Fuzzy ELECTRE approach. A total of 20 products from 5 different brands have been analyzed in this study. These alternatives and the number of reviews of each alternative are listed in Table 4.1. Reviews are crawled from 4 sites:

- vatanbilgisayar.com
- amazon.com.tr
- hepsiburada.com
- gittigidiyor.com

Table 4.1 List of products

Brand	Product	Number of Reviews
Apple	iPhone 11	4934
	iPhone 12	692
	iPhone 12 Pro Max	313
	iPhone SE	2321
Samsung	Galaxy Note 20	225
	Galaxy S21	314
	Galaxy S20 FE	2427
	Galaxy A32	1417
Huawei	P30 Lite	1386
	P40 Lite	1244
	P Smart 2021	230
	P Smart Pro	88
Xiaomi	Redmi 9T	1205
	Redmi Note 10 S	1663
	Mi 11 Lite	943
	Poco X3 Pro	2628
Oppo	Reno 5 Lite	2897
	A54	640
	A74	1508
	A15 s	230

After crawling reviews, steps of sentiment analysis have been implemented as explained in section 3.1. The 20 products are evaluated based on six criteria (please see 3.1.2 Aspect Extraction). Notations used in this section are shown in Table 4.2.

Table 4.2 Notations

Symbol	Definition
C1	Function
C2	Battery
C3	Price
C4	Screen
C5	Appearance
C6	Camera
A1	Samsung Galaxy A32
A2	Samsung Galaxy Note 20
A3	Huawei P30 Lite
A4	Huawei P40 Lite
A5	Huawei P Smart 2021
A6	Huawei P Smart Pro
A7	Apple iPhone 11
A8	Apple iPhone 12 Pro Max
A9	Apple iPhone 12
A10	Apple iPhone SE
A11	Oppo A15
A12	Oppo A54
A13	Oppo A74
A14	Oppo Reno 5
A15	Xiaomi Poco X3 Pro
A16	Samsung Galaxy S20 FE
A17	Samsung Galaxy S21
A18	Xiaomi Mi 11
A19	Xiaomi Redmi 9T
A20	Xiaomi Redmi Note 10
D1	Decision maker 1
D2	Decision maker 2
D3	Decision maker 3
D4	Decision maker 4
D5	Decision maker 5

After the sentiment analysis phase, Fuzzy ELECTRE steps are implemented as explained in section 3.3.2. In this chapter, every step of the developed decision support system is shown in tables and all the numbers are rounded to two digits after the decimal point.

In the first step of Fuzzy ELECTRE method, the importance of each weight is determined by five decision makers (Table 4.3). Linguistic variables which are shown in Table 3.6 have been used for determining the importance of the criteria (Chen, 2000).

Table 4.3 Importance of criteria

	Function	**Battery**	**Price**	**Screen**	**Design**	**Camera**
D1	M	H	H	MH	M	ML
D2	H	H	VH	M	ML	M
D3	H	VH	ML	MH	MH	H
D4	VH	VH	M	MH	MH	VH
D5	M	H	MH	ML	VH	H

Aggregated fuzzy importance weights have evaluated based on importance of each criteria using the equation (3.7) (Table 4.4) and normalized using equation (3.8) (Table 4.5). For example, five decision makers determined importance of Function criterion medium, high, high, very high and medium respectively. Fuzzy triangular numbers corresponding to these importance values are show in the Function row of Table 4.4. (l_j, m_j, u_j) values of Function criterion are evaluated using equation (3.7). *l* value of this criterion is the minimum value of the first row of Function section which is 0.3, *m* value of this criterion is average of the second row which is 0.8, and the *u* value of this criterion is the maximum value of third row which is 1.0.

Table 4.4 Calculation of the aggregated fuzzy importance weights

	y_{ik}					
	D1	**D2**	**D3**	**D4**	**D5**	(l_j, m_j, u_j)
Function	0.3	0.7	0.7	0.9	0.3	**0.3**
	0.5	0.9	0.9	1.0	1.0	**0.8**
	0.7	1.0	1.0	1.0	0.7	**1.0**
Battery	0.7	0.7	0.9	0.9	0.7	**0.7**
	0.9	0.9	1.0	1.0	0.9	**0.9**
	1.0	1.0	1.0	1.0	1.0	**1.0**
Price	0.7	0.9	1.0	0.3	0.5	**0.1**
	0.9	1.0	0.3	0.5	0.7	**0.7**
	1.0	1.0	0.5	0.7	0.9	**1.0**
Screen	0.5	0.3	0.5	0.5	0.1	**0.1**
	0.7	0.5	0.7	0.7	0.3	**0.6**
	0.9	0.7	0.9	0.9	0.5	**0.9**
Appearance	0.3	0.1	0.5	0.5	0.9	**0.1**
	0.5	0.3	0.7	0.7	1.0	**0.6**
	0.7	0.5	0.9	0.9	1.0	**1.0**
Camera	0.1	0.3	0.7	0.9	0.7	**0.1**
	0.3	0.5	0.9	1.0	0.9	**0.7**
	0.5	0.7	1.0	1.0	1.0	**1.0**

Table 4.5 Normalized aggregated fuzzy importance weight matrix

	W_1	**W_2**	**W_3**
C1	0.074	0.146	0.164
C2	0.032	0.130	0.164
C3	0.223	0.167	0.164
C4	0.223	0.195	0.182
C5	0.223	0.195	0.164
C6	0.223	0.167	0.164

The decision matrix has developed using the results of sentiment analysis and normalized using equation (3.1). Decision matrix X is shown in Table 4.6 and normalized decision matrix R is shown in Table 4.7.

Table 4.6 Decision matrix X

	C1	C2	C3	C4	C5	C6
A1	151.576	96.238	175.740	77.627	73.795	111.665
A2	27.127	11.808	9.653	15.058	5.463	14.605
A3	223.947	105.391	264.648	75.969	161.336	227.706
A4	246.809	208.619	184.490	62.206	56.946	158.209
A5	15.815	16.011	19.548	14.635	9.238	16.363
A6	14.197	0.747	24.066	6.429	0.458	5.232
A7	756.526	282.350	585.949	139.169	152.667	282.211
A8	43.550	24.171	67.512	27.575	17.436	35.800
A9	107.562	37.435	88.477	58.391	65.877	57.783
A10	531.485	229.676	442.006	230.301	121.596	278.472
A11	23.048	6.844	36.906	5.404	16.083	7.096
A12	94.617	69.790	167.003	28.581	9.456	50.157
A13	135.158	133.213	201.949	122.380	94.876	100.145
A14	537.993	596.694	637.707	333.981	338.234	526.208
A15	588.414	400.093	550.976	238.016	-34.325	353.943
A16	655.796	357.743	467.451	390.526	171.503	501.359
A17	87.874	50.039	45.064	62.365	72.619	64.176
A18	338.606	186.442	211.855	171.179	522.362	252.620
A19	134.971	99.980	187.514	35.575	14.910	44.777
A20	308.595	237.424	295.694	151.012	110.586	183.272

Table 4.7 Normalized decision matrix R

	C1	C2	C3	C4	C5	C6
A1	0.099	0.098	0.129	0.111	0.102	0.110
A2	0.018	0.012	0.007	0.022	0.008	0.014
A3	0.147	0.107	0.194	0.109	0.223	0.225
A4	0.162	0.212	0.135	0.089	0.079	0.157
A5	0.010	0.016	0.014	0.021	0.013	0.016
A6	0.009	0.001	0.018	0.009	0.001	0.005
A7	0.495	0.287	0.430	0.200	0.211	0.279
A8	0.029	0.025	0.050	0.040	0.024	0.035
A9	0.070	0.038	0.065	0.084	0.091	0.057
A10	0.348	0.233	0.324	0.330	0.168	0.276
A11	0.015	0.007	0.027	0.008	0.022	0.007
A12	0.062	0.071	0.123	0.041	0.013	0.050
A13	0.088	0.135	0.148	0.175	0.131	0.099
A14	0.352	0.606	0.468	0.479	0.468	0.521
A15	0.385	0.406	0.404	0.341	-0.047	0.350
A16	0.429	0.363	0.343	0.560	0.237	0.496
A17	0.058	0.051	0.033	0.089	0.100	0.064
A18	0.222	0.189	0.156	0.245	0.723	0.250
A19	0.088	0.102	0.138	0.051	0.021	0.044
A20	0.202	0.241	0.217	0.217	0.153	0.181

Fuzzy weighted normalized decision matrices V^1, V^2 and V^3 which are calculated using equation (3.11) are shown respectively in Table 4.8, Table 4.9 and Table 4.10. For example, v_{11}^1 (0.007) which corresponds to the first item in matrix V^1 is calculated by multiplying r_{11} (0.099) which corresponds to the first item in the normalized decision matrix *R* and w_{11} (0.074) which corresponds to the first item in the normalized aggregated fuzzy importance weight matrix $\widetilde{W}$.

