The Power of Innovation in Marketing

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Content

CHAPTER I

Data-Driven Marketing: Analyzing Retail Sales Data with ARIMA Model

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Introduction

Marketing plays a critical role in achieving growth and sustainable success for businesses today. Modern marketing strategies extend beyond creative advertising campaigns and customer relationship management, incorporating innovative methods such as data analytics, predictive modeling, and artificial intelligence technologies. Particularly in the retail sector, the in-depth analysis of sales data offers significant opportunities for accurately forecasting customer demands, optimizing inventory management, and personalizing marketing strategies (Chong et al., 2017). Retail sales data provide businesses with valuable insights for measuring the effectiveness of marketing strategies, understanding consumer behavior, and evaluating market dynamics. These data can include annual, monthly, or even daily sales volumes, product types, supplier relationships, campaign impacts, and various other critical

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information. However, for raw data to be transformed into meaningful analyses, it must undergo effective data cleaning, processing, and modeling procedures. Data analytics facilitates this process and serves as a crucial tool for enhancing data accuracy and predicting future sales trends (Kotler & Keller, 2016).

The analysis of retail sales data typically consists of two stages: first, exploratory data analysis (EDA) is used to uncover the structure, trends, and relationships within the data. Following this, predictive modeling techniques are employed to use these insights for forecasting future sales. Exploratory data analysis helps understand the overall structure of the data by identifying missing values, outliers, and fundamental distribution characteristics (Tufano, 2017). For instance, missing data analysis is essential for determining how to handle gaps in the dataset, often requiring decisions such as filling in missing values with mean, median, or similar methods. Additionally, addressing outliers is a critical part of data preparation, as these anomalies can affect the reliability and validity of the dataset. Deciding how to manage such irregularities ensures the dataset is ready for accurate and meaningful analysis.

The second stage involves predictive modeling, which primarily incorporates time series analysis to forecast future trends. Time series analysis examines temporal variations in retail sales data, helping identify factors such as seasonal trends, patterns, and cycles. The results of these analyses can be utilized to optimize the timing of marketing strategies and improve inventory planning. For instance, seasonal changes like increased sales during holiday periods or summer months provide businesses with insights into when to launch marketing campaigns most effectively (Hyndman & Athanasopoulos, 2018). Accurately predicting seasonal variations in retail sales aids not only in refining sales strategies but also in optimizing the product supply chain. Consequently, the accuracy of sales forecasts plays a critical role in managing inventory levels, organizing supplier relationships, and determining promotional strategies (Berman & Thelen, 2004).

One widely used predictive modeling technique for analyzing time series data is the ARIMA (AutoRegressive Integrated Moving Average) model. ARIMA is highly effective in forecasting future values based on historical data and is frequently employed in retail sales predictions. Shaping marketing strategies based on data-driven insights enables businesses not only to understand their current situation but also to take proactive steps toward the future. In this context, data-driven marketing offers significant opportunities to better understand consumer behavior, reach the right target audience, and optimize marketing activities.

However, the accurate processing and interpretation of data are crucial; otherwise, the analyses conducted may be misleading, resulting in incorrect business decisions. Thus, the analysis of data, such as retail sales, serves as a critical step in making informed decisions when developing marketing strategies (Chong et al., 2017).

This study aims to develop an approach to enhance the effectiveness of marketing strategies by analyzing retail sales data and utilizing the ARIMA model. Through exploratory data analysis, the structure and trends of the dataset will be uncovered, while predictive modeling will be employed to forecast future sales. The findings will provide businesses with strategic insights to improve the effectiveness of their marketing activities, enabling significant enhancements in areas such as marketing, inventory management, and supplier relationships. As the results are based on the specific dataset used in this study, they may not be generalizable to all sectors and businesses. However, the methodology employed can serve as a roadmap for businesses to evaluate their own data effectively.

1. Literature Review

Data-driven approaches are becoming increasingly critical for modern businesses in the development of marketing strategies. The acceleration of digitalization, advancements in big data technologies, and the integration of next-generation tools such as artificial intelligence into marketing processes have enabled marketing strategies to become more personalized, targeted, and efficient (Chong et al., 2017). The retail sector, where customer behaviors change rapidly and competition is intense, exemplifies the significant impact of data-driven marketing practices. This literature review examines the evolution of data-driven marketing strategies, the analysis of retail sales data, and the effects of predictive modeling techniques on marketing strategies.

1.1. Data-Driven Marketing Strategies and Methods

Data-driven marketing refers to the use of data analytics and modeling techniques to understand consumer behavior and develop corresponding strategies. In recent years, particularly with the rise of digital marketing, businesses have increasingly adopted data-driven methods in their decision-making processes. Data collected from digital marketing and e-commerce platforms provides businesses with opportunities to enhance the effectiveness of their marketing activities. The foundation of data-driven marketing strategies lies in collecting accurate data, analyzing it appropriately, and developing strategies based on the analysis results (Keller & Kotler, 2016). With the transition to data-driven marketing strategies, it has become possible to deliver more specific and personalized campaigns to target audiences. In this context, data analysis is utilized not only for customer segmentation but also for accurately predicting consumer needs. This approach enables businesses to allocate their marketing budgets more effectively and distribute resources efficiently. Additionally, by accurately measuring the outcomes of marketing activities, feedback can be obtained to update and improve strategies (Chaffey, 2020). Data-driven marketing also plays a crucial role in campaign management. With the help of data analytics, marketing campaigns can reach more accurate target audiences and be designed more effectively. Monitoring interactions during campaigns aids in optimizing campaign strategies and contributes to increasing ROI (Return on Investment) in marketing processes (Zeng, 2020).

1.2. Analysis and Importance of Retail Sales Data

Retail sales data serve as a vital tool in shaping marketing strategies. Analyzing retail sales data not only provides insights into past sales but also establishes a foundation for businesses to forecast future demand. In the retail sector, accurate analysis of sales data plays a critical role in optimizing customer demand predictions, product inventory levels, and sales strategies (Berman & Thelen, 2004). The analysis of retail sales data begins with Exploratory Data Analysis (EDA), which examines the structural characteristics of the dataset and verifies its accuracy. This step involves processes such as analyzing missing data, detecting outliers, and checking data types. Missing data and outliers are commonly encountered challenges in the analysis of retail data. Decisions regarding how to handle missing values and whether to include outliers in the analysis can directly affect the accuracy of the results (Little & Rubin, 2002). Outliers, which often reflect specific situations in retail sales (such as returns or inventory losses), must either be corrected or excluded from the analysis, depending on their relevance. Proper processing of retail sales data offers significant opportunities for businesses to measure the effectiveness of their marketing strategies and predict future sales trends. Identifying factors such as seasonal variations, holiday periods, and the impact of promotional campaigns allows businesses to implement marketing strategies with precise timing. Furthermore, product-level analyses help determine which products are in high demand and which underperform. These insights can be leveraged to develop more effective product strategies, allocate marketing budgets more accurately, and optimize overall business performance (Kotler & Keller, 2016).

1.3. Predictive Modeling and Time Series Analysis

Predictive modeling holds a significant role in the development of marketing strategies. Time series analysis is a widely used method for forecasting future sales based on historical data. This type of analysis enables businesses to predict future sales for a specific product or category, shaping marketing and inventory management strategies accordingly. Time series analysis is a powerful tool for identifying seasonal effects, trends, and cycles (Hyndman & Athanasopoulos, 2018). The ARIMA (AutoRegressive Integrated Moving Average) model is a frequently employed method for analyzing time series data. It enables the prediction of future sales based on historical trends and has been shown to be particularly effective in handling time-based data, such as retail sales. One of the key advantages of the ARIMA model is its ability to forecast future trends, allowing businesses to accurately schedule marketing activities (Box, Jenkins, & Reinsel, 2015). Analyzing retail sales data not only evaluates the current situation but also predicts future trends. Predictive modeling provides valuable insights for optimizing inventory management, utilizing marketing budgets more efficiently, and scheduling campaigns during the most effective time periods (Berman & Thelen, 2004). Additionally, methods such as regression analysis can be used to examine the relationship between marketing expenditures and sales, providing a clearer understanding of the impact of marketing investments on sales performance.

1.4. The Future of Data-Driven Marketing Strategies

The future of data-driven marketing strategies will be shaped significantly by the integration of advanced technologies such as artificial intelligence (AI) and machine learning (ML). These technologies enhance the speed and accuracy of data analytics, enabling businesses to make more strategic marketing decisions. Machine learning algorithms can analyze consumer behavior to predict future demand, allowing businesses to develop personalized marketing strategies accordingly. Additionally, AI-powered data analytics facilitates the optimization of marketing strategies and ensures that businesses can effectively reach the right target audiences (Chong et al., 2017).

