GALATASARAY UNIVERSITY

GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

ANALYSIS OF BANKING CUSTOMERS' HABITS AND BEHAVIOURS IN THE COVID-19 PANDEMIC PERIOD

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JULY 2021

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(BANKACILIK MÜŞTERİLERİNİN COVID-19 PANDEMİ DÖNEMİNDE ALIŞKANLIK VE DAVRANIŞLARININ ANALİZİ)

by

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Thesis

Submitted in Partial Fulfillment

of the Requirements

for the Degree of

MASTER OF SCIENCE

in

INDUSTRIAL ENGINEERING

in the

GRADUATE SCHOOL OF SCIENCE AND ENGINEERING

of

GALATASARAY UNIVERSITY

JULY 2021

ACKNOWLEDGEMENTS

Foremost, I would like to express my sincere gratitude to my advisor Dr. Tuncay Gürbüz, for his patience, unlimited guidance and continuous support of my research.

Also I would like to thank to Okan Çetinkaya, Ender Uygun and all of my team and bank who allowed me to use retail banking customer data and actualize my research.

Completion of this project could not have been accomplished without the love and support of my two lovely best friends and my whole family and my dear husband. Without their unconditional support, this study would be incomplete.

July 2021
İdil YAVUZ AYDIN

TABLE OF CONTENTS

LIST OF SYMBOLS ..... **v**
LIST OF FIGURES ..... **vi**
LIST OF TABLES ..... **vii**
ABSTRACT ..... **viii**
ÖZET ..... **x**
1. INTRODUCTION **1**
2. LITERATURE REVIEW **5**
2.1 Covid-19 Pandemics and Turkey's Status 5
2.2 Consumer Behaviour Changes due to Covid-19 Pandemic 8
2.3 The Process of Behaviour Becoming a Habit 20
2.4 Consumer Behaviour Analysis in Banking 22
2.4.1 Time Series Clustering 23
2.4.1.1 Similarity Measures 24
2.4.1.1.1 Euclidean, Dynamic Time Warping and Soft-DTW 25
2.4.1.2 Silhouette Index 27
3. METHODOLOGY **28**
4. RESULTS **32**
4.1 Spending Behaviour 32
4.2 Digital Behaviour 37
5. CONCLUSION **41**
5.1 Thesis Contribution 42
5.2 Limitations and Future Work 43
REFERENCES **44**
BIOGRAPHICAL SKETCH **50**

LIST OF SYMBOLS

ATM	**:** Automatic Teller Machine
BBVA	**:** Banco Bilcao Vizcaya Argentaria
CRM	**:** Customer Relationship Management
DTW	**:** Dynamic Time Warping
HMM	**:** Hidden Markov Models
IQR	**:** Inter Quartile Range
LCSS	**:** Longest Common Sub-Sequence
MIT	**:** Massachusetts Institute of Technology
ONS	**:** Office for National Statistics
POS	**:** Point of Sales
TSC	**:** Time Series Clustering
UK	**:** United Kingdom
WHO	**:** World Health Organization

LIST OF FIGURES

Figure 2.1: Graph of the Daily Patient Number Percentages in Relation to the Daily Number of Tests 7

Figure 2.2: Graph of the Daily Demise Numbers 8

Figure 3.1: Flow of the Methodology 28

Figure 3.2: Silhouette Index Matrix 31

Figure 4.1: Cluster Trend Lines for Spending Behaviour Patterns in 2019 33

Figure 4.2: Cluster Trend Line for Outlier Pattern in 2019 34

Figure 4.3: Cluster Trend Lines for Spending Behaviour Patterns in 2020 34

Figure 4.4: Comparison Between 2019 and 2020 in terms of Spending Behaviour 35

Figure 4.5: Numerical Comparison Matrix of Spending Behaviour 35

Figure 4.6: Cluster Trend Lines for Digital Behaviour Patterns in 2019 37

Figure 4.7: Cluster Trend Lines for Digital Behaviour Patterns in 2020 38

Figure 4.8: Comparison Between 2019 and 2020 in terms of Digital Behaviour 39

Figure 4.9: Numerical Comparison Matrix of Digital Behaviour 39

LIST OF TABLES

Table 2.1: Characteristics of Covid Era Consumer 9

Table 2.2: Summary of the Literature about Consumer Behaviours in Covid-19 11

Table 2.3: Summary of Consumer Behaviours during the Pandemic 19

Table 2.4: Dynamic Clustering Methods 24

Table 2.5: Similarity Measures and Characteristics 25

Table 3.1: Decisive Variables 29

ABSTRACT

Covid-19 pandemic caused a great panic and crisis in the world while it changed everything radically. Before the pandemic, a slow and steady transformation process was ongoing between banks and their customers. However; because of imposed restrictions and concerns of the future, customer behaviours were changed way faster than it is expected during the pandemic. Customers gained new behaviours to cope with this new situation; like wearing masks, washing shopping products, social distance, etc. Besides; the probability of these new behavioural patterns become permanent is high due to the long-term existence of changed environmental conditions, even they can transform into new habits. Therefore; banks need to comprehend the new behaviours and habits of the customers in order to stay in the market and be resilient. The purpose of this paper is to explain the dynamic change in retail banking customers' behaviours and habits during Covid-19 pandemic period in terms of banking. Usually, Customer Relationship Management department is dealing with customer-related problems in banking by using data mining and machine learning techniques. One of the main applications that the department uses to understand behaviour patterns is customer segmentation. However; usually static segmentation methods are used for this purpose although the customer behaviours have dynamic nature. With consideration of behavioural pattern nature, the study uses one of the most common dynamic segmentation methods, Time Series Clustering. The mentioned method is applied to the March-December periods of 2019 and 2020 with the purpose of comparing the pandemic period in 2020 and the non-pandemic period in 2019. Relevant two periods are compared in an effort to detect behavioural patterns and analyze the change in retail banking customers' behaviours. The data of 200 customers that selected by random sampling has given by the Customer Relationship Management department of one of the 5 main private banks in Turkey. The data includes spending and digital score variables that are selected according to psychological and economical studies.

Spending and digital score variables are created from variables that play a decisive role from the digital activity and card sales data of retail banking customers in 2019 and 2020. After the preprocessing, the partitioning clustering method is applied with the similarity measures of Euclidean, Dynamic Time Warping and Soft Dynamic Time Warping in a Python environment. Silhouette analysis calculated by Euclidean distance is used to determine the best similarity measures and the best number of clusters. As a result, the study shows that the pandemic has irreversibly affected customer behaviours. Looking at the transitions between clusters, it is possible to say that the pandemic has negatively affected spending habits. All clusters switched to the lower clusters at an average rate of 67%, while Low cluster remained the same at a rate of approximately 70%. The impact of the pandemic on digital behaviour is more striking. About 63% of Low cluster moved to the higher digital usage clusters. In order to understand whether these behavioural changes are permanent, it may not be enough to look at only this part of the pandemic period; yet, it seems that especially the behaviours of the customers who are newly acquainted with digital are permanent. The main contribution of this study to the literature is revealing dynamic behavioural patterns of retail banking customers during Covid-19 pandemic. Static behaviours of customers for the outbreak period of the pandemic are widely studied, in the literature related to Covid-19 pandemic. The common feature of these studies is to provide quick and leading analyzes to the literature about this new event that has never studied before. However, for the adaption of the businesses and especially banks that have dealt with a great economic challenge, dynamic behaviour analysis of customers that contains more than the March-May period is a need in the literature for Covid-19 pandemic. This study only covers the period until the end of the year 2020. As time goes on, this study needs to be repeated with more customers and different methods to be bettered and to understand the behavioural patterns in the vaccination process and next steps of the Covid-19 that are not encountered yet.

ÖZET

Covid-19 pandemisi her şeyi kökten değiştirirken dünyada büyük bir panik ve krize neden olmuştur. Pandemi öncesinde bankalar ve müşterileri arasında yavaş ve istikrarlı bir dönüşüm süreci devam etmekteydi. Ancak; dayatılan kısıtlamalar ve gelecek endişeleri nedeniyle, müşteri davranışları pandemi sırasında beklenenden çok daha hızlı değişmiştir. Müşteriler bu yeni durumla başa çıkmak için yeni davranışlar kazanmıştırlar; maske takmak, alışveriş ürünlerini yıkamak, sosyal mesafe vb. Ayrıca; değişen çevre koşullarının uzun süreli varlığı nedeniyle bu yeni davranış kalıplarının kalıcı hale gelme olasılığı yüksektir, hatta yeni alışkanlıklara dönüşebilirler. Bu nedenle; bankaların piyasada kalabilmeleri ve koşullara uyum sağlayabilmeleri için müşterilerin yeni davranış ve alışkanlıklarını anlamaları gerekmektedir. Bu çalışmanın literatüre temel katkısı, bireysel bankacılık müşterilerinin Covid-19 pandemisi sürecindeki dinamik davranış kalıplarını ortaya çıkarmasıdır. Bankacılıkta müşteriler ile ilgili sorunlarla genellikle Müşteri İlişkileri Yönetimi departmanı, veri madenciliği ve makine öğrenmesi tekniklerini kullanarak ilgilenmektedir. Departmanın davranış kalıplarını anlamak için kullandığı ana uygulamalardan biri müşteri segmentasyonudur. Ancak; her ne kadar müşteri davranışları dinamik bir yapıya sahip olsa da genellikle müşterileri segmente etmek amacıyla statik kümeleme yöntemleri kullanılmaktadır. Davranış örüntüsü doğası göz önüne alındığında, bu çalışma en yaygın dinamik kümeleme yöntemlerinden biri olan Zaman Serileri Kümeleme'yi kullanır. Söz konusu yöntem, 2020'deki pandemi dönemi ile 2019'daki pandemi dışı dönemi karşılaştırmak amacıyla 2019 ve 2020 Mart-Aralık dönemlerine uygulanmaktadır. Bireysel bankacılık müşterilerinin davranış kalıplarını tespit etmek ve davranışlarındaki değişimi analiz etmek amacıyla ilgili iki dönem karşılaştırılmıştır. Türkiye'deki 5 ana özel bankadan birine ait Müşteri İlişkileri Yönetimi departmanı tarafından verilen, rastgele örnekleme yöntemi ile seçilmiş 200 müşteriye ait veriler çalışmada kullanılmıştır.

Veriler, psikolojik ve ekonomik çalışmalara göre seçilen harcama ve dijital puan değişkenlerini içerir. 2019 ve 2020 yıllarında bireysel bankacılık müşterilerinin dijital aktivite ve kart satış verilerinde belirleyici rol oynayan değişkenlerden harcama ve dijital puan değişkenleri oluşturulmuştur. Veri ön işlemeden geçirildikten sonra, veriye Python ortamında Öklid, Dinamik Zaman Bükme ve Yumuşak Dinamik Zaman Bükme benzerlik ölçüleri kullanılarak bölümleme kümeleme yöntemi uygulanmıştır. Öklid mesafesi ile hesaplanan siluet analizi, en iyi benzerlik ölçülerini ve en iyi küme sayısını belirlemek için kullanılmıştır. Sonuç olarak çalışma, pandeminin müşteri davranışlarını geri dönülemez bir şekilde etkilediğini göstermektedir. Kümeler arası geçişlere bakıldığında pandeminin harcama alışkanlıklarını olumsuz etkilediğini söylemek mümkündür. Tüm kümeler ortalama %67 oranında alt kümelere geçerken, Alt küme yaklaşık %70 oranında aynı kalmıştır. Pandeminin dijital davranış üzerindeki etkisi daha da çarpıcıdır. Düşük kümenin yaklaşık %63'ü daha yüksek dijital kullanım kümelerine taşınmıştır. Bu davranış değişikliklerinin kalıcı olup olmadığını anlamak için pandemi döneminin sadece bu kısmına bakmak yeterli olmayabilir; ancak özellikle dijitalle yeni tanışan müşterilerin davranışlarının kalıcı olduğu görülmektedir. Bu çalışmanın literatüre temel katkısı, bireysel bankacılık müşterilerinin Covid-19 pandemisi sürecindeki dinamik davranış kalıplarını ortaya çıkarmasıdır. Müşterilerin pandeminin salgın dönemindeki statik davranışları, Covid-19 pandemisi ile ilgili literatürde geniş çapta çalışılmaktadır. Bu çalışmaların ortak özelliği, daha önce hiç çalışılmamış bu yeni olay hakkında literatüre hızlı ve yol gösterici analizler sunmasıdır. Ancak işletmelerin ve özellikle büyük bir ekonomik zorlukla uğraşan bankaların adaptasyonu için literatürde, Covid-19 pandemisine dair Mart-Mayıs dönemini aşan süreçte müşterilerin dinamik davranış analizine ihtiyaç duyulmaktadır. Bu çalışma sadece 2020 yılı sonuna kadar olan dönemi kapsamaktadır. Zaman geçtikçe bu çalışmanın daha iyi hale getirilmesi ve Covid-19 aşılama süreci veya henüz karşılaşılmayan daha sonraki süreçlerindeki davranış kalıplarının anlaşılması için daha fazla müşteri ve farklı yöntemlerle tekrarlanması gerekmektedir.