Table 4.8 Matrix V^1

	C1	C2	C3	C4	C5	C6
A1	0.007	0.003	0.029	0.025	0.023	0.025
A2	0.001	0.000	0.002	0.005	0.002	0.003
A3	0.011	0.003	0.043	0.024	0.050	0.050
A4	0.012	0.007	0.030	0.020	0.018	0.035
A5	0.001	0.001	0.003	0.005	0.003	0.004
A6	0.001	0.000	0.004	0.002	0.000	0.001
A7	0.037	0.009	0.096	0.045	0.047	0.062
A8	0.002	0.001	0.011	0.009	0.005	0.008
A9	0.005	0.001	0.015	0.019	0.020	0.013
A10	0.026	0.007	0.072	0.074	0.038	0.062
A11	0.001	0.000	0.006	0.002	0.005	0.002
A12	0.005	0.002	0.027	0.009	0.003	0.011
A13	0.007	0.004	0.033	0.039	0.029	0.022
A14	0.026	0.019	0.105	0.107	0.105	0.116
A15	0.029	0.013	0.090	0.076	-0.011	0.078
A16	0.032	0.012	0.077	0.125	0.053	0.111
A17	0.004	0.002	0.007	0.020	0.022	0.014
A18	0.017	0.006	0.035	0.055	0.161	0.056
A19	0.007	0.003	0.031	0.011	0.005	0.010
A20	0.015	0.008	0.048	0.048	0.034	0.041

Table 4.9 Matrix V^2

	C1	C2	C3	C4	C5	C6
A1	0.015	0.013	0.022	0.022	0.020	0.018
A2	0.003	0.002	0.001	0.004	0.001	0.002
A3	0.021	0.014	0.032	0.021	0.044	0.038
A4	0.024	0.028	0.023	0.017	0.015	0.026
A5	0.002	0.002	0.002	0.004	0.002	0.003
A6	0.001	0.000	0.003	0.002	0.000	0.001
A7	0.072	0.037	0.072	0.039	0.041	0.047
A8	0.004	0.003	0.008	0.008	0.005	0.006
A9	0.010	0.005	0.011	0.016	0.018	0.010
A10	0.051	0.030	0.054	0.064	0.033	0.046
A11	0.002	0.001	0.005	0.002	0.004	0.001
A12	0.009	0.009	0.020	0.008	0.003	0.008
A13	0.013	0.018	0.025	0.034	0.026	0.017
A14	0.051	0.079	0.078	0.093	0.091	0.087
A15	0.056	0.053	0.068	0.067	-0.009	0.059
A16	0.063	0.047	0.057	0.109	0.046	0.083
A17	0.008	0.007	0.006	0.017	0.020	0.011
A18	0.032	0.025	0.026	0.048	0.141	0.042
A19	0.013	0.013	0.023	0.010	0.004	0.007
A20	0.030	0.031	0.036	0.042	0.030	0.030

Table 4.10 Matrix V^3

	C1	C2	C3	C4	C5	C6
A1	0.016	0.016	0.021	0.020	0.017	0.018
A2	0.003	0.002	0.001	0.004	0.001	0.002
A3	0.024	0.018	0.032	0.020	0.037	0.037
A4	0.026	0.035	0.022	0.016	0.013	0.026
A5	0.002	0.003	0.002	0.004	0.002	0.003
A6	0.002	0.000	0.003	0.002	0.000	0.001
A7	0.081	0.047	0.070	0.036	0.035	0.046
A8	0.005	0.004	0.008	0.007	0.004	0.006
A9	0.012	0.006	0.011	0.015	0.015	0.009
A10	0.057	0.038	0.053	0.060	0.028	0.045
A11	0.002	0.001	0.004	0.001	0.004	0.001
A12	0.010	0.012	0.020	0.007	0.002	0.008
A13	0.014	0.022	0.024	0.032	0.021	0.016
A14	0.058	0.099	0.077	0.087	0.077	0.085
A15	0.063	0.067	0.066	0.062	-0.008	0.057
A16	0.070	0.059	0.056	0.102	0.039	0.081
A17	0.009	0.008	0.005	0.016	0.016	0.010
A18	0.036	0.031	0.025	0.045	0.118	0.041
A19	0.014	0.017	0.023	0.009	0.003	0.007
A20	0.033	0.039	0.036	0.039	0.025	0.030

Different weights of each criterion (wj1, wj2, wj3) are used to calculate the concordance and discordance indexes using equations (3.13) and (3.14). In order to calculate concordance and discordance indexes, concordance and discordance sets are used which are shown in Table 4.11 and Table 4.12 respectively. Concordance and discordance indexes are shown in Table 4.13, Table 4.14, Table 4.15, Table 4.16, Table 4.17, Table 4.18.

It can be seen in the first row of Table 4.11 that in pairwise comparison, Alternative 1 is better than Alternative 2 in all criteria. Therefore, all concordance indexes of Alternative equals to 1. On the other hand, Alternative 1 is better than Alternative 4 in only two criteria, Criteria 4 and Criteria 5. Therefore, C_{14}^{1} is sum of $w_{41} + w_{51}$ which equals to 0.45. This correspond to the forth value of the first row at Table 4.13.

Table 4.11 Concordance set C(*p*,*q*)

	C1	C2	C3	C4	C5	C6
A1A2	1	1	1	1	1	1
A1A3	0	0	0	1	0	0
A1A4	0	0	0	1	1	0
A1A5	1	1	1	1	1	1
A1A6	1	1	1	1	1	1
A1A7	0	0	0	0	0	0
A1A8	1	1	1	1	1	1
A1A9	1	1	1	1	1	1
A1A10	0	0	0	0	0	0
A1A11	1	1	1	1	1	1
A1A12	1	1	1	1	1	1
A1A13	1	0	0	0	0	1
A1A14	0	0	0	0	0	0
A1A15	0	0	0	0	1	0
A1A16	0	0	0	0	0	0
A1A17	1	1	1	1	1	1
A1A18	0	0	0	0	0	0
A1A19	1	0	0	1	1	1
A1A20	0	0	0	0	0	0
A2A1	0	0	0	0	0	0
A2A3	0	0	0	0	0	0
A2A4	0	0	0	0	0	0
A2A5	1	0	0	1	0	0
A2A6	1	1	0	1	1	1
A2A7	0	0	0	0	0	0
A2A8	0	0	0	0	0	0
A2A9	0	0	0	0	0	0
A2A10	0	0	0	0	0	0
A2A11	1	1	0	1	0	1
A2A12	0	0	0	0	0	0
A2A13	0	0	0	0	0	0
A2A14	0	0	0	0	0	0
A2A15	0	0	0	0	1	0
A2A16	0	0	0	0	0	0
A2A17	0	0	0	0	0	0
A2A18	0	0	0	0	0	0
A2A19	0	0	0	0	0	0
A2A20	0	0	0	0	0	0
A3A1	1	1	1	0	1	1
A3A2	1	1	1	1	1	1
A3A4	0	0	1	1	1	1
A3A5	1	1	1	1	1	1

Table 4.11 Continues

A3A6	1	1	1	1	1	1
A3A7	0	0	0	0	1	0
A3A8	1	1	1	1	1	1
A3A9	1	1	1	1	1	1
A3A10	0	0	0	0	1	0
A3A11	1	1	1	1	1	1
A3A12	1	1	1	1	1	1
A3A13	1	0	1	0	1	1
A3A14	0	0	0	0	0	0
A3A15	0	0	0	0	1	0
A3A16	0	0	0	0	0	0
A3A17	1	1	1	1	1	1
A3A18	0	0	1	0	0	0
A3A19	1	1	1	1	1	1
A3A20	0	0	0	0	1	1
A4A1	1	1	1	0	0	1
A4A2	1	1	1	1	1	1
A4A3	1	1	0	0	0	0
A4A5	1	1	1	1	1	1
A4A6	1	1	1	1	1	1
A4A7	0	0	0	0	0	0
A4A8	1	1	1	1	1	1
A4A9	1	1	1	1	0	1
A4A10	0	0	0	0	0	0
A4A11	1	1	1	1	1	1
A4A12	1	1	1	1	1	1
A4A13	1	1	0	0	0	1
A4A14	0	0	0	0	0	0
A4A15	0	0	0	0	1	0
A4A16	0	0	0	0	0	0
A4A17	1	1	1	0	0	1
A4A18	0	1	0	0	0	0
A4A19	1	1	0	1	1	1
A4A20	0	0	0	0	0	0
A5A1	0	0	0	0	0	0
A5A2	0	1	1	0	1	1
A5A3	0	0	0	0	0	0
A5A4	0	0	0	0	0	0
A5A6	1	1	0	1	1	1
A5A7	0	0	0	0	0	0
A5A8	0	0	0	0	0	0

Table 4.11 Continues

A5A9	0	0	0	0	0	0
A5A10	0	0	0	0	0	0
A5A11	0	1	0	1	0	1
A5A12	0	0	0	0	0	0
A5A13	0	0	0	0	0	0
A5A14	0	0	0	0	0	0
A5A15	0	0	0	0	1	0
A5A16	0	0	0	0	0	0
A5A17	0	0	0	0	0	0
A5A18	0	0	0	0	0	0
A5A19	0	0	0	0	0	0
A5A20	0	0	0	0	0	0
A6A1	0	0	0	0	0	0
A6A2	0	0	1	0	0	0
A6A3	0	0	0	0	0	0
A6A4	0	0	0	0	0	0
A6A5	0	0	1	0	0	0
A6A7	0	0	0	0	0	0
A6A8	0	0	0	0	0	0
A6A9	0	0	0	0	0	0
A6A10	0	0	0	0	0	0
A6A11	0	0	0	1	0	0
A6A12	0	0	0	0	0	0
A6A13	0	0	0	0	0	0
A6A14	0	0	0	0	0	0
A6A15	0	0	0	0	1	0
A6A16	0	0	0	0	0	0
A6A17	0	0	0	0	0	0
A6A18	0	0	0	0	0	0
A6A19	0	0	0	0	0	0
A6A20	0	0	0	0	0	0
A7A1	1	1	1	1	1	1
A7A2	1	1	1	1	1	1
A7A3	1	1	1	1	0	1
A7A4	1	1	1	1	1	1
A7A5	1	1	1	1	1	1
A7A6	1	1	1	1	1	1
A7A8	1	1	1	1	1	1
A7A9	1	1	1	1	1	1
A7A10	1	1	1	0	1	1
A7A11	1	1	1	1	1	1
A7A12	1	1	1	1	1	1
A7A13	1	1	1	1	1	1

