



**REPUBLIC OF TÜRKİYE
ADANA ALPARSLAN TÜRKER SCIENCE AND TECHNOLOGY
UNIVERSITY**

**GRADUATE SCHOOL
INDUSTRIAL ENGINEERING DEPARTMENT**

**PRICE FLUCTUATION ANALYSIS IN E-COMMERCE SECTOR
DURING DISASTER PERIOD: A CASE STUDY IN TURKEY**

BÜŞRA MAT

M.Sc.

ADANA 2024



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**THESIS ADVISOR
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ADANA, 2024

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a situation is found contrary to my statement regarding my work.

15/01/2024

Büşra MAT

ÖZET

AFET DÖNEMLERİNDE E-TİCARET SEKTÖRÜNDE UYGULANAN FİYAT DALGALANMALARI ANALİZİ: TÜRKİYE ÖRNEĞİ

Büşra MAT

Yüksek Lisans, Endüstri Mühendisliği Anabilim Dalı

Danışman: Doç.Dr. Pırıl TEKİN

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Günümüz gelir yönetimi anlayışı, müşterilerin internet ortamında birçok veriyi karşılaştırmalı olarak elde ederek rekabet durumunu daha akıllı ve kısa sürede analiz etmelerine olanak sağlamaktadır. Mağazaların fiziksel ortamlarından yapılan alışverişler, hem müşterilerin yaşadığı bedensel yorgunluklar hem de fiyat alternatiflerini daha göreceli ve yüksek zamanlarda değerlendirmeleri nedenlerinden dolayı son yıllarda yerini e-ticaret siteleri üzerinden gerçekleştirilen online alışverişlere bırakmıştır. E-ticaret özellikle müşterilere zaman kazandırması dolayısıyla son yıllarda daha çok tercih edilmeye başlamışken, dünya genelinde yaşanan COVID-19 salgını nedeniyle yaşanan kapanmalarla tercih eğilimini artırmıştır.

Dinamik fiyatlandırma, online alışveriş siteleri için oldukça cazip görünen ve son yıllarda sıklıkla kullanılan bir strateji haline gelmiştir. Doğru uygulanması ile yüksek kar miktarlarını kurumlara kazandıran bu yaklaşım, birçok şirket tarafından rekabet avantajı yaratmak için tercih edilmektedir.

Farklı sitelerinden toplanan fiyat bilgileri nedeniyle internet ortamındaki fiyat, tüketicinin ürün hakkındaki temel belirleyicisi olmakta, bu nedenle de müşteriler fiyat üzerine daha çok odaklanmaktadır. Ele alınan bu çalışma kapsamında, Türkiye’de çok tercih edilen bir online alışveriş sitesinde yer alan içecekler, elektronik aletler ve hijyen ürünleri kategorilerindeki en çok satan ürünlerin fiyatları, COVID-19 dönemi birinci, ikinci, üçüncü dalgalanma dönemleri ve 11 ili etkileyen deprem döneminde uygulanan online fiyatlandırma yaklaşımları çerçevesinde incelenmiştir. Gelir yönetimi yaklaşımlarının afet dönemleri arasından en çok etkilediği dönemleri tespit etmek amacıyla, farklı kriterlere bağlı olarak çok kriterli karar verme yöntemlerinden AHP ve TOPSIS kullanılmıştır.

Anahtar Kelimeler : E-ticaret Sektörü,Gelir Yönetimi,Dinamik Fiyatlandırma,AHP,TOPSİS



ABSTRACT

PRICE FLUCTUATION ANALYSIS IN E-COMMERCE SECTOR DURING DISASTER PERIOD: A CASE STUDY IN TURKEY

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Today's revenue management approach allows customers to analyze the competitive situation more intelligently and in a shorter time by obtaining many comparative data on the internet. Shopping done in the physical environments of stores has been replaced by online shopping through e-commerce sites in recent years, due to both the physical fatigue experienced by customers and the fact that they evaluate price alternatives at more relative and higher prices. While e-commerce has become more preferred in recent years, especially because it saves time for customers, the trend of preference has increased with the closures experienced worldwide due to the COVID-19 epidemic.

Dynamic pricing has become a very attractive and frequently used strategy for online shopping sites in recent years. This approach, which brings high profit amounts to institutions when applied correctly, is preferred by many companies to create a competitive advantage.

Due to the price information collected from different sites, the price on the internet becomes the consumer's main determinant of the product, and therefore customers focus more on the price. Within the scope of this study, the prices of the best-selling products in the categories of beverages, electronic devices and hygiene products on a widely preferred online shopping site in Turkey, the prices applied during the first, second and third surge periods of the COVID-19 period and the earthquake period that affected 11 provinces. examined within the framework of online pricing approaches. In order to determine the periods most affected by income management approaches among disaster periods, AHP and TOPSIS, multi-criteria decision-making methods, were used depending on different criteria.

Keywords: E-Commerce Sector, Revenue Management, Dynamic Pricing, AHP, TOPSIS

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LIST OF ABBREVIATIONS

n	: Size
$\lambda_{\max}$	: Largest Eigenvalue
m	: Number Of Decision Points
R	: Normalizing the Decision Matrix
V	: Weighted Standard Decision Matrix
w^i	: Weights
A^+	: Positive Ideal
A^-	: Negative Ideal
S_i^*	: Positive Ideal Separation
S_i^-	: Negative Ideal Separation
C_i^*	: Ideal Solution

LIST OF SYMBOLS

AHP	: Analytic Hierarchy Process
CI	: Consistency Index
CR	: Consistency Rate
MCDM	: Multi-Criteria Decision Making
TOPSIS	: Technique For Order Preference By Similarity To Ideal Solution
COVID-19	: Coronavirus
MSE	: Mean Square Error
R²	: R-squared
GBM	: Gradient Boosting Machines
WOLSTM	: Weight-Optimized Long Short-Term Memory
DRL-DP	: Deep Reinforcement Learning-Based Dynamic Pricing
ITHs	: International Tourist Hotels
SFA	: Stochastic Frontier Approximation
FSC	: Full-Service Carrier
VRP	: Vehicle Routing Problem
MDP	: Markov Decision Process
VFA	: Value Function Approximation
B2C	: Business-to-Consumer
KMO	: Kaiser-Meyer-Olkin

1. REVENUE MANAGEMENT

In today's business world, where competition is intense, companies must adopt a series of strategies to survive and achieve sustainable success. One of the most crucial of these strategies is revenue management, which is essential for maintaining the cash flow necessary for an organization's survival. Revenue management is a strategic process that influences and directs the revenues a business generates. Process mentioned is achieved through the strategic use of various sources such as sales, service, and investment revenues, directly affecting the financial health of the business.

The importance of revenue management in the business world has been increasing in recent years. Global competition, technological advancements, changing customer preferences, and current economic fluctuations are encouraging businesses to develop and implement revenue management strategies. The concept of revenue management is not just about maximizing income but also involves considering a range of factors such as cost control, customer satisfaction, sustainability, and competitive advantage in maintaining system flow. Revenue management is a strategic process implemented to optimize, increase, and sustainably manage the revenues a business generates. This process aims to gain control over various revenue sources, effectively manage costs, increase customer satisfaction, and achieve a competitive advantage. Revenue management typically involves creating revenue strategies by considering market conditions, demand fluctuations, competition, cost factors, and various other elements.

The concept of revenue management, defined as offering the right product to the right customer at the right time and price, is an inevitable necessity for organizations today to gain a competitive advantage and optimize their financial performance. Revenue management not only improves financial figures in businesses but also offers multifaceted advantages such as increasing customer satisfaction, strengthening operational efficiency, and quickly adapting to market conditions. Successful implementation of revenue management allows businesses to develop flexible and competitive strategies in line with market dynamics. Therefore, the concept of revenue management is considered one of the fundamental building blocks for a business to achieve healthy growth and sustainable success in today's business world.

Effectively managing revenue sources is critically important for businesses to sustainably exist and grow. The revenue sources used in revenue management represent the fundamental sources of income for businesses. Hence, these sources play a key role in determining the revenue management strategies of businesses. Effectively managing these sources allows businesses to increase their financial success, gain a competitive advantage, and provide an opportunity for sustainable growth. The most important strategy implemented in revenue management is pricing strategy. Pricing strategies involve price policies determined considering customer demands, competitive conditions, business objectives, and current economic conditions.

A common pricing strategy encountered today is competitive pricing, which is based on the principle of businesses setting prices similar to or based on a competitive advantage over their competitors. This strategy, often used for price-sensitive customers, aims to attract customer attention and gain a competitive advantage by offering lower prices compared to similar products and services in the market. The value pricing strategy involves setting prices by emphasizing the unique value of the product or service offered by the business. Factors such as superior quality, features, customer service, or brand reputation form the basis of the value pricing strategy. This strategy is commonly used in premium markets and sectors where brand loyalty is important. Another common practice is flexible pricing strategy. Businesses adopt a flexible pricing policy according to variables such as demand levels, seasonal changes, stock status, or customer segmentation, striving for a more dynamic revenue management. This strategy aims to quickly adapt to demand fluctuations and gain a competitive advantage. These widely used pricing strategies play a key role in shaping the marketing efforts and customer relationships of businesses. Proper implementation of the chosen strategy can increase customer satisfaction, provide a competitive advantage, and support long-term financial success. Businesses must apply these strategies flexibly, considering the competitive environment and customer expectations, and continuously optimize their revenue management.

The widespread use of pricing strategy is supported by different revenue management studies in various areas of businesses. A commonly used method at this stage is the creation of customer segmentation and the development of suitable strategies for different customer

groups. Revenue management requires developing strategies tailored to customer needs and focusing on these strategies. In this context, customer segmentation and targeting play a significant role in the marketing and revenue management processes of businesses. Customer profiling is a strategy used by businesses to better understand their customer base and offer customized services to different customer groups. This step involves defining specific customer segments based on customers' demographic characteristics, shopping behaviors, preferences, income levels, and other important features. For example, a retail business might target different groups like young professionals, families, or elderly individuals. Data analysis, customer feedback, and market research play a significant role in customer profiling. With this information, businesses can better understand the needs of different customer segments and adjust their strategies accordingly. Customer profiling is a fundamental step for creating more effective marketing campaigns, personalizing products and services, and increasing customer satisfaction.

In many cases where the consumer base is broad and diverse, it is often ineffective for businesses to target everyone. Target market analysis is a current strategy that helps businesses focus on a specific market segment. Target market analysis based on identified customer profiles helps businesses focus on their strengths and customer base. This strategy not only focuses on a specific customer segment but also provides the opportunity to use the marketing budget and efforts more effectively. This strategy allows for the customization of advertising campaigns, promotions, and product development to appeal to a specific audience. In conclusion, customer segmentation and targeting form the basis of revenue management strategies. Businesses effectively implement these strategies to understand their customer base, offer customized solutions, and gain a competitive advantage. Customer-centric approaches help strengthen long-term customer relationships and assist businesses in achieving sustainable revenue.

In cases where the consumer base is broad and varied, it's generally ineffective for businesses to target everyone. Target market analysis is a contemporary strategy that enables businesses to focus on a specific market segment. Target market analysis based on defined customer profiles aids businesses in concentrating on their strengths and customer base. This strategy also allows for the more efficient use of marketing budgets and efforts. It enables the customization of ad campaigns, promotions, and product development to cater specifically to

a targeted audience. Ultimately, customer segmentation and targeting are fundamental to revenue management strategies. Businesses apply these strategies effectively to comprehend their customer base, provide tailored solutions, and achieve a competitive edge. Customer-focused approaches contribute to the strengthening of long-term customer relationships and support businesses in generating sustainable revenue.

Among revenue management strategies, diversifying product and service portfolios to increase revenue sources and reduce risks holds a significant place for businesses. In this context, portfolio diversification and strategies for entering new markets play a critical role in providing businesses with a competitive advantage and increasing their revenues. Portfolio diversification is a strategy that involves adding new elements to a business's existing product and service portfolio, thereby reaching a broader customer base. This diversification typically occurs in two ways:

- Horizontal Diversification: Businesses expand into similar or related product and service categories while operating in their current markets. For example, a sportswear brand can implement a horizontal diversification strategy by adding related products like accessories or sports equipment to its portfolio.
- Vertical Diversification: Businesses adopt a vertical diversification strategy by expanding into different stages of the production chain. For instance, a furniture manufacturer could diversify vertically by starting to operate retail outlets.

Portfolio diversification allows businesses to reduce risks while creating new sources of revenue and increasing customer loyalty. Expanding the customer base enhances competitive advantage and sustainable growth for businesses. Additionally, the strategy of entering new markets, frequently implemented in recent years, targets increasing revenues by expanding into new geographical regions or different demographic segments besides existing markets. This strategy often aims to reach new customers, increase competitive advantage, and create demand.

- Geographic Expansion: Businesses can expand into new markets outside their current geographic regions. This expansion can be in the form of entering global markets or strengthening their presence in local markets.

- Demographic Segmentation: Businesses can enter new markets by directing their products and services to different demographic groups. For example, a brand catering to young consumers can adopt a demographic segmentation strategy by creating a new product line for older consumers.

The strategy of entering new markets increases the growth potential of businesses and helps them gain a competitive advantage. However, market research and a good understanding of local market dynamics are important when implementing this strategy. In conclusion, product and service diversification plays a significant role in businesses' revenue management strategies. Portfolio diversification and entering new markets contribute to enhancing the competitive advantage and achieving sustainable growth for businesses.

The strategies implemented and mentioned above are carried out with the objective of maintaining a pricing balance. Revenue management, considered as the concept of offering the right product to the right customers at the right time and price, has especially increased its importance and application areas in recent years. Rapidly changing environmental conditions in today's world are also altering the current system flow of customers and supply providers in the marketing concept. Approaches to dynamic pricing, a fundamental area of revenue management, have also increased their application within this framework. Particularly with the widespread adoption of artificial intelligence, dynamic pricing systems can be monitored throughout the day via software systems, enabling real-time detection of customer demand frequency and intensity. The instantaneous shaping of product prices and their control via software, along with the storage of past data through these systems, is facilitated. Storing past data provides significant ease in examining customer demands over time and helps systems to be easily revised or adapted according to instant situations.

In light of all these findings, it is a fact that the COVID-19 period has changed consumption habits in favor of e-commerce. Because, thanks to e-commerce, individuals can access many products via the internet within seconds and make contactless payments. In addition, product diversity is also very high in e-commerce. With e-commerce, shopping can be done regardless of time and place. COVID-19 has accelerated the spread of e-commerce. The coronavirus epidemic has made digitalization important in all sectors in Turkey. As discussed in detail within the scope of the thesis, the e-commerce volume in our country increased in 2020

compared to 2019. Shopping in many sectors, especially the food sector, has been carried out using the e-commerce method.

E-commerce activities intensified rapidly in the country, especially in March, April and May, when the pandemic had an intense impact. In order to reduce the risk of transmission of the epidemic disease, individuals have started to use payment methods such as money transfer/EFT much more frequently. During the pandemic, the transactions of cargo and transportation companies also increased rapidly with the increase in e-commerce volume.

Many e-commerce companies have established their own logistics networks, and there has been an increase in sales volume in almost every field on a sectoral basis. The highest growth in e-commerce volume was seen in the food and supermarket sectors, followed by chemical/hygienic products. With the widespread use of income management studies, consumers have become able to shop quickly and easily.

With the emergence of the COVID-19 pandemic in 2019, countries around the world imposed restrictions. Individuals who faced severe restrictions such as curfews had to stay at home. It has been observed that there have been changes in the social and cultural lives of individuals confined to their homes, as well as changes in their forms of trade. The pandemic has brought about a social transformation. Social and commercial life is now completely under the influence of digitalization. The rapid advancement of internet technology and the spread of the situation to the global area have caused individuals' consumption habits to change. Individuals confined to home during the pandemic period started to purchase products mostly via e-commerce, that is, on the internet. E-commerce in many sectors started to increase 2.3 times with the pandemic. E-commerce, which developed before the pandemic, reached its peak with the pandemic. Individuals who have to stay at home due to the pandemic, who do not prefer to shop physically in the same environment, and who want to isolate themselves from crowded environments, make purchases via e-commerce. When the data in Turkey and the world are compared, it is seen that the e-commerce volume increased significantly after the pandemic. It can be interpreted that purchasing actions made through e-commerce will continue after the pandemic. In almost all studies, more than half of individuals stated that they will continue to shop from e-commerce after the pandemic. It can be conducted that e-commerce volume will continue to increase rapidly after the pandemic. When we look at the development of e-commerce on a sectoral basis, we see that there are large increases

especially in some sectors. There have been significant increases in health products, household goods, cleaning and food products. Especially with the pandemic, the cleaning sector coming to the fore and the demands of individuals to stock food products can be cited as among the most important reasons for the increase in these sectors. On the contrary, there have been decreases in the travel, agency, accommodation services, flight tickets, luxury consumer goods, accessories and clothing sectors, which were preferred via e-commerce before the pandemic. Aforesaid result has caused changes in the social and cultural lives of individuals and has also led to changes in their consumption habits. As a result, with COVID-19, individuals are in a new social system and want to adapt themselves to this system. The situation has caused changes in the social and cultural behavior of individuals. The fact that e-commerce is preferred at double and above levels after the pandemic can be seen as a reflection of this situation. In today's society dominated by e-commerce, individuals have become more dependent on social networks and social media. The result shows us that a social transformation has occurred.

1.1. Dynamic Pricing Approach

Dynamic pricing refers to the practice of pricing products under different conditions and the variation of these prices over time. In other words, it is a pricing strategy in which companies make changes to prices based on supply and demand. With dynamic pricing, companies continuously monitor prices and competitors. For example, the pricing strategy of an online store determines how successful it will be. Setting the right price for products in organizations will influence people's purchasing decisions. Here, dynamic pricing will be implemented, meeting every need for your pricing. It is a pricing strategy that allows a business to change the prices of its products or services when necessary.

Dynamic pricing strategies are examined under four different categories. The first is 'Time-Based Pricing'. This pricing method is based on the principle of altering prices based on maximum/minimum sales volume by offering products for sale within specific date ranges. At this stage, the limited nature of time can increase customers' desire and attitude to purchase. The second pricing strategy, 'Segment-Based Pricing', allows for variations in product prices according to product models and capacities. In that method, the goal is to provide the maximum product segment according to the maximum payment capacity of customers. For example, companies like Apple offer different product prices based on different capacities.

According to the 'Peak Pricing' strategy, it is based on the principle of offering different pricing alternatives to customers according to the balance of stock and demand. When stocks are low or demand is assumed to be high, product prices are decreased or increased accordingly. Lastly, in the 'Penetration Pricing' approach, the interest of customers is tried to be increased in light of new retailers in the market offering lower prices than competing companies. In the later stages of this method, product prices can rise to normal market conditions. These dynamic pricing approaches, where different strategies are applied at different times, are becoming increasingly common in various sectors. Understanding and optimizing sector-specific dynamics requires the development of revenue management strategies specific to each sector. Each sector has its own market dynamics and customer expectations. Therefore, considering the sector-specific characteristics of revenue management strategies is a critical factor in the success of businesses.