1. INTRODUCTION

Banking practices and customers have been two parts of a transformation process that has affected each other over the years. Banks have to keep up with the habits of the new generations and advancing technology in order to gain new customers and have a corner on the market. Over time, past generations are also discovering how they can benefit from new banking practices. Thus, there is a slow and steady transformation process between banking practices and customers. However, the Covid-19 pandemic, which is a global crisis period, accelerated and destabilized this process. While customers were trying to get use to this new order in which they faced the fear of prohibitions and uncertainty, they changed or had to change their banking behaviour as they did with everything else. They sought ways to do their transactions "remotely" or digitally in order not to leave the house, wanted to make transactions without touching ATMs and were exposed to long lines affected by weather conditions in accordance with the precautions taken at branches. While the pandemic period changed customer behaviours radically; it became a challenging process to adapt to the uncertainty of this new crisis that is not only financial but also health-related.

The Covid-19 pandemic has emerged in Wuhan, China and has become a major problem in our country and in the world within a month or two. Its rapid spread and the risk of sudden death caused a panic wave throughout humanity. Depending on the fluctuation of the number of cases and deaths, it is possible to say that there have been two main waves so far during the pandemic period. In the first wave that started in March in Turkey, due to the panic brought on by the pandemic, people adhered to the prohibitions and tried to take all possible precautions. Staying at home as much as possible, washing hands continuously, washing shopping products, maintaining social distance can be considered as a few of the examples of these precautions. The two main topics that are most frequently mentioned in the literature regarding the radical change

in customer behaviour are digitalization and spending. The risk of contagion by touching has brought people closer to digital life and has radically changed their shopping habits. However, when these measures were taken in the first wave, humanity was unaware of how long this pandemic would last. Due to the fact that the virus is not resistant to heat, the number of cases decreased with the warming of the weather. But people who had been under pressure for three months started not to take the risk of getting sick as seriously as they used to, as the government eased the restrictions. Therefore, with the cooling of the weather, it became inevitable for the number of cases to increase again, and thus the second wave began. Although the second wave started, the panic experienced in the first wave did not repeated and this situation led to the evolution of behavioural patterns in different directions within certain groups. The pandemic was no longer a new and terrifying event, it has became the "new normal". Since the disease had a subjective effect on every person, people began to take an approach based on their own experiences. Moreover, since having the disease causes the formation of antibodies in the body, contact was not avoided as much as before.

While the pandemic causes different behaviour patterns, some researchers believe that it can make some behaviours such as digital transformation or spending behaviours turn into habits due to the length of its duration. Yet, continuing a behaviour for a long time is not enough to form a habit. A habit is gained by the constant repetition of a three-principle cycle; motivation, routine and reward. The motivation for behaviours gained in the Covid-19 pandemic is not contracting the coronavirus or simply surviving. Routine can be considered as one of many behaviours gained with this motivation, for example, doing grocery shopping online. The reward of these routines is achieving motivation, in other words, achieving not being sick or not having a risk of death. In brief, it is reasonable to suspect that the new behaviours of the pandemic may turn into habits and it is a problem to consider for banks in order to realize the change in their customers.

Customer Relationship Management (CRM) is the department that deals with the customer related challenges of banking like customer segmentation, risk management, customer churn prediction, etc. Analytical CRM is the part of the CRM that uses data

mining and machine learning methods to extract customer behaviour patterns from data (Ngai et al., 2009). The main occupation of Analytical CRM is to discover similar groups of customers according to the problem in hand to find the most proper way to serve customers. Segmentation is a widely used method to extract similar customer groups out of the data. In order to cluster customers that have same behaviour patterns within a certain time period, dynamic customer segmentation is convenient because of its property of considering the dynamic nature of the behaviour and Time Series Clustering (TSC) is one of the main approaches of it.

This study uses TSC to extract behavioural patterns of customers in pandemic period and also in the March-December period of the former year in purpose of comparing the change in customer behaviours. 200 retail banking customers are selected by random sampling, they selected among retail banking customers that uses banking services actively during 2019-2020 in order not to interrupt the behaviour pattern. Economical and psychological studies that mentioned in second section of this paper; show that customers' spending behaviours show variances and customers use digital channels to overcome their daily activities. Hence; variables that play a decisive role in the digital activity and card sales data of retail banking customers in 2019 and 2020 are used to create spending and digital score variables. After the preparation of the data preprocessing is applied. Partitioning type of TSC is applied to the data by K-means clustering algorithm using Euclidean, DTW and Soft-DTW similarity measures. Best similarity measures and number of clusters are determined according to silhouette scores calculated by Euclidean distance. All applications to the data are completed in Python environment.

Research of the impact of Covid-19 pandemic on sectors and customer behaviour; it is not only limited to banking, but is of great importance in preserving the short and long-term decision making skills of all sectors. Both the ability of companies to continue their commercial activities and the protection of the public health are shaped by these decisions. However; generally past studies focus on the short-term effects of the pandemic, both due to the fact that this is a globally new circumstance and the need for rapid analysis. Analysis results of short-term effects are essential for agility although;

the long-term effects are required to devise effective strategies. Therefore; the aim of this study is to consider the pandemic as a whole and examine the dynamic patterns of customers throughout the process, rather than just the outbreak period. Another purpose of the study is to try to understand whether the behaviours gained during the pandemic turn into habits. On the other hand, it should be kept in mind that this study can only extend until the end of 2020. Therefore, this study should be repeated and improved as the pandemic progresses and after it ends, in order to fully understand the dynamic customer behaviours in the process we live in.

Rest of this paper is as follows; in the second section, information is given about the former researches in the literature related to the subject, method and the progress of the pandemic process from past to present. The third section provides explanations about the data, used methods and materials. Fourth chapter presents results and make interpretations about the outputs of the study. Finally, in the fifth chapter, conclusions of the research are stated.

2. LITERATURE REVIEW

The coronavirus, which emerged in Wuhan, China in the last months of 2019, spread rapidly and affected the world in a short span of time. Considering the rate and severity of its spread, this disease was declared as pandemic by WHO (World Health Organization) on March 11th, 2020.[1] The inability to control the rate of spreading has caused global panic and countries have had to take some drastic measures to contain this unexpected situation. Workplaces, schools, theaters, cinemas, public transportation systems where communities coexist were closed; lockdowns started to be declared on city basis and then country basis. Borders have been closed; intercity entrances and exits were prohibited or brought under control (Arabacı & Yücel, 2020). The measures taken helped to prevent the spread while caused economic wounds at the same time; it has affected the future of businesses, working conditions, financial markets, caused radical changes in customer consumption habits and brought some sectors such as tourism and air transport to a standstill (TCMB, 2020). The uncertainty about how the pandemic process will progress made the situation inextricable and deeply affected the consumers.

2.1 Covid-19 Pandemics and Turkey's Status

In Turkey, although early action has been taken, controlling the spread has not been effortless. Following the scientific committee established on January 10th, restrictions and regulations were introduced for the transportation of foreign passengers and goods.

[1] https://www.who.int/emergencies/diseases/novel-coronavirus-2019/interactive-timeline#event-0 [access date: December 31th, 2020]

Two months passed without positive cases in Turkey after these restrictions are introduced until the 10th of March. This date was the date that the ministry of health announced that the Covid-19 test was positive for a Turkish citizen for the first time. During the following month after the announcement, all activities that will allow groups of people to gather were banned and nearly all the institutions that serve the same purpose closed. Age groups those under high risk are restricted from being outside. Grocery and food stores were encouraged to serve by package service as much as possible, the working hours of the service sector and the number of people they could have in the shops were rearranged, and some workplaces such as hairdressers / barbers have been temporarily suspended. At the end of March, intercity bans were imposed, international flights were completely terminated and local lockdowns began in settlements.

As of the beginning of April, the use of masks has been made compulsory, and the government initiated a free mask distribution practice for the age group 20-65 who are allowed to go out at certain hours. In the pronouncements made at the beginning of May, promising statements were made regarding the transition to the "new normal" period between the end of May and the beginning of June. Most of the restrictions applied since March 10th have been lifted, as of the 1st of June , after two four-day long consecutive lockdowns across the country, which started on the 16th of May and 23th of May. While the management of the pandemic continued in this way until the beginning of September, as a result of the increasing number of cases after the summer season, on September 7th, the public was encouraged to continue taking precautions with small restrictions. Whereas the number of cases continued to increase despite the warnings, consecutive lockdowns were announced for the 12th and 18th of November. These lockdowns were relatively milder than the first period of the pandemic but stricter compared to the summer period. The curfew hours of risky age groups and the working hours of the service sector were rearranged; it was decided to impose a general curfew on weekday evenings and weekends. As in the period of March-May, when the first attacks of the Covid-19 pandemic were experienced, a lockdown was declared on a public holiday for 4 days, starting from December 31st.[2]

[2] https://www.dtr-ihk.de/tr/koronavirus/oenlemler [access date: December 31th, 2020]

On its website that is created exclusively for the pandemic, the ministry of health shared the total number of Covid-19 tests. According to the data announced on December 31th, 2020; the total number of tests was 24.504.567, the total number of cases was 2.208.652 and the total number of demise was 20.881. Figure 2.1 shows the graph of the daily patient number percentages in relation to the daily number of tests between March 27th and December 30th in Turkey. In order to better observe the last period, the section of the same graphic since the lifting of the curfews on June 1st is also presented in the upper right corner of the original graph. Figure 2.1 represents a summary of Covid-19 pandemic in Turkey. Compared to the tests performed, it is observed that at the end of the year, the percentage of the number of patients returned to the levels observed during summertime. Nevertheless, the graph of the daily death numbers between March 27th and December 30th, presented in Figure 2.2, reveals that the number of demise has become much more severe than the first wave.