Table 4.11 Continues

A7A14	1	0	0	0	0	0
A7A15	1	0	1	0	1	0
A7A16	1	0	1	0	0	0
A7A17	1	1	1	1	1	1
A7A18	1	1	1	0	0	1
A7A19	1	1	1	1	1	1
A7A20	1	1	1	0	1	1
A8A1	0	0	0	0	0	0
A8A2	1	1	1	1	1	1
A8A3	0	0	0	0	0	0
A8A4	0	0	0	0	0	0
A8A5	1	1	1	1	1	1
A8A6	1	1	1	1	1	1
A8A7	0	0	0	0	0	0
A8A9	0	0	0	0	0	0
A8A10	0	0	0	0	0	0
A8A11	1	1	1	1	1	1
A8A12	0	0	0	0	1	0
A8A13	0	0	0	0	0	0
A8A14	0	0	0	0	0	0
A8A15	0	0	0	0	1	0
A8A16	0	0	0	0	0	0
A8A17	0	0	1	0	0	0
A8A18	0	0	0	0	0	0
A8A19	0	0	0	0	1	0
A8A20	0	0	0	0	0	0
A9A1	0	0	0	0	0	0
A9A2	1	1	1	1	1	1
A9A3	0	0	0	0	0	0
A9A4	0	0	0	0	1	0
A9A5	1	1	1	1	1	1
A9A6	1	1	1	1	1	1
A9A7	0	0	0	0	0	0
A9A8	1	1	1	1	1	1
A9A10	0	0	0	0	0	0
A9A11	1	1	1	1	1	1
A9A12	1	0	0	1	1	1
A9A13	0	0	0	0	0	0
A9A14	0	0	0	0	0	0
A9A15	0	0	0	0	1	0
A9A16	0	0	0	0	0	0
A9A17	1	0	1	0	0	0
A9A18	0	0	0	0	0	0

Table 4.11 Continues

A9A19	0	0	0	1	1	1
A9A20	0	0	0	0	0	0
A10A1	1	1	1	1	1	1
A10A2	1	1	1	1	1	1
A10A3	1	1	1	1	0	1
A10A4	1	1	1	1	1	1
A10A5	1	1	1	1	1	1
A10A6	1	1	1	1	1	1
A10A7	0	0	0	1	0	0
A10A8	1	1	1	1	1	1
A10A9	1	1	1	1	1	1
A10A11	1	1	1	1	1	1
A10A12	1	1	1	1	1	1
A10A13	1	1	1	1	1	1
A10A14	0	0	0	0	0	0
A10A15	0	0	0	0	1	0
A10A16	0	0	0	0	0	0
A10A17	1	1	1	1	1	1
A10A18	1	1	1	1	0	1
A10A19	1	1	1	1	1	1
A10A20	1	0	1	1	1	1
A11A1	0	0	0	0	0	0
A11A2	0	0	1	0	1	0
A11A3	0	0	0	0	0	0
A11A4	0	0	0	0	0	0
A11A5	1	0	1	0	1	0
A11A6	1	1	1	0	1	1
A11A7	0	0	0	0	0	0
A11A8	0	0	0	0	0	0
A11A9	0	0	0	0	0	0
A11A10	0	0	0	0	0	0
A11A12	0	0	0	0	1	0
A11A13	0	0	0	0	0	0
A11A14	0	0	0	0	0	0
A11A15	0	0	0	0	1	0
A11A16	0	0	0	0	0	0
A11A17	0	0	0	0	0	0
A11A18	0	0	0	0	0	0
A11A19	0	0	0	0	1	0
A11A20	0	0	0	0	0	0
A12A1	0	0	0	0	0	0
A12A2	1	1	1	1	1	1
A12A3	0	0	0	0	0	0

Table 4.11 Continues

A12A4	0	0	0	0	0	0
A12A5	1	1	1	1	1	1
A12A6	1	1	1	1	1	1
A12A7	0	0	0	0	0	0
A12A8	1	1	1	1	0	1
A12A9	0	1	1	0	0	0
A12A10	0	0	0	0	0	0
A12A11	1	1	1	1	0	1
A12A13	0	0	0	0	0	0
A12A14	0	0	0	0	0	0
A12A15	0	0	0	0	1	0
A12A16	0	0	0	0	0	0
A12A17	1	1	1	0	0	0
A12A18	0	0	0	0	0	0
A12A19	0	0	0	0	0	1
A12A20	0	0	0	0	0	0
A13A1	0	1	1	1	1	0
A13A2	1	1	1	1	1	1
A13A3	0	1	0	1	0	0
A13A4	0	0	1	1	1	0
A13A5	1	1	1	1	1	1
A13A6	1	1	1	1	1	1
A13A7	0	0	0	0	0	0
A13A8	1	1	1	1	1	1
A13A9	1	1	1	1	1	1
A13A10	0	0	0	0	0	0
A13A11	1	1	1	1	1	1
A13A12	1	1	1	1	1	1
A13A14	0	0	0	0	0	0
A13A15	0	0	0	0	1	0
A13A16	0	0	0	0	0	0
A13A17	1	1	1	1	1	1
A13A18	0	0	0	0	0	0
A13A19	1	1	1	1	1	1
A13A20	0	0	0	0	0	0
A14A1	1	1	1	1	1	1
A14A2	1	1	1	1	1	1
A14A3	1	1	1	1	1	1
A14A4	1	1	1	1	1	1
A14A5	1	1	1	1	1	1
A14A6	1	1	1	1	1	1
A14A7	0	1	1	1	1	1
A14A8	1	1	1	1	1	1

Table 4.11 Continues

A14A9	1	1	1	1	1	1
A14A10	1	1	1	1	1	1
A14A11	1	1	1	1	1	1
A14A12	1	1	1	1	1	1
A14A13	1	1	1	1	1	1
A14A15	0	1	1	1	1	1
A14A16	0	1	1	0	1	1
A14A17	1	1	1	1	1	1
A14A18	1	1	1	1	0	1
A14A19	1	1	1	1	1	1
A14A20	1	1	1	1	1	1
A15A1	1	1	1	1	0	1
A15A2	1	1	1	1	0	1
A15A3	1	1	1	1	0	1
A15A4	1	1	1	1	0	1
A15A5	1	1	1	1	0	1
A15A6	1	1	1	1	0	1
A15A7	0	1	0	1	0	1
A15A8	1	1	1	1	0	1
A15A9	1	1	1	1	0	1
A15A10	1	1	1	1	0	1
A15A11	1	1	1	1	0	1
A15A12	1	1	1	1	0	1
A15A13	1	1	1	1	0	1
A15A14	1	0	0	0	0	0
A15A16	0	1	1	0	0	0
A15A17	1	1	1	1	0	1
A15A18	1	1	1	1	0	1
A15A19	1	1	1	1	0	1
A15A20	1	1	1	1	0	1
A16A1	1	1	1	1	1	1
A16A2	1	1	1	1	1	1
A16A3	1	1	1	1	1	1
A16A4	1	1	1	1	1	1
A16A5	1	1	1	1	1	1
A16A6	1	1	1	1	1	1
A16A7	0	1	0	1	1	1
A16A8	1	1	1	1	1	1
A16A9	1	1	1	1	1	1
A16A10	1	1	1	1	1	1
A16A11	1	1	1	1	1	1
A16A12	1	1	1	1	1	1
A16A13	1	1	1	1	1	1

Table 4.11 Continues

A16A14	1	0	0	1	0	0
A16A15	1	0	0	1	1	1
A16A17	1	1	1	1	1	1
A16A18	1	1	1	1	0	1
A16A19	1	1	1	1	1	1
A16A20	1	1	1	1	1	1
A17A1	0	0	0	0	0	0
A17A2	1	1	1	1	1	1
A17A3	0	0	0	0	0	0
A17A4	0	0	0	1	1	0
A17A5	1	1	1	1	1	1
A17A6	1	1	1	1	1	1
A17A7	0	0	0	0	0	0
A17A8	1	1	0	1	1	1
A17A9	0	1	0	1	1	1
A17A10	0	0	0	0	0	0
A17A11	1	1	1	1	1	1
A17A12	0	0	0	1	1	1
A17A13	0	0	0	0	0	0
A17A14	0	0	0	0	0	0
A17A15	0	0	0	0	1	0
A17A16	0	0	0	0	0	0
A17A18	0	0	0	0	0	0
A17A19	0	0	0	1	1	1
A17A20	0	0	0	0	0	0
A18A1	1	1	1	1	1	1
A18A2	1	1	1	1	1	1
A18A3	1	1	0	1	1	1
A18A4	1	0	1	1	1	1
A18A5	1	1	1	1	1	1
A18A6	1	1	1	1	1	1
A18A7	0	0	0	1	1	0
A18A8	1	1	1	1	1	1
A18A9	1	1	1	1	1	1
A18A10	0	0	0	0	1	0
A18A11	1	1	1	1	1	1
A18A12	1	1	1	1	1	1
A18A13	1	1	1	1	1	1
A18A14	0	0	0	0	1	0
A18A15	0	0	0	0	1	0
A18A16	0	0	0	0	1	0
A18A17	1	1	1	1	1	1
A18A19	1	1	1	1	1	1