Machine learning stands out as one of the most powerful tools in data-driven marketing, particularly in the areas of big data clustering, segmentation, and targeting. These technologies enable more accurate identification of customer segments, leading to more effective targeting of marketing activities. This, in turn, allows businesses to utilize their marketing budgets more efficiently and focus their efforts on the most relevant segments, ultimately improving the effectiveness and precision of their marketing strategies.

2. Methodology

2.1. Analyzing the Structure of the Data Set

The dataset utilized in this study includes retail sales data, supplier information, product details, and sales figures. The dataset titled "Retail Sales Data with Seasonal Trends & Marketing [Data set]", shared by Abdullah (2024) on the Kaggle platform, was selected for this research. The variables in this dataset are deemed suitable for the research objectives and possess the necessary characteristics for ARIMA modeling. In research, the initial structural examination of a dataset is crucial for transforming the data into a meaningful and analyzable form. Identifying variables and understanding data types provide essential insights into the dataset's overall characteristics (Kang & Yoo, 2018). At this stage, details such as the number of observations and variables, variable names, data types, and the presence of missing values will be outlined. Information regarding the dimensions of the data, the status of missing values, and the general structure of the variables will provide the first clues for exploratory data analysis (Little & Rubin, 2002). Following the organization and normalization of the dataset, the ARIMA model will be implemented.

2.2. First Observation of the Data Set and Missing Data Analysis

In the initial step, the dataset was loaded and reviewed to assess the overall structure and identify whether any columns contained missing data. Missing data analysis methods were employed during this process to ensure data integrity and to appropriately address potential missing values, a common practice in such analyses (Allison, 2001). The dataset comprises a total of 30,001 observations and 9 columns. It was noted that the dataset includes a header row for variable names, which facilitated understanding the purpose of certain columns. Taking this into account, the first row was treated as the header, and the dataset was reorganized accordingly.

Regarding missing values, 33 missing entries were identified in the **Unnamed: 2** column, and 1 missing entry in the **Unnamed: 6** column. Addressing these missing values is crucial, as they could lead to data loss or inaccurate interpretations during analysis. The approach to handling missing values depends on the nature of the study and the extent of missing data (Little & Rubin, 2002). Ensuring the proper treatment of these gaps is essential for maintaining the accuracy and reliability of the analysis.

The first row of the dataset was organized as the header, making the columns more comprehensible and ensuring accurate interpretation during the analysis process. After renaming and organizing the header, the structure and content of the dataset became clearer. The updated column names and their descriptions are as follows:

YEAR: Year information

MONTH: Month information

SUPPLIER: Supplier name

ITEM CODE: Product code

ITEM DESCRIPTION: Product description

ITEM TYPE: Product type (e.g., WINE or BEER)

RETAIL SALES: Retail sales quantity

RETAIL TRANSFERS: Retail transfer quantity

WAREHOUSE SALES: Warehouse sales quantity

This reorganization clarified the variables and provided a better understanding of the dataset's overall structure. Following this step, missing data analysis continued to evaluate the nature of the missing values, transitioning into the data cleaning process. This stage ensured the dataset was ready for subsequent analytical procedures.

The missing values in the dataset were addressed as follows:

- **SUPPLIER Column**: There are 33 missing values. The absence of supplier information may hinder the evaluation of the source of specific products in the analysis. These missing values were either excluded from analysis or filled with an average value, as suggested by standard practices (Little & Rubin, 2002).
- **RETAIL SALES Column**: One missing value was identified. Since missing sales quantities could lead to deviations in forecasts, this value was filled with the column's mean value, ensuring consistency in the dataset.

At this stage, two options can be considered for handling missing data. The first option involves highlighting missing data, which could reduce the influence of certain products in the analysis. The second option is to fill a single missing sales value with the mean or median sales value. However, it is also possible to proceed with the analysis without removing the missing data. In this study, filling missing data with the mean value was preferred.

After the missing data imputation process, the distribution and summary statistics of the variables were analyzed to further detail the dataset's structure. In this context, the missing value in the **RETAIL SALES** column was filled with the column's mean value, resolving the issue in this column. However, the **SUPPLIER** column still contains 33 missing values, which will be considered in qualitative analyses related to supplier information.

In the next step, the summary statistics of the variables were extracted, and the distribution and fundamental structure of the data were analyzed.

2.3. Summary Statistics for the Data Set

In light of the summary statistics obtained, the general structure of the dataset and the distribution of variables can be described as follows:

- **YEAR and MONTH**: These variables contain information about the year and month, respectively. The data only covers observations from the year 2020 and includes four distinct months.
- **SUPPLIER**: There are 290 unique suppliers across 29,000 observations. The most common supplier is **THE COUNTRY VINTNER, LLC DBA WINEBOW**.
- **ITEM CODE and ITEM DESCRIPTION**: The dataset contains 15,668 unique product codes and 15,732 unique product descriptions. The most frequently occurring product is **LINGANORE BLACK RAVEN - 750ML**.
- **ITEM TYPE**: Eight distinct product types are present, with **WINE** being the most frequently encountered type.
- **RETAIL SALES**:
    - The average retail sales value is 6.94, with a standard deviation of 33.08.
    - Sales values range from -0.42 to 2739.0. The negative minimum value may indicate special cases such as stock returns or losses (Little & Rubin, 2002).
- **RETAIL TRANSFERS**:
    - The average transfer value is 6.59, with a standard deviation of 27.88.
    - The range is from -6 to 1507; negative values could represent returns or reductions during transitions from warehouses to retail outlets.
- **WAREHOUSE SALES**:
    - The average value is 27.43, with a standard deviation of 272.17.
    - Values range from -3999 to 18,317, reflecting the impact of warehouse inflows and outflows.

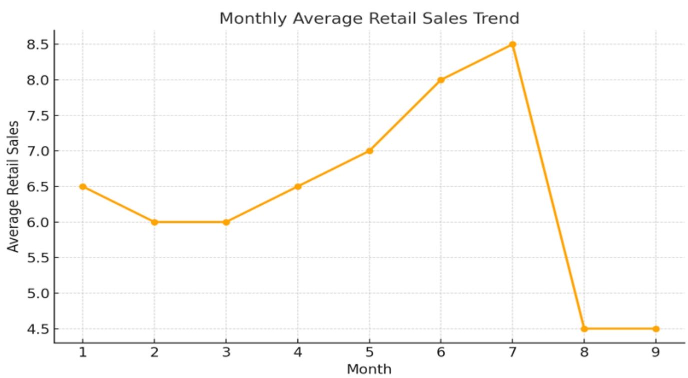
These distributions indicate the presence of outliers and negative values in retail sales and transfers, highlighting the need for deeper analysis and potential outlier detection. In the next step, data visualizations were used to conduct detailed analyses of these distributions.

2.4. Data Visualization and Distribution Analysis

The visualization steps applied to better understand the basic structure of the data, including the distribution of variables, seasonal trends, and the impacts of marketing activities, are as follows:

- **Monthly Sales Trends**: Examining changes in sales figures on a monthly basis to identify any increases or decreases in retail sales during specific periods.
- **Sales Distribution by Product Type**: Comparing sales of different product types.
- **Retail and Warehouse Sales Distributions**: Evaluating the overall distribution of sales figures, including outliers and negative values, through visualization.

Firstly, the time series graph created to analyze monthly retail sales trends is shown in Graph 1.



Graph 1. Monthly trends

Graph 1 shows the monthly average retail sales trends. By analyzing the changes in sales by month, it is possible to observe whether there is an increase or decrease during a specific period. Examining this trend is important to better understand the impact of factors such as seasonal effects, marketing activities, or changes in product demand.

In the next step, sales distributions by product types were analyzed, and the differences in sales across various categories were visualized.

The basic processes required during the data preparation phase have been generally completed; however, additional checks may be beneficial to ensure every detail is addressed. The actions performed so far and the additional steps necessary for complete data preparation can be summarized as follows:

Actions Taken So Far:

1. Dataset Review and Organization: The initial dataset structure was reviewed, the header row was adjusted, and the column names were properly updated.

2. Missing Data Analysis and Imputation: Missing data were identified, and appropriate values were imputed using the mean.