1.2. Sectoral Applications of Dynamic Pricing

Dynamic pricing applications offer the highest advantage in sectors where market conditions and consumer behaviors change rapidly. Additionally, the prevalence of dynamic pricing strategies varies across sectors based on the intensity of software infrastructure usage. Although changing current conditions may alter the ranking of commonly used sectors, the most known and accepted primary application area for dynamic pricing is usually the airline industry. Airlines measure customer reactions by changing the prices of flight tickets during periods of high and low demand, thereby managing revenue through rapid price changes without causing loss to the businesses. Another common practice in this sector is updating prices as the number of empty seats on a flight decreases.

In the e-commerce sector, another common area of application, prices are updated in real-time based on information such as the products consumers are viewing, the rate at which customers add these products to their carts, the time customers spend on the site, and past purchasing behaviors. With the proliferation of electronic labels, dynamic pricing applications have become easily implementable in retail stores. These systems, which allow instant tracking of results, also enable checks on product expiration dates, facilitating the immediate offering of perishable food items at lower prices to customers. This approach not only reduces the stock costs of the selling organization but also ensures good stock management. Thus, a retailer can raise prices when demand exceeds capacity and lower them when demand falls.

Dynamic pricing approaches are now commonly used in areas such as seasonal ticket pricing for sports events or setting match day ticket prices. For example, ticket prices for a Fenerbahçe-Galatasaray match differ from those for a Fenerbahçe-Adana Demir Spor match. The fundamental reason for this is the higher demand for a derby match compared to a regular match. In restaurants, two main elements are crucial for implementing dynamic pricing approaches within revenue management: duration control and correct product pricing. In the hotel industry, which is another sector focused on customer satisfaction, the most important aspect is offering the right room, at the right time, to the right customer, at the right price. Additionally, pricing other service areas within the hotel's scope (such as restaurants, minibar usage, etc.) with various promotional infrastructures will be a key element in increasing revenue.

The application areas of dynamic pricing approaches are rapidly expanding in our country as well. For instance, İstanbul Deniz Otobüsleri A.Ş has recently started allowing passengers to determine ticket prices. In this context, the company provides customers the opportunity to purchase tickets at more economical prices by offering the chance to buy tickets early. Another new application is the principle of differentiating tolls for highways and bridges based on customer usage intensity without causing loss to the operators.

1.3. Impact of the Pandemic on Dynamic Pricing Approach

Technological advancements cause rapid changes in various sectors. In recent years, with the development of internet technology, the concept of e-commerce has emerged, rapidly popularizing the concept of revenue management in this area. As a result, organizations can market and sell their products under any conditions, anytime and anywhere. From the customer's perspective, especially those who face time constraints due to a busy work schedule, have become able to access products without visiting stores. Hence, in recent years, many businesses have shifted their focus from traditional commerce to e-commerce practices.

E-commerce offers numerous advantages to both customers and companies. For customers, it allows time savings, the ability to compare various products simultaneously, and choose the best price or the best price-performance ratio products. From a business perspective, it has become more preferred due to stock cost savings, reduced physical store expenses, and easier access to a wider and more varied customer portfolio.

While technological developments have accelerated the adaptation to e-commerce, the pandemic conditions experienced globally in recent years have significantly boosted the growth of this sector. The quarantine periods caused by past pandemics have proven to affect economic growth, the environment, and human activities. Especially, pandemic diseases and disaster periods have always impacted countries and people economically. Sectors where social distancing is challenging were most affected during this period, leading to temporary closures.

A similar and significant event that deeply impacted our recent history started with the reporting of 27 different pneumonia cases of unknown etiology in Wuhan, China, by Chinese health authorities on December 31, 2019. These cases were later identified as a disease caused by the Coronavirus (COVID-19), which led to severe acute respiratory problems and initiated the pandemic period. The spread of the pandemic couldn't be contained as the number of cases outside China increased from the beginning of 2020. The first case in our country was announced on March 10, 2020, and the first death related to the disease occurred on March 15, 2020. Many countries, including ours, had to undergo a long period of social isolation simultaneously or in phases, and customer preferences inevitably shifted during this period. The effects of this change were observed extensively in various fields, including e-commerce, technology, business travel, and the economy.

The primary reason for the increased interest in e-commerce sites during the pandemic was the greater accessibility to products through virtual means during a closed cycle and the ease of accessing information statistically at any time. For instance, the increase in case numbers leading to the closure of shopping malls, curfews, or the necessity of shifting to remote education accelerated people's transition to e-commerce. Measures taken have quickly shifted certain evolutionary processes from an inclusion stage to a widespread phase.

Especially during the pandemic, the closure of physical stores led to the rapid spread of delivery applications like Getir in Turkey, enabling the most hygienic and convenient way to shop for groceries from home. Additionally, food delivery applications brought restaurants home, minimizing the impact level on people and stores. The rapid and practical nature of these applications led other e-commerce companies to join the sector, incorporating the food and beverage segment into the online shopping system. Promotional effects and dynamic pricing approaches for products, especially considering the significant parameter of

consumption due to expiration dates, have greatly influenced customers, rapidly increasing the popularity of these applications.

In light of these information, the shift from physical to e-commerce environments has accelerated. E-commerce, one of the most affected sectors during this period, transformed the negative impact of physical stores into a positive shift towards online shopping. Mentioned online shopping mentality, quickly adapted into our lives, has maintained its importance in our country even during a major disaster period affecting 11 provinces. Especially during the pandemic and disaster periods, various parameter changes, such as customers' purchasing power, necessities, priorities, and sensitivities regarding products, have been reflected in the product prices by companies. Although various conditions affect customer demands, measurements of price-demand sensitivity during such sensitive periods will be enlightening for future periods. Particularly, products that can be dynamically priced according to future different condition fluctuations based on predicted future data, and the determined prices for these products, will be of great importance for profitability for organizations.

1.4. Impact of the Pandemic on Revenue Management

Pandemic diseases are infectious diseases that spread over a vast area, such as an entire continent or the entire world. The World Health Organization declared COVID-19, which became noticeable at the end of 2019 and rapidly spread worldwide by 2020, as a pandemic to promote the implementation of general protective measures due to its impact on human health. This quick shift to a quarantine phase, before people fully understood what was happening, deeply affected many sectors, especially e-commerce.

The Corona period, which began at the end of February 2020, has been termed as the first phase of COVID-19 (COVID-1). During this shocking phase worldwide, factories were closed, halting production, and people spent a long time in quarantine at home. All stores and shopping malls were shut down, and all forms of gatherings where people could congregate were banned. During COVID-19, although the global economy was not yet heavily impacted, people began stockpiling products out of fear of shortages, despite their high purchasing power. As production ceased, product stocks were predicted to run out, leading to significant price hikes. Consequently, companies began to offer discounts to customers more sparingly.

The second phase of COVID-19 in 2021, also known as COVID-2, was a period when factories worldwide were operational, production continued, but the threat of closure was always present. The economic impact of the COVID-1 phase led to a gradual increase in inflation rates. With the discovery and administration of vaccines, customer responses to discount policies became more positive as inflation and unemployment rose. Customers' stockpiling of products decreased compared to the first phase, and their purchasing power gradually declined. Given these reasons, stock shortages became less frequent, and the focus shifted to discount policies, purchasing power, and inflation.

The third phase of COVID-19 (COVID-3) saw factories continuing full-time production, and everyone tried to resume their normal lives under the guise of normalization. In this phase, to prevent the economy from being further impacted, death rates decreased with necessary precautions (vaccination, masks, social distancing, etc.) and the virus's reduced lethality. However, the economic challenges created by the first two waves began to emerge, with rising inflation and rapidly decreasing customer purchasing power, making discount policies more impactful on sales volumes.

1.5. Impact of Natural Disasters on Revenue Management

The pandemic, which deeply affected the entire world with three different waves and altered the economic trajectory, was followed by two major earthquakes affecting 11 provinces in our country, impacting all sectors, including e-commerce. During this period, when systems collapsed, transportation came to a halt, supply chains were damaged, stores were destroyed, products became unavailable, and a scarcity situation prevailed, negatively affecting many people in these provinces and surrounding areas.

While efforts were being made to recover from the pandemic, this natural disaster, along with the loss of lives, significantly increased its importance with a multiplier effect, starting regionally and then affecting all provinces of our country. The e-commerce sector was negatively impacted for a long time due to this natural disaster in our country, with stock shortages occurring as other citizens tried to help the region. Additionally, rapid changes in pricing policies and logistical challenges in the affected area shifted the revenue management efforts of the e-commerce sector to a different dimension. Both from the customer and the corporate perspective, the impact level on revenue management should be calculated, and improvements should be made for both sides.

1.6. Sustainability in Revenue Management

Revenue management is a strategic management style that increases profitability for businesses. Recent natural processes, which have developed beyond human intervention and have different effects, as discussed in the previous sections, have increased the importance of this concept. However, ensuring the continuity of the system will bring greater advantages to companies. For this purpose, sustainability is built on environmental, social, and economic dimensions. These three fundamental aspects of sustainability interact with each other and have intersecting points.

Environmental and economic sustainability unite to make living conditions suitable until societal unrest increases. Environmental and social sustainability come together to make living conditions bearable until financial resources are exhausted. Until the point where the Earth can no longer sustain human life, economic sustainability unites to make living conditions fair.

Economic sustainability foresees a circular economy. In the current economic model, production is a straight line. Especially the online sales of products with a short expiration date are priced considering all kinds of damage they may encounter during sales or the possibility of not being sold. Disadvantages that customers may encounter in the product they purchase can be eliminated with correct pricing, thereby increasing the profitability of the institutions. Decreased customer interest in a product or deformations that may occur in products can be dynamically priced based on the principle of getting rid of the products as soon as possible.

In general, the circular economy aims to reduce/eliminate waste and pollution. In a circular economy, producers design their products for durability and reuse. This principle foresees repairing products if they are worn out, remanufacturing them, or reusing their components/materials for another product or the same product. In the present case, many strategic approaches must now be displayed to make sustainable all these processes that customers pay the most attention to during online shopping and that institutions need to take care of. Both today and in the future, for sustainability to be achieved, it should not be overlooked that no economic activity and social structure can be evaluated independently of environmental factors.

In such case, the thesis work undertaken examines dynamic pricing policies for product groups in different categories during the period starting with the pandemic and including the earthquake period affecting eleven provinces. In the economic dimensions phase, government policies, company policies, product pricing, and confidence intervals were addressed. In the social dimension, the importance of e-commerce during the pandemic and the difficulties in supply due to the inadequacy of cargo during the earthquake period were analyzed in detail. In the environmental dimension, evaluations from customers regarding natural disasters and climate differences were considered.



2. LITERATURE REVIEW

In recent years, the e-commerce sector has rapidly expanded due to the growing importance of online sales. The literature review examined numerous articles that address pricing approaches in the e-commerce sector from different perspectives, such as artificial neural networks, machine learning, and statistical methods. While many of these articles aim to increase product sales, predict order arrivals, and estimate poverty rates based on e-commerce data, it has been observed that there is a lack of extensive research on the continued impact of natural disasters like COVID-19 and their multiplier effects or predictions of price fluctuations in subsequent disaster periods.

2.1. Data Mining Techniques

Kaushik et al. (2018) focused on prominent e-commerce platforms, finding that user reviews play a significant role in forming product perception and affecting sales. Prior literature reviews have explored how summary statistics of reviews from various e-commerce platforms impact product sales. This study investigated how the sequence of useful reviews, along with other review features like volume, informativeness, and the value of reviews (summary statistics), affects product sales.

In the study conducted by Ballestar, M. T., Grau-Carles, P., & Sainz, J. (2019), a predictive model was developed for companies, leading to the design of recommendation-based digital marketing strategies. This model utilized machine learning methods and big data mining techniques to personalize financial incentives for customers revisiting the website for refunds.

Bandyopadhyay, S., & Thakur, S. S. (2020) examined instances where customers remained indecisive about products on e-commerce sites and their purchasing behaviors in such states of indecision. The aim of this study was to increase product sales by meeting the needs of loyal customers. To develop accurate predictions for future customer needs, the study leveraged artificial neural networks, considering general purchasing habits of students and luxury item purchasing habits of graduates.

La Gatta, V., et al. (2020) developed new epidemic models during the COVID-19 period to predict the spread of the virus and analyze the extent to which different quarantine strategies could affect the spread of the epidemic. Their article proposed a new machine learning-based

framework capable of predicting parameters of any epidemiological model, such as contact rates and recovery rates, based on static and dynamic characteristics of locations.

Leung, K. H., et al. (2020) found that accurate prediction of order demand in multi-channel supply chains enhances decision-making abilities at strategic, tactical, and operational levels of management. They aimed to develop a predictive methodology for estimating real-time e-commerce order arrivals in distribution centers. Their study proposes a new machine learning prediction methodology by developing an adaptable neuro-fuzzy inference system integrated with time series data features.

Machmud and Minghat (2020) investigated hand sanitizer prices in Indonesia during the COVID-19 period. They observed that prices remained consistent during certain phases of the pandemic and projected that prices would return to normal post-pandemic.

Šaković Jovanović et al. (2020) assumed that the impact of e-commerce on firm performance is not direct and should be analyzed using intermediary factors. They used the Ordinary Least Squares (OLS) model for small and medium-sized enterprises. The findings supported the mediation hypothesis, emphasizing the significance of the mediating effect and advancing research in e-commerce.

Wijaya et al. (2020) conducted research on numerous big data sources in Indonesia, including social media, financial transactions, transportation, customer search records, and e-commerce. During the data processing phase, periodic surveys were used to monitor the country's development indicators, such as customers' purchasing power/poverty levels. Particularly, data from e-commerce were found to potentially represent households' actual expenditures and align better with the official calculation of the poverty threshold. The literature contribution of this research is to make a poverty rate estimate based on e-commerce data using machine learning algorithms.

In the literature study, data mining methods were applied in the e-commerce sector. However, it was noted that these studies did not address the changes in product prices during quarantine in online retailing or the prediction of product prices based on fluctuations during the COVID-19 period. No research was found on predicting product prices for future fluctuations based on different COVID-19 phases or comparing these dynamic approaches across periods.

2.2. Dynamic Pricing Techniques

Jayaraman, V., & Baker, T.(2003)'s work initially examined factors affecting the use of dynamic pricing in the past. The second objective was to summarize the concept of dynamic pricing over the Internet. The third goal was to study different methods for collecting dynamic demand data online. One literature review explored pricing as a function of inventory and time for hotel applications. The proliferation of digital marketplaces in e-commerce was presented. These new markets offer potential for dynamic pricing. Electronic intermediaries suggest that companies could compete in dynamic pricing markets in the future. Future research should consider whether demand and pricing data collected online can be generalized for non-Internet-based buyers.

Yasar, A., & Tien, J. M.(2004)'s study aimed to analyze and measure significant factors influencing price tracking among online consumers, including shopping experience, price perceptions, and awareness of dynamic pricing. The literature review indicated an increasing tendency among online shoppers to monitor product prices and wait for discounts before making purchase decisions. Using PLS SEM, this study analyzed the effects of price perceptions on overall shopping experience and consumers' price tracking behavior. The study discussed presenting consumers with found prices, positively impacting business by maintaining customer loyalty. Therefore, it is advised to keep price fluctuations within a certain range without adversely affecting consumers' price perceptions.

Lee, S., et al. (2004)'s study aimed to adopt a consumer relationship to investigate the effects of price fairness in the context of online auctions and group buying. It's known that these two variables have strong impacts on consumers' decision-making processes and outcomes. Dynamic pricing has become a critical part of all e-commerce, offering increased revenues, lower costs, and improved processes to accelerate growth. The study shows that consumers' perception of illusion control in price setting and advantageous side consumer relationship significantly influences the perception of price fairness. The findings are expected to help managers develop better pricing strategies and effective dynamic pricing mechanisms.

Hwang, S. B., & Kim, S.(2006)'s work described an automated sales pricing algorithm for online markets in a competitive environment, aimed at maximizing profits and minimizing sales duration. The dynamic pricing algorithm demonstrated its value in practice in the DVD

film sales market. Although more time is needed to estimate how much profit can be increased using the dynamic pricing algorithm, it certainly ensures dynamic pricing.

In the study by Daoquan Liu and Bocheng Chen (2012), dynamic pricing policies for the seasonal products of a company operating two online stores on two different B2C platform websites were observed. This article categorizes two online stores into different inventory management rules (independent inventory model, semi-independent inventory model, and combined inventory model with three models). The study examined the discriminatory pricing model, and in a numerical experiment, revenue differences between the two models were analyzed. It was determined that decisions on demand characteristics of e-tailer products were made when different B2C platform websites were chosen for setting up online stores and deciding on pricing policies.

In Boer's (2015) literature study, a brief introduction to the historical roots of quantitative research on pricing and demand forecasting is made, and dynamic pricing policies are examined in detail. The aim of the research is to find an optimal pricing policy and to prove optimal features in models. However, contributions from marketing, economics, econometrics, and computer sciences are also mentioned. The behaviors of these policies are analyzed in demand models and proposed pricing policies. This article, in general, discusses the interrelationships of research areas and attempts to identify new and different directions for future research.

In the study conducted by Sert et al. (2017), it is stated that e-commerce markets are highly dynamic due to constant competition. The primary aim of the study is to analyze customer attitudes considering users' repricing strategies that examine profit and revenue situations, comparing them with different performance measurements. For this purpose, the system was designed as a scalable microservice-based, using the Python programming language at this stage. The platform was created to facilitate data-driven strategies with easy access to past market data.

In the study by Fisher, et al. (2018), the first issue addressed random pricing. The second issue was resolved by considering the stocks of the retailer and their competitors as a consumer resource, in addition to changes in competitors' prices. This practice involved empirically modeling consumer choices for substitute products in retail. The pricing strategy,

based on these predictions, was monitored and observed over five weeks. Finally, product areas, entries and exits of competitors, and market conditions for online retailers change rapidly. Therefore, retailers need to be regularly reviewed to adapt to the evolving market and implement an effective dynamic pricing strategy.

Schlosser, et al. (2018) explored how companies in e-commerce compete using dynamic pricing and order strategies. A simulation platform was created to study pricing competition in online markets. Additionally, different pricing and ordering strategies, ranging from cutting-edge demand learning techniques to complex data-driven strategies based on efficient dynamic optimization models, were compared. The study concluded that efficient dynamic programming optimization approaches perform well.

Victor, V., et al.(2018)'s work explored consumer behaviors influencing factors and their potential online purchase decisions within a dynamic pricing context using exploratory factor analysis. The survey asked participants to rate their responses to 27 environment-related items. The Bartlett test of sphericity was applied to check if the correlation matrix was an identity matrix, and the Kaiser-Meyer-Olkin (KMO) test for sample adequacy was conducted. The study identified, measured, and classified various online dynamic pricing environment measurements that could influence consumer behavior and purchase decisions. The research indicates that dynamic pricing decisions should be made carefully, considering their effects on consumer reactions, aligning with previous studies. The research investigated the impact of dynamic pricing in the context of India's online retail, suggesting that the results are more applicable to the Indian e-commerce industry.