Table 4.11 Continues

A18A20	1	0	0	1	1	1
A19A1	0	1	1	0	0	0
A19A2	1	1	1	1	1	1
A19A3	0	0	0	0	0	0
A19A4	0	0	1	0	0	0
A19A5	1	1	1	1	1	1
A19A6	1	1	1	1	1	1
A19A7	0	0	0	0	0	0
A19A8	1	1	1	1	0	1
A19A9	1	1	1	0	0	0
A19A10	0	0	0	0	0	0
A19A11	1	1	1	1	0	1
A19A12	1	1	1	1	1	0
A19A13	0	0	0	0	0	0
A19A14	0	0	0	0	0	0
A19A15	0	0	0	0	1	0
A19A16	0	0	0	0	0	0
A19A17	1	1	1	0	0	0
A19A18	0	0	0	0	0	0
A19A20	0	0	0	0	0	0
A20A1	1	1	1	1	1	1
A20A2	1	1	1	1	1	1
A20A3	1	1	1	1	0	0
A20A4	1	1	1	1	1	1
A20A5	1	1	1	1	1	1
A20A6	1	1	1	1	1	1
A20A7	0	0	0	1	0	0
A20A8	1	1	1	1	1	1
A20A9	1	1	1	1	1	1
A20A10	0	1	0	0	0	0
A20A11	1	1	1	1	1	1
A20A12	1	1	1	1	1	1
A20A13	1	1	1	1	1	1
A20A14	0	0	0	0	0	0
A20A15	0	0	0	0	1	0
A20A16	0	0	0	0	0	0
A20A17	1	1	1	1	1	1
A20A18	0	1	1	0	0	0
A20A19	1	1	1	1	1	1

Table 4.12 Discordance set D(*p*,*q*)

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
A1A2	0	0	0	0	0	0
A1A3	1	1	1	0	1	1
A1A4	1	1	1	0	0	1
A1A5	0	0	0	0	0	0
A1A6	0	0	0	0	0	0
A1A7	1	1	1	1	1	1
A1A8	0	0	0	0	0	0
A1A9	0	0	0	0	0	0
A1A10	1	1	1	1	1	1
A1A11	0	0	0	0	0	0
A1A12	0	0	0	0	0	0
A1A13	0	1	1	1	1	0
A1A14	1	1	1	1	1	1
A1A15	1	1	1	1	0	1
A1A16	1	1	1	1	1	1
A1A17	0	0	0	0	0	0
A1A18	1	1	1	1	1	1
A1A19	0	1	1	0	0	0
A1A20	1	1	1	1	1	1
A2A1	1	1	1	1	1	1
A2A3	1	1	1	1	1	1
A2A4	1	1	1	1	1	1
A2A5	0	1	1	0	1	1
A2A6	0	0	1	0	0	0
A2A7	1	1	1	1	1	1
A2A8	1	1	1	1	1	1
A2A9	1	1	1	1	1	1
A2A10	1	1	1	1	1	1
A2A11	0	0	1	0	1	0
A2A12	1	1	1	1	1	1
A2A13	1	1	1	1	1	1
A2A14	1	1	1	1	1	1
A2A15	1	1	1	1	0	1
A2A16	1	1	1	1	1	1
A2A17	1	1	1	1	1	1
A2A18	1	1	1	1	1	1
A2A19	1	1	1	1	1	1
A2A20	1	1	1	1	1	1
A3A1	0	0	0	1	0	0
A3A2	0	0	0	0	0	0
A3A4	1	1	0	0	0	0
A3A5	0	0	0	0	0	0

Table 4.12 Continues

A3A6	0	0	0	0	0	0
A3A7	1	1	1	1	0	1
A3A8	0	0	0	0	0	0
A3A9	0	0	0	0	0	0
A3A10	1	1	1	1	0	1
A3A11	0	0	0	0	0	0
A3A12	0	0	0	0	0	0
A3A13	0	1	0	1	0	0
A3A14	1	1	1	1	1	1
A3A15	1	1	1	1	0	1
A3A16	1	1	1	1	1	1
A3A17	0	0	0	0	0	0
A3A18	1	1	0	1	1	1
A3A19	0	0	0	0	0	0
A3A20	1	1	1	1	0	0
A4A1	0	0	0	1	1	0
A4A2	0	0	0	0	0	0
A4A3	0	0	1	1	1	1
A4A5	0	0	0	0	0	0
A4A6	0	0	0	0	0	0
A4A7	1	1	1	1	1	1
A4A8	0	0	0	0	0	0
A4A9	0	0	0	0	1	0
A4A10	1	1	1	1	1	1
A4A11	0	0	0	0	0	0
A4A12	0	0	0	0	0	0
A4A13	0	0	1	1	1	0
A4A14	1	1	1	1	1	1
A4A15	1	1	1	1	0	1
A4A16	1	1	1	1	1	1
A4A17	0	0	0	1	1	0
A4A18	1	0	1	1	1	1
A4A19	0	0	1	0	0	0
A4A20	1	1	1	1	1	1
A5A1	1	1	1	1	1	1
A5A2	1	0	0	1	0	0
A5A3	1	1	1	1	1	1
A5A4	1	1	1	1	1	1
A5A6	0	0	1	0	0	0
A5A7	1	1	1	1	1	1
A5A8	1	1	1	1	1	1
A5A9	1	1	1	1	1	1
A5A10	1	1	1	1	1	1

Table 4.12 Continues

A5A11	1	0	1	0	1	0
A5A12	1	1	1	1	1	1
A5A13	1	1	1	1	1	1
A5A14	1	1	1	1	1	1
A5A15	1	1	1	1	0	1
A5A16	1	1	1	1	1	1
A5A17	1	1	1	1	1	1
A5A18	1	1	1	1	1	1
A5A19	1	1	1	1	1	1
A5A20	1	1	1	1	1	1
A6A1	1	1	1	1	1	1
A6A2	1	1	0	1	1	1
A6A3	1	1	1	1	1	1
A6A4	1	1	1	1	1	1
A6A5	1	1	0	1	1	1
A6A7	1	1	1	1	1	1
A6A8	1	1	1	1	1	1
A6A9	1	1	1	1	1	1
A6A10	1	1	1	1	1	1
A6A11	1	1	1	0	1	1
A6A12	1	1	1	1	1	1
A6A13	1	1	1	1	1	1
A6A14	1	1	1	1	1	1
A6A15	1	1	1	1	0	1
A6A16	1	1	1	1	1	1
A6A17	1	1	1	1	1	1
A6A18	1	1	1	1	1	1
A6A19	1	1	1	1	1	1
A6A20	1	1	1	1	1	1
A7A1	0	0	0	0	0	0
A7A2	0	0	0	0	0	0
A7A3	0	0	0	0	1	0
A7A4	0	0	0	0	0	0
A7A5	0	0	0	0	0	0
A7A6	0	0	0	0	0	0
A7A8	0	0	0	0	0	0
A7A9	0	0	0	0	0	0
A7A10	0	0	0	1	0	0
A7A11	0	0	0	0	0	0
A7A12	0	0	0	0	0	0
A7A13	0	0	0	0	0	0
A7A14	0	1	1	1	1	1
A7A15	0	1	0	1	0	1

Table 4.12 Continues

A7A16	0	1	0	1	1	1
A7A17	0	0	0	0	0	0
A7A18	0	0	0	1	1	0
A7A19	0	0	0	0	0	0
A7A20	0	0	0	1	0	0
A8A1	1	1	1	1	1	1
A8A2	0	0	0	0	0	0
A8A3	1	1	1	1	1	1
A8A4	1	1	1	1	1	1
A8A5	0	0	0	0	0	0
A8A6	0	0	0	0	0	0
A8A7	1	1	1	1	1	1
A8A9	1	1	1	1	1	1
A8A10	1	1	1	1	1	1
A8A11	0	0	0	0	0	0
A8A12	1	1	1	1	0	1
A8A13	1	1	1	1	1	1
A8A14	1	1	1	1	1	1
A8A15	1	1	1	1	0	1
A8A16	1	1	1	1	1	1
A8A17	1	1	0	1	1	1
A8A18	1	1	1	1	1	1
A8A19	1	1	1	1	0	1
A8A20	1	1	1	1	1	1
A9A1	1	1	1	1	1	1
A9A2	0	0	0	0	0	0
A9A3	1	1	1	1	1	1
A9A4	1	1	1	1	0	1
A9A5	0	0	0	0	0	0
A9A6	0	0	0	0	0	0
A9A7	1	1	1	1	1	1
A9A8	0	0	0	0	0	0
A9A10	1	1	1	1	1	1
A9A11	0	0	0	0	0	0
A9A12	0	1	1	0	0	0
A9A13	1	1	1	1	1	1
A9A14	1	1	1	1	1	1
A9A15	1	1	1	1	0	1
A9A16	1	1	1	1	1	1
A9A17	0	1	0	1	1	1
A9A18	1	1	1	1	1	1
A9A19	1	1	1	0	0	0
A9A20	1	1	1	1	1	1

Table 4.12 Continues

A10A1	0	0	0	0	0	0
A10A2	0	0	0	0	0	0
A10A3	0	0	0	0	1	0
A10A4	0	0	0	0	0	0
A10A5	0	0	0	0	0	0
A10A6	0	0	0	0	0	0
A10A7	1	1	1	0	1	1
A10A8	0	0	0	0	0	0
A10A9	0	0	0	0	0	0
A10A11	0	0	0	0	0	0
A10A12	0	0	0	0	0	0
A10A13	0	0	0	0	0	0
A10A14	1	1	1	1	1	1
A10A15	1	1	1	1	0	1
A10A16	1	1	1	1	1	1
A10A17	0	0	0	0	0	0
A10A18	0	0	0	0	1	0
A10A19	0	0	0	0	0	0
A10A20	0	1	0	0	0	0
A11A1	1	1	1	1	1	1
A11A2	1	1	0	1	0	1
A11A3	1	1	1	1	1	1
A11A4	1	1	1	1	1	1
A11A5	0	1	0	1	0	1
A11A6	0	0	0	1	0	0
A11A7	1	1	1	1	1	1
A11A8	1	1	1	1	1	1
A11A9	1	1	1	1	1	1
A11A10	1	1	1	1	1	1
A11A12	1	1	1	1	0	1
A11A13	1	1	1	1	1	1
A11A14	1	1	1	1	1	1
A11A15	1	1	1	1	0	1
A11A16	1	1	1	1	1	1
A11A17	1	1	1	1	1	1
A11A18	1	1	1	1	1	1
A11A19	1	1	1	1	0	1
A11A20	1	1	1	1	1	1
A12A1	1	1	1	1	1	1
A12A2	0	0	0	0	0	0
A12A3	1	1	1	1	1	1
A12A4	1	1	1	1	1	1
A12A5	0	0	0	0	0	0