3. Data Type Conversions: Numerical columns were made suitable for analysis.

4. Summary Statistics: The distribution, central tendencies, and outliers of each variable were examined.

Additional Steps for Complete Data Preparation:

1. Outlier Analysis and Handling:

o Analyzing the impact of extreme high or negative values, particularly in the RETAIL SALES, RETAIL TRANSFERS, and WAREHOUSE SALES columns, to assess and handle outliers.

2. Converting and Encoding Categorical Variables:

o Transforming categorical columns like ITEM TYPE or SUPPLIER into usable formats (e.g., label encoding or dummy variable conversion) for analysis, especially beneficial for machine learning models or regression analysis.

3. Reorganizing Time Variables (Optional):

o Combining the separate YEAR and MONTH columns into a single time variable (e.g., datetime), which could be useful for time-series analysis.

Outlier Analysis Results:

The following outliers were identified during the analysis:

- RETAIL SALES: 299 outliers
- RETAIL TRANSFERS: 359 outliers
- WAREHOUSE SALES: 166 outliers

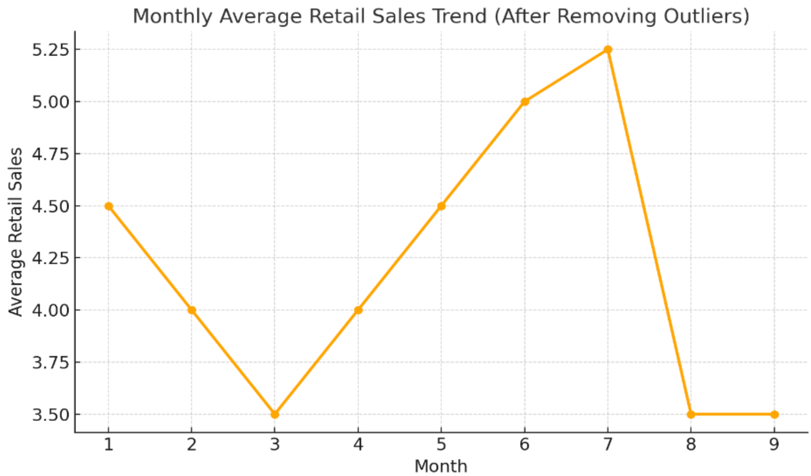
These outliers may result from data entry errors, special cases (returns, inventory losses, etc.), or rare observations. The decision on how to handle them depends on the study's objectives. Common approaches include:

1. Retaining Outliers: Outliers can hold meaningful insights and may be directly included in the analysis, especially in retail sales and warehouse operations.

2. Removing Outliers: To reduce sensitivity to extreme values in statistical analysis, outliers can be excluded.

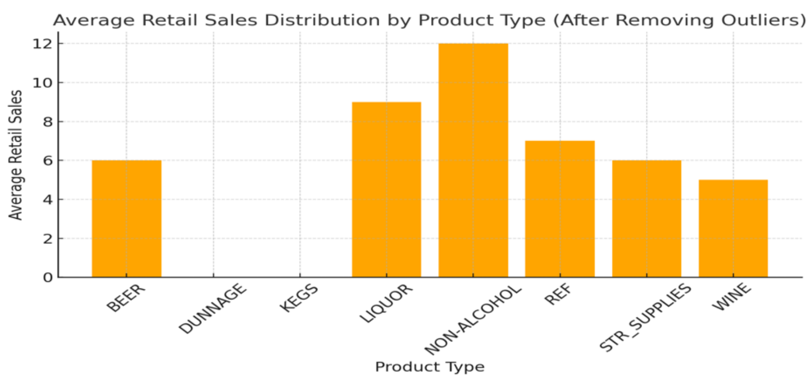
3. Transforming Outliers: Using methods like Z-score or winsorization to minimize their impact.

In this study, the method of removing outliers was chosen. After outliers were removed, the dataset decreased from 30,000 observations to 29,532, excluding 468 observations. This process refined the dataset by removing the influence of extreme values, making it more balanced. In the next step, exploratory data analysis and visualizations were continued using this refined dataset.



Graph 2. Monthly Sales Trend

This graph shows the monthly average retail sales trends after the removal of outliers. In this way, a more balanced trend, free from the influence of extreme values, has been achieved. This trend is more suitable for examining whether certain months have higher or lower average sales compared to others. In the next step, the analysis continued by visualizing the sales distribution by product type.



Graph 3. Sales distribution by product type

This graph shows the average retail sales distribution by product type after the removal of outliers. Differences in the sales performance of product types reveal which product categories have higher sales. This analysis is a significant indicator for determining which products marketing strategies could focus on or for examining changes in demand. Subsequently, the overall distribution of retail and warehouse sales was analyzed to examine distributions free from the influence of outliers. This process provides a more detailed structural analysis of the dataset.

Graph 4. Retail Sales Distribution ARO

Graph 5. Warehouse sales distribution ARO

These histograms illustrate the distributions of retail and warehouse sales after the removal of outliers:

- **Retail Sales Distribution**: There is a concentration around the average retail sales value; lower sales frequencies are more common, though some observations show higher sales values.
- **Warehouse Sales Distribution**: The distribution of warehouse sales exhibits a wider variation, indicating the presence of substantial warehouse activity. While warehouse sales are concentrated within certain ranges, their frequencies extend to higher values.

These distributions indicate that retail and warehouse sales exhibit a more homogeneous structure after the removal of outliers. In the next step, more advanced analyses, such as examining the impact of marketing activities, were conducted.

2.5. Marketing Impact Analysis

To evaluate the impact of marketing campaigns on sales quantitatively, the relationship between marketing activities and sales can be examined through correlation analysis. This method is a fundamental tool to understand how marketing activities affect sales. Additionally, during periods when marketing activities are carried out regularly, time series models (e.g., ARIMA, SARIMA) can be applied to observe seasonal effects on sales and perform more comprehensive analyses. These models are particularly useful for making forecasts for specific periods and analyzing the potential impacts of marketing campaigns. Furthermore, for those seeking more detailed analyses, the effects of increases or decreases in marketing expenditures on sales can be modeled using multiple regression models. This optional method can be considered to gain a more detailed understanding of the impact of marketing activities on sales performance.

The analysis began by examining the correlation between marketing and sales. If there is a variable related to marketing, it will be compared with the sales data; if not, alternative approaches will be explored. The dataset was reviewed to check whether it directly contains information on marketing campaigns. If such a variable is present, the analysis will proceed with correlation analysis. If there is no direct information on marketing campaigns, the impacts of marketing will be evaluated indirectly by analyzing sales trends and time-based factors.

The dataset does not contain any direct variables related to marketing campaigns or promotions. In this case, alternative methods were considered to analyze the effects of marketing indirectly:

Time series analysis is an effective method for evaluating the periodic effects of marketing activities by examining seasonal or time-dependent changes in sales. Through this analysis, it is possible to investigate how sales change during specific periods and how these changes reflect marketing strategies. Additionally, by analyzing sales changes based on products or suppliers, the sales performance of specific product groups or suppliers can be compared across different periods. For example, detailed analyses can be conducted to observe and evaluate the impact of campaigns specific to a particular supplier or product type. These methods contribute to the strategic planning of marketing activities to make them more effective.

Initially, sales trends for the year 2020 were analyzed using time series analysis. In this analysis, the trend and seasonal components of retail sales were separated to understand whether there was any seasonal effect.

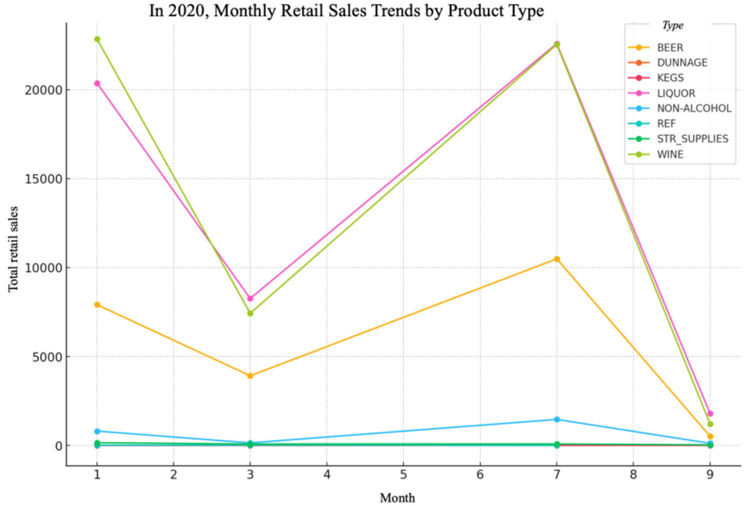
In time series analysis, it was observed that the dataset only includes data for the year 2020, which does not provide a sufficient cycle length. Since at least two years of data are required to separate seasonal components, it is not possible to perform seasonal analysis with the available data. In this case, to perform an analysis suitable for the available data:

Periodic comparisons allow us to analyze the sales trends between different months of 2020 to understand the changes in sales performance. This method can be used to evaluate the effectiveness of marketing strategies by examining the sales dynamics of specific periods. Additionally, seasonal analyses based on product groups or suppliers can be performed to observe the differences in performance for specific products or suppliers. These analyses are useful for observing indirect marketing impacts and evaluating performance differences based on specific products or suppliers. These approaches contribute to optimizing sales strategies and planning marketing activities more effectively.