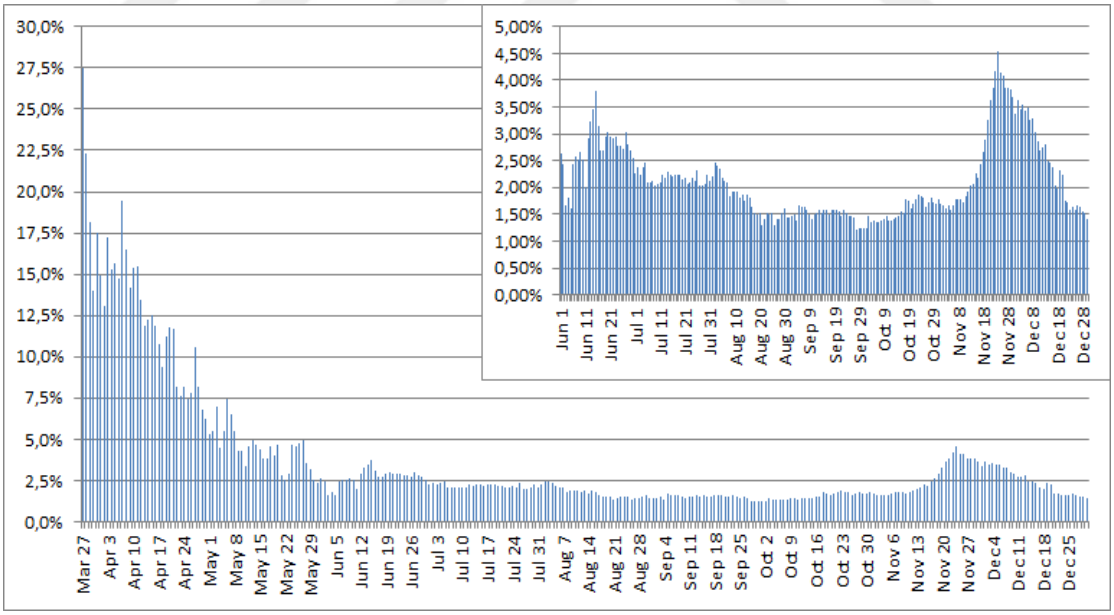


Figure 2.1: Graph of the Daily Patient Number Percentages in Relation to the Daily Number of Tests[3]

[3] https://covid19.saglik.gov.tr/ [access date: December 31th, 2020]

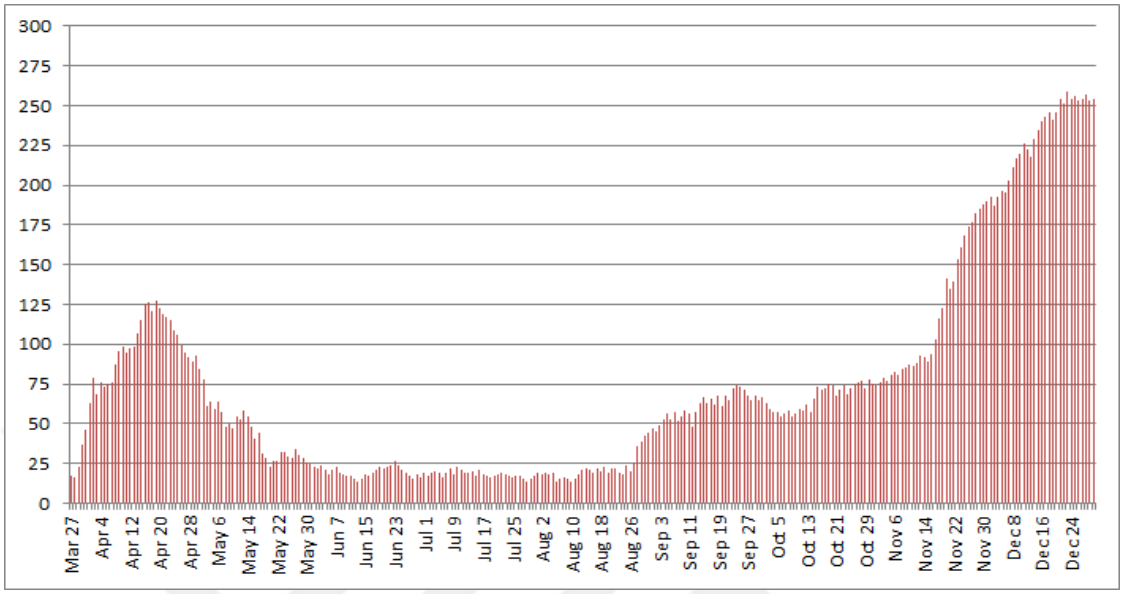


Figure 2.2: Graph of the Daily Demise Numbers

At the beginning of the pandemic, getting infected by Coronavirus seemed like a remote possibility for everyone, however with the advent of 2021, Turkey goes through a period that most people are sick and/or their first-degree relatives are infected. The arrival of the mutated Coronavirus from England to Turkey being one of the first news of the year was a cause for increasing tension just like the hesitations about vaccination, the uncertainty about the pandemic's course, and the continuation of the lockdowns were.

2.2 Consumer Behaviour Changes due to Covid-19 Pandemic

Times of crisis have always tended to change consumer behaviours. Most consumers have shown tendencies such as austerity or being more responsible and demanding during these periods (Voinea & Filip, 2011). In addition, risks such as running out of money, borrowing, job loss, or not getting a salary have caused worries about the future. Consumer preferences have also been affected by this concern for the future; consumers

have been tended not to buy products that do not address their basic needs, even if they could afford those (Mansoor & Jalal, 2011). Also, some extreme sensitivity behaviours have been the kind of behaviours that consumers tend to show in times of crisis. Researches on customer behaviours during the Covid-19 pandemic shows that some customer groups have adopted habits such as controlling the food ingredients of the products they buy and stopping to prefer "Corona" beer because of its name (Widayat & Arifin, 2000).[4] As countries were getting used to the "new normal" period, consumers have changed many behavioural patterns that can allow the virus to be shared, such as preferring online markets in food shopping, staying at home, and reducing to share items between each other (Zwanka & Buff, 2021). The following expressions, presented in the Table 2.1, can be listed as the characteristics of the Covid era consumer (Yıldız, 2020).

Table 2.1: Characteristics of Covid Era Consumer

Characteristic	Explanation
Stay at Home	Work from home and keep within doors.
Social Distance	Pay attention to social distance rules with other individuals, except for those who do not live in the same house or who do not pose a danger in the family.
Digital Opportunity	Adapt to online shopping and contactless payment concepts.
Origin Sensibility	Not to buy products of foreign origin.
Product Disinfection	Prefer to wash the products or waiting before opening.

The measures taken to control the Covid-19 pandemic and the details about the course of the disease have spread uncertainty and concern among the public. The fact that the virus can be transmitted easily has made everything that requires contact scary in the first periods of its spread. Since the incubation period of the virus is very long, the

[4] https://som.yale.edu/blog/the-behavioural-science-of-covid-19 [access date: December 31th, 2020]

uncertainty about being infected left no choice but to move social life into the digital age. It is difficult to predict how economic and social life will continue after this point. The course of outbreaks generally progresses in the following four stages; initial suspicion and investigation, initiation and acceptance, acceleration and peaking, decline and dissolution (Demir, 2020). However, the Covid-19 pandemic continues with a curve that causes fluctuations to occur more than once, due to the speed of transmission, the length of the incubation period and the fact that economic activities cannot be stopped long enough for the disease to end completely. Until most of the population is vaccinated, it is expected that the number of cases will continue to rise and fall depending on various variables such as the rise in temperature, the measures taken by the government, and the awareness of the society. The main two fluctuations until the end of 2020 were named as the "first wave" and the "second wave" according to the rising periods of the number of cases.

Like everything related to the Covid-19 pandemic, the impact of this "second wave" period, which comes right after the new normalization process, on consumers is not very definite. Although the risk factor remains the same and the process of coping with the disease is subjective, the pandemic process is accustomed due to the long treatment and vaccination processes. Having the disease and surviving is now common, and it gives confidence to some groups because this condition provides immunity for a period of time. Lockdown is no longer a newly experienced situation and it has started to be ignored. Although humanity is still afraid of the risk of transmission and the situations that may be experienced as a result of the disease, the dimensions of the experience for those who have had the disease directly affect the behaviours after recovery. At the same time, the differentiation of the effects of the virus on age groups and individuals with chronic diseases plays an active role in the differentiation of the behaviour of these groups (Demir, 2020). In addition to these facts, while the hopes of treatment and vaccination bring new uncertainties, the pessimism of the first period is removed for some groups. But this new glimmer of hope does not shine strong enough to ignore that the economic effects of the crisis are still continuing and that costs may increase exponentially (IMF, 2020).

Even in crisis environments, organizations need to analyze their customers' behaviours correctly and understand their needs in order to survive in the market (Yıldız, 2020). Although vaccination studies are progressing positively, it does not seem that the Coronavirus will be a part of history in the next few months. Besides; it should be kept in mind that customer behaviours that vary due to the pandemic may be permanent due to the length of exposure (Çakıroğlu et al., 2019). Permanence of new behaviour patterns indicates the need to re-analyze and understand these behaviours. Because moving forward with what was already known will no longer serve the new desires of customers.

In the literature, the change in consumer behaviours in the Covid-19 pandemic has been discussed from various aspects and has been widely studied in foreign and national studies. Researches mainly concentrated on the first period of the pandemic; the focus was on consumer purchasing habits and digitalization subjects. Since it is a global crisis, behavioural patterns in various countries and regions have been studied using both survey data and data held in various sources. In the rest of this section, the mentioned studies are explained in detail, and Table 2.2 is the summary table of these studies.

Table 2.2: Summary of the Literature about Consumer Behaviours in Covid-19

Author(s)	Subject of Study	Behaviour Change
Andersen et al. (2020a)	Impact of the lockdown duration on consumer spending in Denmark and Sweden	Consumer spending decreased regardless of lockdown duration.
Andersen et al. (2020b)	Change in customer behaviours after Covid-19 in Denmark	Total card expenditures decreased 25%
Auer et al. (2020)	Preference of cash in spending during Covid-19	Pandemic agitated consumer concerns about cash usage
Bachas et al. (2020)	Effects of the pandemic on household spending and saving in US	Household spending is decreased, savings are increased

Baicu et al. (2020)	Effects of Covid-19 on the behaviours of retail banking customers in Romania	Internet and mobile banking usage increased due to pandemic
Baker et al. (2020)	Consumption habits of US households during the pandemic	Household spending routines changed in many categories
Bounie et al. (2020)	How consumers responded to economic shocks in France	Online shopping saved some sectors, total consumption decreased 60% in lockdown
Chen et al. (2020a)	Impact of the lockdown in Wuhan on the Chinese economy	Grocery shopping increased while others decreased
Chen et al. (2020b)	Change in consumption caused by the Covid-19 pandemic in China	Daily consumption decreased by 32%, mostly in Wuhan
Chetty et al. (2020)	Covid-19 pandemic effects on the economy of US	Spending decreased especially in high risk zones
Coibion et al. (2020)	Impact of the changes in durations of local lockdowns on the US household spending	Households in lockdown spent less, total spending decreased
Carvalho et al. (2020a)	Impact of the lockdown on consumer spending between 2018 and 2020 in Portugal	Essential spending increased. Spending habits are changed.
Carvalho et al. (2020b)	Changes in consumer spending during the Covid-19 pandemic in Spain	General consumer expenditures decreased immediately after lockdown.
Crawford et al. (2020)	Household spending during the Covid-19 pandemic in UK	Expenditure tendencies have changed
Jha and Pradhan (2020)	Consumer spending during the lockdown in the UK	Arbitrary shopping decreased, grocery shopping increased
Koçak (2020)	Card expenditure behaviour change during the pandemic in sectoral detail in Turkey	Grocery shopping increased others decreased, sectoral shifts were permanent

Koşaroğlu et al. (2020)	Effects of the Covid-19 pandemic on the demand structure of consumers in Turkey	Online shopping, hobby expenditure, contactless payment usage increased
Moulton et al. (2020)	Use of technology and the adoption of e-banking during the Covid-19 pandemic	E-banking provided the continuity of banking operations in pandemic
Verma & Jain (2020)	E-banking usage of consumers and their level of satisfaction with this service	Satisfaction of e-banking was %80 due to ease of use and fast transaction capacity

Andersen et al. (2020b); used transaction-level bank account data from a major Danish bank to find the change in consumer behaviour after the Covid-19 pandemic. In the research, a 25 percent decrease was observed in the total card expenditures; especially for the product categories that their trade was restricted by the government. Andersen et al. (2020a) with a similar study; examined the impact of the lockdown duration on consumer spending by transaction-level bank account data from Swedish and Danish banks. In the study, the consumer spending patterns of Denmark and Sweden were compared in terms of lockdown implementations of the government. While the Danish government needed a lockdown to reduce the number of cases during the pandemic, Sweden did not require it. The findings of the study showed that, regardless of the government regulations, consumer spending decreased significantly in both countries during the period when Denmark was under lockdown. The most significant reduction was observed among young consumers under the age of 29.

Auer et al. (2020); studied the preference of cash in spending during the Covid-19 pandemic and made comments on the future of expenditures. Research findings suggested that the pandemic agitated consumer concerns about cash usage, and this may accelerate digital transformation. At the same time, it is stated that this rapid transformation may not be welcomed by those who do not use banks or the elderly.