Table 4.12 Continues

A12A6	0	0	0	0	0	0
A12A7	1	1	1	1	1	1
A12A8	0	0	0	0	1	0
A12A9	1	0	0	1	1	1
A12A10	1	1	1	1	1	1
A12A11	0	0	0	0	1	0
A12A13	1	1	1	1	1	1
A12A14	1	1	1	1	1	1
A12A15	1	1	1	1	0	1
A12A16	1	1	1	1	1	1
A12A17	0	0	0	1	1	1
A12A18	1	1	1	1	1	1
A12A19	1	1	1	1	1	0
A12A20	1	1	1	1	1	1
A13A1	1	0	0	0	0	1
A13A2	0	0	0	0	0	0
A13A3	1	0	1	0	1	1
A13A4	1	1	0	0	0	1
A13A5	0	0	0	0	0	0
A13A6	0	0	0	0	0	0
A13A7	1	1	1	1	1	1
A13A8	0	0	0	0	0	0
A13A9	0	0	0	0	0	0
A13A10	1	1	1	1	1	1
A13A11	0	0	0	0	0	0
A13A12	0	0	0	0	0	0
A13A14	1	1	1	1	1	1
A13A15	1	1	1	1	0	1
A13A16	1	1	1	1	1	1
A13A17	0	0	0	0	0	0
A13A18	1	1	1	1	1	1
A13A19	0	0	0	0	0	0
A13A20	1	1	1	1	1	1
A14A1	0	0	0	0	0	0
A14A2	0	0	0	0	0	0
A14A3	0	0	0	0	0	0
A14A4	0	0	0	0	0	0
A14A5	0	0	0	0	0	0
A14A6	0	0	0	0	0	0
A14A7	1	0	0	0	0	0
A14A8	0	0	0	0	0	0
A14A9	0	0	0	0	0	0
A14A10	0	0	0	0	0	0

Table 4.12 Continues

A14A11	0	0	0	0	0	0
A14A12	0	0	0	0	0	0
A14A13	0	0	0	0	0	0
A14A15	1	0	0	0	0	0
A14A16	1	0	0	1	0	0
A14A17	0	0	0	0	0	0
A14A18	0	0	0	0	1	0
A14A19	0	0	0	0	0	0
A14A20	0	0	0	0	0	0
A15A1	0	0	0	0	1	0
A15A2	0	0	0	0	1	0
A15A3	0	0	0	0	1	0
A15A4	0	0	0	0	1	0
A15A5	0	0	0	0	1	0
A15A6	0	0	0	0	1	0
A15A7	1	0	1	0	1	0
A15A8	0	0	0	0	1	0
A15A9	0	0	0	0	1	0
A15A10	0	0	0	0	1	0
A15A11	0	0	0	0	1	0
A15A12	0	0	0	0	1	0
A15A13	0	0	0	0	1	0
A15A14	0	1	1	1	1	1
A15A16	1	0	0	1	1	1
A15A17	0	0	0	0	1	0
A15A18	0	0	0	0	1	0
A15A19	0	0	0	0	1	0
A15A20	0	0	0	0	1	0
A16A1	0	0	0	0	0	0
A16A2	0	0	0	0	0	0
A16A3	0	0	0	0	0	0
A16A4	0	0	0	0	0	0
A16A5	0	0	0	0	0	0
A16A6	0	0	0	0	0	0
A16A7	1	0	1	0	0	0
A16A8	0	0	0	0	0	0
A16A9	0	0	0	0	0	0
A16A10	0	0	0	0	0	0
A16A11	0	0	0	0	0	0
A16A12	0	0	0	0	0	0
A16A13	0	0	0	0	0	0
A16A14	0	1	1	0	1	1

Table 4.12 Continues

A16A15	0	1	1	0	0	0
A16A17	0	0	0	0	0	0
A16A18	0	0	0	0	1	0
A16A19	0	0	0	0	0	0
A16A20	0	0	0	0	0	0
A17A1	1	1	1	1	1	1
A17A2	0	0	0	0	0	0
A17A3	1	1	1	1	1	1
A17A4	1	1	1	0	0	1
A17A5	0	0	0	0	0	0
A17A6	0	0	0	0	0	0
A17A7	1	1	1	1	1	1
A17A8	0	0	1	0	0	0
A17A9	1	0	1	0	0	0
A17A10	1	1	1	1	1	1
A17A11	0	0	0	0	0	0
A17A12	1	1	1	0	0	0
A17A13	1	1	1	1	1	1
A17A14	1	1	1	1	1	1
A17A15	1	1	1	1	0	1
A17A16	1	1	1	1	1	1
A17A18	1	1	1	1	1	1
A17A19	1	1	1	0	0	0
A17A20	1	1	1	1	1	1
A18A1	0	0	0	0	0	0
A18A2	0	0	0	0	0	0
A18A3	0	0	1	0	0	0
A18A4	0	1	0	0	0	0
A18A5	0	0	0	0	0	0
A18A6	0	0	0	0	0	0
A18A7	1	1	1	0	0	1
A18A8	0	0	0	0	0	0
A18A9	0	0	0	0	0	0
A18A10	1	1	1	1	0	1
A18A11	0	0	0	0	0	0
A18A12	0	0	0	0	0	0
A18A13	0	0	0	0	0	0
A18A14	1	1	1	1	0	1
A18A15	1	1	1	1	0	1
A18A16	1	1	1	1	0	1
A18A17	0	0	0	0	0	0
A18A19	0	0	0	0	0	0
A18A20	0	1	1	0	0	0

Table 4.12 Continues

A19A1	1	0	0	1	1	1
A19A2	0	0	0	0	0	0
A19A3	1	1	1	1	1	1
A19A4	1	1	0	1	1	1
A19A5	0	0	0	0	0	0
A19A6	0	0	0	0	0	0
A19A7	1	1	1	1	1	1
A19A8	0	0	0	0	1	0
A19A9	0	0	0	1	1	1
A19A10	1	1	1	1	1	1
A19A11	0	0	0	0	1	0
A19A12	0	0	0	0	0	1
A19A13	1	1	1	1	1	1
A19A14	1	1	1	1	1	1
A19A15	1	1	1	1	0	1
A19A16	1	1	1	1	1	1
A19A17	0	0	0	1	1	1
A19A18	1	1	1	1	1	1
A19A20	1	1	1	1	1	1
A20A1	0	0	0	0	0	0
A20A2	0	0	0	0	0	0
A20A3	0	0	0	0	1	1
A20A4	0	0	0	0	0	0
A20A5	0	0	0	0	0	0
A20A6	0	0	0	0	0	0
A20A7	1	1	1	0	1	1
A20A8	0	0	0	0	0	0
A20A9	0	0	0	0	0	0
A20A10	1	0	1	1	1	1
A20A11	0	0	0	0	0	0
A20A12	0	0	0	0	0	0
A20A13	0	0	0	0	0	0
A20A14	1	1	1	1	1	1
A20A15	1	1	1	1	0	1
A20A16	1	1	1	1	1	1
A20A17	0	0	0	0	0	0
A20A18	1	0	0	1	1	1
A20A19	0	0	0	0	0	0

Final concordance and discordance indexes C^* and D^* which are shown in Table 4.19 and Table 4.20 are calculated using equation group (3.15). After obtaining concordance and discordance indexes, final values are calculated using equation (3.16).