Initially, the retail sales trends across the months of 2020 were analyzed;

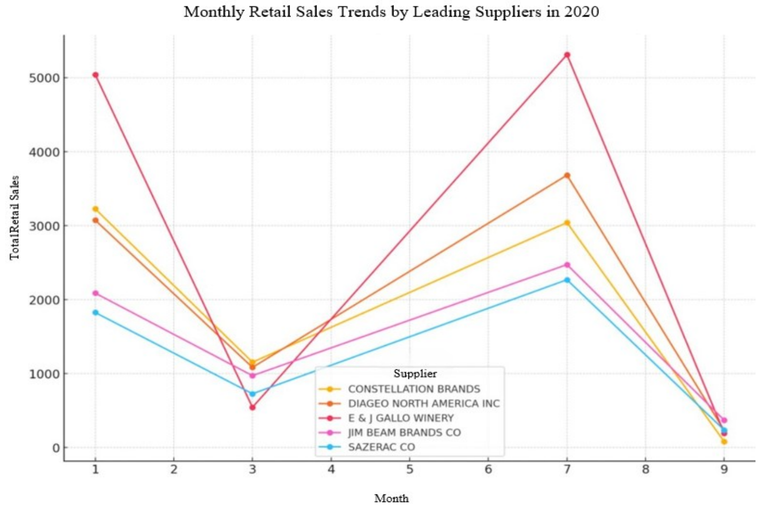
Graph 6. Total retail sales trends

This graph shows the monthly total retail sales trends throughout 2020. The variations between months reveal increases or decreases during specific periods. Such analyses can indirectly reflect the impacts of marketing activities or seasonal effects. Subsequently, the aim is to obtain a more detailed perspective by analyzing sales trends for different periods based on products or suppliers. For instance, monthly sales changes for a specific product type or supplier can be examined.



Graph 7. Sales trends by product type

This graph illustrates the monthly retail sales trends for different "product types" throughout 2020. The monthly sales changes for each product type indicate that certain products experience higher demand during specific periods, offering potential focal points for marketing strategies. This analysis can help understand how the sales performance of products changes seasonally. A similar analysis can be conducted based on suppliers to examine how sales for specific suppliers fluctuate and how these trends can be leveraged in marketing strategies.



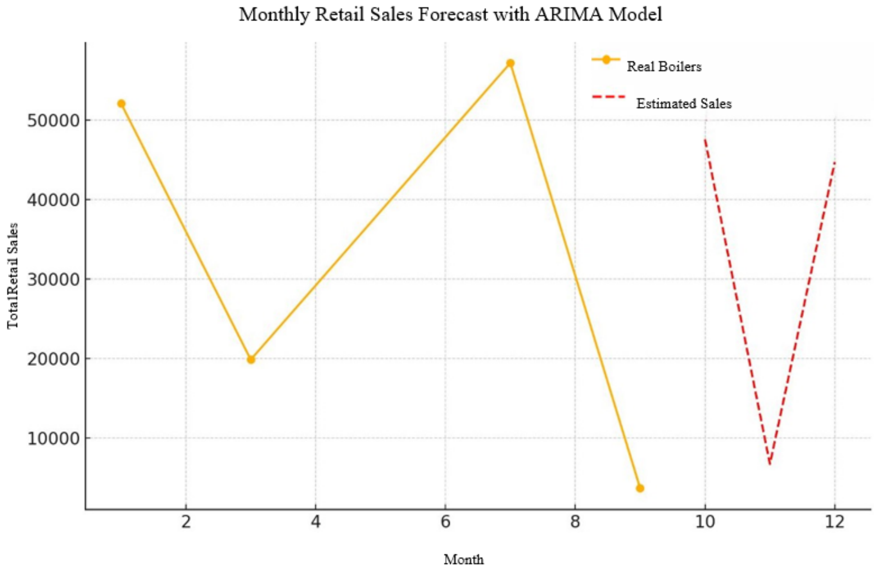
Graph 8. Monthly retail sales forecasts by suppliers

This graph displays the monthly retail sales trends for the top five suppliers with the highest sales volumes throughout 2020. The seasonal sales variations among suppliers reveal that some suppliers perform better during specific months. This information can be valuable for collaboration with suppliers in terms of marketing strategies or inventory management. In the subsequent phase, predictive modeling and more detailed analyses were conducted. In this section, the findings obtained from the dataset were used to forecast future sales performance or to derive insights for marketing strategies.

3. Predictive Modeling

Predictive modeling is a crucial method that supports businesses in making strategic decisions by analyzing sales trends and the factors influencing these trends. In the retail sector, accurate forecasts enable more effective planning of marketing, inventory management, and supply chain processes. In this context, the ARIMA (Autoregressive Integrated Moving Average) model, based on time series analysis, is frequently preferred for forecasting future sales by accounting for trends and seasonality in historical data. The accuracy and flexibility of the ARIMA model make it particularly prominent in commercial applications (Box & Jenkins, 1976; Hyndman & Athanasopoulos, 2018). In this study, the ARIMA model was chosen to evaluate its effectiveness in forecasting retail sales. Additionally, methods such as regression analysis are effective tools for examining the factors that influence sales in detail and identifying which variables have significant impacts. These analyses help businesses allocate resources more efficiently and develop targeted marketing strategies.

Initially, future sales performance was analyzed by applying the ARIMA model for time series forecasting.

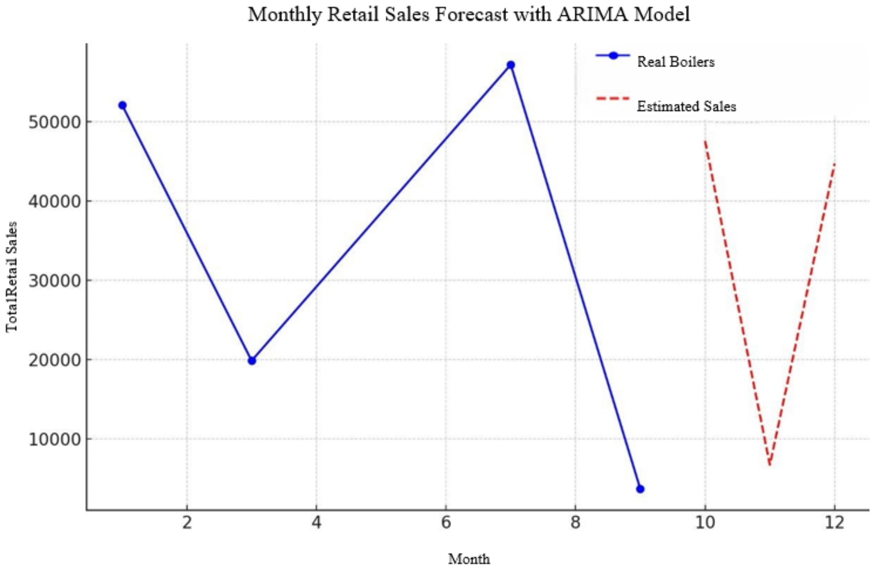


Graph 9. Monthly retail sales forecest

As a result of the forecast using the ARIMA model, the predicted retail sales values for the next three months are as follows:

- **Month 4**: 47,548.61
- **Month 5**: 6,719.14
- **Month 6**: 44,718.03

These forecasts indicate that sales exhibit seasonal fluctuations and that certain months may differ significantly from others. This information can be considered when making forward-looking decisions regarding marketing and inventory planning.