Kurnaz (2018) utilized eye-tracking technology to monitor visual behavior. Eye tracking is a data collection technique that conducts empirical studies on human perception behavior. The research analyzed the eye movement behavior of participants shopping on online store websites using the eye-tracking method. This study aimed to measure consumer attention activations towards web pages of online stores. Analysis of individual attention behavior identified variables affecting consumers' decision-making processes. Differences were found in the time participants spent making purchases on Ideefix, D&R, and Kitap Yurdu websites. However, this difference did not constitute a statistically significant variation. Eye movement and visual attention were observed using eye-tracking tools to better understand individuals'

eye movements. This allows determining the stress level, excitement, and active brain areas when looking at a specific point.

In the research by Ijegwa et al. (2019), a Bayesian Network was developed. In this context, the process of collecting random survey information and converting it into probability forms, integrating expert information, and participants' responses into a Bayesian system model was carried out. The resulting model was designed to analyze factors affecting corporate-level KPIs like customer satisfaction, thereby assessing customer satisfaction as a performance indicator in businesses. This study showed that the approach could be applied in large business corporations, and models based on survey data produced by this approach could be used by managers as a powerful decision-making tool.

Yapıcıoğlu (2019) found that while consumers prefer to buy certain products online, they choose to purchase others in stores, particularly grocery items. The study aimed to identify consumer thoughts on shopping for groceries in stores versus online, conducting T Tests and ANOVA Tests. The analysis suggests that a notable number of consumers choose not to purchase groceries online, whereas another considerable group does indeed shop for groceries online.

Nevruz (2019) examined how elements used in online store design, such as non-product images, site rewards, and security badges, are intended to achieve a certain customer outcome. The study's goal was to explore the effect of these online atmospheric elements on the customer's approach intentions towards the site. Hypotheses were established based on the ANOVA table showing whether the model as a whole is meaningful. An e-retail simulation was created, and the data obtained from experimental research were evaluated through multiple regression analysis. Virtual store customers perceive e-retail sites holistically, similar to physical store customers.

Mammadov (2019) aimed to demonstrate that offline and online trust in a multi-channel retailer significantly impacts consumers. The study first addressed the retail sector, its development, and types, including brick-and-mortar and non-store retailers, and e-commerce. The study compared the online and offline environments, revealing that trust in both the digital and physical channels of H&M and Zara has a positive effect on in-store purchases.

This indicates that enhancing trust in both channels can increase the number of shoppers visiting stores.

Banerjee, T., et al. (2019)'s study explained the dynamic pricing mechanism and analyzed its relation to agricultural marketing. It discussed the challenges of researching dynamic pricing approaches in e-commerce, highlighting the importance of factors like demand, supply, and freshness/sensitivity to age in developing a pricing mechanism for agricultural products. Despite numerous studies on dynamic pricing models, the current work focused on vegetable marketing. A gap was identified in dynamic pricing models for agricultural products and other perishables traded online. The research aimed to propose a suitable dynamic pricing model for the e-commerce of agricultural products.

Mangiaracina, R., et al. (2019)'s article had a dual purpose: first, to review and classify scientific publications concerned with innovative solutions aiming to enhance the efficiency of Business-to-Consumer (B2C) e-commerce deliveries; and second, to outline directions for future research in this area. Three main article classes were identified based on these methodologies: quantitative models (analytic models and simulations), empirical analyses (surveys, interviews, and case studies), and conceptual models or frameworks (including literature reviews). The study had two main limitations. First, the analyzed contributions may not be exhaustive. However, the authors are confident that the general picture emerging from the review is reliable regarding both cost factors and innovative last-mile delivery solutions, and that the findings reflect the most up-to-date understanding of the topic. Second, the proposed research directions are focused on innovative solutions, not on cost factors or cost components.

Chornous, G., & Horbunova, Y.(2020) aimed to investigate the experience of modeling dynamic pricing and to predict prices in e-commerce using personalized pricing strategies. They proposed including PLS regression for examination. The study explored pricing approaches in e-commerce and identified characteristics of different personalized pricing types (dynamic, customized, operational). Approaches for modeling dynamic pricing were researched.

Ulmer, M. W.(2020)'s research demonstrated that dynamic pricing can significantly increase both revenue and the number of customers served on the same day. The relevant pricing and

routing problem was modeled as a Markov decision process (MDP). A value function approximation (VFA) was used for this purpose. The research showed the benefit of dynamic pricing for dynamic SDD routing. Customers were offered SDD deadline options, each with a price. The challenge was to present appropriate, customer-dependent prices to encourage customers to choose effective delivery dates for maximizing current and expected future revenue. This expected revenue depends on the fleet's flexibility to serve future customers if an option is chosen. To estimate this flexibility, an APRP consisting of a pricing rule, policy search, state space merging, and VFA was developed.

Victor, V., & Bhaskar, M.(2021) studied the impact of dynamic pricing on consumer behaviors. This research focused particularly on the influence of dynamic pricing used in the e-commerce sector on consumer satisfaction levels and potential purchasing decisions. A survey study was conducted using the Likert scale and t-tests were applied as a method to test pre- and post-purchase. The study concluded that consumers were not satisfied with frequent and significant price fluctuations.

Strauss, A., et al.(2021) introduced flexible delivery time slots, defined as any combination of regular time windows, to capitalize on this type of customer flexibility. This can advance demand management and vehicle routing literature for home delivery. A simulation study was conducted, showing that flexible slots, especially when demand is low compared to existing delivery capacity, have significant potential to reduce delivery costs. However, as the simulation study showed, even flexible products brought significant routing cost savings.

Strauss, et al.(2021) presented a menu of delivery time windows to e-commerce customers, usually requiring them to select exactly one. A Vehicle Routing Problem (VRP) with flexible time slot reservations was applied. The output of this linear program provided information about the (approximate) opportunity cost associated with specific orders, informing a trackable dynamic pricing policy for regular and flexible slots.

In their study, Prakash, D., & Spann, M. (2022) develop suggestions regarding the effect of dynamic pricing on the internal reference price effect based on the decreasing demand model and test these suggestions with a field experiment and an online laboratory experiment. Both experiments systematically manipulate two dimensions of dynamic price change (amplitude and frequency). We found that customers react strongly to price increases but not to price

decreases. However, higher amplitude and higher frequency of price changes weaken internal reference price effects in the field experiment. The online laboratory experiment provides additional information in a more controlled environment that measures the internal reference price and additional covariates. Dynamic pricing may therefore provide an additional benefit for retailers by reducing potentially harmful reference price effects on demand.

According to a study by Gabor, et al. (2022) study, air transportation has its own characteristics that contribute to the final price of the travel ticket and differentiate airline companies. The aim of this article is to analyze whether the concept of revenue management is implemented by the Romanian national full-service airline TAROM and to highlight what criteria can be used to evaluate airlines, the differences between full-service carrier (FSC) and full-service carrier (FSC). The methodology is based on dynamic pricing analysis by simulation method for a full-service carrier and two low-cost carriers in Romania. The research results confirm that for the companies studied, return management involves strategic control of available resources, which means selling the product to the right customer at the right time, at the right price, thus filling a gap in international research.

The study of Ye, et al. (2023) evaluates the degree of information asymmetry in terms of accommodation prices of international tourist hotels (ITHs). This study estimates the degree of information asymmetry and inefficiencies by applying the concept of stochastic frontier approximation (SFA). Estimation results show that hotel location, traveler type, operation type may cause different information asymmetry. Compared to the asymmetry before the pandemic, the asymmetry in accommodation price information was found to have decreased since the start of the COVID-19 outbreak. This shows that the COVID-19 pandemic has changed the structure of consumer groups in hotel operations, subsequently affecting the hotelier's pricing strategy.

In the study of Poh, et al. (2023), dynamic pricing was integrated with real-time parking data to optimize parking usage and reduce traffic congestion. Dynamic pricing is the practice of changing the price of a product or service based on market trends. This approach has the potential to manage vehicle traffic in the parking area during peak and off-peak hours. The dynamic pricing method can set the parking fee to a higher price during peak hours and a lower price during off-peak hours. In this article, a method called deep reinforcement learning-based dynamic pricing (DRL-DP) is proposed. Dynamic pricing is segmented and

shifted back and forth on an hourly basis. Park usage rates and profits have been viewed as incentives for pricing control.

The work of Suresh Kumar, et al. (2023) focuses on weight-optimized long short-term memory (WOLSTM) for customer buy-in or purchase-based DP solutions . Behaviors on EC platforms.) proposes a new deep learning algorithm called. The proposed study consists of five stages. The missing value imputation and normalization preprocessing technique was first applied to the collected data set. The relevant features are then extracted from the preprocessed data set. Then, the dimensionality of the extracted feature set is reduced using the improved principal component analysis method. Then similar customers are grouped using k-means approach based on hamming silhouette coefficient and finally DP estimation for grouped customers is done using WOLSTM. The efficiency of the proposed system is analyzed using electronic products and pricing dataset.

The work of El Youbi, et al. (2023) presents a study on dynamic pricing that uses machine learning techniques to develop an accurate and effective pricing model. The study uses historical transaction data from an e-commerce platform and applies model selection to determine the most appropriate machine learning algorithm. Gradient Boosting Machines (GBM) are emerging as the primary model due to their ability to capture complex relationships and provide accurate predictions. The GBM model was evaluated using the Mean Square Error (MSE) and R-squared (R²) score. The findings mentions the potential of machine learning in optimizing revenue and increasing customer satisfaction through personalized pricing strategies.

Although there are many studies in many different sectors regarding dynamic pricing when the general literature is changed, no study has been found that discusses the evaluation of the pandemic period, which had an impact worldwide, and the multiplier effect of the natural disaster period after the pandemic.

3. MATERIAL AND METHOD

3.1. Material

The particular thesis in the e-commerce sector, focusing on revenue management, examines the impact of pandemics and natural disasters on customer purchasing behaviors and habits, particularly how these factors influence the dynamic pricing policies of products. The material of the study consists of data from the first quarter of 2020 to the second quarter of 2023, obtained from the website of a major e-commerce chain in Turkey. This includes daily price changes of products, gathered from various sectoral product groups available online. During the testing phase, the data for the most preferred product groups were obtained through daily observations on the company's website.

The effects of natural disasters like pandemics and earthquakes, which directly impact consumers, producers, and global markets, on the dynamic pricing of e-commerce sites are significant. The data collected in this research is limited to price information obtained from the e-commerce site and information obtained from the literature. The aim is investigating the dynamic pricing changes during different pandemic periods of a popular e-commerce platform in Turkey, focusing on three categories (Beverages, Electronic Devices and Hygiene Products) with periodic observations of their prices.

The prices of favorite products on the e-commerce site during the disaster period which includes pandemic period were examined from May 15, 2020, to January 18, 2023 and also for the earthquake period, data were recorded from February 6, 2023, to May 6, 2023.

3.2. Method

In the present section of the study in the e-commerce sector examines price fluctuations, identifying customer attitudes and sales volumes encountered during disaster periods. The study assesses customer purchase behaviors influencing product pricing to enhance revenue. The comparison of dynamic pricing systems based on determined customer criteria is conducted, contributing to the literature. Using the scale, the Analytic Hierarchy Process (AHP) is applied for pairwise comparisons of criteria. The criteria weights obtained from AHP are then used in the TOPSIS method to assess the impact of dynamic pricing during these periods.

The product criteria, based on Saaty's 9-point scale, are aimed at pairwise comparisons. Pairwise comparison matrices were created by looking at the literature. The study assesses the impact of various factors affecting customer purchasing behavior during natural disasters and pandemics, using data from an e-commerce site. The weights of these criteria are determined using AHP and TOPSIS methods, which are then applied to rank the influence on dynamic pricing in these periods.

In that section of the study, the impact of market conditions on customer perspective and the weighting of criteria are evaluated for a major e-commerce company. The selection of criteria was based on literature and also data collection was taken from e-commerce sites. The collected data are used to create pairwise comparison matrices in MS Excel. Geometric means of these comparisons are taken to combine them into a single matrix. The elements in the columns of the pairwise comparison matrix are summed and divided by the column totals to obtain a normalized matrix. Row averages of normalized matrices are taken to derive priority vectors. A consistency test is performed to ensure the results are reliable, expecting a consistency ratio of less than 0.1.

After weighting the criteria using the AHP method, a TOPSIS normalization matrix was created for evaluating the determined four periods. A weighted normalized matrix was formed using the normalized values. At this stage, the highest values in the columns of the weighted normalized matrix represent the positive ideal solution values, and the smallest values represent the negative ideal solution values. Distance calculations and relative closeness assessments were then conducted, resulting in a selection and ranking for the periods of pandemics and natural disasters.

Multi-criteria decision-making (MCDM) consists of methods developed to make decisions in situations with multiple criteria and alternatives. The objective of MCDM methods is to make the most accurate decision, which involves selecting, ranking, or classifying alternatives. The goal varies with the problem: in a selection problem, it's choosing the best alternative; in a ranking problem, it's ordering alternatives from best to worst; in classification, it's dividing alternatives into classes. Common features of MCDM methods include identifying alternatives and criteria, and selecting the best alternative for the purpose. There's no fixed rule for choosing the most suitable MCDM technique.

3.2.1. AHP

The Analytic Hierarchy Process (AHP) in the dissertation consists of 6 steps, which form the basis for many applications;

Step 1: Establishing the Hierarchical Structure

The first step involves organizing the decision problem hierarchically to make it understandable and assessable. Setting up the main goal, criteria, sub-criteria, and alternatives in a hierarchical structure is included, as shown in Figure 3.1

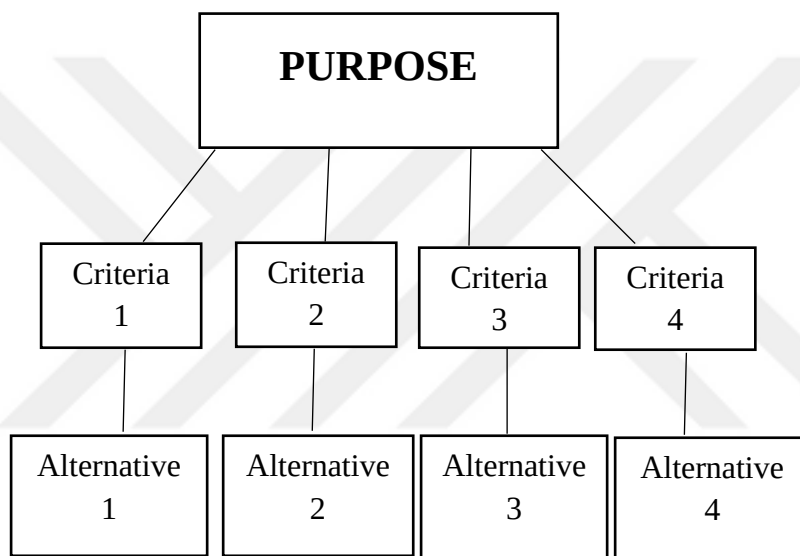


Figure 3.1. Three-Level Analytical Hierarchy Model

Step 2: Determining Priorities

Saaty developed a scale for comparing decision criteria pairwise, as seen in Table 3.1. By that provision, decision criteria and options are evaluated with a value between 1 and 9 through pairwise comparisons. Decision-makers choose the expression on the scale that reflects their opinion about the pair being compared. The numerical value corresponding to this expression is then used in subsequent calculations.

Table 3.1. 1-9 Scale Used in the Paired Comparison Method

DEGREES	DEFINITION
1	Equal Important
3	A Little More Matters
5	Strongly Important
7	Very Strongly Important
9	Extremely Important
2,4,6,8	Consensus (Average) Values

Step 3: Pairwise Comparison Matrix

The term 'pairwise comparison' refers to comparing two factors or criteria against each other and relies on the decision-maker's judgment. The Analytic Hierarchy Process (AHP) considers individual or group priorities, evaluating both quantitative and qualitative variables. It involves taking pairs of elements within the established hierarchy, comparing them based on a criterion, and ensuring separate judgments for each element without involving other criteria.

The pairwise comparisons of different criteria are shown in Table 3.2 In the comparison matrix, 'n' represents the number of criteria, with rows and columns arranged from $i=1,2,...,n$ and $j=1,2,...,n$ respectively. The term w_i/w_j in the matrix indicates how much more important the i. criterion is compared to the j. criterion in achieving the objective.

Table 3.2. Creating a Pairwise Comparison Matrix for Criteria

	Criterion 1	Criterion 2		Criterion n
Criterion 1	w_1/w_1	w_1/w_2		w_1/w_n
Criterion 2	w_2/w_1	w_2/w_2		w_2/w_n
.....				
Criterion n	w_n/w_1	w_n/w_2		w_n/w_n

Mathematically, relationship is expressed as $w_i / w_j = a_{ij}$ ($i,j = 1,2,...,n$), where w_i is the weight of the i. alternative, and w_j is the weight of the j. nci alternative. The pairwise comparison matrix 'A' can be illustrated as follows.

$$A = \begin{bmatrix} 1 & \cdots & a_{ij} & \cdots & a_{mn} \\ \vdots & 1 & \cdots & \cdots & \vdots \\ 1/a_{ij} & \cdots & 1 & \cdots & \vdots \\ \vdots & \cdots & \cdots & 1 & \vdots \\ 1/a_{mn} & \cdots & \cdots & \cdots & 1 \end{bmatrix} \quad (3.1)$$

While the upper part of the comparison matrix is filled in by decision makers, the lower part is obtained with the help of the formula below.

$$a_{ji} = \frac{1}{a_{ij}} \quad (3.2)$$

Step 4: Normalization of Pairwise Comparison Matrices

After the pairwise comparison matrix is created, the elements in the columns of the matrix are added and each element is divided by the column total. Therefore, the normalization process is carried out. The normalization formula is as follows.

$$C_{ij} = \frac{a_{ij}}{\sum_{i=1}^n x_{ij}} \quad (3.3)$$

Step 5: Creating the Priority Vector

The rows of the normalized matrix are summed and divided by the number of elements. Hence, the priority vector is obtained. With such process, the importance levels of the criteria and alternatives are determined. Another thing to consider at already stated stage is that the sum of each column of the normalized matrix must be 1.

$$W_i = \left(\frac{1}{n}\right) \sum_{j=1}^n c_{ij} \quad (3.4)$$

Step 6: Calculating the Consistency Ratio

It is necessary to check whether the pairwise comparison matrix is consistent within itself. In order to calculate the consistency ratio, the consistency index must be calculated. The formula below is used to calculate the consistency index (CI).

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (3.5)$$

In order to find the CI value, the λ_{max} value must first be calculated. In order to calculate CI value, the binary comparison matrix and the priority vector must first be multiplied. With such process, the weighted total vector is found.

$$A.W = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{12} & a_{22} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \cdot \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_n \end{bmatrix} \quad (3.6)$$

The corresponding elements of the weighted total vector and the priority vector W are divided by each other. With this process, the di value is obtained.

$$d_i = \frac{x_i}{w_i} \quad (3.7)$$

Then, the λ_{max} value is obtained by averaging the obtained values.

$$\lambda_{max} = \frac{\sum_{i=1}^n d_i}{n} \quad (3.8)$$

In order to calculate the consistency ratio (CR), the consistency index must be divided by the random index (RI).

$$CR = \frac{CI}{RI} \quad (3.9)$$

As a result of these calculations, the consistency ratio is expected to be less than 0.1. If the consistency ratio is found to be greater than 0.1 as a result of the operations performed, it is understood that the comparison matrix is inconsistent. In the present case, the pairwise comparison matrix needs to be reviewed.