Table 4.13 Concordance indexes C^1

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	-	1.00	0.22	0.45	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.30	0.00	0.22	0.00	1.00	0.00	0.74	0.00
A2	0.00	-	0.00	0.00	0.30	0.78	0.00	0.00	0.00	0.00	0.55	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00
A3	0.78	1.00	-	0.89	1.00	1.00	0.22	1.00	1.00	0.22	1.00	1.00	0.74	0.00	0.22	0.00	1.00	0.22	1.00	0.45
A4	0.55	1.00	0.11	-	1.00	1.00	0.00	1.00	0.78	0.00	1.00	1.00	0.33	0.00	0.22	0.00	0.55	0.03	0.78	0.00
A5	0.00	0.70	0.00	0.00	-	0.78	0.00	0.00	0.00	0.00	0.48	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00
A6	0.00	0.22	0.00	0.00	0.22	-	0.00	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.22	0.00	0.00	0.00	0.00	0.00
A7	1.00	1.00	0.78	1.00	1.00	1.00	-	1.00	1.00	0.78	1.00	1.00	1.00	0.07	0.52	0.30	1.00	0.55	1.00	0.78
A8	0.00	1.00	0.00	0.00	1.00	1.00	0.00	-	0.00	0.00	1.00	0.22	0.00	0.00	0.22	0.00	0.22	0.00	0.22	0.00
A9	0.00	1.00	0.00	0.22	1.00	1.00	0.00	1.00	-	0.00	1.00	0.74	0.00	0.00	0.22	0.00	0.30	0.00	0.67	0.00
A10	1.00	1.00	0.78	1.00	1.00	1.00	0.22	1.00	1.00	-	1.00	1.00	1.00	0.00	0.22	0.00	1.00	0.78	1.00	0.97
A11	0.00	0.45	0.00	0.00	0.52	0.78	0.00	0.00	0.00	0.00	-	0.22	0.00	0.00	0.22	0.00	0.00	0.00	0.22	0.00
A12	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.78	0.26	0.00	0.78	-	0.00	0.00	0.22	0.00	0.33	0.00	0.22	0.00
A13	0.70	1.00	0.26	0.67	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	-	0.00	0.22	0.00	1.00	0.00	1.00	0.00
A14	1.00	1.00	1.00	1.00	1.00	1.00	0.93	1.00	1.00	1.00	1.00	1.00	1.00	-	0.93	0.70	1.00	0.78	1.00	1.00
A15	0.78	0.78	0.78	0.78	0.78	0.78	0.48	0.78	0.78	0.78	0.78	0.78	0.78	0.07	-	0.26	0.78	0.78	0.78	0.78
A16	1.00	1.00	1.00	1.00	1.00	1.00	0.70	1.00	1.00	1.00	1.00	1.00	1.00	0.30	0.74	-	1.00	0.78	1.00	1.00
A17	0.00	1.00	0.00	0.45	1.00	1.00	0.00	0.78	0.70	0.00	1.00	0.67	0.00	0.00	0.22	0.00	-	0.00	0.67	0.00
A18	1.00	1.00	0.78	0.97	1.00	1.00	0.45	1.00	1.00	0.22	1.00	1.00	1.00	0.22	0.22	0.22	1	-	1	0.74
A19	0.26	1.00	0.00	0.22	1.00	1.00	0.00	0.78	0.33	0.00	0.78	0.78	0.00	0.00	0.22	0.00	0.33	0.00	-	0.00
A20	1.00	1.00	0.55	1.00	1.00	1.00	0.22	1.00	1.00	0.03	1.00	1.00	1.00	0.00	0.22	0.00	1.00	0.26	1.00	-

Table 4.14 Concordance indexes C^2

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	-	1.00	0.19	0.39	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.31	0.00	0.19	0.00	1.00	0.00	0.70	0.00
A2	0.00	-	0.00	0.00	0.34	0.83	0.00	0.00	0.00	0.00	0.64	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.00	0.00
A3	0.81	1.00	-	0.72	1.00	1.00	0.19	1.00	1.00	0.19	1.00	1.00	0.68	0.00	0.19	0.00	1.00	0.17	1.00	0.36
A4	0.61	1.00	0.28	-	1.00	1.00	0.00	1.00	0.81	0.00	1.00	1.00	0.44	0.00	0.19	0.00	0.61	0.13	0.83	0.00
A5	0.00	0.66	0.00	0.00	-	0.83	0.00	0.00	0.00	0.00	0.49	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.00	0.00
A6	0.00	0.17	0.00	0.00	0.17	-	0.00	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.00	0.00
A7	1.00	1.00	0.81	1.00	1.00	1.00	-	1.00	1.00	0.81	1.00	1.00	1.00	0.15	0.51	0.31	1.00	0.61	1.00	0.81
A8	0.00	1.00	0.00	0.00	1.00	1.00	0.00	-	0.00	0.00	1.00	0.19	0.00	0.00	0.19	0.00	0.17	0.00	0.19	0.00
A9	0.00	1.00	0.00	0.19	1.00	1.00	0.00	1.00	-	0.00	1.00	0.70	0.00	0.00	0.19	0.00	0.31	0.00	0.56	0.00
A10	1.00	1.00	0.81	1.00	1.00	1.00	0.19	1.00	1.00	-	1.00	1.00	1.00	0.00	0.19	0.00	1.00	0.81	1.00	0.87
A11	0.00	0.36	0.00	0.00	0.51	0.81	0.00	0.00	0.00	0.00	-	0.19	0.00	0.00	0.19	0.00	0.00	0.00	0.19	0.00
A12	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.81	0.30	0.00	0.81	-	0.00	0.00	0.19	0.00	0.44	0.00	0.17	0.00
A13	0.69	1.00	0.32	0.56	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	-	0.00	0.19	0.00	1.00	0.00	1.00	0.00
A14	1.00	1.00	1.00	1.00	1.00	1.00	0.85	1.00	1.00	1.00	1.00	1.00	1.00	-	0.85	0.66	1.00	0.81	1.00	1.00
A15	0.81	0.81	0.81	0.81	0.81	0.81	0.49	0.81	0.81	0.81	0.81	0.81	0.81	0.15	-	0.30	0.81	0.81	0.81	0.81
A16	1.00	1.00	1.00	1.00	1.00	1.00	0.69	1.00	1.00	1.00	1.00	1.00	1.00	0.34	0.70	-	1.00	0.81	1.00	1.00
A17	0.00	1.00	0.00	0.39	1.00	1.00	0.00	0.83	0.69	0.00	1.00	0.56	0.00	0.00	0.19	0.00	-	0.00	0.56	0.00
A18	1.00	1.00	0.83	0.87	1.00	1.00	0.39	1.00	1.00	0.19	1.00	1.00	1.00	0.19	0.19	0.19	1.00	-	1.00	0.70
A19	0.30	1.00	0.00	0.17	1.00	1.00	0.00	0.81	0.44	0.00	0.81	0.83	0.00	0.00	0.19	0.00	0.44	0.00	-	0.00
A20	1.00	1.00	0.64	1.00	1.00	1.00	0.19	1.00	1.00	0.13	1.00	1.00	1.00	0.00	0.19	0.00	1.00	0.30	1.00	-

Table 4.15 Concordance indexes C^3

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	-	1.00	0.18	0.35	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.33	0.00	0.16	0.00	1.00	0.00	0.67	0.00
A2	0.00	-	0.00	0.00	0.35	0.84	0.00	0.00	0.00	0.00	0.67	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00
A3	0.82	1.00	-	0.67	1.00	1.00	0.16	1.00	1.00	0.16	1.00	1.00	0.65	0.00	0.16	0.00	1.00	0.16	1.00	0.33
A4	0.65	1.00	0.33	-	1.00	1.00	0.00	1.00	0.84	0.00	1.00	1.00	0.49	0.00	0.16	0.00	0.65	0.16	0.84	0.00
A5	0.00	0.65	0.00	0.00	-	0.84	0.00	0.00	0.00	0.00	0.51	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00
A6	0.00	0.16	0.00	0.00	0.16	-	0.00	0.00	0.00	0.00	0.18	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00
A7	1.00	1.00	0.84	1.00	1.00	1.00	-	1.00	1.00	0.82	1.00	1.00	1.00	0.16	0.49	0.33	1.00	0.65	1.00	0.82
A8	0.00	1.00	0.00	0.00	1.00	1.00	0.00	-	0.00	0.00	1.00	0.16	0.00	0.00	0.16	0.00	0.16	0.00	0.16	0.00
A9	0.00	1.00	0.00	0.16	1.00	1.00	0.00	1.00	-	0.00	1.00	0.67	0.00	0.00	0.16	0.00	0.33	0.00	0.51	0.00
A10	1.00	1.00	0.84	1.00	1.00	1.00	0.18	1.00	1.00	-	1.00	1.00	1.00	0.00	0.16	0.00	1.00	0.84	1.00	0.84
A11	0.00	0.33	0.00	0.00	0.49	0.82	0.00	0.00	0.00	0.00	-	0.16	0.00	0.00	0.16	0.00	0.00	0.00	0.16	0.00
A12	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.84	0.33	0.00	0.84	-	0.00	0.00	0.16	0.00	0.49	0.00	0.16	0.00
A13	0.67	1.00	0.35	0.51	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	-	0.00	0.16	0.00	1.00	0.00	1.00	0.00
A14	1.00	1.00	1.00	1.00	1.00	1.00	0.84	1.00	1.00	1.00	1.00	1.00	1.00	-	0.84	0.65	1.00	0.84	1.00	1.00
A15	0.84	0.84	0.84	0.84	0.84	0.84	0.51	0.84	0.84	0.84	0.84	0.84	0.84	0.16	-	0.33	0.84	0.84	0.84	0.84
A16	1.00	1.00	1.00	1.00	1.00	1.00	0.67	1.00	1.00	1.00	1.00	1.00	1.00	0.35	0.67	-	1.00	0.84	1.00	1.00
A17	0.00	1.00	0.00	0.35	1.00	1.00	0.00	0.84	0.67	0.00	1.00	0.51	0.00	0.00	0.16	0.00	-	0.00	0.51	0.00
A18	1.00	1.00	0.84	0.84	1.00	1.00	0.35	1.00	1.00	0.16	1.00	1.00	1.00	0.16	0.16	0.16	1.00	-	1.00	0.67
A19	0.33	1.00	0.00	0.16	1.00	1.00	0.00	0.84	0.49	0.00	0.84	0.84	0.00	0.00	0.16	0.00	0.49	0.00	-	0.00
A20	1.00	1.00	0.67	1.00	1.00	1.00	0.18	1.00	1.00	0.16	1.00	1.00	1.00	0.00	0.16	0.00	1.00	0.33	1.00	-