Graph 10. Forecast with ARIMA model

This graph illustrates the monthly retail sales forecasts based on the ARIMA model, presented alongside the existing sales data. The forecasted values for the next three months, represented by the red dashed line, indicate the expected sales amounts. This visualization is useful for evaluating how the predictive model aligns with the overall sales trend. In this way, it provides valuable insights for better planning future sales trends and determining marketing strategies.

Conclusion

This study was conducted to analyze retail sales data in detail, identify the factors influencing sales performance, and forecast future sales trends. In the initial phase, the structural characteristics of the dataset were examined, and missing values and outliers were addressed to prepare the data for analysis. These preparatory steps were a critical part of ensuring the accuracy and reliability of the data. Exploratory data analysis revealed seasonal trends in retail sales throughout 2020 and the impact of various product types and suppliers on sales. Monthly analyses highlighted periods of increases or decreases in sales, which may be linked to seasonal demand or indirect marketing effects. Sales trends varying by product type indicated which categories experienced high demand, offering insights for shaping marketing strategies. Supplier-based analysis showed that certain suppliers exhibited stronger sales performance during specific months.

During the predictive analysis phase, the ARIMA model provided a three-month forecast for retail sales. The results indicated notable fluctuations in sales during certain months, underscoring the need to consider these variations in marketing strategies. The forecasted sales values for upcoming periods provided crucial insights for proactive steps in inventory and marketing planning. In conclusion, this study contributed to better decision-making in marketing and inventory management by analyzing the structural characteristics and seasonal variations of retail sales data. The findings highlighted the importance of optimizing marketing strategies based on seasonal demand and approaching supplier collaborations more strategically. This research serves as a significant example of analyzing retail data and making forecasts through predictive modeling, providing a foundation for businesses to optimize their marketing and inventory management strategies.

The future of retail sales analysis is expanding to include the integration of larger and more diverse data sources. Future studies incorporating additional data sources such as marketing campaign information, customer behavior data, and competitive analysis will enable more comprehensive forecasting. Machine learning and AI-based models, in particular, can offer far more accurate sales predictions and be utilized to develop tailored marketing strategies for different customer segments. Furthermore, seasonal analyses conducted with longer-term, multi-year datasets will allow for identifying not only intra-year changes but also trends across years.

Such analyses will support the digital transformation of the retail sector, enabling more strategic, data-driven decisions and creating a competitive advantage.

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CHAPTER II

The Relationship of the Concept of Neuromarketing with the Psychological Purchasing Process

Nazmiye SONAR[1]

Introduction

Technological advances and increasing global competition make it inevitable to develop new approaches in marketing management. While competitors, products, services and customer structure change on the one hand, there are also radical changes in communication channels, market mix structure and market rules. During this entire process, the classical and static marketing approach of the past is giving way to a more dynamic marketing structure that follows changes and developments. The increasing competition in global markets and the increasing number of companies every passing day bring with it the fact that not only product or service quality but also marketing methods should be more innovative and different in the marketing of products and services.

While direct communication channels were used to reach customers in classical marketing methods, more cognitive methods are

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preferred to reach customers today (Jain and Yadav, 2017; Latif et al, 2014; Jefkinds, 2012). The main reason for this is that in order to adapt to the hedonic preferences of the changing customer structure, it is necessary to better understand the current dynamics of the customer. For this reason, the concept and methods of neuromarketing are one of the important issues emphasized in literature and practice.

In its most general definition, neuromarketing refers to marketing processes carried out within the framework of some neurological information and findings in the marketing process (Fisher et al, 2010; Lee et al, 2007). Although the conceptual and theoretical framework of neuromarketing contains many variables, the most basic and important element of neuromarketing is simply the use of neuroscientific and cognitive marketing communication channels instead of classical communication channels (Lim, 2018; Fortunato et al, 2014). In this respect, neuromarketing can actually be described as a marketing method that combines the processes necessary for the formation of purchasing behavior with neurological processes, which are carried out through metacognitive channels for individuals.

Although the concept of neuromarketing is relatively new compared to other marketing concepts, it has been the subject of many studies in the literature. However, there are not enough studies on the psychological purchasing process, not the purchasing process itself. Therefore, in this section, the effects of neuromarketing on the psychological purchasing process are emphasized.

Neuromarketing

Neuromarketing is a marketing technique in which marketing strategies are created to determine what affects the conscious or subconscious mind of the consumer. Neuromarketing is a marketing technique that aims to find the way to the buy button in the brain. With the help of neuromarketing, it tries to understand how the consumer makes the purchase decision in real life, not how he/she makes the purchase decision (Morin, 2011). Neuromarketing methods are used to determine changing consumer preferences, analyze emotional effects and the purchase decision-making process (Yücel and Coşkun, 2018).

With the application of the neuromarketing approach to the marketing field, a new perspective on the brand pyramid model has become necessary. As a result, it has become clear that brand value should be evaluated by the producer. In the research conducted within the scope of this information; In addition to the concept of a one-sided consumer branding pyramid, brand value has been addressed from the producer's perspective and the elements that constitute the brand value have also been evaluated from the producer's perspective. In other words, a new model has been proposed that takes into account the brand value explained only one-way from the consumer's perspective and two-way from the producer's perspective (Yücel and Çubuk, 2014).

It is important to define the concepts of neurobiology and psychophysiology to understand neuromarketing. Neuroscience describes the branch of science that studies the anatomy, physiology, biochemistry or molecular biology of the nervous system and the relationship of nerves and nervous tissue to behavior and learning. Neuroscience and psychophysiology are also closely related, and psychophysiology studies the relationship between the human brain and body. Psychophysiology is the process of measuring physiological control and the physiological responses resulting from this control to better understand the relationship between mental and physical processes of consumers. Psychophysiology includes psychological processes, including emotional responses and cognitive processes. Psychophysiology is used to determine the reactions of marketing stimuli in the human brain and body (Ustaahmetoğlu, 2015).

As a result of the spread of marketing in every field, the possibility of application in the field of neuromarketing and the adaptation of this method to marketing, neuromarketing has entered the literature as one of the marketing methods. According to neuromarketing, consumers discover their unwanted abilities while making a decision, rational and irrational decisions. These irrational decisions are made based on emotional, impulsive stimuli perceived by our five senses (Yücel and Çubuk, 2013).

Neuromarketing has begun to be used to understand what motivates consumers, and pioneering neuroscientists have used FMRI to understand people's decision-making processes. This is done by examining which part of the brain tells them what to do. This is achieved by measuring the amount of blood flow in different areas of the brain associated with emotions such as desire, indecision and hesitation. The techniques used in neuromarketing help us understand how the brain responds, especially unconsciously, to advertisements, brands and products (Tüzel, 2010).

Neuromarketing attempts to understand the consumer using two types of methods: biometrics and neuroimaging. Biometric measurements measure and record the body's physiological responses to stimuli that are beyond the control of the person, such as visual, sound, smell, shape, or word combinations. Examples include eye tracking, skin conductance, and face reading devices. Brain imaging techniques analyze which nerve impulses these stimuli cause in the brain and deeper structures (Akın and Sütütemiz, 2014).

Neuromarketing is a growing field that combines consumer behavior research with neuroscience, and significant amounts of money are spent on advertising campaigns worldwide each year. However, traditional methods often fail in terms of the impact of these investments on the consumer. Companies are not able to effectively profit from the money they spend on advertising campaigns. Because these methods directly depend on how well the consumer can express their emotions when they encounter this advertisement. At this stage, neuromarketing offers another method that directly examines the consumer's brain, regardless of their competence or desire (Yücel and Şimşek, 2018).

Neuromarketing is used to understand the factors that affect the mechanisms of consumer choices and to recreate the same meaning.

This new field of marketing uses medical technology to measure the brain's response to a product. Measuring activity changes in different parts of the brain reveals not only why consumers choose a product, but also which part of the brain is active when making that choice (Ural, 2008).

Psychological Buying behavior

The term consumer behavior refers to the consumer's purchasing behavior, and various models have been developed in the literature to systematically explain consumer purchasing behavior. The basic models that attempt to explain purchasing behavior are models developed in various fields of social sciences and attempt to explain consumer purchasing behavior from the perspective of their own discipline. Although concrete and highly reliable results have not been obtained on this subject, significant progress has been made in the area of consumer preference through the processes and procedures that guide the consumer to the purchasing decision (Hacıoğlu Deniz, 2011).