3.2.2. TOPSIS

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a multi-criteria decision-making method developed by Hwang and Yoon. It's designed on the principle that the ideal alternative solution should be closest to the positive-ideal solution and farthest from the negative-ideal solution. TOPSIS can be directly applied to data without the need for qualitative conversion. The computational steps for the TOPSIS method include:

Stage 1: Creating the Decision Matrix (A)

The first step in TOPSIS is to create the decision matrix (A), where rows represent the alternatives and columns represent the evaluation criteria. The matrix element A_{ij} denotes the number of decision points (m) and the number of evaluation criteria (n).

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \quad (3.10)$$

Stage 2: Normalizing the Decision Matrix (R)

$$r_{ij} = \frac{a_{ij}}{\sum_{k=1}^m a_{2kj}} \quad i = 1, 2, \dots, m \quad j = 1, 2, \dots, n \quad (3.11)$$

At that phase, the decision matrix is normalized. Each value in the decision matrix is divided by the square root of the sum of the squares of all the values in its column. That process results in the normalized decision matrix, represented as R below.

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad (3.12)$$

Stage 3: Weighting the Normalized Decision Matrices (V)

Initially, weights (w_i) for evaluation criteria are established. Subsequently, elements in each column of the R matrix are multiplied by their respective w_i values to form the Weighted Standard Decision Matrix (V). The V matrix is then constructed as follows:

$$\sum_{i=1}^m w_i = 1 \quad (3.13)$$

The weights for the evaluation criteria are identified as $W_1, W_2, \dots, W_n$. The columns of the V matrix are calculated by multiplying the values in the R matrix columns with the corresponding evaluation criterion weight values.

$$V_{ij} = \begin{bmatrix} w_1 r_{12} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_2 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \quad (3.14)$$

Stage 4: Positive Ideal (A^+) and Negative Ideal (A^-) Solutions

TOPSIS assumes each evaluation criterion increases or decreases monotonically. The ideal solution is determined by selecting the largest values from the weighted standard decision matrix's column values. The method for identifying the positive ideal solution set is shown below.

Positive Ideal Solution Set:

$$A^* = \{(max_{vij}|j \in J|), (min_{vij}|j \in J|)\} \quad (3.15)$$

The negative ideal solution set is formed by choosing the smallest values from the weighted standard decision matrix's column values. The method for identifying the negative ideal solution set is shown below.

Negative Ideal Solution Set:

$$A^- = \{(min_{vij}|j \in J|), (max_{vij}|j \in J|)\} \quad (3.16)$$

Stage 5: Calculating Separation Measures

In TOPSIS, the Euclidean Distance Approach is utilized to determine the deviations of each decision point's evaluation criterion values from the positive ideal and negative ideal solution sets. These deviation values are termed as Positive Ideal Separation (S_i^*) and Negative Ideal Separation (S_i^-). The formulas for calculating Positive Ideal Separation (S_i^*) and Negative Ideal Separation (S_i^-) are as follows: The number of (S_i^*) and (S_i^-) to be calculated naturally equals the number of alternatives.

$$S_i^* = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^*)^2} \quad (3.17)$$

$$S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (3.18)$$

Stage 6: Calculating the Relative Closeness to the Ideal Solution

The relative closeness of each decision point to the ideal solution (C_i^*) is calculated using the positive ideal and negative ideal separation measures. Mentioned criterion represents the proportion of the negative ideal separation measure in the total separation measure. The calculation of the relative closeness to the ideal solution is shown below:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*} \quad (3.19)$$

The value of (C_i^*) falls within a certain range and indicates the absolute closeness of the respective decision point to the ideal solution and the negative ideal solution.

3.2.3. Confidence Interval Calculation

Dynamic pricing strategies enable businesses to change prices periodically. When consumers know these periods, they tend to visit the company's website more often. Dynamic pricing can yield significant benefits, particularly during price fluctuations. However, it can also negatively impact customer opinions about the product. To better understanding, the confidence interval of product prices has been calculated. Prices outside this range could potentially reduce customer satisfaction. The confidence interval helps determine the certainty level about a data group, essentially indicating how close the data are to the mean.

4. FINDINGS

During that phase of the study, the AHP and TOPSIS methods from multi-criteria decision-making techniques will be used to identify the most significantly affected period in revenue management due to dynamic pricing across different COVID pandemic waves and an earthquake period. The study will determine the criterion weights using the AHP method and then apply the TOPSIS method to select the period most affected.

4.1. Weighting Criteria Using the AHP Method

Current stage involves creating a hierarchical structure with four criteria affecting e-commerce pricing and four alternative periods. The alternatives are named COVID-1, COVID-2, COVID-3, and the Earthquake period. COVID-1 covers the initial phase of the pandemic in 2020. COVID-2, the second wave, began in 2021, followed by COVID-3, the third wave, in 2022. The Earthquake period analysis includes data from one month following February 6, 2023.

4.1.1. Creating the Hierarchical Structure

The hierarchical structure for that section of the study includes the following periods as alternatives: COVID-1, COVID-2, COVID-3, and the earthquake period. The criteria selected for assessment are listed as follows:

- Purchasing Power,
- Inflation,
- Discounts,
- Low Supply.

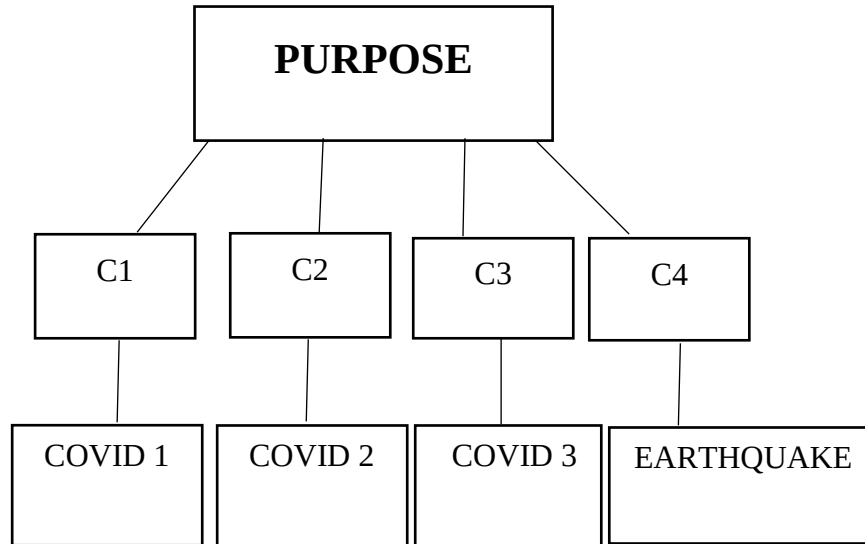


Figure 4.1. Three-Level Analytical Hierarchy Model

Using these criteria, the study aims to rank the contribution of revenue management from a customer perspective during pandemic and natural disaster periods, focusing on a leading company in the e-commerce sector.

Table 4.1. Criteria Specified for Application

Criteria No	Criteria
C1	Purchasing Power
C2	Inflation
C3	Discount
C4	Low Supply

4.1.2. Creating Pairwise Comparison Matrices

Each criterion in the hierarchical structure is determined according to its level of importance. In the process, the 9-point scale developed by Saaty was used. Here, literature was used to determine the period most affected by natural disasters in e-commerce, based on customer purchasing behavior. Equations 3.1 and 3.2 were used.

Table 4.2. Pairwise Comparison Matrix of C1

C1				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	1.000	2.000	3.000	5.000
COVID 2	0.500	1.000	2.000	4.000
COVID 3	0.333	0.500	1.000	3.000
Earthquake	0.200	0.250	0.333	1.000
Sum	2.033	3.750	6.333	13.000

Table 4.3. Pairwise Comparison Matrix of C2

C2				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	1.000	0.500	0.333	0.200
COVID 2	2.000	1.000	0.333	0.250
COVID 3	3.000	3.000	1.000	0.500
Earthquake	5.000	4.000	2.000	1.000
Sum	11.000	8.500	3.667	1.950

Table 4.4. Pairwise Comparison Matrix of C3

C3				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	1.000	0.330	0.330	1.000
COVID 2	3.000	1.000	1.000	2.000
COVID 3	3.000	1.000	1.000	2.000
Earthquake	1.000	0.500	0.500	1.000
Sum	8.000	2.830	2.830	6.000

Table 4.5. Pairwise Comparison Matrix of C4

C4				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	1.000	5.000	2.000	4.000
COVID 2	0.200	1.000	1.000	0.200
COVID 3	0.500	1.000	1.000	0.333
Earthquake	0.250	5.000	3.000	1.000
Sum	1.950	12.000	7.000	5.533

Table 4.6. Comparison Matrix of Criteria Pairwise

Criteria Pairwise Comparison Matrix				
	Purchasing Power	Inflation	Discount	Low Supply
Purchasing Power	1.000	1.000	4.000	1.000
Inflation	1.000	1.000	4.000	2.000
Discount	0.250	0.250	1.000	0.200
Low Supply	1.000	0.500	5.000	1.000
Sum	3.250	2.750	14.000	4.200

4.1.3. Normalization of the Pairwise Comparison Matrix

Normalization of the pairwise comparison matrix was calculated by Equation 3.3. First, the values in each column were collected. After obtaining the column totals, each criterion was divided by the column total. With this process, normalized decision matrices are obtained. The normalized decision matrices of the criteria are given below.

Table 4.7. Purchasing Power Criteria Normalized Matrix

Purchasing Power Criteria Normalized Matrix				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	0.492	0.533	0.474	0.385
COVID 2	0.246	0.267	0.316	0.308
COVID 3	0.164	0.133	0.158	0.231
Earthquake	0.098	0.067	0.053	0.077

Table 4.8. Inflation Criteria Normalized Matrix

Inflation Criteria Normalized Matrix				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	0.091	0.059	0.091	0.103
COVID 2	0.182	0.118	0.091	0.128
COVID 3	0.273	0.353	0.273	0.256
Earthquake	0.455	0.471	0.545	0.513

Table 4.9. Discount Criteria Normalized Matrix

Discount Criteria Normalized Matrix				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	0.125	0.117	0.117	0.167
COVID 2	0.375	0.353	0.353	0.333
COVID 3	0.375	0.353	0.353	0.333
Earthquake	0.125	0.177	0.177	0.167

Table 4.10. Low Supply Criteria Normalized Matrix

Low Supply Criteria Normalized Matrix				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	0.513	0.417	0.286	0.723
COVID 2	0.103	0.083	0.143	0.036
COVID 3	0.256	0.083	0.143	0.060
Earthquake	0.128	0.417	0.429	0.181

Table 4.11. Criterias Normalized Matrix

Criteria Normalized Matrix				
	COVID 1	COVID 2	COVID 3	Earthquake
COVID 1	0.308	0.364	0.286	0.238
COVID 2	0.308	0.364	0.286	0.476
COVID 3	0.077	0.091	0.071	0.048
Earthquake	0.308	0.182	0.357	0.238

4.1.4. Calculating the Priority Vector

The process for calculating the priority vector involved summing the values in each row of the normalized matrix and then dividing by the number of elements. This step resulted in the creation of the priority vector. The priority vector obtained from these calculations is presented below by using equation 3.4 was used.

4.1.5. Calculating the Consistency Ratio

At that part, equations 3.5, 3.6, 3.7, 3.8 and 3.9 were used. The consistency of the pairwise comparison matrix is determined by calculating the consistency index. To find the consistency index, λ_{max} value is first computed by multiplying the pairwise comparison matrix with the priority vector, resulting in a weighted sum vector. The weighted sum vector obtained from the calculation is then used to calculate λ_{max} . This involves dividing the row sums of the weighted sum vector by the corresponding elements in the priority vector, and then taking the arithmetic mean of the resulting d_i values to find λ_{max} , which is calculated to be 0.0325.

Table 4.12. Consistency Ratio Calculation Tables

A.W=	Criterias Comparison Matrix				X	Criteria Preference Matrix		=		
	1	1	4	1		0,2988			1,2152	
	1	1	4	2		0,3583			1,4863	
	1/4	1/4	1	0,2		0,0717			0,2902	
	1	1/2	5	1		0,2712			1,1077	

CI Index = 0,0289

CI/RI = 0,0325

4.2. Creating the TOPSIS Decision Matrix

The criterion weights obtained using the AHP method are utilized to determine the period most affected in e-commerce. At that section, equation 3.10 was used. To apply the TOPSIS method, the first step is to create a decision matrix. This matrix evaluates the periods identified as alternatives - COVID-1, COVID-2, COVID-3, and the earthquake period - in terms of criteria. The evaluation based on criteria involves assigning numerical values between 1-9 to the criteria. The decision matrix, which includes the evaluation of alternatives according to criteria within the TOPSIS method, is presented below.

Table 4.13. Consistency Ratio Calculation Table

	Non Beneficial	Beneficial	Non Beneficial	Beneficial
Weights	0.299	0.358	0.072	0.271
Criteria	Purchasing Power	Low Supply	Discount	Inflation
COVID-1	6	8	2	4
COVID-2	4	2	3	6
COVID-3	3	4	5	7
EARTHQUAKE PERIOD	2	7	5	9

4.2.1. Normalization of the Decision Matrix

By using equations 3.13 and 3.14, a normalized decision matrix was created. In the TOPSIS method, the decision matrix is normalized by dividing the values in each criterion column by the square root of the sum of the squares of the values in that column. Mentioned process ensures the comparability of criteria by standardizing the range of values.

Table 4.14. TOPSIS Normalized Decision Matrix

	Purchasing Power	Low Supply	Discount	Inflation
COVID-1	0.7442	0.6937	0.2520	0.2965
COVID-2	0.4961	0.1734	0.3780	0.4447
COVID-3	0.3721	0.3468	0.6299	0.5189
EARTHQUAKE PERIOD	0.2481	0.6070	0.6299	0.6671

4.2.2. Weighting the Normalized Decision Matrix

Each value in the normalized decision matrix is multiplied by the criterion weights derived through the AHP method. The relative importance of each criterion into the analysis is integrated, allowing for a more accurate evaluation of the alternatives under consideration.

Table 4.15. Criterion Weights and Normalized Decision Matrix

	Purchasing Power	Low Supply	Discount	Inflation
COVID-1	0.2225	0.2483	0.0181	0.0804
COVID-2	0.1483	0.0621	0.0272	0.1205
COVID-3	0.1113	0.1242	0.0454	0.1406
EARTHQUAKE PERIOD	0.0742	0.2173	0.0454	0.1808

4.2.3. Determining Ideal and Non-Ideal Solution Values

By using equations 3.15 and 3.16, determining the ideal and non-ideal solution values in the weighted normalized matrix is involved. The maximum and minimum values in each column of the weighted normalized matrix are identified for this purpose. The maximum values are considered as the positive ideal solution values, while the minimum values represent the negative ideal solution values.

Table 4.16. Positive Ideal and Negative Ideal Solution Values

	Purchasing Power	Low Supply	Discount	Inflation
COVID-1	0.2225	0.2483	0.0181	0.0804
COVID-2	0.1483	0.0621	0.0272	0.1205
COVID-3	0.1113	0.1242	0.0454	0.1406
EARTHQUAKE PERIOD	0.0742	0.2173	0.0454	0.1808
A+	0.2225	0.2483	0.0454	0.1808
A-	0.0742	0.0621	0.0181	0.0804

4.2.4. Calculating Distance Values

In the current phase, the distance to the positive ideal points is calculated by subtracting each criterion in the weighted normalized matrix from its corresponding positive ideal solution value and then squaring these differences. Calculations were made using equations 3.17 and 3.18. The squared values are summed and their square roots are taken to calculate the distance to the positive ideal. The same process is repeated to calculate the distance to the negative ideal points, where each criterion is subtracted from its corresponding negative ideal solution value.

Table 4.17. Positive Ideal and Negative Ideal Solution Values

S_i^+	S_i^-
0.1041	0.2381
0.2101	0.0848
0.1715	0.0980
0.1516	0.1869

4.2.5. Calculating Relative Closeness

The relative closeness is calculated using the negative ideal solution value and the positive ideal solution value obtained in the previous step. To calculate the relative closeness values, first, the total distance value is obtained by summing the positive and negative ideal solution values. Then, the relative closeness value is derived by dividing the negative ideal solution value by the total distance value. Calculations were made using equations 3.19.

Table 4.18. Relative Closeness Values

Alternatives	C_i	Sorting
COVID-1	0.695882755	1
COVID-2	0.287627289	4
COVID-3	0.363620243	3
EARTHQUAKE PERIOD	0.552166657	2

The particular study focused on determining e-commerce customer preferences, the AHP method was used to define criterion weights. Using these weights, the period most affecting e-commerce customers was identified. An examination of the relative closeness values of the alternatives revealed that the COVID-1 period, with a relative closeness value of 0.6958, was the most impacted. The earthquake period ranked second with a value of 0.56, and the third wave of COVID-19 (COVID-3) was third with a value of 0.36. The COVID-2 period, having the least impact, ranked last with a value of 0.29. Among these periods, COVID-1 was the most affected, while COVID-2 was the furthest from the ideal solution.

4.3. Confidence Interval Calculation

In this study, a confidence interval calculation was conducted using the prices of the most popular products in categories such as beverages, electronic devices, and hygiene products. Based on the TOPSIS calculations from previous sections, it was observed that the COVID-1 period was the most affected. Therefore, the confidence interval calculation for the COVID-1 period was specifically performed.

Table 4.19. Confidence Level of Black Tea and Herbal Tea Products

BLACK TEA	Confidence Level ($\alpha=0,05$)		Confidence Level ($\alpha=0,1$)		Confidence Level ($\alpha=0,9$)		Confidence Level ($\alpha=0,95$)		Confidence Level ($\alpha=0,01$)	
Brand 1	25.2	26.5	25.3	26.4	25.8	25.9	25.8	25.9	25.0	26.7
Brand 2	27.4	29.4	27.6	29.3	28.3	28.5	28.4	28.4	27.1	29.7
Brand 3	30.4	31.3	30.4	31.2	30.8	30.9	30.8	30.8	30.2	31.5
Brand 4	48.3	50.5	48.5	50.3	49.3	49.5	49.4	49.4	48.0	50.8
Brand 5 (Herbal Tea)	7.2	7.5	7.2	7.5	7.3	7.4	7.4	7.4	7.1	7.6

Due to the wide variety of products and the suitability of product groups for comparison, the confidence intervals were determined by evaluating 31-day price data of black tea products from different brands. The calculation results, detailed in Table 4.19, indicate that products with a 99% confidence interval have a wider range than those with a 95% confidence interval. The possibility of customers encountering prices outside these intervals could negatively affect customer satisfaction, an important factor in uncertainty. For herbal teas, an alternative to black tea in online sales, it was found that the confidence interval for Brand 4 herbal tea over a month was narrower compared to other product groups.