Table 4.16 Discordance indexes D^1

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	-	0.00	0.99	0.66	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.89	1.00	0.86	1.00	0.00	1.00	0.04	1.00
A2	1.00	-	1.00	1.00	0.83	0.24	1.00	1.00	1.00	1.00	0.60	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
A3	0.01	0.00	-	0.06	0.00	0.00	0.98	0.00	0.00	0.90	0.00	0.00	0.20	1.00	0.72	1.00	0.00	0.95	0.00	0.60
A4	0.34	0.00	0.94	-	0.00	0.00	1.00	0.00	0.05	1.00	0.00	0.00	0.62	1.00	0.87	1.00	0.08	1.00	0.01	1.00
A5	1.00	0.17	1.00	1.00	-	0.08	1.00	1.00	1.00	1.00	0.50	1.00	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00
A6	1.00	0.76	1.00	1.00	0.92	-	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
A7	0.00	0.00	0.02	0.00	0.00	0.00	-	0.00	0.00	0.38	0.00	0.00	0.00	0.95	0.42	0.85	0.00	0.58	0.00	0.03
A8	1.00	0.00	1.00	1.00	0.00	0.00	1.00	-	1.00	1.00	0.00	0.91	1.00	1.00	0.94	1.00	0.91	1.00	0.98	1.00
A9	1.00	0.00	1.00	0.95	0.00	0.00	1.00	0.00	-	1.00	0.00	0.32	1.00	1.00	0.88	1.00	0.39	1.00	0.43	1.00
A10	0.00	0.00	0.10	0.00	0.00	0.00	0.62	0.00	0.00	-	0.00	0.00	0.00	1.00	0.48	1.00	0.00	0.63	0.00	0.00
A11	1.00	0.40	1.00	1.00	0.50	0.04	1.00	1.00	1.00	1.00	-	0.96	1.00	1.00	0.95	1.00	1.00	1.00	0.99	1.00
A12	1.00	0.00	1.00	1.00	0.00	0.00	1.00	0.09	0.68	1.00	0.04	-	1.00	1.00	0.94	1.00	0.61	1.00	0.90	1.00
A13	0.11	0.00	0.80	0.38	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	-	1.00	0.82	1.00	0.00	1.00	0.00	1.00
A14	0.00	0.00	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	-	0.01	0.20	0.00	0.22	0.00	0.00
A15	0.14	0.04	0.28	0.13	0.05	0.04	0.58	0.06	0.12	0.52	0.05	0.06	0.18	0.99	-	0.91	0.12	0.59	0.06	0.26
A16	0.00	0.00	0.00	0.00	0.00	0.00	0.15	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.09	-	0.00	0.37	0.00	0.00
A17	1.00	0.00	1.00	0.92	0.00	0.00	1.00	0.09	0.61	1.00	0.00	0.39	1.00	1.00	0.88	1.00	-	1.00	0.47	1.00
A18	0.00	0.00	0.05	0.00	0.00	0.00	0.42	0.00	0.00	0.37	0.00	0.00	0.00	0.78	0.41	0.63	0.00	-	0.00	0.09
A19	0.96	0.00	1.00	0.99	0.00	0.00	1.00	0.02	0.57	1.00	0.01	0.10	1.00	1.00	0.94	1.00	0.53	1.00	-	1.00
A20	0.00	0.00	0.40	0.00	0.00	0.00	0.97	0.00	0.00	1.00	0.00	0.00	0.00	1.00	0.74	1.00	0.00	0.91	0.00	-

Table 4.17 Discordance indexes D^2

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	-	0.00	0.99	0.79	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.88	1.00	0.88	1.00	0.00	1.00	0.05	1.00
A2	1.00	-	1.00	1.00	0.72	0.18	1.00	1.00	1.00	1.00	0.55	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
A3	0.01	0.00	-	0.23	0.00	0.00	0.98	0.00	0.00	0.92	0.00	0.00	0.23	1.00	0.77	1.00	0.00	0.96	0.00	0.71
A4	0.21	0.00	0.77	-	0.00	0.00	1.00	0.00	0.04	1.00	0.00	0.00	0.49	1.00	0.88	1.00	0.06	0.98	0.01	1.00
A5	1.00	0.28	1.00	1.00	-	0.06	1.00	1.00	1.00	1.00	0.47	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
A6	1.00	0.82	1.00	1.00	0.94	-	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00
A7	0.00	0.00	0.02	0.00	0.00	0.00	-	0.00	0.00	0.32	0.00	0.00	0.00	0.90	0.44	0.83	0.00	0.51	0.00	0.03
A8	1.00	0.00	1.00	1.00	0.00	0.00	1.00	-	1.00	1.00	0.00	0.92	1.00	1.00	0.95	1.00	0.93	1.00	0.98	1.00
A9	1.00	0.00	1.00	0.96	0.00	0.00	1.00	0.00	-	1.00	0.00	0.35	1.00	1.00	0.90	1.00	0.44	1.00	0.51	1.00
A10	0.00	0.00	0.08	0.00	0.00	0.00	0.68	0.00	0.00	-	0.00	0.00	0.00	1.00	0.57	1.00	0.00	0.60	0.00	0.01
A11	1.00	0.45	1.00	1.00	0.53	0.04	1.00	1.00	1.00	1.00	-	0.96	1.00	1.00	0.96	1.00	1.00	1.00	0.99	1.00
A12	1.00	0.00	1.00	1.00	0.00	0.00	1.00	0.08	0.65	1.00	0.04	-	1.00	1.00	0.95	1.00	0.61	1.00	0.94	1.00
A13	0.12	0.00	0.77	0.51	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	-	1.00	0.85	1.00	0.00	1.00	0.00	1.00
A14	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	-	0.02	0.21	0.00	0.19	0.00	0.00
A15	0.12	0.04	0.23	0.12	0.04	0.03	0.56	0.05	0.10	0.43	0.04	0.05	0.15	0.98	-	0.89	0.10	0.54	0.05	0.23
A16	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.79	0.11	-	0.00	0.34	0.00	0.00
A17	1.00	0.00	1.00	0.94	0.00	0.00	1.00	0.07	0.56	1.00	0.00	0.39	1.00	1.00	0.90	1.00	-	1.00	0.52	1.00
A18	0.00	0.00	0.04	0.02	0.00	0.00	0.49	0.00	0.00	0.40	0.00	0.00	0.00	0.81	0.46	0.66	0.00	-	0.00	0.11
A19	0.95	0.00	1.00	0.99	0.00	0.00	1.00	0.02	0.49	1.00	0.01	0.06	1.00	1.00	0.95	1.00	0.48	1.00	-	1.00
A20	0.00	0.00	0.29	0.00	0.00	0.00	0.97	0.00	0.00	0.99	0.00	0.00	0.00	1.00	0.77	1.00	0.00	0.89	0.00	-

Table 4.18 Discordance indexes D^3

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	-	0.00	0.99	0.83	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.88	1.00	0.90	1.00	0.00	1.00	0.05	1.00
A2	1.00	-	1.00	1.00	0.70	0.18	1.00	1.00	1.00	1.00	0.53	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00
A3	0.01	0.00	-	0.29	0.00	0.00	0.99	0.00	0.00	0.93	0.00	0.00	0.24	1.00	0.81	1.00	0.00	0.96	0.00	0.74
A4	0.17	0.00	0.71	-	0.00	0.00	1.00	0.00	0.03	1.00	0.00	0.00	0.44	1.00	0.90	1.00	0.05	0.98	0.01	1.00
A5	1.00	0.30	1.00	1.00	-	0.06	1.00	1.00	1.00	1.00	0.45	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00
A6	1.00	0.82	1.00	1.00	0.94	-	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.00	1.00
A7	0.00	0.00	0.01	0.00	0.00	0.00	-	0.00	0.00	0.29	0.00	0.00	0.00	0.89	0.47	0.82	0.00	0.45	0.00	0.03
A8	1.00	0.00	1.00	1.00	0.00	0.00	1.00	-	1.00	1.00	0.00	0.94	1.00	1.00	0.96	1.00	0.93	1.00	0.99	1.00
A9	1.00	0.00	1.00	0.97	0.00	0.00	1.00	0.00	-	1.00	0.00	0.39	1.00	1.00	0.92	1.00	0.44	1.00	0.56	1.00
A10	0.00	0.00	0.07	0.00	0.00	0.00	0.71	0.00	0.00	-	0.00	0.00	0.00	1.00	0.64	1.00	0.00	0.55	0.00	0.02
A11	1.00	0.47	1.00	1.00	0.55	0.04	1.00	1.00	1.00	1.00	-	0.97	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
A12	1.00	0.00	1.00	1.00	0.00	0.00	1.00	0.06	0.61	1.00	0.03	-	1.00	1.00	0.96	1.00	0.58	1.00	0.94	1.00
A13	0.12	0.00	0.76	0.56	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	-	1.00	0.88	1.00	0.00	1.00	0.00	1.00
A14	0.00	0.00	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.00	0.00	0.00	0.00	-	0.03	0.21	0.00	0.15	0.00	0.00
A15	0.10	0.03	0.19	0.10	0.03	0.02	0.53	0.04	0.08	0.36	0.04	0.04	0.12	0.97	-	0.87	0.08	0.48	0.04	0.19
A16	0.00	0.00	0.00	0.00	0.00	0.00	0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.79	0.13	-	0.00	0.29	0.00	0.00
A17	1.00	0.00	1.00	0.95	0.00	0.00	1.00	0.07	0.56	1.00	0.00	0.42	1.00	1.00	0.92	1.00	-	1.00	0.57	1.00
A18	0.00	0.00	0.04	0.02	0.00	0.00	0.55	0.00	0.00	0.45	0.00	0.00	0.00	0.85	0.52	0.71	0.00	-	0.00	0.14
A19	0.95	0.00	1.00	0.99	0.00	0.00	1.00	0.01	0.44	1.00	0.00	0.06	1.00	1.00	0.96	1.00	0.43	1.00	-	1.00
A20	0.00	0.00	0.26	0.00	0.00	0.00	0.97	0.00	0.00	0.98	0.00	0.00	0.00	1.00	0.81	1.00	0.00	0.86	0.00	-