Bachas et al. (2020); studied the effects of the pandemic on consumer spending and saving using bank account data up to the 30th of May at the household level in the United States. The research showed that all household spending decreased from March to the beginning of April, and it was directly related to the pandemic, not the state of the labor market. The mentioned decrease was usually due to a decline in non-essential consumption that could be identified as products and services other than essential needs. When the data analyzed according to income distribution, it is determined that low-income households were the fastest ones that have recovered their expenditure level since mid-April, regardless of geographical location and employment level. Concerning savings, divergence was observed for the April-May period substantially compared to the same period of the previous year. Although saving behaviour was common across all income levels, it was possible to say that the percentages of savings increase, spread more evenly across income levels compared to the February period. The income group that saved the greatest amount was the high-income level with dollar savings. Another outcome of the research was the increase in savings is directly related to the sectors affected by the virus. Besides, it must be said that the research has established cause-effect relationships for the outcomes but the relationships established were inferential. For example, in the research, it was said that the recovery of low-income households was proportional to the incentives and assistance provided in the same period.

Baicu et al. (2020); examined how the Covid-19 pandemic affects the behaviour patterns of retail banking customers in Romania with the survey data applied to 738 retail banking customers. In the research, it was determined that internet and mobile banking usage increased during the pandemic. In addition, it was determined that the mood caused by the pandemic was directly proportional to the adoption of internet banking and mobile banking for retail banking customers and positively affected the adoption of these banking applications.

Baker et al. (2020); investigated the consumption habits of United States households during the pandemic through transaction-level financial data of households obtained from a non-profit finance website. Research showed that household spending routines have changed radically in many categories with the increase in the number of cases.

Especially retail and food categories faced sharp increases at the beginning of the pandemic, followed by a decrease in total expenditures. The research explained that the severity of the reactions of consumers to the pandemic was directly related to the impact of the epidemic on the consumer. It has been observed that the relationship between demographic characteristics and response to the pandemic causes much higher levels of heterogeneity than the relationship between income and response to the pandemic.

Bounie et al. (2020); used customer card spending data of more than hundred banks in France to investigate how consumer behaviours responded to economic shocks. In this context, the responses to the imposed restrictions, the changes in the mobility of consumers due to social isolation, and the dimensions of online and traditional spending were studied. The results showed that some sectors have suffered less from economic shocks through online shopping than other sectors. In addition, depending on the lockdown, it has been observed that most of the shopping was made from nearby places and the total consumption decreased by up to 60 percent in both volume and value in the weeks following the lockdown.

Chen et al. (2020a); used the data published by NBS (National Statistics Bureau) in China until the end of March, evaluated the impact of the lockdown in Wuhan, Hubei on the Chinese economy. The decrease in the population of workplaces and the increase in the population of shopping malls were accepted as a normal flow in urban activities. However, when this flow was examined during the lockdown, a large decrease was encountered in both populations. Although the flow in the workplaces was recovering faster after the lockdown, the economic effects of the lockdown seemed to be permanent because; the numbers of being in shopping malls and workplaces in the last week of March were corresponding to approximately half of the levels before the lockdown. Retail sales were also affected by the lockdown, declined by 21 percent in January and February. Foodservice revenues decreased by 43 percent in line with the decrease in the ratio of being in a shopping mall. In the same months, digital and electronic product sales, which previously covered two-thirds of total sales, also showed a radical decline. Grocery shopping substituted digital and electronic product sales with a large percentage.

Chen et al. (2020b); researched the change in consumption caused by the Covid-19 pandemic through daily expenditure data from 214 cities in China covering almost 90 percent of the urban population. The research showed that there has been a 32 percent decrease in daily traditional consumption. Considering the main categories, product consumption had the highest decrease with a 34 percent decrease and consumption in the service sector followed with a 33 percent decrease. When the sub-categories of consumption decrease are considered, food expenditures with 64 percent and entertainment and tourism expenditures with 59 percent had the highest rates respectively. In terms of location, the highest spending decrease was found in Wuhan, the city where the pandemic first started, with 70 percent. Although consumption started to normalize at the end of March, when the effects of the pandemic were diminished in China, consumption fell 20 percent in April due to the second wave.

Chetty et al. (2020); through a public database created with anonymized data collected from private companies; examined how the Covid-19 pandemic affected the economy of the United States based on daily statistics of key indicators in groups such as location, employment, and income. The findings showed that in the early stages of the pandemic, there was a sharp decline in the spending of the high-income group, especially in sectors where the disease spread more and social isolation was not achieved. The research also concluded that government incentive payments have had a positive effect on the consumption expenditures of the low income group.

Coibion et al. (2020); used surveys of more than 10.000 respondents to examine the impact of the changes in the durations of local lockdowns on the United States household spending. The authors found that total consumption expenditures, especially travel and clothing, fell significantly. Approximately 50 percent of the respondents stated that they faced the loss of savings and income and households in lockdown expected pessimistic scenarios of future. In addition, it has been observed that households in lockdown spent less than other households, due to the restriction of daily activities and concerns about the future of economic conditions.

Carvalho et al. (2020a); examined the impact of lockdown on consumer spending between 2018 and 2020 using POS (Point of Sales) usage and online payment data in Portugal. Research results showed that purchases of essential products have increased; on the other hand, spending in the tourism-related sectors, especially in entertainment venues and food places closed by the government, has faced huge decreases. It has been determined that consumers have changed their shopping strategies. They preferred to spend less frequently and with larger amounts from shopping malls and also preferred to shop from nearby grocery stores and markets. Consumers tended to delay basic expenditure on health and government. Gas stations have been found to suffer less damage compared to the general transportation sector, and this output was associated with the preference of personal vehicle use. Carvalho et al. (2020b); has also studied a similar topic in Spain with another team. Researchers studied the changes in consumer spending during the Covid-19 pandemic in geographical, sectoral, and sales categories based on the 2019-2020 retail banking customer data of BBVA, Spain's second-largest bank. According to the results of the research, while customers did not encounter major changes in pre-lockdown expenditures, they encountered sudden changes after lockdown. Although there were differences in the decreases between product categories, general consumer expenditures showed substantial decreases in the post-lockdown period.

Crawford et al. (2020); researched household spending during the Covid-19 pandemic using data from the UK National Bureau of Statistics and the 2017 ONS Cost of Living and Food Survey. The results of the research showed that before the pandemic, households allocated a quarter of their expenditures for goods and services that were prohibited during the pandemic. These expenditures did not continue to be similar expenditures for all groups, and expenditure tendencies changed in consumer groups that diverged due to the pandemic. Concurrently, research showed that since most of the expenditures of low-income groups were devoted to basic needs, it seemed more difficult for these groups to overcome the income shock due to the pandemic compared to other groups.

Jha & Pradhan (2020); studied consumer spending during the lockdown in the UK with the help of a 23 million transaction dataset from January 1st to April 7th provided by a fin-tech company. Researchers divided the pandemic period into five phases according to the progress of the pandemic between January and April. Research results showed that arbitrary spending started to decline in the period immediately after the spread of the pandemic and continued to decrease throughout the lockdown period. Just after the WHO (World Health Organization) declared Covid-19 disease as pandemic; a substantial amount of increase was discovered in the groceries expenditure. In addition, although consumer expenditures varied according to product categories, location and demographic information; it was emphasized in the research that the bans imposed by the government affected consumer expenditures during the pandemic period.

Koçak (2020); researched change in card expenditure behaviour during the pandemic in sectoral detail, using the weekly card spending data of consumers in Turkey for the period between 2014 and 2020. Also; the effect of the pandemic on shifts between sectors identified with regression models and these shifts were classified like "permanent", "first panic then permanent", "intensified", "first panic then intensified". Research results revealed that there was synchronization between sectors that spending was made with credit cards. Sectoral shifts because of the pandemic were mostly determined as "permanent". In addition, while spending in the shopping and grocery sectors increased, a decrease was observed in all other sectors, especially in the entertainment, dining venues and air transport sectors, which were closed by the government during the pandemic.

Koşaroğlu et al. (2020); analyzed the effects of the Covid-19 pandemic on the demand structure of consumers, using the data they obtained through a survey applied to 1003 people living in various provinces of Turkey. The findings revealed that significant changes have been detected in the expenditures of consumers who were constantly in lockdown during the pandemic. While the first response of consumers to the pandemic was the stockpiling of essential foods, it was observed that there was interest in online shopping in the following period. In addition to grocery shopping, it has been determined that expenditures in cultural fields have also increased due to consumers'

wish of creating a hobby to do at home. In addition to taking advantage of e-commerce, consumers also preferred payment methods such as contactless payment to prevent the spread of the virus.

Moulton et al. (2020); through the questionnaire applied to 1,067 people; researched the use of technology and the adoption of e-banking during the Covid-19 pandemic. The findings of the study showed that the amount of information, perceived ease of use and perceived usefulness were effective in the adoption of online banking. As a result, it was emphasized how important e-banking is in order to continue banking transactions during the pandemic period.

Verma & Jain (2020); investigated the e-banking use of consumers and their level of satisfaction with this service during Covid-19, through the data collected by an online survey answered by 121 people. According to the study, 97 percent of the population was using e-banking and the average satisfaction level was above 80 percent. Results showed that e-banking application was keeping customer satisfaction at the highest level due to its ease of use and fast transaction capacity.

The following statements in Table 2.3 summarize the main crisis-era behaviours of consumers according to the literature.

Table 2.3: Summary of Consumer Behaviours during the Pandemic

Statement	Explanation
Basic needs were the top priority in times of crisis.	Consumers prioritized to meet their basic needs and postponed their non-essential needs such as travel and entertainment.
Pessimistic thoughts caused by environment overcame.	Whereby the pessimistically changing environment, consumers tended to deepen the negativity around them. Pressure caused consumers to think more about their actions, they started comparing products and prices more often.
Needs and requests	Consumers could not meet their needs and requests, which

were not fulfilled because of the lack of free will.	they meet in their natural routine, because they cannot act with their own free will and are restricted. As a result, they tried to change or rearrange their needs and wishes.
Savings were more popular than investments.	Since the risk factor was at the forefront in crises, consumers were careful about their investments and savings. The aim was to avoid risks as much as possible and to be prepared for bad situations. Therefore, consumers tended to keep the money in their pocket (Berber, 2009).
Online was safer.	In the process of adaptation to the pandemic, consumers have increased the usage of credit cards and contactless payment due to concerns about cash usage and have made more transactions through digital channels such as internet banking or mobile banking (Yıldız, 2020). Depending on the change in purchasing preferences, they used online channels for both purchases and comparisons.
If going out of home was a necessity than the closest market/shop was the best.	Consumers avoided physically being at shopping places and with the limited time outside, they either shopped from local markets or reduced their frequency of going to large and distant markets and increased the basket amounts.

2.3 The Process of Behaviour Becoming a Habit

The Covid-19 pandemic has transformed from a health crisis into an economic crisis. Both consumers and financial companies have undergone significant changes in this crisis, overcame the difficulties and are still trying to (Kelecic, 2020). Banks have to adapt to, shape and even get ahead of this new period. Being beyond this period requires understanding the dynamics of the future as well as understanding the period. The new economy will be shaped by the changing purchasing habits of consumers and their adaptation processes to digitalization, as has been widely studied in the literature. Understanding and correct use of consumer purchasing behaviour and digitalization concepts will play a decisive role in the future of companies. Although it was known

before the pandemic, it was understood much better during the pandemic that digitalization is inevitable in the future and a digital transformation much closer than we think, is waiting for us. It is obvious how important digitalization is, not only in banking but also in all sectors, and digitalization has become one of the main criteria that will determine the losers and winners after the pandemic ends (Uca & Karakaya, 2020).

In order for the Covid-era consumer behaviours and this new digital transformation to shape the future economy; the behaviours acquired in this process must be permanent, that is, they must turn into a habit. Sheth (2020); stated that activities that creates daily routines of consumers like business, entertainment etc., demographic characteristics and methods of keeping up with the radical changes of technology, will create post-pandemic habits of consumers.