Table 4.20. Confidence Level of Colognes and Disinfectant

COLOGNE	Confidence Level ($\alpha=0.05$)		Confidence Level ($\alpha=0.1$)		Confidence Level ($\alpha=0.9$)		Confidence Level ($\alpha=0.95$)		Confidence Level ($\alpha=0.01$)	
Brand 1	29.73	30.00	29.75	29.98	29.86	29.87	29.86	29.87	29.68	30.05
Brand 2	30.76	35.78	31.16	35.38	33.11	33.43	33.19	33.35	29.97	36.57
Brand 3	31.18	35.16	31.50	34.84	33.05	33.30	33.11	33.24	30.56	35.79
DISINFECTANT	Confidence Level ($\alpha=0.05$)		Confidence Level ($\alpha=0.1$)		Confidence Level ($\alpha=0.9$)		Confidence Level ($\alpha=0.95$)		Confidence Level ($\alpha=0.01$)	
Brand 4	9.90	9.90	9.90	9.90	9.90	9.90	9.90	9.90	9.90	9.90
Brand 5	47.32	49.31	47.48	49.15	48.25	48.38	48.28	48.35	47.01	49.62

The confidence intervals for disinfectant products are calculated in Table 4.20, focusing on a one-month period. For products with a 95% confidence interval, it was found that Brand 2 and Brand 3 branded products have wider intervals compared to other categories, indicating greater price fluctuations. In contrast, Brand 4 products showed no significant price movement, as indicated by the consistency in their confidence interval range.

Table 4.21. Confidence Level of Powdered Gloves and Powder Free Gloves

POWDERED GLOVES	Confidence Level ($\alpha=0.05$)		Confidence Level ($\alpha=0.1$)		Confidence Level ($\alpha=0.9$)		Confidence Level ($\alpha=0.95$)		Confidence Level ($\alpha=0.01$)	
Brand 1	46.35	47.02	46.40	46.97	46.67	46.71	46.68	46.70	46.24	47.13
Brand 2	52.75	56.32	53.03	56.03	54.42	54.65	54.48	54.59	52.19	56.88
Brand 3	50.82	51.06	50.84	51.04	50.93	50.95	50.94	50.94	50.78	51.09
Brand 4	46.62	47.62	46.70	47.54	47.09	47.15	47.10	47.13	46.46	47.78
POWDER-FREE GLOVES	Confidence Level ($\alpha=0.05$)		Confidence Level ($\alpha=0.1$)		Confidence Level ($\alpha=0.9$)		Confidence Level ($\alpha=0.95$)		Confidence Level ($\alpha=0.01$)	
Brand 5	48.42	48.90	48.46	48.86	48.64	48.68	48.65	48.67	48.34	48.98
Brand 6	59.79	64.24	60.15	63.89	61.88	62.16	61.95	62.09	59.09	64.94
Brand 7	50.40	51.34	50.48	51.27	50.84	50.90	50.86	50.89	50.26	51.49

In Table 4.21, the 10% confidence interval ($\alpha=0.9$) was analyzed. It was observed that the price difference for Brand 1 powdered gloves was a maximum of 3 ₺, while for powder-free gloves, it was 1.5 ₺. Upon analyzing the data, it was determined that the confidence intervals for products in the hygiene category are very close. Consequently, it can be interpreted that as the confidence interval narrows, the reliability of the prices increases.

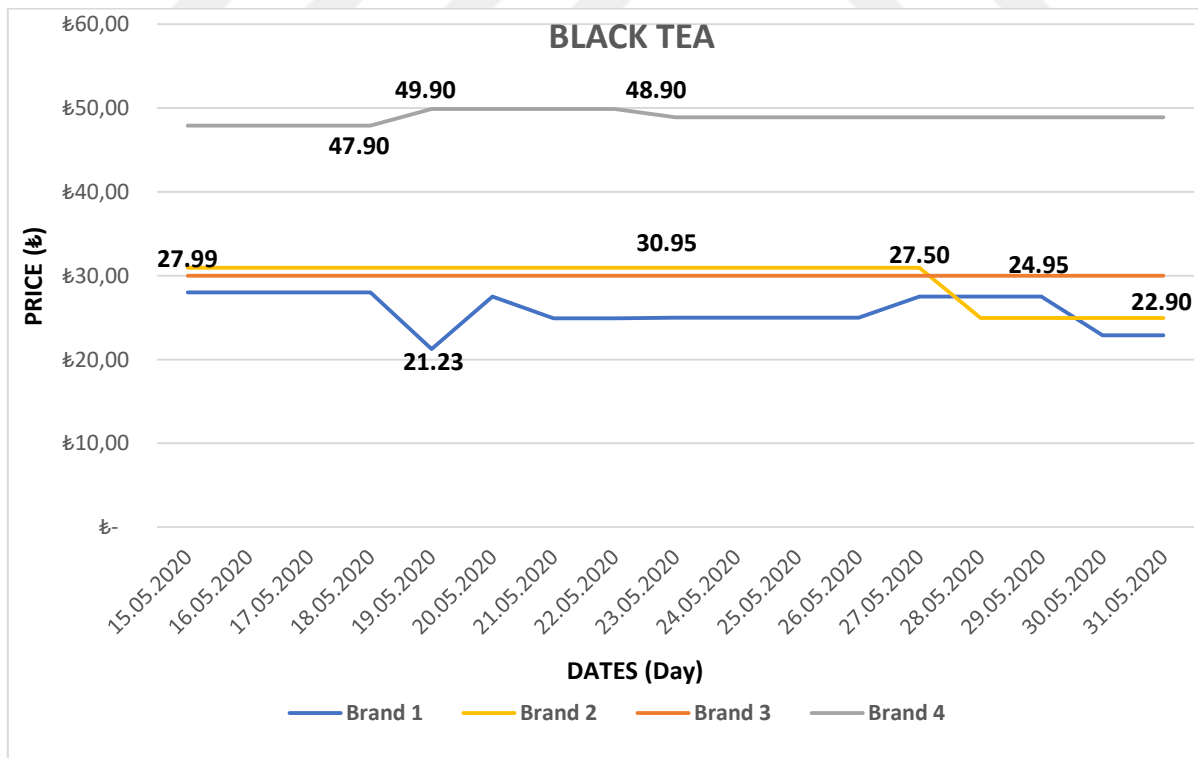


Figure 4.2. Approximately Two-Week Price Distribution of Black Tea by Brand

During the COVID-19 period, the brand-based price analysis of black tea products, which were frequently chosen by customers staying at home, is presented in Figure 4.2. That category, within the beverage segment, showed that price variations were not significant across different brands. Particularly, Brand 1 branded black tea products exhibited more price changes compared to other brands. Customers' brand-based preferences contribute to variability in the online market is observed.

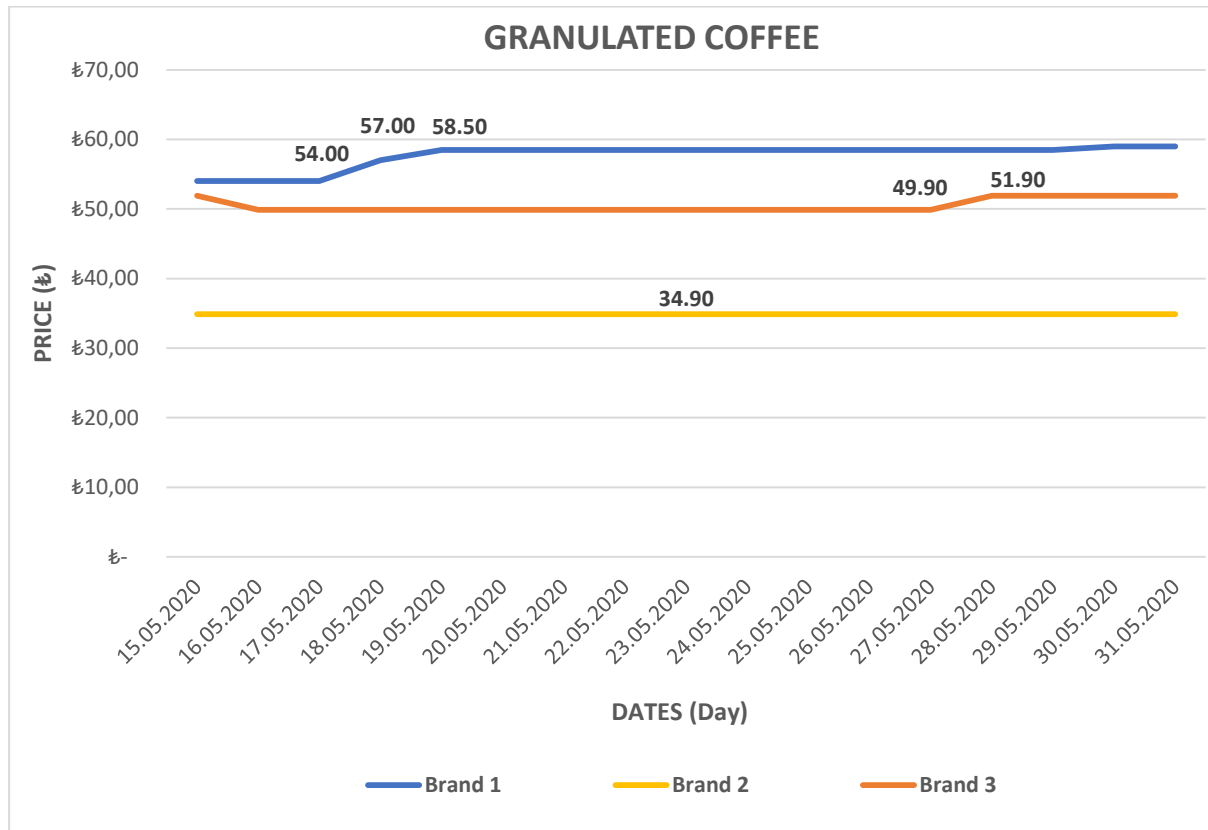


Figure 4.3. Approximately Two-Week Price Distribution of Granulated Coffee by Brand

In the analysis of customer purchases from a leading Turkish e-commerce online store, a 15-day price variation of granulated coffee products during the COVID-19 period is illustrated in Figure 4.3. It indicates that dynamic pricing was more prevalent in Brand 1 products. When observing other brands, it was found that Brand 2 products maintained stable prices over approximately two weeks, and Brand 3 products showed minimal price changes. Based on that information, Brand 1 was identified as the most preferred and best-selling brand in the granulated coffee category among customers.

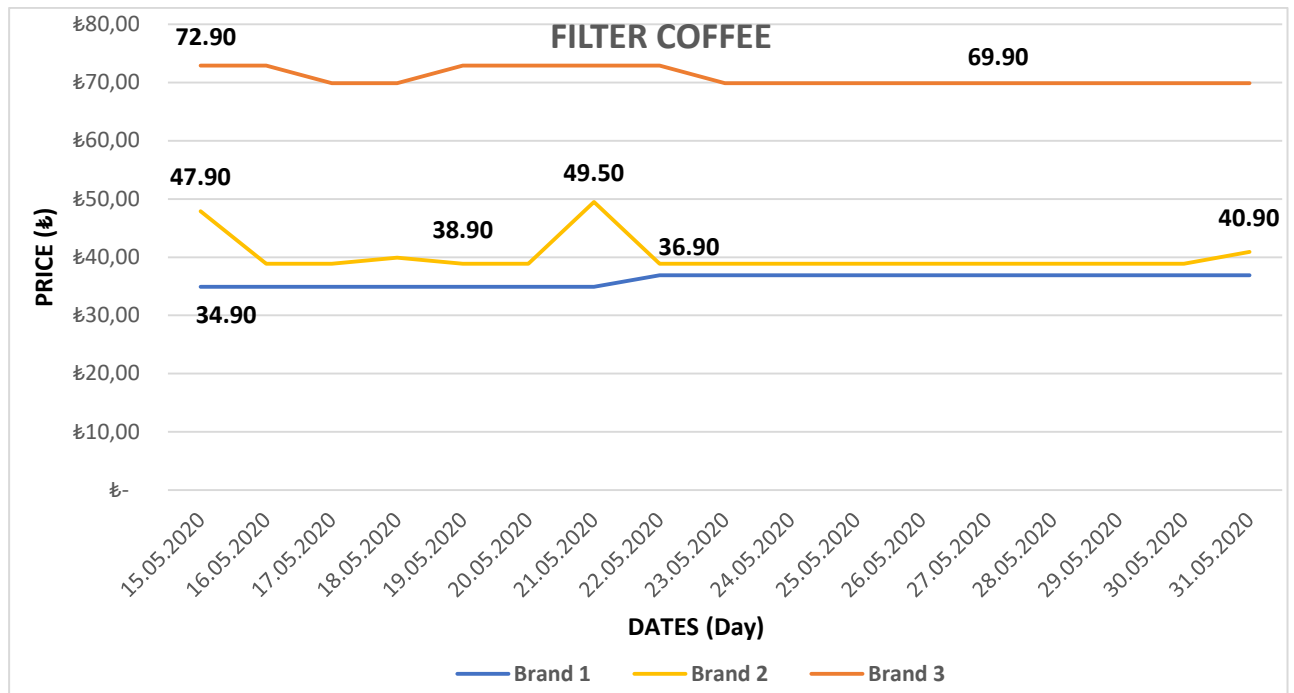


Figure 4.4. Approximately Two-Week Price Distribution of Filter Coffee Products by Brand

In the analysis of filter coffee product prices depicted in Figure 4.4, dynamic pricing was observed in three brands, with price fluctuations identified. Specifically, Brand 2 products showed sudden increases and decreases, indicating high demand variability. Contrary to general expectations, no significant price changes were observed during the festive period (May 24-26, 2021) in Turkey, a time typically associated with active revenue management and dynamic pricing in the online sector.

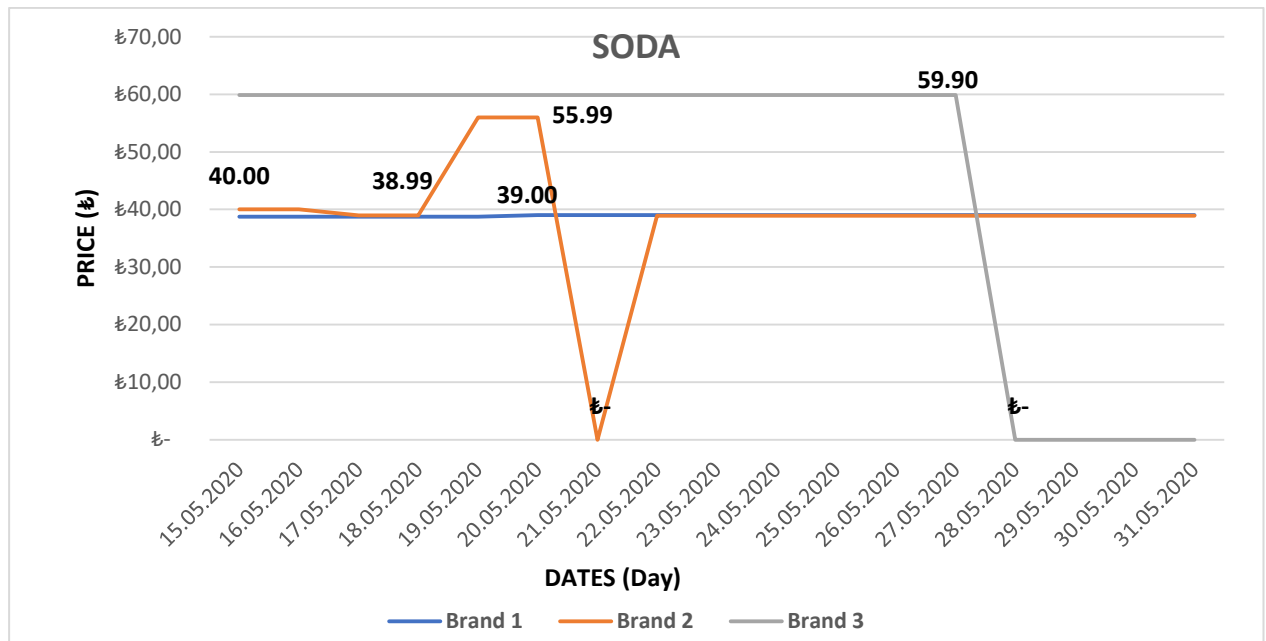


Figure 4.5. Approximately Two-Week Price Distribution of Soda Products from the Cold Drink Category by Brand

In the cold beverages category, the pricing of soda products is detailed in Figure 4.5. The data suggests that dynamic pricing was more pronounced for Brand 2 products compared to other brands, with more frequent price fluctuations.

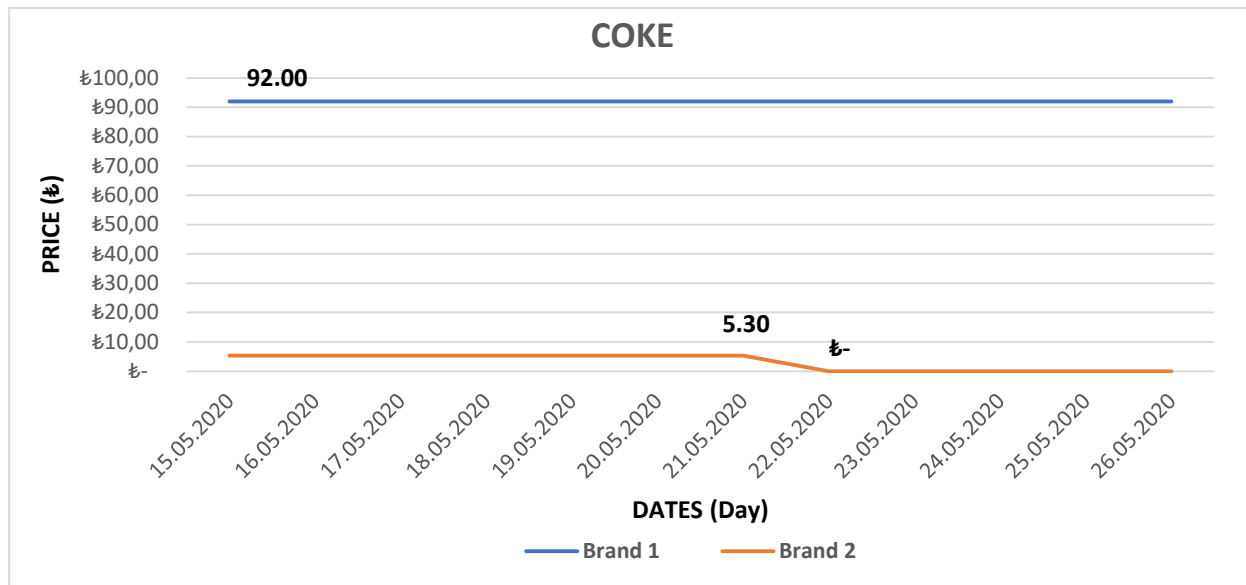


Figure 4.6. Price Distribution of Brands with Coke Products

Regarding coke products, another popular item in the cold beverages category, the data in Figure 4.6 indicates that due to the high demand for Brand 2, it was often out of stock, leading to its 'sold out' status for customers. Consequently, Brand 1's prices were mostly unchanged and offered to customers without significant price alterations.