In consumer behavior, the choices made by the consumer are important, and the consumer can understand the outcome of his/her choice after purchasing a product or service. This exposes the consumer to risk and uncertainty. Consumers perceive risk due to the uncertainty and possible undesirable situations they may encounter as a result of the purchase. As consumers' risk perception increases, their purchase probability decreases. For this reason, consumers often use risk reduction strategies such as gathering information before purchasing to reduce their risks (Koçoğlu, 2016).

In the decision-making phase, consumers can experience the effect of anticipated regret to a great extent, especially when faced with uncertain situations. As a result, consumers can shape their purchasing behavior according to this feeling. According to the regret theory; A person's decision to choose depends on the emotions caused by the consequences of the option not chosen. In other words; The individual thinks that he/she has purchased the product, compares it with what would have happened if a different choice had been made, and experiences some emotions as a result of this comparison. If the predicted result is more positive than the actual one, sadness is felt; If the opposite is felt, joy is felt (Can and Şen, 2018).

In general, there is a psychological feeling underlying all consumer behaviors, whether for need or consumption. Therefore, it is actually possible to match every purchasing behavior with a psychological decision-making process. In this respect, when purchasing behavior is considered, it is possible to say that the psychological approach in marketing management plays an important role in creating and managing purchasing behavior.

When consumers make a purchase decision and make a purchase, they do not only feel a need or desire, but also a sense of power. Purchasing power or economic power is a situation that expresses the capacity and power of individuals to purchase the products or services they want. Therefore, when addressing the psychological aspect of purchasing, it can be argued that not only needs and desires, but also the power image of purchasing itself expresses a psychological process.

Regardless of the psychological purpose and process underlying the psychological purchasing decision, it is undoubtedly possible to state that every factor affecting psychology also affects the purchasing process. Although there are many factors affecting the psychology of individuals in daily life, it is possible to associate a large part of these factors with today's popular culture, urbanization and digital environments. Environmental and technological factors, which have come to the fore in a large part of the studies conducted in the field of psychology in recent years, reveal that the customer and consumer structure are increasingly similar to each other and that the new customer structure is more skeptical, scientific and analytical, controlling, hedonistic and utilitarian compared to the past. For this reason, in order to understand the reasons underlying the purchasing process and decision, the factors that create these reasons must also be analyzed and presented well.

To summarize briefly, psychological purchasing is actually a general term that refers to the psychological processes underlying all purchasing processes, including the mechanisms of psychological processes that drive and affect the purchasing decision. In marketing management and modern marketing integration, psychological purchasing decision and behavior is one of the most important keys to an effective and successful marketing process.

The effect of neuromarketing on psychological purchasing

In terms of psychology, ensuring that an individual makes a purchase decision actually includes psychologically guiding individuals. In other words, psychological management and guidance are essential for making a psychological purchase decision. However, in the use of the concepts of guidance and management, actions that are carried out completely within the limits permitted by marketing, apart from a limited area and basic features, should be included. Perhaps, instead of managing psychologically, the concept of guidance can be used more adequately on its own.

Neuromarketing basically refers to the neurological effects that an advertising or marketing process leaves on individuals and the neurological outcomes of the changes that the marketing process creates on psychology. From this point of view, it is possible to consider the neurological marketing process as a marketing management and method that is carried out by evaluating marketing outcomes through neurons.

During the purchasing process, individuals' meeting their needs and their secondary or other needs that they accept as needs allows individuals to feel a sense of satisfaction and relief. Therefore, in fact, each purchasing process also represents a psychological satisfaction and pleasure level change and process in individuals. Therefore, in monitoring psychological marketing and evaluating and developing methods and techniques, the relationship between the methods used and their outputs should be addressed and evaluated effectively. In other words, the methods and techniques used should be evaluated and developed through feedback.

As a result, it is possible to define neuromarketing as a field of measurement and evaluation for developing the evaluation and methods of psychological marketing. In this respect, neuromarketing actually has a structure that allows compiling field data and reconstructing them for each field, stage, method and application of psychological marketing. If it is necessary to evaluate the effect of neuromarketing on psychological purchasing in this respect, it is possible to define it as the numerical and empirical field of psychological marketing.

Conclusion

The most important purpose of a marketing process is to make a purchasing decision and to realize it, in other words, to have the target audience buy that product or service and pay the price set for it. Therefore, it is actually possible to evaluate the marketing process as a process that ends with the realization of purchasing behavior. In order for individuals to realize purchasing behavior, not only economic status, cash flow and need status, but also a number of psychological and sociological requirements emerge as important factors.

In general, the needs of individuals are actually quite limited in the physical sense. In other words, it is possible to say that a large portion of the products or services that individuals purchase today are needs other than physical needs. While the determination, classification and evaluation of physical needs are more quantitative and dependent on specific criteria, the psychological evaluation of needs is a relatively more complex and multivariable process. At this point, the purchasing behaviors of individuals should also be evaluated and addressed together with the psychological purchasing process decisions. Therefore, the psychological purchasing process can be described as the most important stage in making a purchasing decision, which is actually the main purpose of the marketing process.

Neuromarketing is a process that determines the possible neurological effects of individuals' psychological changes, which will directly reveal the relationship between psychological purchasing behaviors and marketing. Therefore, it would be more appropriate to evaluate neuromarketing as a determinant and decision maker of the psychological purchasing process and use it accordingly in marketing processes. Although quantitative studies on neuromarketing are relatively limited today, it is possible to foresee that there will be more quantitative studies on neuromarketing in the near future with the increasing number of studies.

As a result, neuromarketing is of vital importance in terms of understanding, evaluating, managing and directing the psychological purchasing levels of individuals. For this reason, more field studies are needed in terms of determining, designing, implementing and evaluating the results of psychological purchasing processes. For this reason, multi-center, multivariate analyses are needed on many different samples and structures, and on different fields and sectors. In addition to these, the development of more measurement tools in neuromarketing, the integration of existing measurement tools into neuromarketing and the evaluation of the outputs are of great importance both for the literature and for field applications.

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CHAPTER III

Does Brand Loyalty Matter? Customer Churn in the Turkish Mobile Telecommunication Industry

Pelin BAYRAM[1]

1. Introduction

The mobile telecommunication market among the fastest-growing and intensely competitive industries. The industry is also becoming increasingly more saturated, with many subscribers switching their mobile operators between competing operators (Alboukaey et al., 2020). The same pattern is proven valid for the Turkish mobile telecommunication industry and the market is reaching its maturity stage (Aydin and Ozer, 2005). When the pool of potential customers becomes limited due to market saturation, the industry shifts its strategic focus from acquiring new customers to retaining existing customers to avoid churn (Hung, et al., 2006). Thus, customer retention has become a more significant and industry-wide concern than customer acquisition. Moreover, according to Liu, (2011) retaining current customers is more cost-efficient compared to

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acquiring new customers. This research suggests that this shift in focus arises from the need to manage high customer churn in a highly competitive industry. It emphasizess the importance of effective churn management as a priority for the mobile telecommunications sector to thrive in a mature market.

In the mobile telecommunication industry, switching service providers were observed to be very common due to several different reasons, such as being unsatisfied with the overall service quality, lack of loyalty towards the operator, and customers' personal or professional preferences may change over time (Jain et al., 2020). Therefore, overcoming customer churn is the industry's priority concern and becoming a vital issue as the market matures (Ahn, et al., 2006). Although the extant literature has identified different reasons behind churn still, the topic should be further explored as many global mobile operators' churn rates are quite high and range between 20 to 40 percent (Keramati and Ardabili, 2011). In parallel, as of December 2017, churn rates in Turkey were reported to be even higher, according to the Bilgi Teknolojileri ve İletişim Kurumu (BTK, 2018).

The nature of a saturated market is characterized by intense competition, product differentiation, innovation, and a lack of significant growth in consumption. Consumers can access nearly identical product offerings from various companies/brands in a saturated market (Puspa and Kühl, 2006). When the number of subscribers reaches saturation in the mobile telecommunications sector, the acquisition cost of new subscribers becomes considerably more costly than retaining existing ones. As a result, core marketing strategies focus on customer retention through value and brand loyalty (Kim et al., 2004).

This research explores whether brand loyalty positively affects customer retention and thus negatively affects customer churn within Turkey's mobile telecommunication sector. Previous studies related to the telecom sector suggest that the determinants of loyalty include customer satisfaction, service quality, brand image, and switching cost (Kim et al., 2004; Lee et al., 2001; Aydin et al., 2005; Kim and Yoon, 2004;). In this study brand loyalty construct will be evaluated using the following determinants: brand image, trust, perceived value, and psychological cost. The result of this research will assist practitioners in identifying the drivers of churn in their businesses and enhance customer lifetime value in the mobile telecommunications industry.