Habit is the name given to behaviour patterns that are repeated regularly and no longer require consciousness. To understand how the habit is acquired, it is necessary to understand the habit cycle well. The habit cycle consists of three basic steps; motive, routine and reward (Chen, 2020c). These steps are needed to be followed repeatedly in order to gain a new habit. Motivation refers to the emotion, thought or event that led to the emergence of this habit, routine represents the behaviour pattern that is triggered by this motive and that is done continuously in an order, and lastly reward refers to the feeling of individual satisfaction gained by practicing this routine (Chen, 2020c). The motivation of the habits that will be formed during the pandemic stems from the desire to cope with the pandemic or simply “stay alive” and it has become necessary to implement routines that can serve this impulse during the pandemic. Some of the mentioned routines are as follows; washing hands when coming home, maintaining social distance, using online channels as much as possible, etc. The reward of these routines is the feeling of coping with the pandemic, which is, being able to live with the difficulties brought by the pandemic. Therefore, the pandemic itself unwittingly becomes a much stronger source of motivation than the regular impulse of a consumer to create a habit in the normal period. Wendy Wood; a Duke University psychology and neuroscience professor, used the following sentence when talking about habits;

"Many of our repeated behaviours are cued by everyday environments, even though people think they're making choices all the time."[5] Wood has stated that in a way, this pandemic period, which has radically changed our daily lives for a long time, may already have created new habits. Another thing to discuss in order to evaluate the probability of developing pandemic habits is how long it takes to acquire a habit. Tara Swart, a senior lecturer at MIT, writes in her book Neuroscience for Leadership (Swart et al., 2015); "Depending on the complexity of the activity, four and a half months, 144 days or even three months for a new brain map, equal in complexity to an old one, to be created in the motor cortex."[6] The above-mentioned arguments are evidence that consumers are likely to adopt new habits during the pandemic.

2.4 Consumer Behaviour Analysis in Banking

Nowadays; banks are using machine learning and data mining techniques for many problems they encounter such as customer segmentation, risk management, customer churn prediction, fraud detection, etc. (Chitra & Subashini, 2013; Patil & Dharwadkar, 2017). Customer relationship management (CRM) is the department of a bank deals with the problems such as gaining customers and maintaining the presence of acquired customers. Ngai et al. (2009) has found it appropriate to classify CRM activities into two main categories: operational CRM and analytical CRM. Main purpose of analytical CRM is to understand customer characteristics and behavioural patterns from data whereas operational CRM aims to automate business processes. Analytical CRM is the CRM branch that uses data mining and machine learning techniques in order to fulfill the bank strategies.

Segmentation is a common method analytical CRM uses to understand customer behaviours and help the marketing department develop effective strategies. With this method, analytical CRM discovers similar customer groups that exhibit the same behavioural patterns to solve the problem at hand. In this context, "customer dynamics"

[5] https://today.duke.edu/2007/12/habit.html [access date: January 3rd, 2020]
[6] https://www.fastcompany.com/3045424/what-it-takes-to-change-your-brains-patterns-after-age-25 [access date: January 3rd, 2020]

is one of the main subjects that need to be considered in customer segmentation design (Akhondzadeh-Noughabi & Albadvi, 2015). Customer behaviour is not stable but changes over time, psychology and environment (Akhondzadeh-Noughabi & Albadvi, 2015). Especially when talking about a continuous psychological and environmental change and uncertainty under the effect of Covid-19, accepting customer behaviour as stable is contrary to the purpose of the study. Therefore, this study found it more appropriate to examine customer behaviours during the Covid-19 period with dynamic customer segmentation. One of the main approaches in dynamic customer segmentation is the inclusion of time in the system (Abbasimehr & Shabani, 2019). It is much more beneficial to try to interpret the behavioural pattern within a certain period of time rather than trying to interpret the instant behaviour of the customer. One of the most useful methods in this context is Time Series Clustering.

2.4.1 Time Series Clustering

The clustering of time series is the process of separating unlabeled time series data into various clusters according to the similarities of inputs (Rani & Sikka, 2012). TSC is a method to discover hidden patterns in the data therefore it has many usage areas from astronomy to finance, from psychology to medicine (Aghabozorgi et al., 2015). Major traditional (static) clustering methods are classified into five groups by Han & Kamber (2001) such as; partitioning, hierarchical, density-based, grid-based and model-based methods. Five of the three methods mentioned; partitioning, hierarchical and model-based are adapted as dynamic clustering methods (Rani & Sikka, 2012). Details of the methods are presented below, in Table 2.4 (Han & Kamber, 2001; Akhondzadeh-Noughabi & Albadvi, 2015). This study uses partitioning clustering method to reveal dynamic behaviour patterns of customers.

Table 2.3: Dynamic Clustering Methods

Method Name	Explanation
Partitioning	Dividing each object by assigning it to a cluster based on their similarity.
Hierarchical	Agglomerative (Bottom-Up); Creating clusters starting from an object and adding close clusters to each other. Divisive (Top-Down); Starting with all objects, dividing each cluster into a new one until each element remains in a single cluster.
Model - Based	For each cluster; hypothesizing a model and finding the data that fits the best to the default model.

2.4.1.1 Similarity Measures

Study of time series similarity / dissimilarity problem was proposed by Agrawal et al. (1993) and became a main theoretical application for time series clustering method in the data mining community (Aghabozorgi et al., 2015). Similarity is actually a measure of distance; the less distance two time series are from each other, the more similar they are (Geler, 2015). The distance between objects is based on exact matching in static time series, however the distance is approximated in TSC. Therefore there should be a measure to determine how similar the two time series are. Adequate determination of similarity is very important, peculiarly for the time series to be comparable with irregular sampling intervals and length.

There are many different similarity measures, the most commons can be listed as: Euclidean distance, Dynamic Time Warping (DTW), Longest Common Sub-Sequence (LCSS) and Hidden Markov Models (HMM) based distance. Euclidean, DTW, and Soft-DTW, which is a type of DTW, are used in this study; hence only mentioned three similarity measures will be explained later in this section. Characteristics of the

similarity measures that are prepared by Aghabozorgi et al. (2015) are described in Table 2.5.

Table 2.4: Similarity Measures and Characteristics

Similarity Measure	Characteristics	Method
Euclidean	Lock-step measure (one-to-one) using in indexing, clustering and classification, sensitive to scaling.	Shape-based
DTW	Elastic measure (one-to-many / one-to-none), very well in deal with temporal drift, better accuracy than Euclidean distance, low efficiency than Euclidean distance and triangle similarity.	Shape-based
LCSS	Noise robustness	Shape-based
HMM - based	Able to capture not only the dependencies between variables, but also the serial	Model-based

2.4.1.1.1 Euclidean, Dynamic Time Warping and Soft-DTW

Euclidean distance is one of the most common similarity measures in the literature that is used for time series comparison (Geler, 2015). For time series $X = (x_1, x_2, \dots, x_n)$ and $Y = (y_1, y_2, \dots, y_n)$ of the same length n, the Euclidean distance $D(X, Y)$ is calculated below by Equation 2.1 (Faloutsos et al., 1994).

$$\mathrm{D(X, Y)} \equiv \left(\sum_{i=1}^{n} (X[i] - Y[i])^2\right)^{1/2} \tag{2.1}$$

DTW is originally brought to the literature by Sakoe & Chiba (1978) and it is one of the most commonly used similarity measures because of its ability to compare time series even they are not fully compatible with each other. Algorithm is widely used in music and signal processing, natural language processing, data mining and time series clustering and many other areas (Senin, 2008). In application of DTW; for time series $X = (x_1, x_2, \dots, x_n)$ and $Y = (y_1, y_2, \dots, y_m)$, an n-by-m distance matrix is constructed that is named as local cost matrix $D(X, Y)$ (Equation 2.2a), where d_{ij} represents pairwise squared distances between X and Y and calculated below by Equation 2.2b (Senin, 2008; Geler 2015).

$$D(X, Y) = [d_{ij}]_{n,m} \tag{2.2a}$$

$$d_{ij} = (x_i - y_j)^2 \tag{2.2b}$$

Afterward; the algorithm builds alignment or warping paths from the low-cost areas in the local cost matrix and costs of the warping paths are calculated. The cost of a warping path is the summation of all pairwise distances that the warping path consists of. The warping path that has the minimum cost is called the optimal warping path (Senin, 2008; Geler 2015).

Soft-DTW is a smoothed version of DTW formulation that is presented to the literature by Cuturi & Blondel (2017). According to definition of Cuturi & Blondel (2017); Soft-DTW computes the soft-minimum of all possible alignment costs instead of considering costs of only one alignment path. Since the minimization process is not differentiable, DTW is not differentiable based on the inputs; therefore Soft-DTW is a necessary algorithm in the literature. Given the cost matrix $\Delta(x, y)$ and inner product $\langle A, \Delta(x, y) \rangle$ of cost matrix with alignment matrix A; Equation 2.3a and Equation 2.3b show the difference between DTW and Soft-DTW respectively, in the minimization process with a smoothing parameter $\gamma \geq 0$ (Cuturi & Blondel, 2017).

$$DTW_0(X,Y) = \min_{A \in A(n,m)} \langle A, \Delta(x,y) \rangle \tag{2.3a}$$

$$DTW_\gamma(X,Y) = \min^{\gamma}_{A \in A(n,m)} \langle A, \Delta(x,y) \rangle \tag{2.3b}$$

2.4.1.2 Silhouette Index

Concept of silhouettes are presented to the literature by Ruosseeuw (1986). In his study; Ruosseeuw (1986) created a graphical display and a measure to compare clusters with each other. Silhouette width of an object in a cluster helps to understand how fit that object is to its own cluster and how different from other clusters. (Ruosseeuw, 1986). Also it is possible to measure cluster validity and number of clusters to use for a partitioning clustering application with average silhouette width. Silhouette index is applicable with all distance measures (De Amorim & Hennig, 2015); and calculated with Euclidean, DTW and Soft-DTW for this study.

Silhouette width (i) of each point is calculated with two mean distance values. First value (i) is the mean distance of a point M_i to the points its cluster includes. To calculate the second value (i), initially, the mean distance of the same point to the points of the related cluster should be calculated for each cluster. The minimum of these mean distances of the other clusters represents the second value (i). Then; the silhouette width of point M_i can be calculated with Equation 2.4 represented below (De Amorim & Hennig, 2015; Desgraupes, 2017).

$$s(i) = \frac{b(i) - a(i)}{\max(a(i), b(i))} \tag{2.4}$$

3. METHODOLOGY

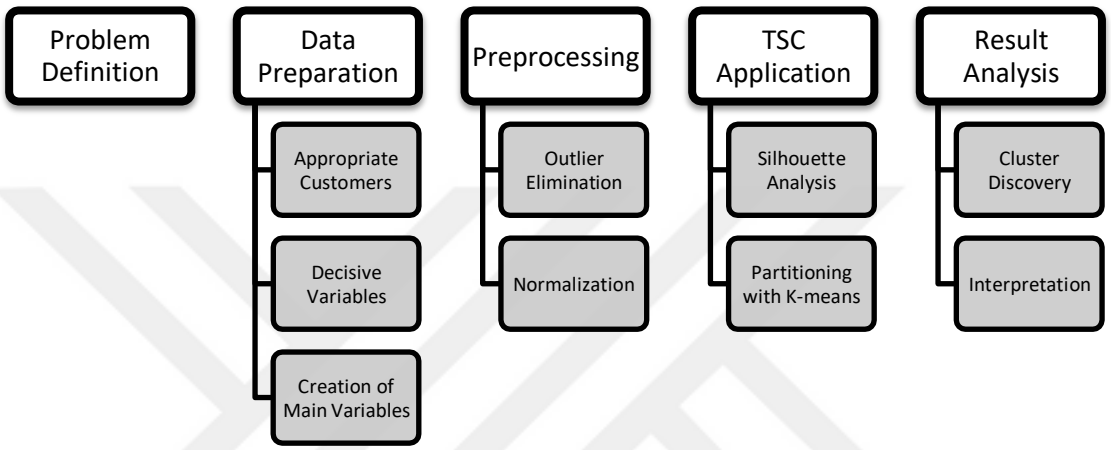


Figure 3.1: Flow of the Methodology

The implementation of the method proceeded as outlined below. Figure 3.1, above, represents a summary of the flow of the methodology. As a first step, the subject of the study was defined mathematically. As a result of this definition, the variables that should be used and the main lines of the customer group have emerged. Digital activity and spending subjects were chosen to study according to the economic and psychological studies in the literature that is explained widely in section 2. Thereafter; the data to be used in the study was created according to the specifications by the CRM department of the collaborating bank. At this stage; retail banking customers' data for 2019 and 2020 were used. Customers between the ages of 18-90 who were actively using bank applications and products during 2019-2020 were selected for the study in order not to interrupt the behaviour pattern. 10 month periods (March-December periods) of 2019 and 2020 were chosen because of the period of pandemics are compared to the previous year in the study.