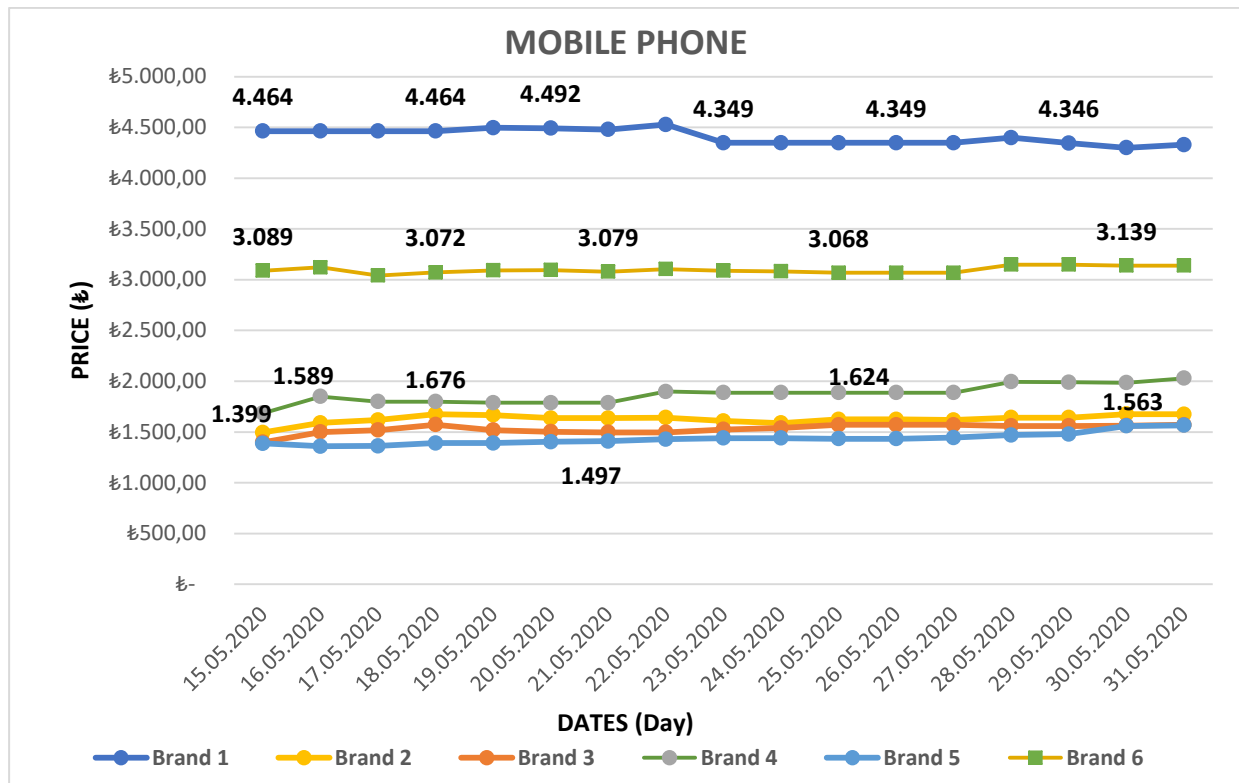


Figure 4.7. Approximately Two-Week Price Distribution of Mobile Phone Products from the Electronic Device Category by Brand

During the COVID-19 period, the electronic devices category experienced more dynamic pricing changes compared to other categories. In the mobile phone category, the most significant price fluctuations were observed in Brand 1 and Brand 4 products. Examining the data in Figure 4.7 reveals that dynamic pricing changes occurred in response to supply and demand. As further detailed in the tables to be shared in the appendices of the thesis, it was observed that over a 17-day period, prices of certain electronic devices were more significantly affected by currency exchange rates compared to other products. In Figure 4.6, it was found that the fluctuation of the dollar exchange rate particularly affected the pricing of Brand 1 mobile phones, while its impact on Brand 2 mobile phones was not as significant. By observing that Brand 1 products, in general, exhibit brand-based price differentiation, largely due to the impact of exchange rates on imported electronic products.

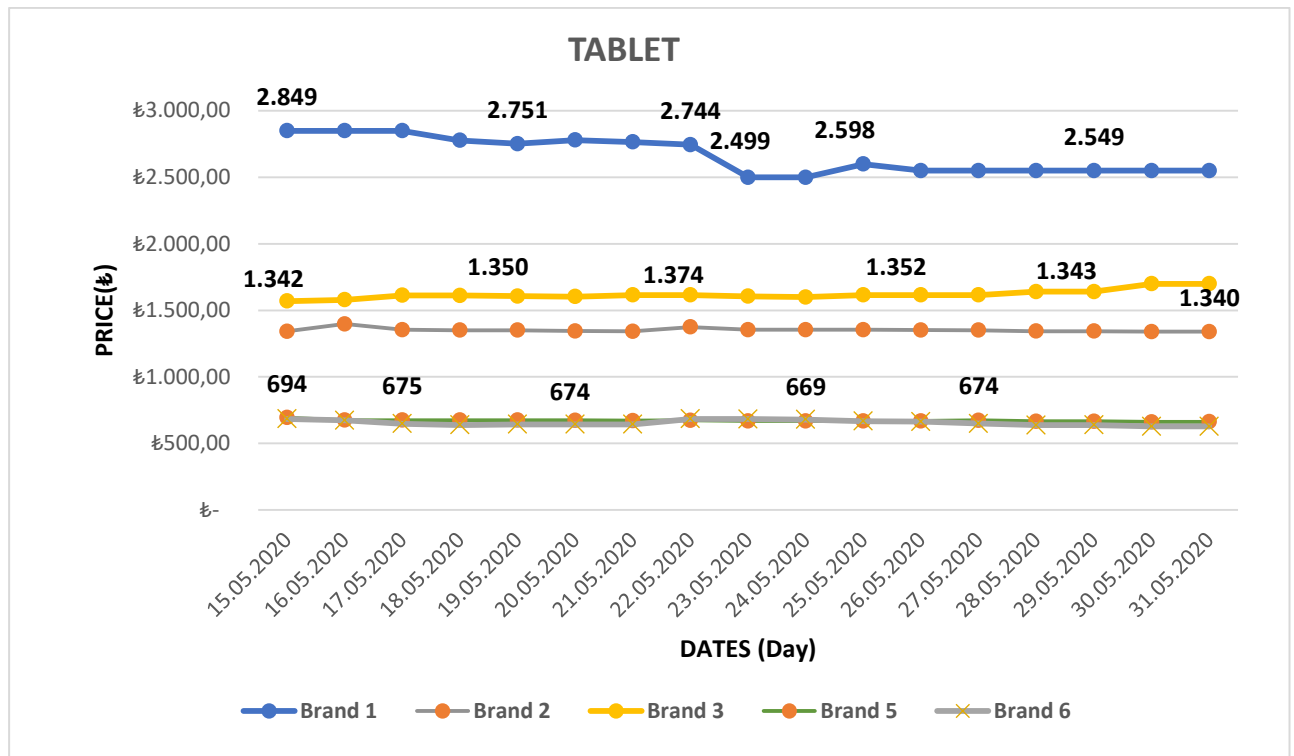


Figure 4.8. Price distribution of brands with Tablet Products

In the analysis of the electronic products category, specifically tablets, it was determined from Figure 4.8 that Brand 1 products experienced rapid changes in system dynamics and had stronger sales (customer preferences) compared to other products. The prices of Brand 4 and Brand 5 products were observed to be very similar to each other.

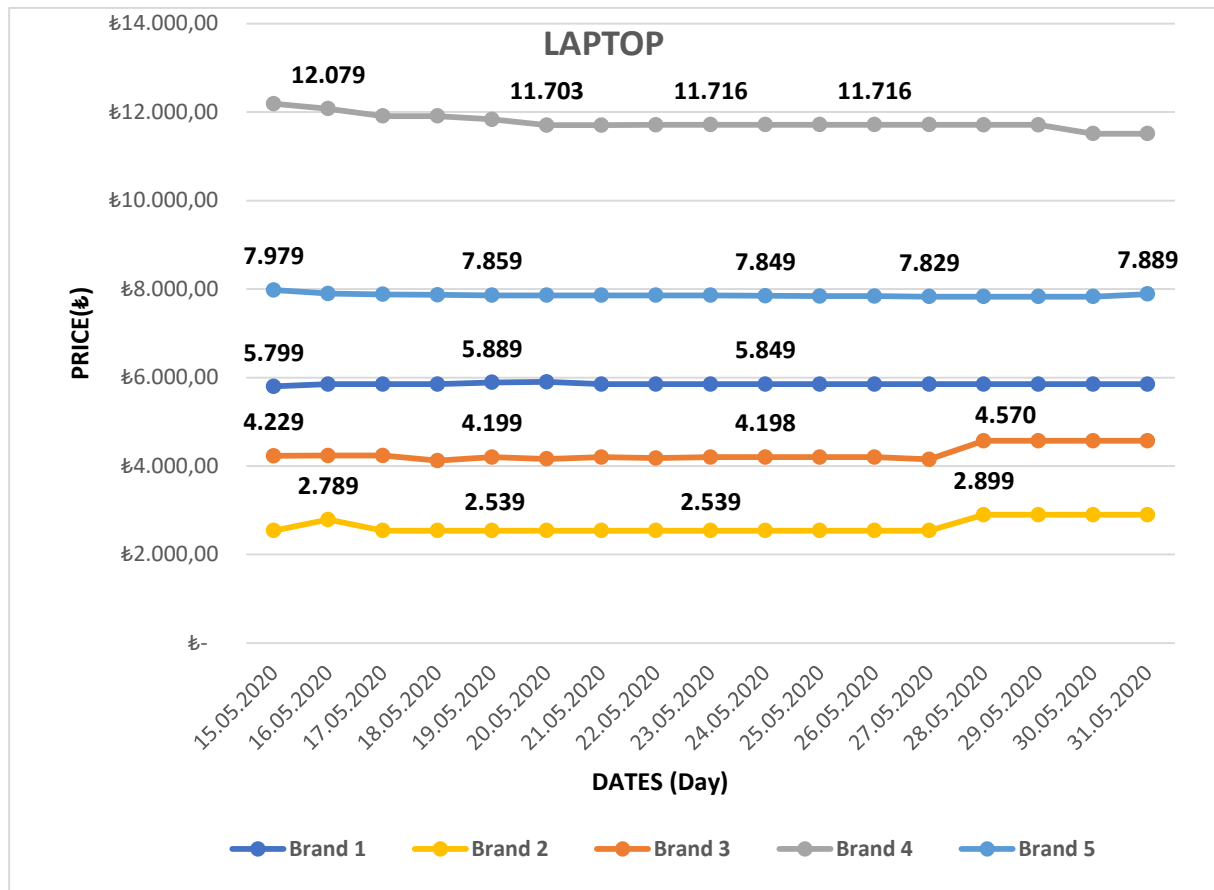


Figure 4.9. Price Distribution of Brands with Laptop Products

In the analysis of laptop products shown in Figure 4.9, it was observed that Brand 2, Brand 3 ve Brand 4 experienced dynamic price changes. In contrast, Brand 1 and Brand 5 products did not show high levels of price fluctuation. This trend could be interpreted as customers preferring other brands over Brand 1 and Brand 5 due to their higher product prices.

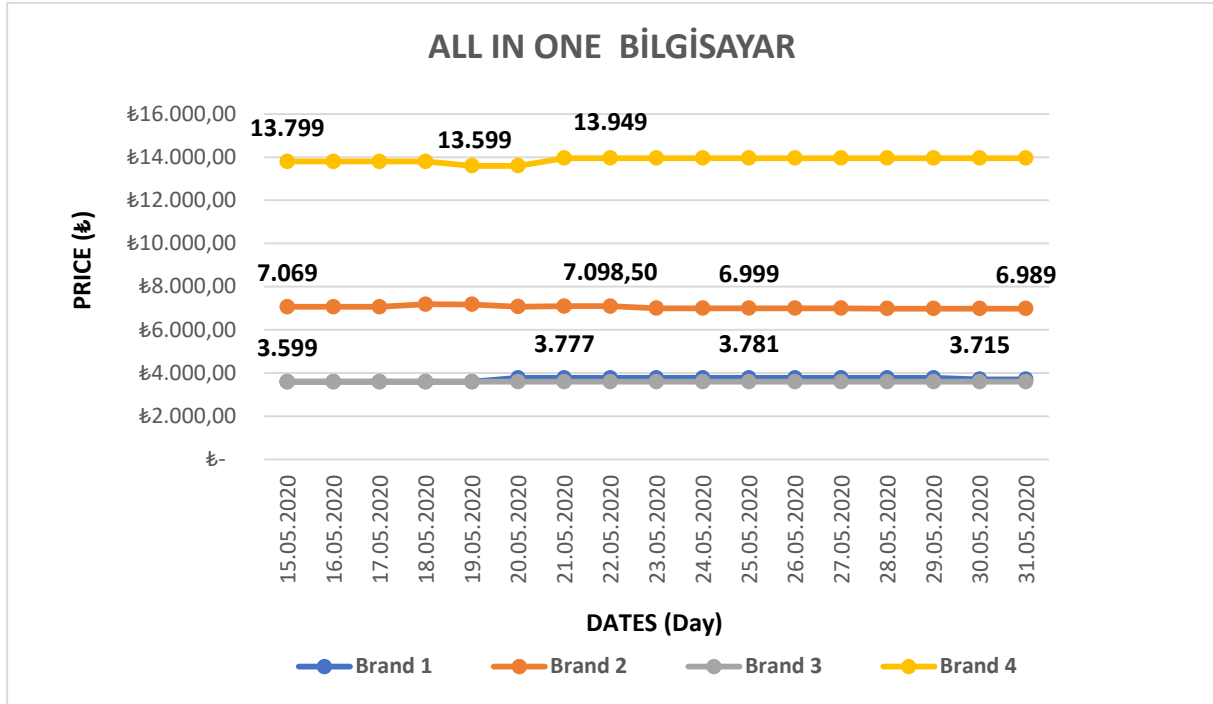


Figure 4.10. Line Chart According To Prices Of Brands With All In One Computer Products

In the all-in-one computer category, the price distribution during the COVID-19 period is displayed in Figure 4.10. Despite the high prices of Brand 4's all-in-one computers, they are preferred by customers, largely due to Brand 4's strong brand image. On the other hand, Brand 3 and Brand 1 products, favored by mid-segment customers, do not exhibit dynamic pricing, and their price flows are observed to be very similar. The sharp brand trends observed in notebook computers, which are generally more expensive, are also evidenced in the all-in-one computer category.

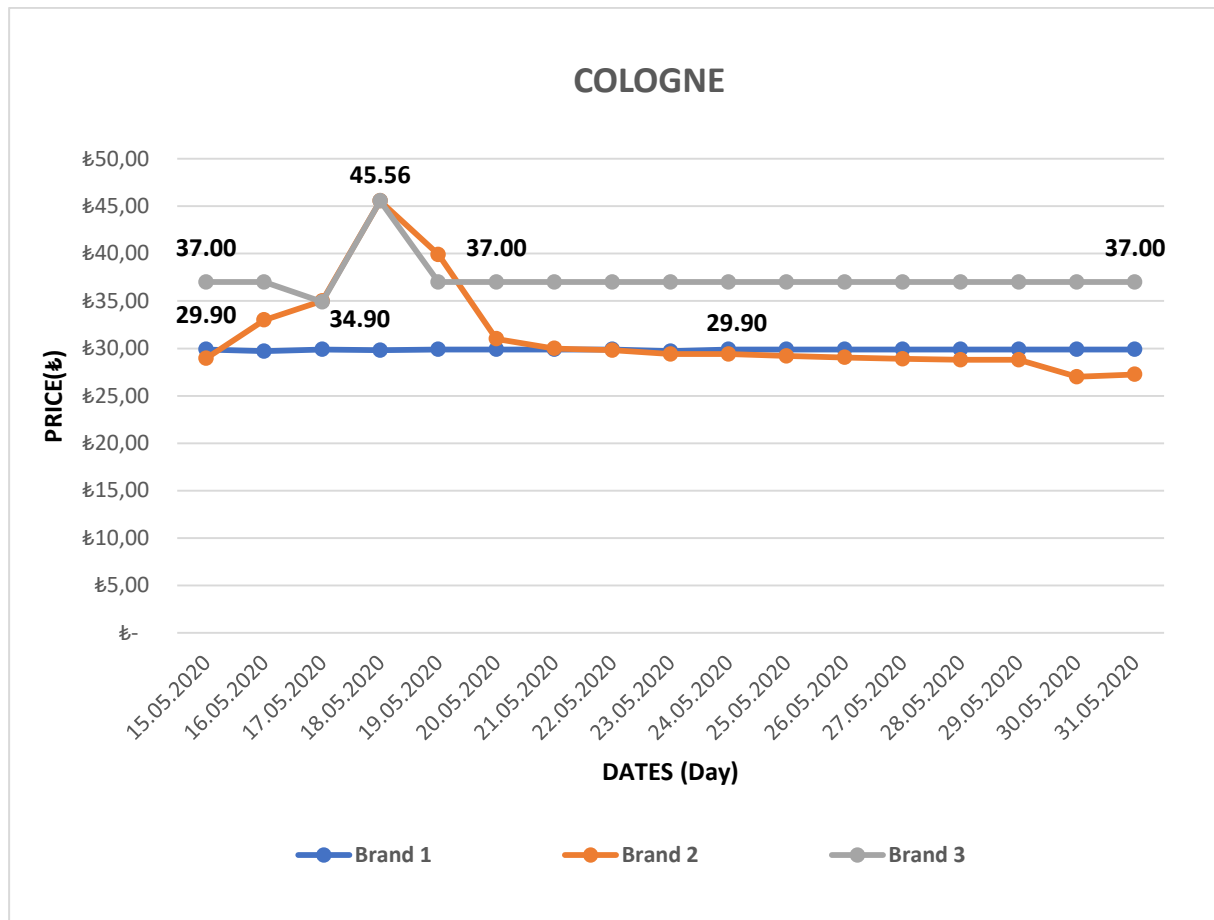


Figure 4.11. Line Chart According to Prices of Cologne Products

In Figure 4.11, cologne brands in the hygiene products category were examined based on seller prices over approximately two weeks. The most significant observation was the increased demand for hygiene products due to the pandemic's impact. Cologne products exhibited a continually dynamic pricing policy, with significant variability in price parameters. Particularly for brands like Brand 2 and Brand 3, the maximum prices for both products were very similar over the period. Factors such as product scarcity, stock inadequacies, and popularity led to substantial price increases, reflecting the pandemic's uncertainty and rising consumer demand.