1.1 Overview of the Turkish mobile industry

In 1991, the first mobile communication occurred over the Global System for Mobile Communications (GSM), also known as 2G. This milestone marked the beginning of significant advancements in information and communication technologies. The global adoption of GSM systems was followed by the introduction of the Third Generation of Mobile Telecommunications (3G), which enabled internet access anytime and anywhere. A key turning point in this evolution was the launch of the iPhone by Steve Jobs in 2007, which revolutionized mobile technology. Soon after, the Fourth Generation of Mobile Telecommunications (4G), also referred to as Long-Term Evolution (LTE), began to dominate the field (Kalem et al., 2020). This global advancement soon extended to Turkey, where the era of GSM-based mobile communication began when Turkcell launched its operations in February 1994 (Engin and Akgoz, 2013).

The Turkish mobile telecommunication industry has grown significantly since its inception. According to the Bilgi Teknolojileri ve İletişim Kurumu (BTK) report (April 2024), over 93 million mobile subscribers currently represent a 109.3% penetration rate. When the population aged 0-9 years is included, the mobile penetration rate rises to over 113%. The industry is dominated by three major players-Turkcell, Vodafone, and TT Mobil who collectively serve a total of 93 million subscribers (BTK, 2024).

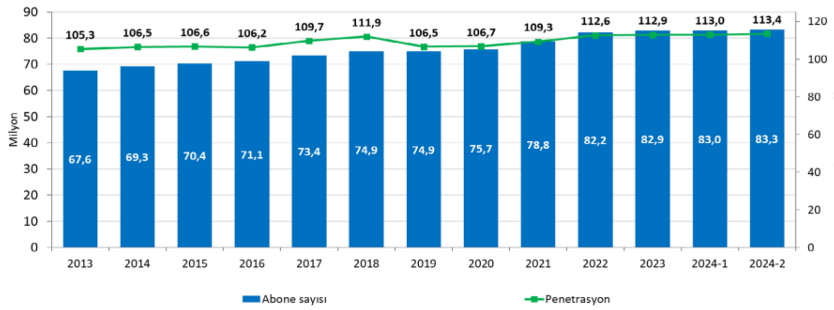


Figure 1: Number of Subscribers and Penetration rate %
(Excluding 0-9 year old population)

Source: (BTK, 2024)

As of the second quarter of 2024, according to the number of subscribers, Turkcell holds 41.2%, Vodafone 30.6%, and TT Mobil 28.2% of the market. Regarding market share, Turkcell accounts for 41.8%, Vodafone for 34.7%, and TT Mobil (former Avea) for 23.5% respectively.

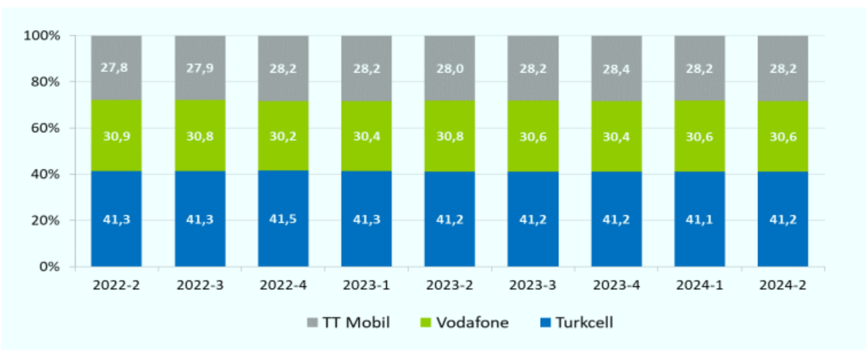
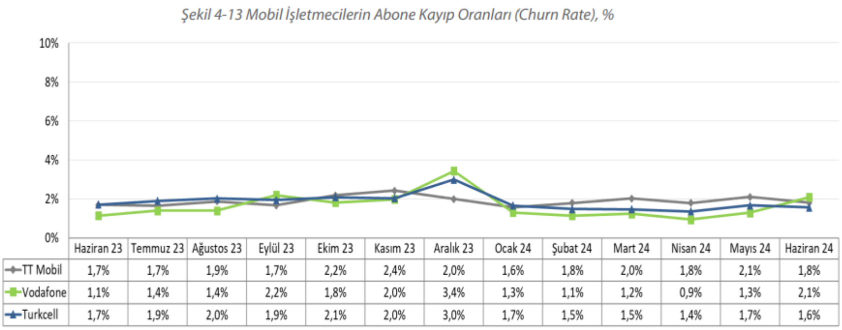


Figure 2: Number of Subscribers by Mobile Operators in Turkey

Source: (BTK, 2024)

Thus, the Turkish Republic, with a population of over 85 million, is served by three highly competitive mobile operators (TUIK, 2022). According to the December 2017 report by BTK, the monthly churn rates for Turkcell, Vodafone, and TT Mobil were 3.6%, 2.5%, and 2.03%, respectively (BTK, 2018). These figures highlight the intense competition among the three major operators in Turkey. As of June 2024, the churn rates for TT Mobil, Vodafone, and Turkcell have decreased to 1.8%, 2.1%, and 1.6%, respectively (BTK, 2024). However, the annual churn rates remain significant, at 21.6% for TT Mobil, 25.2% for Vodafone, and 19.2% for Turkcell.



	Haziran 23	Temmuz 23	Ağustos 23	Eylül 23	Ekim 23	Kasım 23	Aralık 23	Ocak 24	Şubat 24	Mart 24	Nisan 24	Mayıs 24	Haziran 24
TT Mobil	1,7%	1,7%	1,9%	1,7%	2,2%	2,4%	2,0%	1,6%	1,8%	2,0%	1,8%	2,1%	1,8%
Vodafone	1,1%	1,4%	1,4%	2,2%	1,8%	2,0%	3,4%	1,3%	1,1%	1,2%	0,9%	1,3%	2,1%
Turkcell	1,7%	1,9%	2,0%	1,9%	2,1%	2,0%	3,0%	1,7%	1,5%	1,5%	1,4%	1,7%	1,6%

Figure 3: Monthly Churn Ratios of Turkcell, Vodafone, and TT Mobil

Source: (BTK, 2024)

The evidence from the data above shows that customer churn is relatively high, presenting a critical issue for the Turkish mobile telecommunications sector. Further research is necessary to explore additional factors driving churn to address gaps in the current literature. This research aims to build a comprehensive understanding of customer churn and propose impactful marketing strategies and improved churn management techniques to enhance long-term profitability within the Turkish mobile telecommunications sector.

2. Theoretical framework and hypothesis development

2.1 Brand Loyalty

The literature conceptualizes loyalty into two dimensions: attitudinal loyalty and behavioral loyalty (Kardes et al., 2010). According to

Aaker (2015), behavior is the likelihood of customers towards repeat purchases, while attitude represents the overall feeling of a customer toward a product or brand. In other words, the formation of brand loyalty is distinguished from traditional and multi-dimensional approaches. Previous studies on the traditional approach focus on loyalty with the attitudinal, behavioral, or composite approach. The behavioral approach is solely focused on the behavior of a customer who is engaged in repeat purchase behavior of the same brand and can categorized as a loyal customer (Ehrenberg, 1994). However, this approach does not sufficiently explain loyalty as it neglects the decision-making process of a customer and does not consider psychological commitment (Jacoby and Chestnut, 1978; Bowen and Chen, 2001). On the other hand, the attitudinal approach focuses more on emotions and psychological attachments, such as the commitment and trust of a consumer toward a particular product or brand (Back and Parks, 2003). As a result, both the behavioral and attitudinal approaches alone are insufficient in explaining loyalty. The composite approach represents the combination of both attitudinal and behavioral approaches (Oppermann, 2000). According to Day (1969), customers should exhibit both a favorable attitude towards a brand and active involvement in the purchasing process. Thus, the two-dimensional composite approach to measuring brand loyalty enhances the reliability and predictive accuracy of loyalty research.

Oliver (1999) introduced a multi-dimensional framework for understanding brand loyalty. He suggested that true brand loyalty can only be identified by evaluating both the emotional (affect) and the intentional aspects of a customer's attitude. According to Oliver (1999), loyalty develops progressively through cognitive and emotional commitment, eventually leading to conative (behavioral) actions such as repeat purchases. Moreover, Schiffman and Kanuk (2010, p. 249) highlighted that analyzing the components of an attitude- cognitive, affective, and conative dimensions- enhances the ability to predict behavior more accurately.