For ease of calculation and increased explanatory power, data of 200 customers selected by random sampling method were used. After selection of the appropriate customers; variables thought to play decisive role for the study were included and the variables that highly correlated with each other were excluded from the data set. Remaining variables are listed below at Table 3.1.

Table 3.1: Decisive Variables

Column Name	Description
Customer Number	Number that is unique for each customer
Month-Year	Month-year that transactions occurred
Total Credit Card Spending Amount	Summation of spending amount from credit card
Mobil Banking Activity	Activity status of a customer in mobil banking application
Internet Banking Activity	Activity status of a customer in internet banking web-page
Amount of Online Shopping	Online shopping transaction amount
Branch Visit Number	Count of times that customer visited the bank branch
Automatic Bill Payment	Activity status of a customer for automatic bill payment order

Spending and digital activity score variables were created according to the variables listed above. Total credit card spending amount equals to spending variable because of its correlation to the other spending related variables and higher explanatoriness level. The CRM department assigned coefficients to mobile banking activity, internet banking activity, amount of online shopping, branch visit number, automatic bill payment variables that vary in their importance. Based on these coefficients, the digital activity score variable was formed by taking the weighted average. Thus, the main variables were obtained.

In terms of data preprocessing, outliers were eliminated based on IQR range and numeric values were normalized by min-max scaling (Han & Kamber, 2001) in the range of (0,2). For outlier elimination IQR scores were calculated, as Equation 3.1 represents below, for all variables and the points that remain outside of the range of $Q_1 - 1.5IQR$ and $Q_3 + 1.5IQR$ were eliminated where Q_1 and Q_3 are 25th percentiles and 75th percentiles respectively.

$$IQR = Q_3 - Q_1 \tag{3.1}$$

Min-max normalization was used as the second step of preprocessing. Variables were rescaled in a range between [0, 2] to ease the calculations according to the data structure. For an attribute $X = (x_1, x_2, \dots, x_n)$ and a given range [a, b]; Equation 3.2 shows the calculation of min-max scaling for a point x_i of X (Han & Kamber, 2001).

$$x_i' = a + \frac{(x_i - \min(X))(b - a)}{\max(X) - \min(X)} \tag{3.2}$$

Following the data preprocessing, TSC method was applied to the data with the purpose of extracting customer behaviour patterns out of the data. K-means clustering (MacQueen, 1967) which is a partitioning clustering algorithm, was applied to March-December periods of 2019 and 2020 for each variable in a Python environment (Van Rossum, 1995)[7]. TimeSeriesKMeans function of "tslearn" (Tavenard et al., 2020) library was used to apply K-means algorithm to the data. Function allows to the application of three similarity measures: Euclidean, DTW and Soft-DTW which are also mentioned in section 2.

[7] https://pythoninstitute.org/what-is-python/ [access date: January 5th, 2020]

		K=5	K=6	K=7	K=8	K=9	K=10
Spending_2019	Euclidean	0,455	0,255	0,364	0,186	0,251	0,297
	DTW	0,419	0,347	0,199	0,206	0,201	0,208
	Soft-DTW	0,252	0,160	0,064	0,071	0,172	- 0,022
Spending_2020	Euclidean	0,315	0,299	0,324	0,221	0,322	0,221
	DTW	0,351	0,348	0,268	0,311	0,305	0,176
	Soft-DTW	0,210	0,082	0,085	0,043	0,032	0,049
Digital_2019	Euclidean	0,510	0,478	0,491	0,497	0,482	0,490
	DTW	0,463	0,508	0,502	0,460	0,468	0,473
	Soft-DTW	0,511	0,448	0,414	0,432	0,476	0,451
Digital_2020	Euclidean	0,531	0,513	0,535	0,533	0,415	0,446
	DTW	0,392	0,504	0,531	0,511	0,435	0,408
	Soft-DTW	0,406	0,349	0,363	0,336	0,398	0,420

Figure 3.2: Silhouette Index Matrix

Best similarity measures and numbers of clusters for each year and variable are obtained with silhouette index analysis. From 5 to 10 clusters and for each similarity measure, average silhouette width is calculated with Euclidean distance as it is explained in section 2 before. Euclidean distance was used for silhouette index analysis because of the similarity between the index values calculated by other distance metrics and the index values calculated by Euclidean distance. According to the results of silhouette index analysis, chosen number of clusters and similarity measures are highlighted with green in Figure 3.2 above.

By application of the TSC method, in the two dimensions of time and for the two variables, clusters that represent general behavioural patterns of the retail banking customers were generated. To understand and analyze the customer behaviour patterns these clusters were deciphered from numbers to characteristics. The customers included in the clusters were determined and analysis charts were created according to the trend lines of clusters. Graphs were created for both variables according to their normalized values for easy understanding and visualization. Clusters were named and compared according to these graphs. Next section is about the interpretation of these clusters and comments to the results..

4. RESULTS

There are 7 clusters for 2020 digital score data, while there are 5 clusters for each of the remaining cases. Although the naming of these clusters is similar to each other, two clusters named with the same name in different periods do not refer to the same two clusters. The reason for using similar names for clusters is to ease comparison and to assign a rank to the clusters by period and variable. For example, when we consider spending behaviour, the Low cluster in 2020 and the Low cluster in 2019 do not contain exactly the same customers. However, if a customer is in the Low cluster in both 2019 and 2020; This indicates that the customer has not changed their spending behaviour.
More information on cluster distributions is provided in Appendix A and Appendix B.

4.1 Spending Behaviour

Clusters of 2019 for spending behaviour are named Low, Moderate 1, Moderate 2, High 1, and High 2 as they are presented in Figure 4.1. Customers in Low cluster are those that remain relatively stable in quantity throughout the year and spend less. The Moderate 1 cluster is similar in characteristic to Low cluster, but the spending amounts of the customers in the cluster and the differences in spending between months are slightly higher than those in Low cluster. Although the average spending of Moderate 2 cluster is close to Moderate 1 until October, it is clearly separated from Moderate 1 with its incredibly high spending level in November. High 1 cluster shows a slightly higher average throughout the year than Moderate clusters, while spending twice as much as its average in autumn and winter. Similarly, although High 2 cluster is on a similar average with High 1 throughout the year, expenditures raising exponentially in spring and winter periods that can reach three times the average.

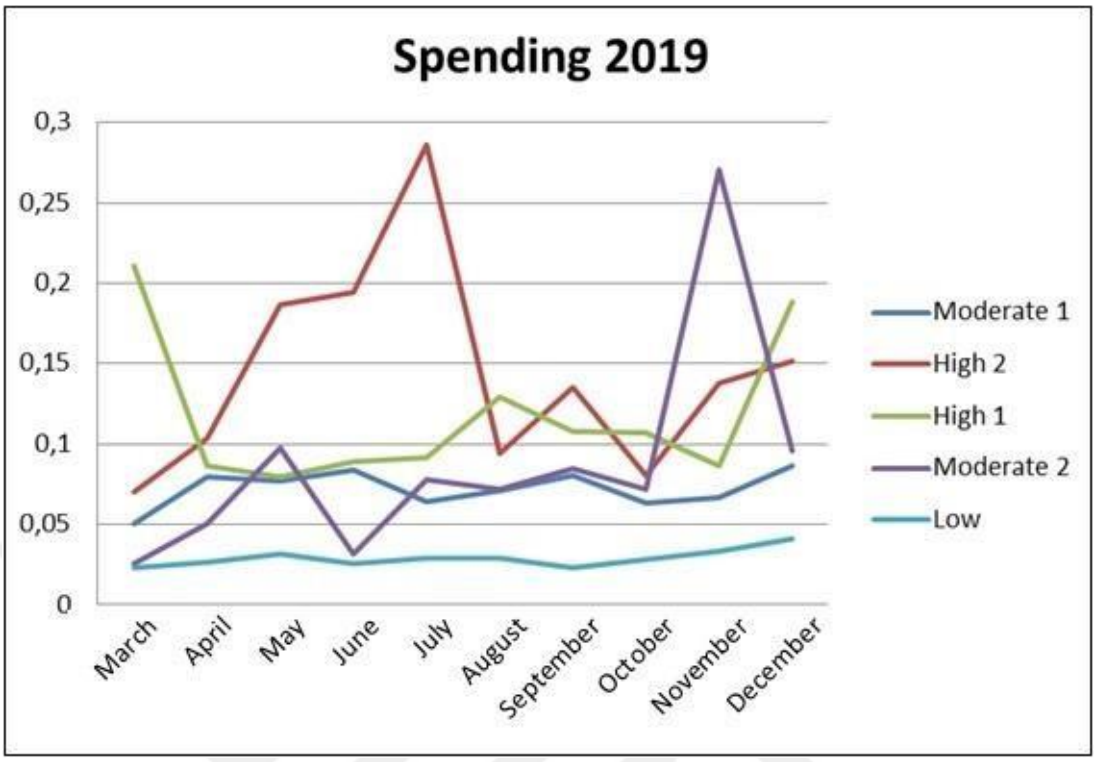


Figure 4.1: Cluster Trend Lines for Spending Behaviour Patterns in 2019

Spending clusters of the year 2019 are obtained with eliminating four outliers during the clustering process. In order to create better dispersed clusters, this group of customers who alone have a very high spending level compared to the others, were eliminated from the group and the clustering was repeated. This group is named Very High and displayed in a different graph from the other clusters, as shown in Figure 4.2 above, in order to increase the readability of the original graph. While these four customers in Very High cluster have a higher spending average in the spring and summer than all other groups, they reduce their amount of spending dramatically as the summer months are over.

Clusters of 2020 for spending behaviour are named Low, Moderate 1, Moderate 2, High, and Very High as they are presented in Figure 4.3 above. In order to follow the progress of the pandemic on the graph better, the graph is divided into two-month segments with vertical lines.