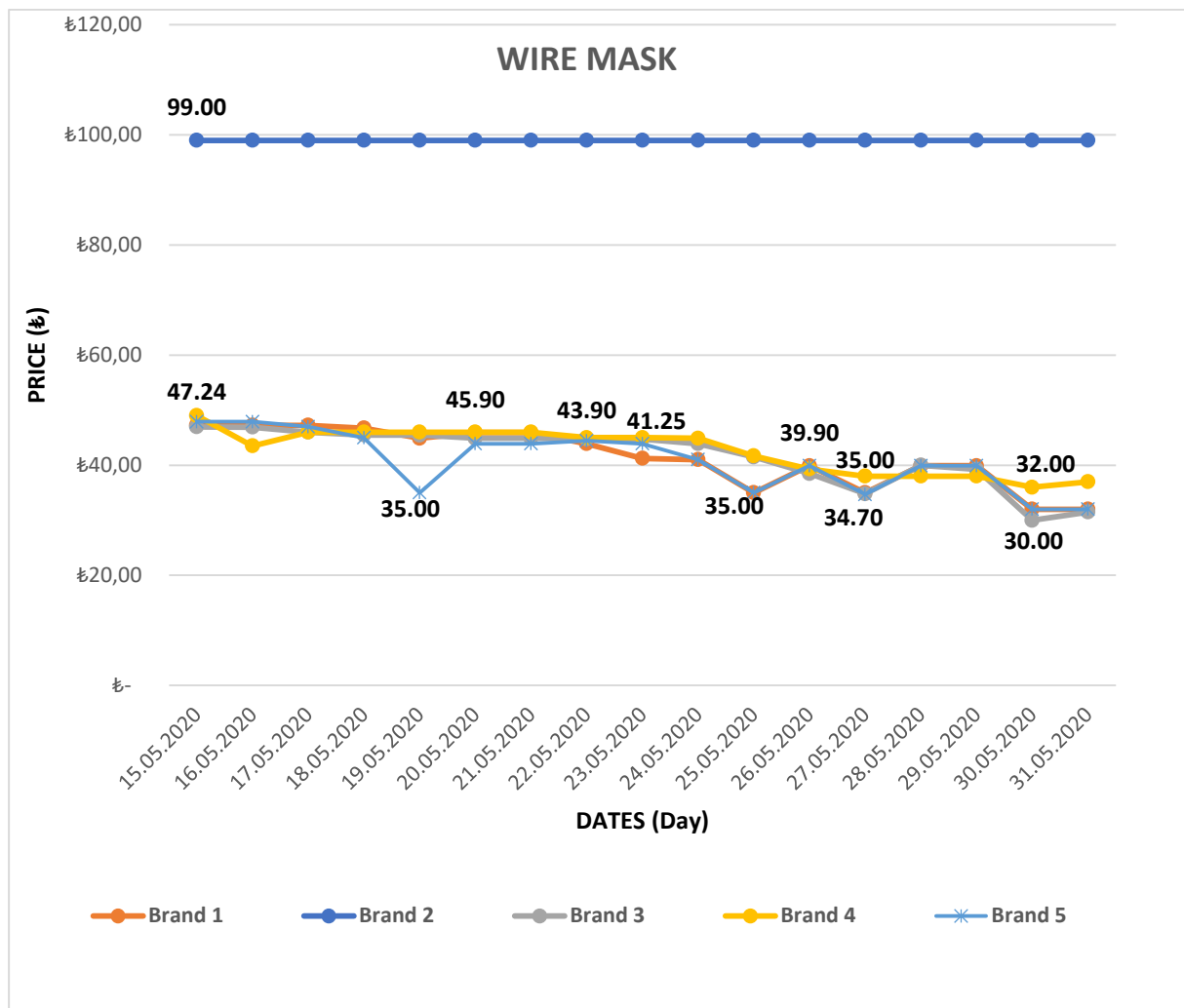


Figure 4.12. Line Graph According to Prices of Wire Mask Products

In Figure 4.12, the price changes of surgical masks during the COVID-19 period are presented. It can be inferred that products priced under 50 ₺ experienced more significant price fluctuations. The variability in prices during the pandemic, especially for lower-priced products, and the increased demand for hygiene products, which were consistently used throughout the pandemic, led to noticeable variations in dynamic pricing. This trend was particularly evident in the hygiene category, where products essential for pandemic response were in high demand.

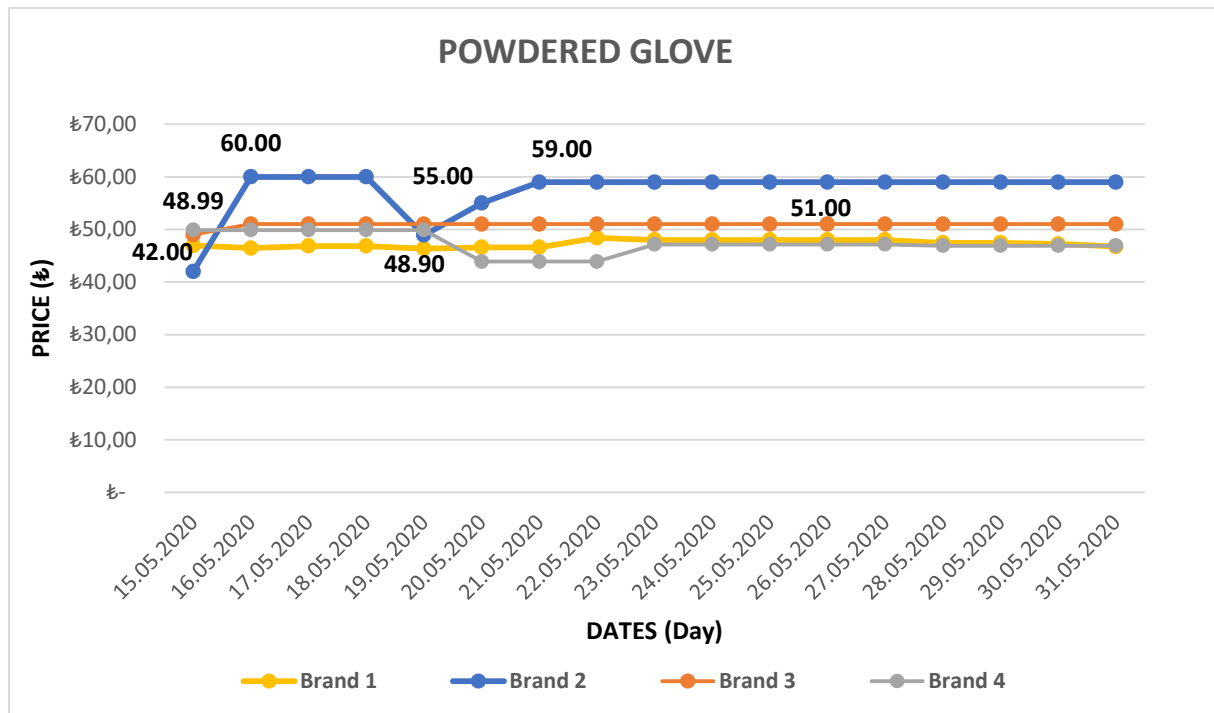


Figure 4.13. Line Chart According to Prices of Powdered Glove Products

In the hygiene category, an analysis of powdered gloves pricing is shown in Figure 4.13, where sudden price changes were observed. Comparing Brand 4 and Brand 2 brands, opposite price trends were noted between May 19 and May 21. Particularly, increased glove usage during the pandemic due to high uncertainty was observed. Price fluctuations were sometimes positive and sometimes negative. A significant price increase of nearly 50% was identified for Brand 2 products. These price changes were primarily influenced by customer preferences.

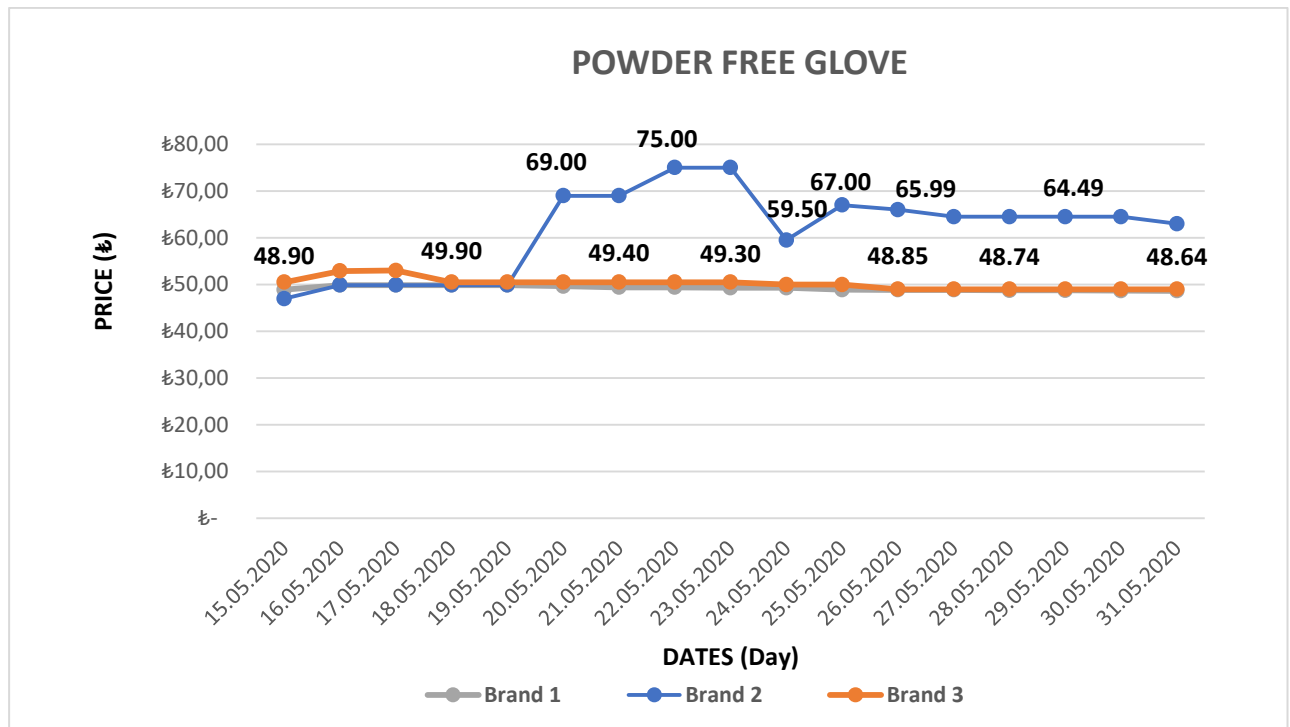


Figure 4.14. Line Graph According to Prices of Powder-Free Glove Products

In Figure 4.14, an examination of the sales profile of powder-free gloves shows sharp decreases and increases in the pricing of Brand 2 products. The dynamic pricing of Brand 1 and Brand 3 was found to be very close, indicating that price variability in Brand 2 products is often influenced by customer demand. There were days when product prices saw increases of up to 60%, highlighting that dynamic pricing in revenue management quickly adapts to consumer attitudes.

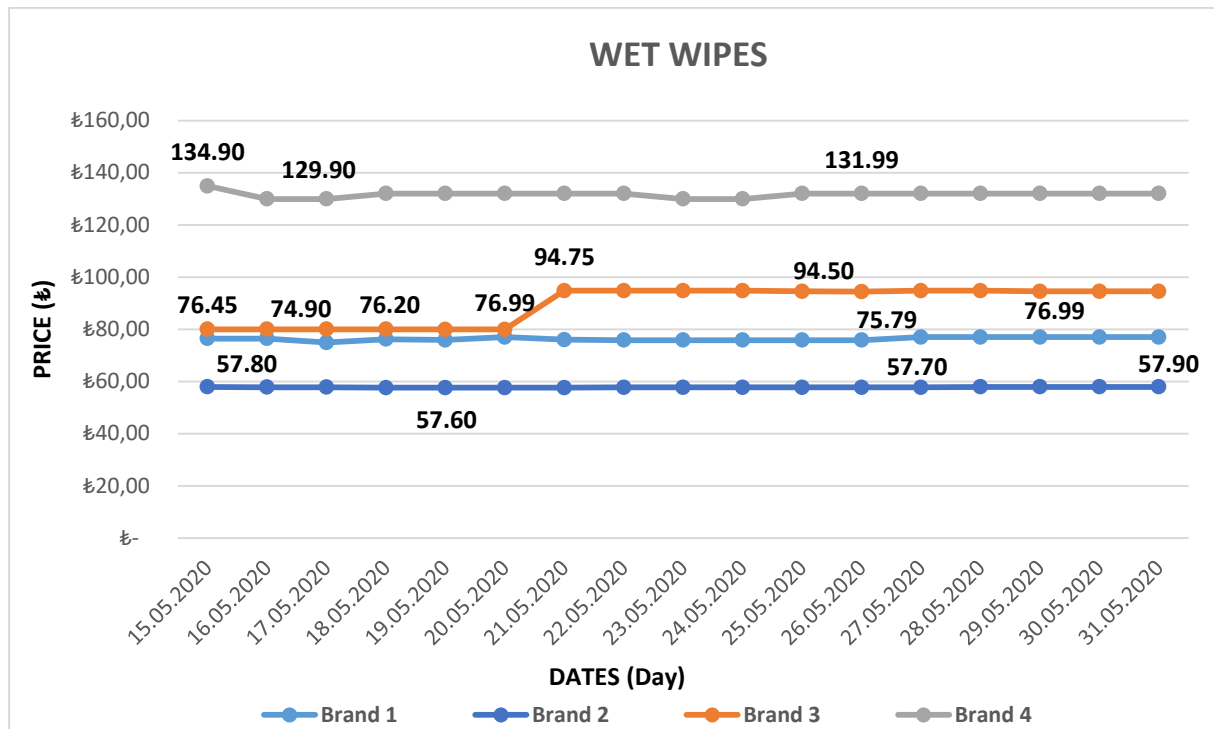


Figure 4.15. Line Graph According to Prices of Wet Wipes Products

In the wet wipes category, as shown in Figure 4.15, it was observed that the dynamic price changes were not as significant for other branded disinfectant products. The analysis of the data reveals that the price of Brand 3 products remained stable with occasional increases, while Brand 4 wet wipes experienced minimal changes. The sudden price increase for the Brand 3 product was determined to be approximately 18%.

The analysis conducted during the COVID-19 period identified that the highest impact on customers was due to the global uncertainty and adaptation challenges posed by the pandemic. While these effects were significant throughout the pandemic's fluctuating phases, another critical factor impacting customer behavior in Turkey was the earthquake period, which caused substantial logistical difficulties. The period's detailed analysis can explain the assessment of its impact more clearly. A detailed examination of that period can lead to the following assessment:

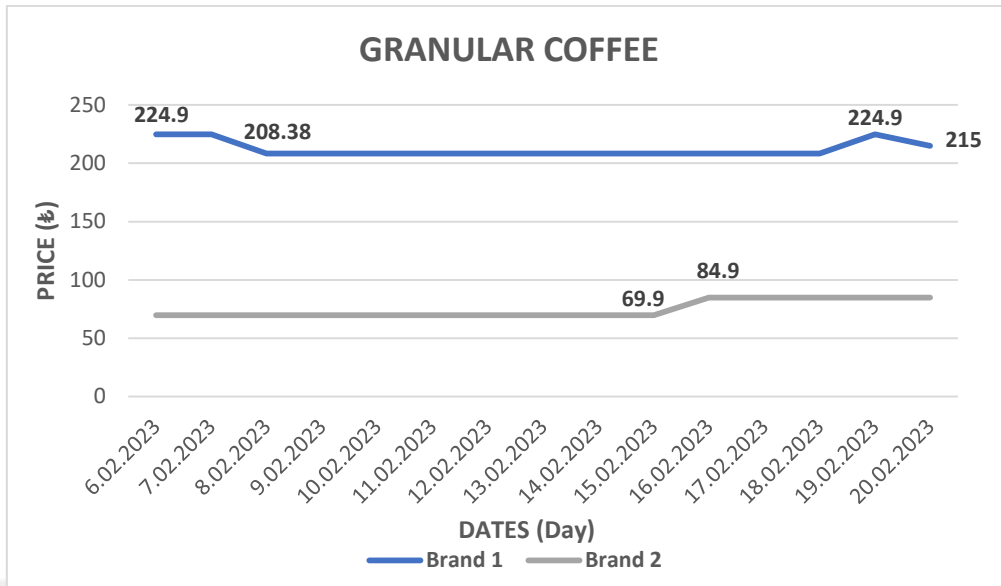


Figure 4.16. Price Distribution of Brands with Granulated Coffee Products

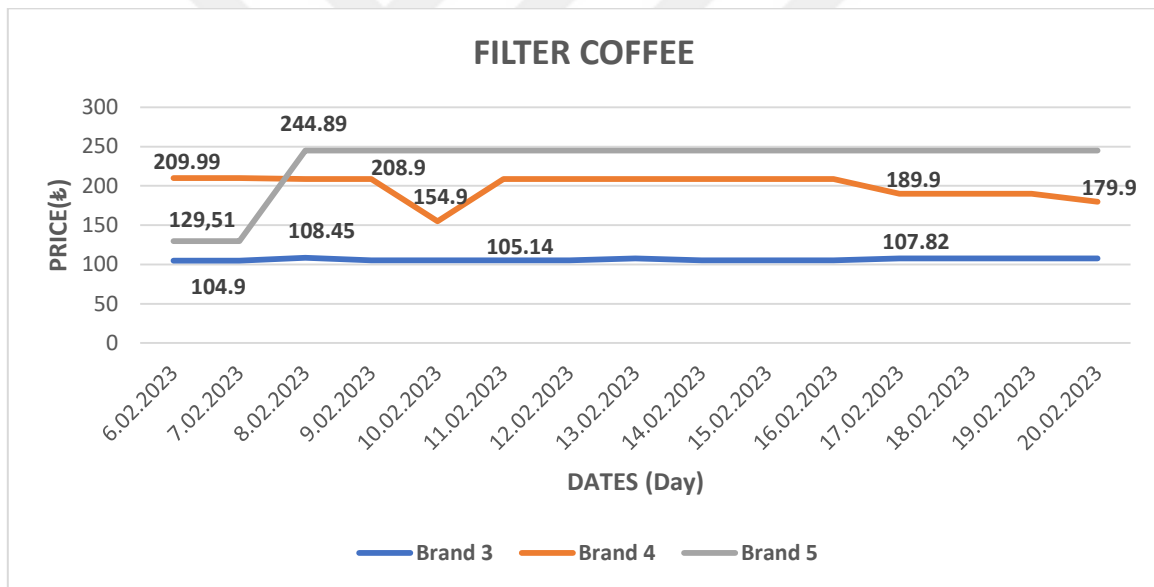


Figure 4.17. Price Distribution of Brands with Filter Coffee Products

During the earthquake period, the pricing of granulated and filter coffee products was analyzed in Figures 4.16 and 4.17. This analysis revealed fluctuations in dynamic pricing across three brands. Particularly, Brand 4 products exhibited rapid increases and decreases. The increased demand for warm beverages like coffee and tea due to cold weather conditions was noted during the earthquake period. However, the regional impact of the earthquake led to limited changes in pricing. Additionally, it was observed that, similar to support shown by

various sectors during the earthquake disaster, online retail also maintained supportive pricing policies, keeping price changes limited as part of their revenue management strategy.