Table 4.19 Final concordance indexes C^*

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	-	1.00	0.20	0.39	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.31	0.00	0.19	0.00	1.00	0.00	0.71	0.00
A2	0.00	-	0.00	0.00	0.33	0.81	0.00	0.00	0.00	0.00	0.62	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.00	0.00
A3	0.80	1.00	-	0.76	1.00	1.00	0.19	1.00	1.00	0.19	1.00	1.00	0.69	0.00	0.19	0.00	1.00	0.18	1.00	0.38
A4	0.60	1.00	0.21	-	1.00	1.00	0.00	1.00	0.81	0.00	1.00	1.00	0.42	0.00	0.19	0.00	0.60	0.09	0.81	0.00
A5	0.00	0.67	0.00	0.00	-	0.81	0.00	0.00	0.00	0.00	0.49	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.00	0.00
A6	0.00	0.18	0.00	0.00	0.18	-	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.19	0.00	0.00	0.00	0.00	0.00
A7	1.00	1.00	0.81	1.00	1.00	1.00	-	1.00	1.00	0.80	1.00	1.00	1.00	0.12	0.51	0.31	1.00	0.60	1.00	0.80
A8	0.00	1.00	0.00	0.00	1.00	1.00	0.00	-	0.00	0.00	1.00	0.19	0.00	0.00	0.19	0.00	0.18	0.00	0.19	0.00
A9	0.00	1.00	0.00	0.19	1.00	1.00	0.00	1.00	-	0.00	1.00	0.71	0.00	0.00	0.19	0.00	0.31	0.00	0.57	0.00
A10	1.00	1.00	0.81	1.00	1.00	1.00	0.20	1.00	1.00	-	1.00	1.00	1.00	0.00	0.19	0.00	1.00	0.81	1.00	0.89
A11	0.00	0.38	0.00	0.00	0.51	0.80	0.00	0.00	0.00	0.00	-	0.19	0.00	0.00	0.19	0.00	0.00	0.00	0.19	0.00
A12	0.00	1.00	0.00	0.00	1.00	1.00	0.00	0.81	0.29	0.00	0.81	-	0.00	0.00	0.19	0.00	0.42	0.00	0.18	0.00
A13	0.69	1.00	0.31	0.57	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	-	0.00	0.19	0.00	1.00	0.00	1.00	0.00
A14	1.00	1.00	1.00	1.00	1.00	1.00	0.87	1.00	1.00	1.00	1.00	1.00	1.00	-	0.87	0.67	1.00	0.81	1.00	1.00
A15	0.81	0.81	0.81	0.81	0.81	0.81	0.49	0.81	0.81	0.81	0.81	0.81	0.81	0.12	-	0.29	0.81	0.81	0.81	0.81
A16	1.00	1.00	1.00	1.00	1.00	1.00	0.69	1.00	1.00	1.00	1.00	1.00	1.00	0.33	0.71	-	1.00	0.81	1.00	1.00
A17	0.00	1.00	0.00	0.39	1.00	1.00	0.00	0.81	0.69	0.00	1.00	0.57	0.00	0.00	0.19	0.00	-	0.00	0.57	0.00
A18	1.00	1.00	0.81	0.89	1.00	1.00	0.39	1.00	1.00	0.19	1.00	1.00	1.00	0.19	0.19	0.19	1.00	-	1.00	0.71
A19	0.29	1.00	0.00	0.18	1.00	1.00	0.00	0.81	0.42	0.00	0.81	0.81	0.00	0.00	0.19	0.00	0.42	0.00	-	0.00
A20	1.00	1.00	0.62	1.00	1.00	1.00	0.20	1.00	1.00	0.09	1.00	1.00	1.00	0.00	0.19	0.00	1.00	0.29	1.00	-

Table 4.20 Final discordance indexes D^*

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	A16	A17	A18	A19	A20
A1	-	0.00	0.99	0.76	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	0.88	1.00	0.88	1.00	0.00	1.00	0.05	1.00
A2	1.00	-	1.00	1.00	0.75	0.20	1.00	1.00	1.00	1.00	0.56	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
A3	0.01	0.00	-	0.16	0.00	0.00	0.98	0.00	0.00	0.92	0.00	0.00	0.22	1.00	0.76	1.00	0.00	0.95	0.00	0.68
A4	0.23	0.00	0.80	-	0.00	0.00	1.00	0.00	0.04	1.00	0.00	0.00	0.51	1.00	0.88	1.00	0.06	0.99	0.01	1.00
A5	1.00	0.24	1.00	1.00	-	0.07	1.00	1.00	1.00	1.00	0.47	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
A6	1.00	0.80	1.00	1.00	0.93	-	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00
A7	0.00	0.00	0.02	0.00	0.00	0.00	-	0.00	0.00	0.33	0.00	0.00	0.00	0.91	0.44	0.84	0.00	0.51	0.00	0.03
A8	1.00	0.00	1.00	1.00	0.00	0.00	1.00	-	1.00	1.00	0.00	0.92	1.00	1.00	0.95	1.00	0.92	1.00	0.98	1.00
A9	1.00	0.00	1.00	0.96	0.00	0.00	1.00	0.00	-	1.00	0.00	0.35	1.00	1.00	0.90	1.00	0.42	1.00	0.50	1.00
A10	0.00	0.00	0.08	0.00	0.00	0.00	0.67	0.00	0.00	-	0.00	0.00	0.00	1.00	0.56	1.00	0.00	0.59	0.00	0.01
A11	1.00	0.44	1.00	1.00	0.53	0.04	1.00	1.00	1.00	1.00	-	0.96	1.00	1.00	0.96	1.00	1.00	1.00	0.99	1.00
A12	1.00	0.00	1.00	1.00	0.00	0.00	1.00	0.08	0.65	1.00	0.04	-	1.00	1.00	0.95	1.00	0.60	1.00	0.93	1.00
A13	0.12	0.00	0.78	0.48	0.00	0.00	1.00	0.00	0.00	1.00	0.00	0.00	-	1.00	0.85	1.00	0.00	1.00	0.00	1.00
A14	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00	0.00	0.00	0.00	0.00	0.00	-	0.02	0.21	0.00	0.18	0.00	0.00
A15	0.12	0.04	0.23	0.12	0.04	0.03	0.56	0.05	0.10	0.43	0.04	0.05	0.15	0.98	-	0.89	0.10	0.53	0.05	0.23
A16	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.79	0.11	-	0.00	0.33	0.00	0.00
A17	1.00	0.00	1.00	0.94	0.00	0.00	1.00	0.08	0.58	1.00	0.00	0.40	1.00	1.00	0.90	1.00	-	1.00	0.52	1.00
A18	0.00	0.00	0.05	0.01	0.00	0.00	0.48	0.00	0.00	0.41	0.00	0.00	0.00	0.81	0.46	0.67	0.00	-	0.00	0.11
A19	0.95	0.00	1.00	0.99	0.00	0.00	1.00	0.02	0.50	1.00	0.01	0.07	1.00	1.00	0.95	1.00	0.48	1.00	-	1.00
A20	0.00	0.00	0.31	0.00	0.00	0.00	0.97	0.00	0.00	0.99	0.00	0.00	0.00	1.00	0.77	1.00	0.00	0.88	0.00	-

Finally, alternatives are ranked by their final values. Table 4.21 shows the final values and rankings of alternatives. According to the results, alternative 14 which is Oppo Reno 5 is the best alternative.

Table 4.21 Final values and rankings

Alternative	Final Index	Ranking
A1	0.25	11
A2	-15.52	19
A3	5.70	8
A4	1.22	10
A5	-14.57	17
A6	-17.91	20
A7	12.87	3
A8	-10.02	16
A9	-5.16	13
A10	10.98	5
A11	-14.65	18
A12	-7.55	15
A13	2.54	9
A14	17.72	1
A15	9.07	6
A16	16.13	2
A17	-5.17	14
A18	11.57	4
A19	-5.04	12
A20	7.46	7

CHAPTER FIVE
CONCLUSION

Online reviews can be useful to both consumers and companies when effectively analyzed. People who wish to purchase a good or service can use online reviews to their advantage in order to select the one that best suits their needs. Companies can identify the components of their goods or services that customers most frequently complain about and the measures that will help them improve customer satisfaction by analyzing customer reviews. However, because there are so many subjective reviews posted online every day, it might be challenging to analyze them. Traditional methods for tracking client satisfaction over an extended period of time are expensive and time-consuming. Within this perspective, this thesis offers a decision support tool that both prospective customers can use to assess the opinions of current users of the product or service they tend to purchase and to choose the best option from a list of alternatives, as well as by businesses to track customer satisfaction related to the product or service they produce or trade in order to take the necessary actions to increase satisfaction. In this study, MCDM and sentiment analysis techniques are combined to construct the decision support tool.

The proposed methodology is divided into two steps.

- In the first step customer satisfaction is measured in order to get performance ratings for potential choices that will be used in the decision-making process.
- Aspect level sentiment analysis based on lexicon is used to complete this stage.
- Aspects are first identified, and then sentiment words are retrieved using a process based on word frequency.
- Natural Language Processing (NLP) techniques are used to analyze sentences and determine whether they contain an opinion.
- Performance scores are created by converting the retrieved positive and negative sentiments from sentences for each criterion and option.
- Using the performance scores obtained in the first step, the product ranking stage is carried out in the second step using the a MCDM method.

- Fuzzy ELECTRE approach which is a fuzzy set based method that allows for the incorporation of uncertainty and subjectivity in the decision-making process is used as a MCDM method.

To demonstrate how to use the developed decision support tool, a case study about internet reviews of mobile phones in Turkish is used. The alternative mobile phones handled in the case study are ranked using it, and the best one is suggested based on the chosen criteria.

An essential contribution of this thesis to the related literature is implementing aspect level sentiment analysis and MCDM methods on Turkish online reviews. A complete product rating is rarely proposed by research that combines aspect level sentiment analysis and MCDM techniques with online Turkish reviews.

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