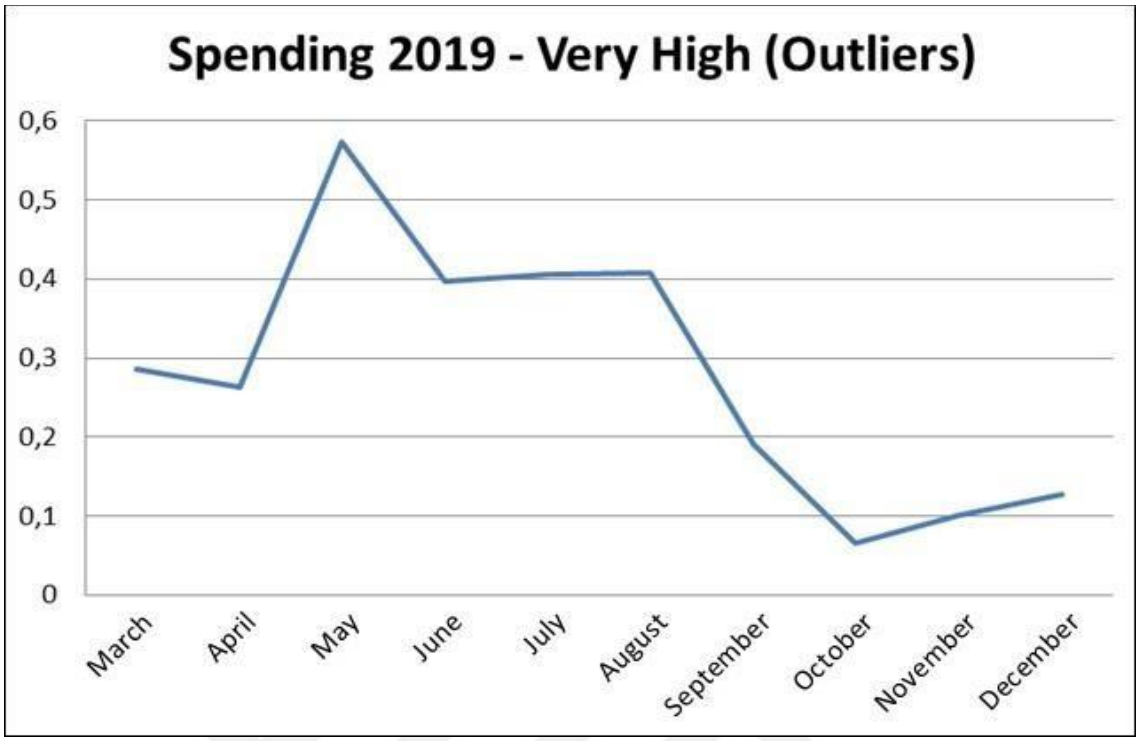


Figure 4.2: Cluster Trend Line for Outlier Pattern in 2019

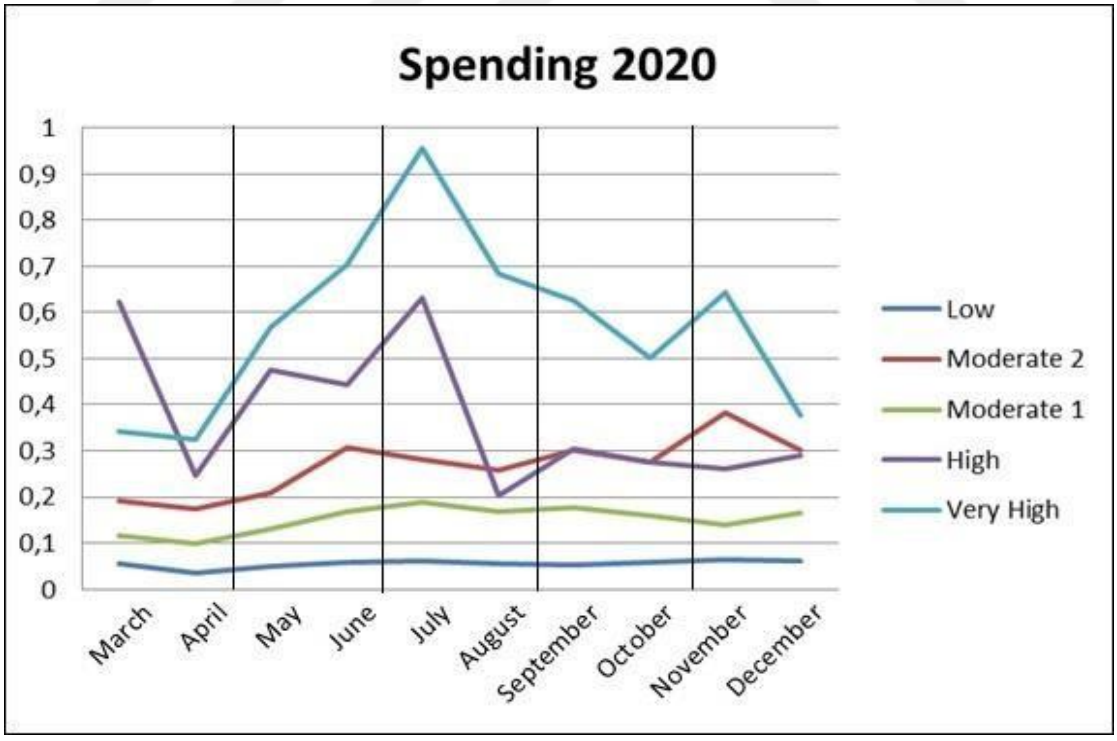


Figure 4.3: Cluster Trend Lines for Spending Behaviour Patterns in 2020

Although Low cluster experienced a decline in May like all other clusters, it followed a steady course for the rest of the year. Moderate 1 cluster generally kept their expenditures in line with the number of cases and remained constant to a certain average throughout the year. In the other hand, customers in Moderate 2 cluster tend to increase their spending averages continuously after the first month of the pandemic. Although High and Very High clusters move along similar lines in behaviour patterns, their spending averages are quite different from each other. While High cluster experienced sharp decreases in spending due to the increase in the number of cases, Very High cluster experienced steady increases and decreases. The spending of customers in Very High cluster creates a special peak, especially in the summer period when the restrictions are relaxed and the tourist season is opened.

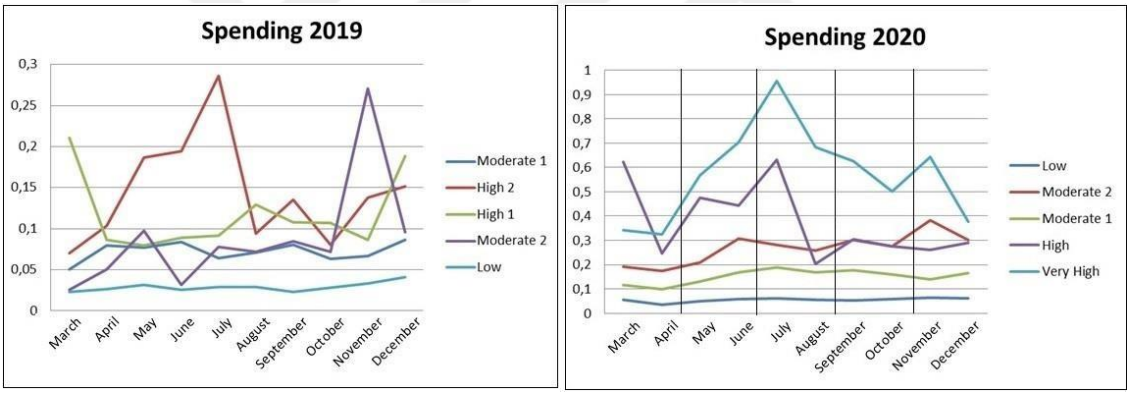


Figure 4.4: Comparison Between 2019 and 2020 in terms of Spending Behaviour

SPENDING	2020						
2019	Low	Moderate 2	Moderate 1	High	Very High	Total	Percentage
Moderate 1	19	2	18			39	19,5%
High 2	2	6	2	1	1	12	6,0%
High 1	3	7	3	2	2	17	8,5%
Moderate 2	1	1	6	1		9	4,5%
Low	83	6	30			119	59,5%
Very High		1	1		2	4	2,0%
Total	108	23	60	4	5	200	100,0%
Percentage	54,0%	11,5%	30,0%	2,0%	2,5%	100,0%	

Figure 4.5: Numerical Comparison Matrix of Spending Behaviour

In Figure 4.4, Figures 4.1 and 4.2 are given side by side for easy comparison. Low cluster of 2020 is similar to Low cluster of 2019 as in terms of behaviour patterns with a slight difference. While the customers in the low cluster of 2019 increased their spending towards the end of the year, like almost all other 2019 clusters, compared to the previous month, those in the low cluster of 2020 did not show any change at the end of the year, but in March, as in all other 2020 clusters, they reduced their spending due to the pandemic effect. Even though there was an increase in all clusters in the last month of the year compared to the previous month in 2019, as a result of the restrictions that came to the second wave in 2020, clusters decided to reduce or stabilize their expenditures. Looking at the y-axis, it can be seen how much the general spending behaviour has changed from 2019 to 2020. Average spending levels have increased for all spending groups, with the increase being less in the lower groups and much bolder in the higher groups. Even though it is possible to explain this general increase with the deterioration in the economy; in order to interpret the dome-shaped increases of clusters which are seen more clearly in High and Very High clusters, more specific comments are needed like the price increase in the tourism sector, spending more money on isolation during the holiday period, etc. However; to arrive at these interpretations, it is necessary to dig deeper into spending habits, therefore interpretations about the causes of these behaviours made in this study are only inferential. However, to put forward an interpretation as a hypothesis, it can be said that the increase experienced after April was aimed at adapting to the pandemic (in order to provide home-office needs or hobby materials that can be made at home) or the need for shopping encouraged by the low morale level experienced in the pandemic; the increase in summer months was due to the holiday period. It is also possible to observe that during the first wave, the groups became similar in terms of movement; yet in the second wave, after August, the common movements are decreased. This observation is a parallel inference to customer behaviours during the first and second waves described in the section 2.

Figure 4.5 represents the transition of customers between clusters. Looking at this comparison image, it is possible to deduce that the pandemic has affected the spending habits of the groups negatively. All clusters switched to the lower clusters at an average rate of 67%, while Low cluster remained the same at a rate of approximately 70%.

While this transition is 63% on average in the Moderate clusters, it is 70% on average in High and Very High clusters.

4.2 Digital Behaviour

Clusters of 2019 for digital behaviour are named Low, High 1, High 2, Very High 1, and Very High 2 as they are presented in Figure 4.6. Although digital clusters did not show sudden changes in 2019, clusters except for Very High 1 cluster increased towards the end of the year. Especially in Low and High clusters, these increases are more pronounced. In addition, there is no moderate class in digital usage in 2019, as it is evident in the Figure 4.6. The gap between Low and High clusters is quite large.