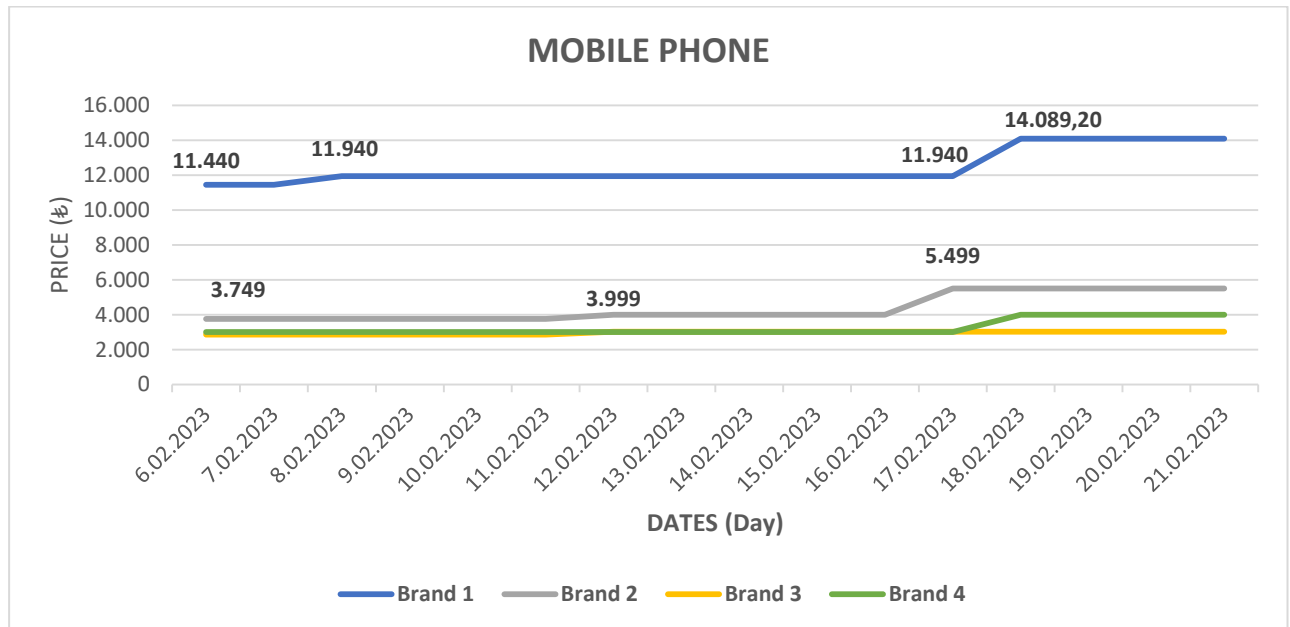


Figure 4.18. Price Distribution of Brands with Mobile Phone Products

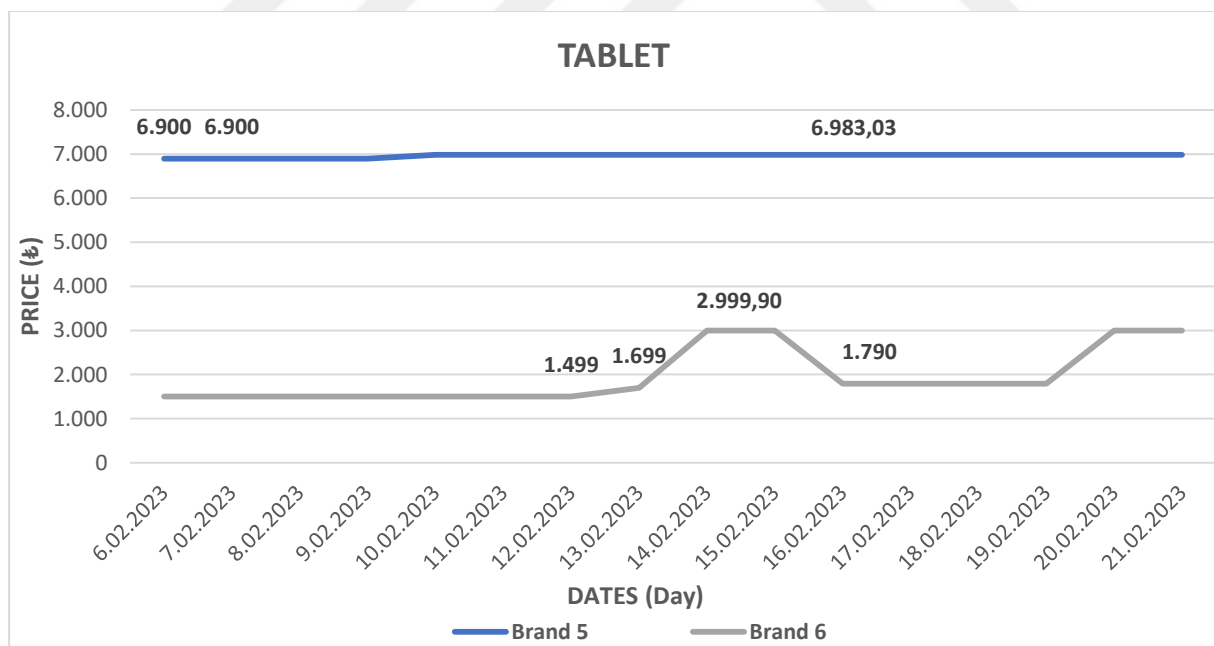


Figure 4.19. Price Distribution of Brands with Tablet Products

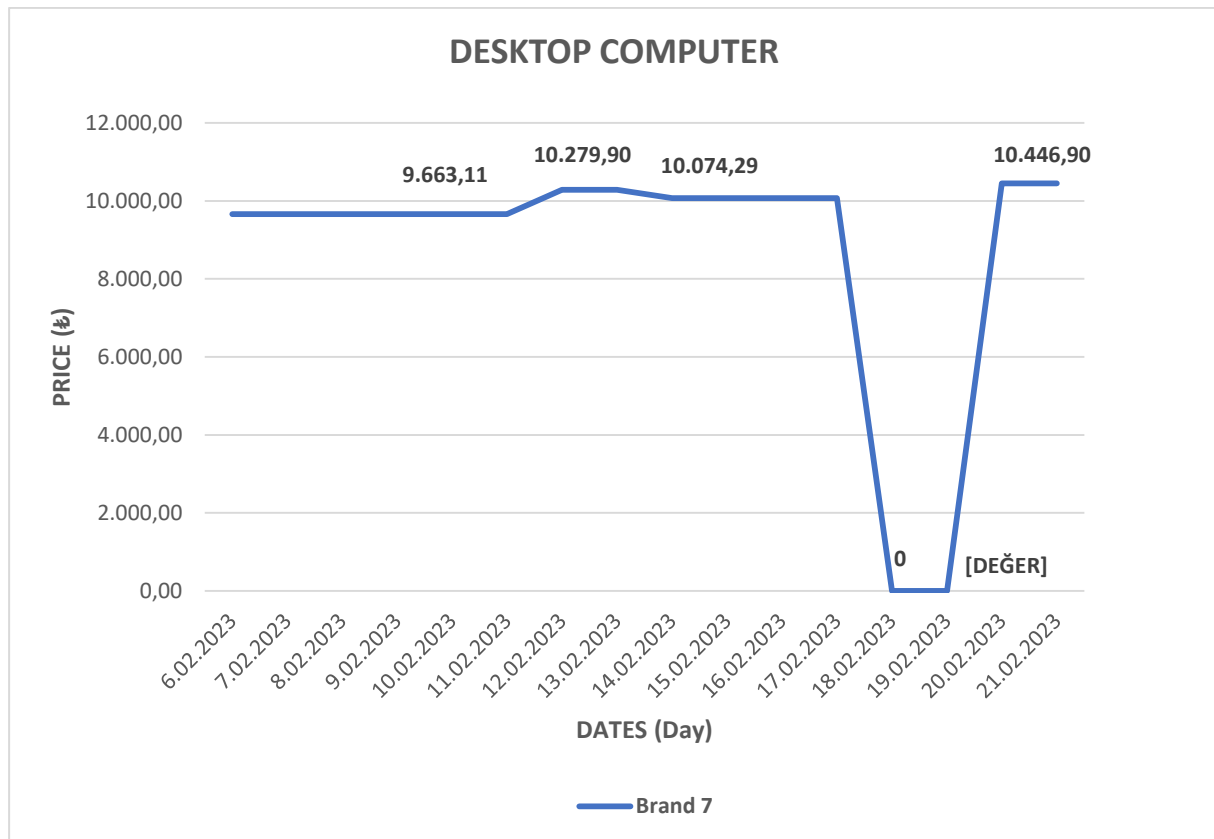


Figure 4.20. Price Distribution of Brands with Desktop Computer Products

Post-earthquake analysis of the Electronics Product category, as seen in Figures 4.18, 4.19, and 4.20, shows limited price fluctuations due to these items not being emergency necessities. However, Brand 7 desktop computers, depicted in Figure 4.20, experienced notable system dynamic changes and higher customer purchasing power compared to other products. On February 18 and 19, it was observed from the graph that Brand 7 products were out of stock and later restocked for customers. The presence of only one desktop computer model during the earthquake period can be attributed to changes in customer preferences due to technological advancements, leading to the introduction of new models and the depletion of older ones. That situation also reflects limitations in data access due to the evolving technology, presenting another constraint in this context.

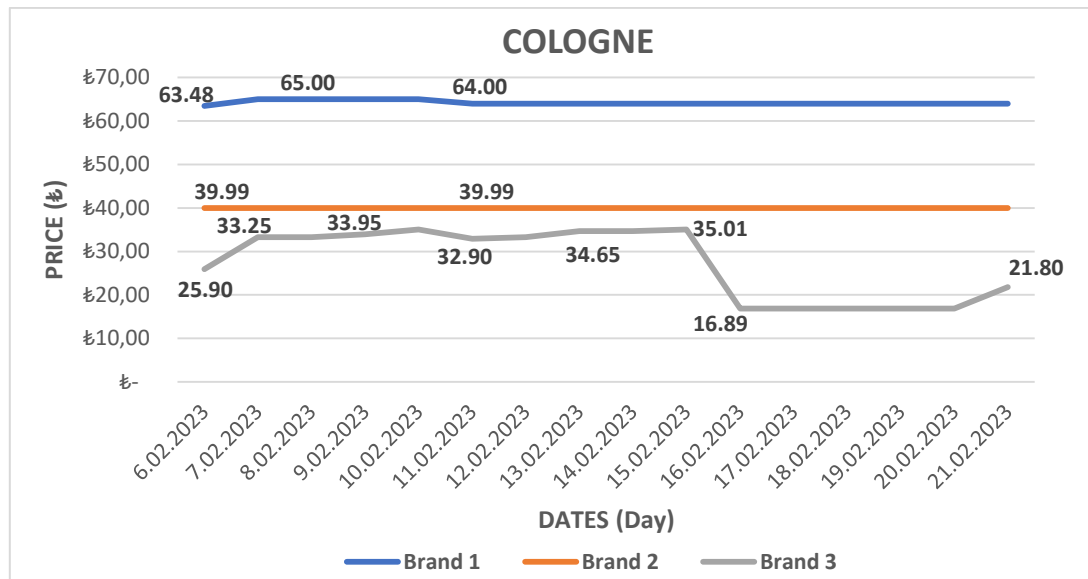


Figure 4.21. Price Distribution of Brands with Cologne Products

In the hygiene products category, the price changes of cologne brands over approximately two weeks were analyzed in Figure 4.21, showing significant variability in system dynamics. Particularly for the Brand 3 of cologne, changes were observed, while for the other two brands, the maximum prices over the two-week period were quite similar and stable. Specified period also showed significant shifts in customer preferences for brands with lower pricing policies, leading to price changes by sellers due to increased consumer demand. Another factor observed during this period was price increases due to product scarcity and high demand.

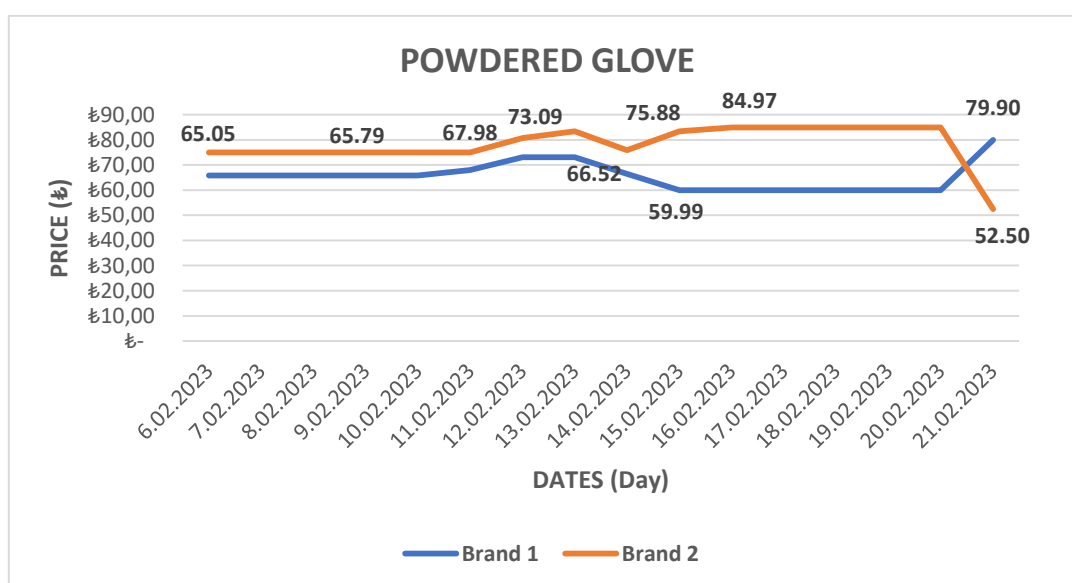


Figure 4.22. Price Distribution of Brands with Powdered Glove Products

When examining the powdered gloves category during the earthquake period, as shown in Figure 4.22, rapid changes in pricing are evident. Comparing Brand 1 and Brand 2 products, opposing price trends were observed on February 20 and 21. During the earthquake, the overall use of priority hygiene products like powdered gloves increased, with price trends varying positively and negatively across brands. For Brand 1 products, a price increase of around 20% was noted post-earthquake, whereas Brand 2 brand showed a decrease of approximately 30%.



5. CONCLUSION

Within the scope of thesis study, dynamic pricing policies of products within the framework of e-commerce sector revenue management were examined. For the particular purpose, AHP and TOPSIS methods, which are multi-criteria decision-making techniques, were used to find the period most affected by natural disasters and pandemic periods within the framework of revenue management, depending on the different criteria that were found to affect the purchasing attitude of customers and, accordingly, the dynamic pricing of the online system. The criteria affecting the pandemic and natural disaster period were weighted with the AHP method, and the most affected period was selected with the TOPSIS method.

A Pairwise comparison of the criteria that are effective in customer preferences was made, taking into account the dynamic pricing stages of online retail products and the purchasing attitudes of customers. The determined criteria; It is classified into purchasing power, inflation, discounting and undersupply. The weighting order of these criteria determined by the AHP method was determined as 0.299 for purchasing power, 0.358 for inflation, 0.072 for discount and 0.271 for low supply.

Using these obtained criterion weights, COVID-1 period, COVID-2 and COVID-3 periods, which are described as the waves of this period, and finally the earthquake period that occurred in our country and had a high level of impact, were examined with the TOPSIS method. Due to the multiplier effect of these periods and changing country conditions, the most affected time period within the scope of the revenue management system has been determined. With the TOPSIS method, it was determined that the most affected period was 0.6959 COVID-1. In the second order of importance, the earthquake was obtained with 0.5522 points, followed by the COVID-3 period with 0.3636. The last place was taken by the COVID-2 period with 0.2876. The reason why the results are close to each other during the COVID-1 and earthquake periods is that while it is known that e-commerce was highly affected due to the health reason that affected the whole world during the COVID-1 period, the earthquake period affected the purchasing attitude of customers with the post-pandemic multiplier effect created throughout the country and the changing economic conditions. In addition, it is conceivable that there was a high level of uncertainty during the earthquake

period and the COVID-1 period, and therefore the logistics leg of the e-commerce sector was physically affected.

As a result of detailed examination, the reason for the high criterion weights during the COVID-1 period is; It can be stated that the uncertainties that affect the whole world and shake the global markets are very intense, and the atmosphere of panic resulting from these uncertainties affects both producers and consumers. It has been observed that the prices of these seasonal products, where the needs of the consumer continue to increase and demand increases, especially beverages and hygiene materials, increase because the producers cannot keep up with the demands (low supply) due to their limited work in these periods. The reason why the discount criterion is less affected during the COVID-1 period is the low coefficient, that is, the supply criterion that cannot keep up with the high demand.

Although the earthquake occurred in 11 provinces, the earthquake victims migrated to all over Turkey and search and rescue activities were carried out by teams from other provinces of Turkey, causing the earthquake to affect the whole of Turkey, and this atmosphere of panic was felt throughout Turkey. High inflation and low purchasing power during the earthquake period, as well as the supply factor that could not keep up with the rapidly increasing demand, also affected the pricing greatly. The COVID-3 period, which is the wave of COVID-1, is the period when factories were open and the fear of closure was felt at the lowest level. During COVID-3 period, rapidly increasing inflation and falling purchasing power made the discount more important. The atmosphere of panic continues in the COVID-1 period, when uncertainties were felt all over the world, and in the first wave after COVID (COVID-2 period), and the closures seem to have decreased significantly compared to the first period. However, the financial effects of COVID-1, which shook global markets, have continued to increase.

For some of the products we examined during the pandemic period, although we carried out the production phase and exported most of the products, it was determined that consumption demands increased during the closure period when customers were at home. It has been determined that products in some product groups and sector categories, especially coffee and tea, are priced according to the change in domestic and foreign demand quantities.

As for electronic devices, it is observed that there are increases and decreases in the prices of products in the mobile phone and tablet categories in all periods. Although the dollar exchange rate is probably the most important criterion for that situation, it can be said that supply and demand are also effective depending on changing needs. While there may be a decrease in price in case of a sharp decrease in the dollar exchange rate, it has been observed that due to the decrease in the dollar exchange rate, customers started to demand much more for the products, the products reached the supply-demand balance, and the effect of the dollar exchange rate was disabled to this extent and did not significantly affect the prices of the products.

Since certain branded mobile phone products affect the demands of middle-income people much more, excessive price reductions may affect customer purchasing power. Because such product groups have a much higher preference rate in terms of sales force than other product groups. However, products with high brand trends, such as Apple, may not be preferred by all customer groups. In other words, it is known that Samsung products are purchased more intensely because they appeal to middle and low-income families. It has been determined that such product groups are not affected much by the dollar exchange rate due to the high number of customers they appeal to as a profile, and are left to people's preference. However, since Apple branded products appeal to high customer groups, price increases and decreases with the effect of the dollar exchange rate have a harsh impact on customer demands. Other than that, it was observed that there were no sudden changes in the prices of laptops, All in One and desktop computers throughout all processes. Accordingly, it can be said that the demand amount is less than other electronic devices.

In hygiene products, sharp decreases have been observed from time to time in the prices of disinfectant products, masks and gloves due to the pandemic. The reason for this is the potential increase in the supply market that wants to be involved in the process due to increasing demand. It has been determined that the prices of products such as toilet paper and paper napkins do not change significantly, but they are out of stock from time to time.

6. RECOMMENDATIONS

In line with the study, we can say that the COVID-19 period was most affected by the COVID-19 periods by looking at the relative closeness value. In this study, we observed the dynamic pricing system of a shopping site of one of the frequently preferred online shopping giants in Turkey. In addition to our studies, it is recommended for other researchers to make predictions for dynamic pricing methods in future literature studies and to improve and compare system processes by integrating risk analysis studies in these processes. In addition, the criteria for stochastic processes that may occur during a new natural disaster or epidemic can be handled by differentiating them. In addition, the effects of these product groups, which are kept for a single online retail channel and whose data are examined, on each other can also be a guide for new studies.

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