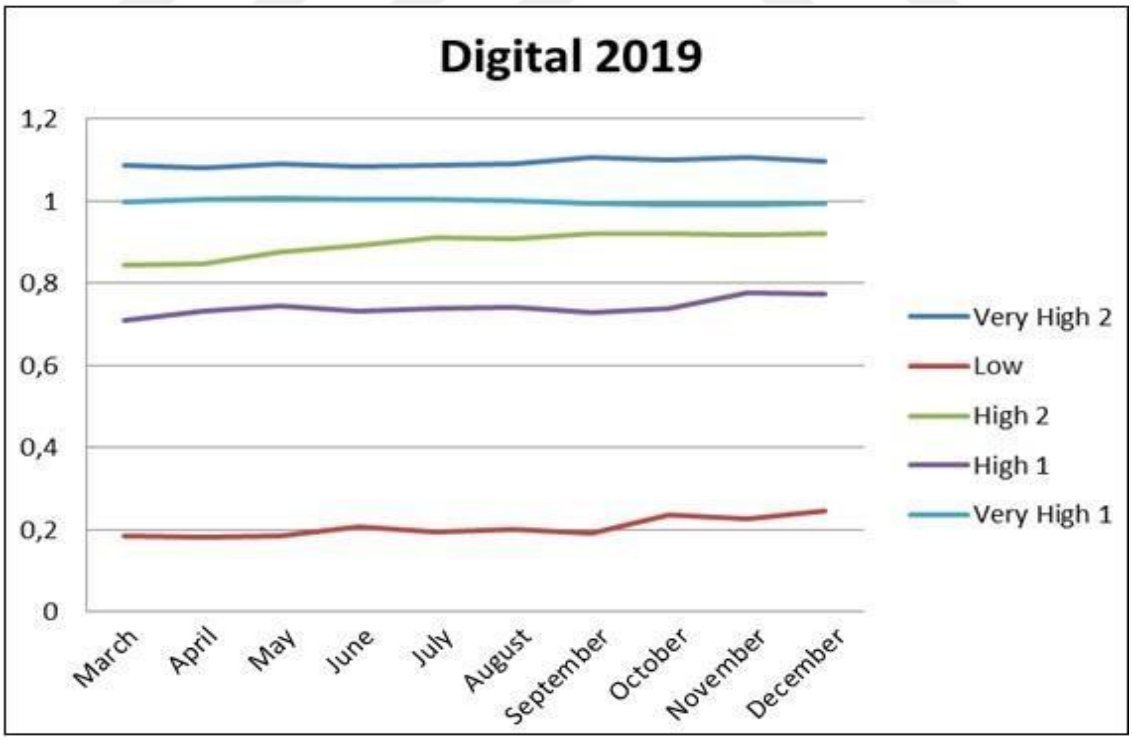


Figure 4.6: Cluster Trend Lines for Digital Behaviour Patterns in 2019

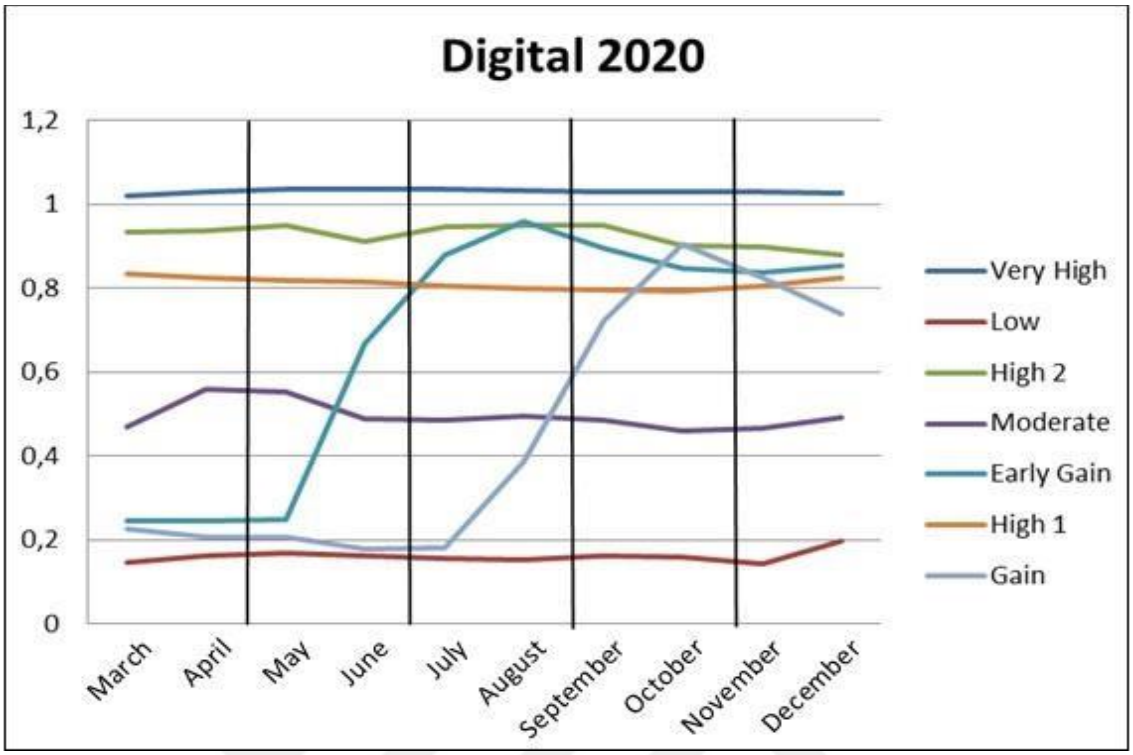


Figure 4.7: Cluster Trend Lines for Digital Behaviour Patterns in 2020

Clusters of 2020 for digital behaviour are named as Low, Early Gain, Gain, Moderate, High 1, High 2, and Very High as they are presented in Figure 4.7. In order to follow the progress of the pandemic on the graph better, the graph is divided into two-month segments with vertical lines. Low cluster has shown a stable progress except for the last months. Early Gain and Gain clusters have progressed from low usage to high usage, with almost the same trajectory. While Early Gain cluster started its uptrend in May, uptrend of Gain cluster started in July and due to this delay, Early Gain cluster reached its peak in August, while the Gain cluster reached its peak in October. After the peaks, both clusters entered the stabilization phase at high usage. Although Moderate cluster showed higher usage than its average in April and May, it showed a stable trend in the rest of the year. The usage in High 1 and High 2 clusters decreased slightly towards the end of the year while Very High cluster remained the same usage level during the year.

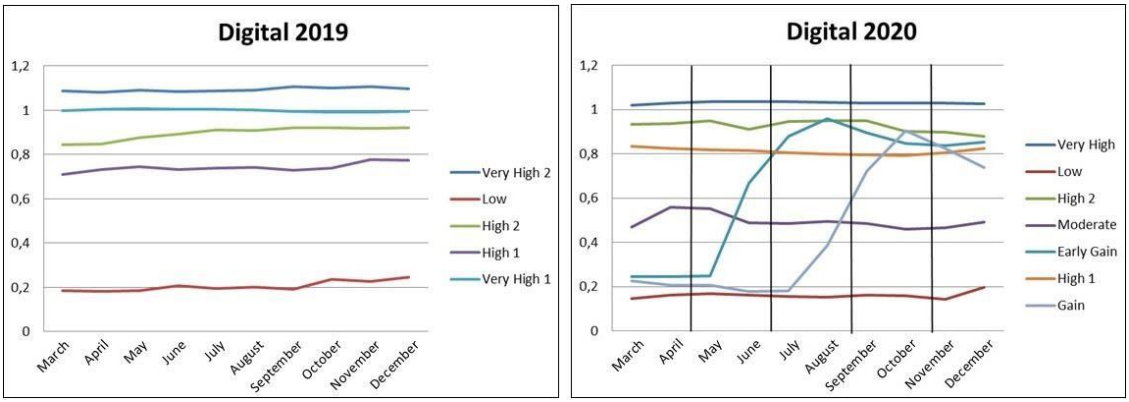


Figure 4.8: Comparison Between 2019 and 2020 in terms of Digital Behaviour

DIGITAL	2020								
2019	Very High	Low	High 2	Moderate	Early Gain	High 1	Gain	Total	Percentage
Very High 2	19							19	9,5%
Low	1	15	2	10	7	2	4	41	20,5%
High 2	9		15	1		11		36	18,0%
High 1	4		6	3		33		46	23,0%
Very High 1	53		2			3		58	29,0%
Total	86	15	25	14	7	49	4	200	100,0%
Percentage	43,0%	7,5%	12,5%	7,0%	3,5%	24,5%	2,0%	100,0%	

Figure 4.9: Numerical Comparison Matrix of Digital Behaviour

In Figure 4.8, Figures 4.6 and 4.7 are given side by side for easy comparison. There is a cluster type in 2020 that is not present in 2019; Moderate cluster. This cluster is a cluster that mostly emerged from the post-pandemic digitization of customers in the Low cluster. In this sense, the other two clusters that are not in 2019 are Early Gain and Gain clusters. Although the Moderate, Gain and Early Gain clusters have a common history of emerging from the Low group, they are different in behaviour patterns. Moderate cluster was separated from Low cluster at the beginning of the pandemic, and with the panic of the pandemic, customers in Moderate cluster displayed a significantly higher usage than their usual during the first three months. However, after the restrictions were relaxed, they got used to this situation and became moderately digitalized, although they did not show as much digital use as in the first three months.

Although Early Gain cluster made a hesitant entry into digitalization by showing a usage just above Low cluster during the first wave, it showed an increasing trend at the end of the pandemic and stabilized itself among the higher clusters by the end of the year. Gain cluster, on the other hand, did not favor digitalization until almost the second wave, and even fell back to its former low level in July. However, after July, it has made an increase similar to Early Gain cluster and it is predicted that this cluster will stabilize itself not in a level as much as Early Gain cluster did but around Moderate cluster. However, due to the long-term hesitation at the first stage, this cluster should be followed closely in the future. If there are any other clusters that need to be followed closely in the future, they are High clusters. High clusters experienced small but unexpected declines towards the end of the year. Many reasons can be listed for these decreases, from the decrease in the number of bank transactions to the decrease in the pandemic panic. However, in a way similar to interpreting the spending behaviour; to arrive at these interpretations, it is necessary to dig deeper into digitalization habits, therefore interpretations about the causes of these behaviours made in this study are only inferential.

Figure 4.9 represents the transition of customers between clusters. Looking at this comparison image, it is possible to deduce that the pandemic has affected the digital habits of the groups positively. About 63% of Low cluster moved to the higher digital usage clusters. Although the rate of moving to higher clusters drops to 23% in high clusters, the rate of staying in the same cluster or moving to higher clusters is 75% on average. Very High clusters remained the same at a rate of approximately 96%.

5. CONCLUSION

Covid-19 pandemic caused drastic changes in customer behaviours and made an effect that cannot be ignored on the adoption of digitalization. Customers developed new behavioural patterns to keep up with changing conditions. These new behavioural patterns gained are likely to be permanent as the Covid-19 pandemic has affected our lives for much longer than expected. However; most of the researches are studied the static behaviours of the customers in outbreak period of pandemic. Although the static behaviour analysis for outbreak period is essential for agility, dynamic behaviour analysis of customers that contains more than the March-May period of Covid-19 is also essential to devise accurate strategies for businesses and especially banks that have dealt with a great economic challenge.

In this paper, dynamic behavioural patterns of customers during Covid-19 pandemics was studied to discover new behavioural patterns gained by the environmental and psychological change and also; to understand if new behaviours are permanent or temporal. In the studies on customer behaviour during the Covid-19 pandemic in the literature, the most frequently mentioned areas of customer behaviour change are spending and digital channel usage; therefore two variables, spending and digital score, were produced to be used in this study. Customer patterns were extracted from March-December periods of 2019 and 2020 by Time Series Clustering method in Python environment. Euclidean, DTW and Soft-DTW similarity measures were applied to detect the meaningful communities in customer groups and Silhouette index analysis was used to determine accurate number of clusters and proper similarity measure to use. Afterwards, the 2019 and 2020 periods were compared for the spending and digital score variables created.

As a result, the study shows that the pandemic has irreversibly affected customer behaviours. In the study, customers who could be divided into clusters with their own unique behaviour pattern in 2019, tended to display much more similar behaviours that progressed with the course of the pandemic during the pandemic period. Looking at the transitions between spending behaviour clusters, it is possible to say that the pandemic has negatively affected spending habits. All clusters switched to the lower clusters at an average rate of 67%, while Low cluster remained the same at a rate of approximately 70%. While this transition is 63% on average in the Moderate clusters, it is 70% on average in High and Very High clusters. The impact of the pandemic for digital behaviour is more striking. Although small unexpected declines are currently observed among high-use clusters, it is clear that the low-use group has been brought into digital life in various ways. About 63% of Low cluster moved to the higher digital usage clusters. In order to understand whether these behavioural changes are permanent, it may not be enough to look at only this part of the pandemic period; yet, it seems that especially the behaviours of the customers who are newly acquainted with digital are permanent.

5.1 Thesis Contribution

Main contribution of this study to the literature is to reveal the dynamic behaviour patterns of retail banking customers in the Covid-19 period. Other economic or psychological studies on customer behaviour changes in the literature have focused on the static behaviours and outbreak period of the pandemic period, March-May 2020, in order to fill the information gap about Covid-19 and due to the lack of sufficient time. However, for the adaption of the businesses and especially banks that have dealt with a great economic challenge, dynamic behaviour analysis of customers that contains more than the March-May period is a need in the literature for Covid-19 pandemic. This study is designed to be easily implemented with banking data.

5.2 Limitations and Future Work

In this study, accessible data only covers the period until the end of the year 2020 and the data of only 200 customers is used. However; humanity still tries to overcome coronavirus. As time goes on, this study needs to be repeated with more customers and different methods to be bettered and to understand the behavioural patterns during Covid-19 better. In addition, the time covered should be increased for mentioned studies until and after the pandemic is over, to cover the vaccination process and other steps of the Covid-19 that are not encountered yet.

This study did not address demographic differences between groups as it wanted to cluster customers purely by behavioural pattern. In future studies, it is necessary to increase the explanatory power by going down to these details and to make special analyzes for these customer groups.

This analysis is designed to present and discuss the general dynamic situation in the simplest and clearest way. Understanding human behaviour is a very difficult process and requires detail and attention. The study should be tried and optimized with different methods. In future studies, the process should be optimized and not only the current situation but also the possibilities should be considered.

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