According to the review of previous research, a positive correlation exists between trust, brand image, psychological cost, perceived value, and brand loyalty. The relationship among these constructs has also been examined in the mobile telecommunication sector context. The proposed relationships between brand image (Kim & Yoon, 2004; Turnbull et al., 2000), trust (Aydin & Ozer, 2005; Lee et al., 2011), psychological cost (Shin & Kim, 2008; Kim et al., 2004), perceived value (Aydin & Ozer, 2005). Hence this study formulated the following brand loyalty hypotheses:

H1: There is a positive relationship between strong brand image and loyalty.

H2: Trust in the operator has a positive effect on loyalty.

H3: Perceived psychological cost has a positive effect on loyalty

H4: Perceived value has a positive effect on loyalty

2.2 Brand Loyalty and Customer Churn and Retention

The marketing literature has yet to clearly establish a theoretical framework outlining the factors that drive customer churn. However, loyalty, customer satisfaction, and switching barriers are widely acknowledged as key determinants influencing customer churn. Research indicates that brand loyalty strongly predicts customer retention, with loyal customers being just as likely to switch to competitors as non-loyal customers (Liu et al., 2011). Reichheld (2003) emphasizes that customer loyalty extends beyond repeat purchases, as loyal customers often share positive recommendations with their friends, families, and colleagues. Based on this, this study proposes the following hypotheses:

H5: Brand loyalty negatively impacts customer churn.

H6: Brand loyalty positively impacts customer retention.

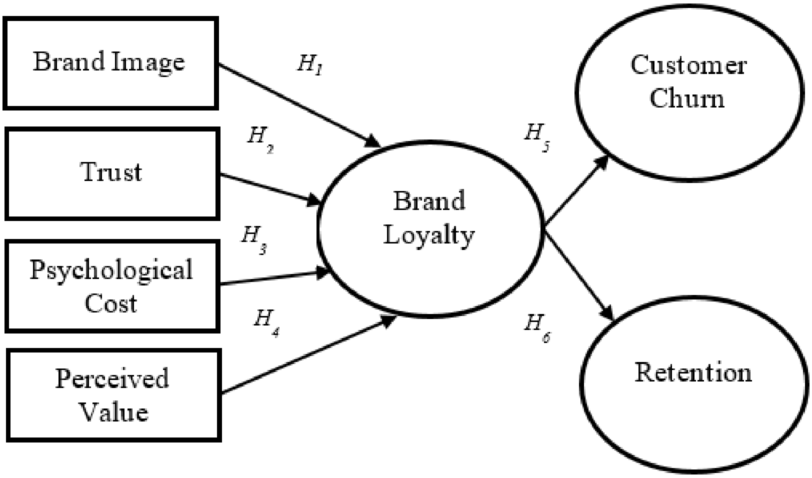


Figure 4: Conceptual Research Model

3. Methodology

3.1 Sampling and Data Collection Procedure

This research focuses on mobile consumers within the Turkish mobile telecommunication sector and the industry has three players: Turkcell, Vodafone, and TT Mobil. Thus, the sample population of this research consisted of subscribers from all three mobile operators in Turkey. The online survey was conducted through a web link and tested the hypotheses of this research. The three big cities in Turkey are: Istanbul, Izmir, and Ankara, and they were chosen as starting locations to gather data. Since an online survey was conducted and through the help of social networking websites, the locations of this research ended up expanding to additional cities in Turkey. All items in the questionnaire are measured using a 10-point Likert scale ranging from 1 (strongly disagree) to 10 (strongly agree). Data was gathered from a sample of 620 Turkish mobile telecommunication subscribers. Some incomplete responses were eliminated and 540 valid responses were collected.

3.2 Measurements

All constructs were measured with multiple-item scales. A pretest with 20 respondents was conducted and based on Cronbach' Alpha's range of 0.71 to 0.85. Lastly, the web links for both the English and Turkish questionnaires were announced to subscribers via e-mail and social networking websites. This research adopted five-items to measure customer churn (Kim and Yoon, 2004; Meenaghan, 1995; Aydin and Ozer, 2005; Labrecque, 2014; Chaabane and Volle, 2010; Jurisic and Azevedo, 2010; Edward and Sahadev, 2011; Aydin et al., 2005). Customer retention was measured by two-items (Reichheld, 2003; A. Eshghi et al., 2007). Loyalty was measured with eight-items (Mellens et al., 1995; Ramos and Franco, 2005; Okyere et al., 2011; Nimako, 2012).

4. Data analysis and result

4.1 Measurement validation

The model and hypotheses shown in Figure 4 were analyzed using the structural equation modeling (PLS-SEM) approach with the SmartPLS graphical software program. The indicator reliability test was performed by checking outer loadings. According to Hulland (1999), 0.70 or higher is the preferred result, and if the research is exploratory, 0.4 or higher is an acceptable level. The outcomes of the outer loading variables are summarized in Table 1.

Table 1 Outer Loadings

Latent Variable	Indicators	Loadings
Component_Brand_Image	CL1	0.873712
	CL2	0.894246
	CL3	0.826803
	CL4	0.419777
Churn	LL1	0.948641
	LL2	0.962711
	LL3	0.971574
	LL4	0.975391
	LL5	0.955586
	LL6	0.947182
Brand Loyalty	BL1	0.897502
	BL2	0.918085
Perceived_Value	CL8	SCI
Psychological_Cost	CL7	SCI
Retention	NP	0.910125
	SW	-0.77007
Trust	CL5	0.936068
	CL6	0.825146

SCI = Single Item Construct

The construct convergent validity and reliability tests were performed, as well as the internal reliability approach (Cronbach Alpha), as shown in Table 2. The acceptable level of average variances extracted (AVE) is larger than 0.5 (Fornell and Lacker, 1981). Nunnally and Bernstein, (1994) indicate that the composite reliability and Cronbach alpha are acceptable when the value is higher than 0.70. Moreover, communality can be required for the acceptance of the measurement model, and it is considered an indicator of quality for constructs (Van Riel et al., 2012). If the value of communality is greater than 0.50 is acceptable.

Table 2 Convergent Validity and Construct Reliability

Constructs	AVE	Composite Reliability	Cronbachs Alpha	Communality
Brand_Image	0.605716	0.852114	0.769385	0.605716
Churn	0.922062	0.986106	0.983069	0.922062
Loyalty	0.824195	0.903615	0.787272	0.824195
Perceived_Value	SCI	SCI	SCI	SCI
Psychological_Cost	SCI	SCI	SCI	SCI
Retention	0.710667	0.032786	-1.549436	0.710667
Trust	0.778545	0.875053	0.729064	0.778545

SCI = Single Item Construct

Next, discriminant validity was assessed. When the square root of an average variance extracted (AVE) in each latent variable can be used to perform discriminant validity (Fornell and Larcker 1981). AVE was greater than each correlation coefficient except for the brand image. Thus, the results indicate adequate discriminant validity in general.

4.2 Structural model analysis

The summary of the research model tested and the results are shown in Table 3. The R2 values ranged between 0.521 to 0.917. The structural model of churn predicts 69%, The coefficient of determination, R2, is 92% (substantial) for customer retention endogenous latent variables.

Table 3 Measurement Model

Variables	R Square
Churn	0.691529
Loyalty	0.521293
Retention	0.917580

The hypothesized path relationship between brand loyalty and customer churn (0.052) and retention (0.092) is not statistically significant as the standardized path coefficients were less than 0.1. Building on the preceding discussion, the following tables reveal the result of the path coefficient (ß) through the PLS algorithm to calculate the impact of one variable on another. In addition, the t-values were computed with the bootstrapping procedure which represents the significance level of an exogenous variable when explaining an endogenous variable. If the critical t-values are 1.65 (significance level = 10%), and 1.96 (significance level = 5 %), the hypothesized relationship is significant (Hair et al., 2011).

Table 4 presents the results of the hypothesis testing for customer churn. H5 proposes that brand loyalty has a negative effect on churn ($\beta = 0.052427$, $t = 1.408031$) and was not supported.

Table 4 Path Coefficients and Hypothesis Testing for Customer Churn

Hypothesis	Relationship	Coefficient	t-value	Supported
H5	Loyalty -> Churn	0.052427	1.408031	No

Table 5 displays the results of the hypothesis testing for customer retention. H6 proposes that brand loyalty has a positive effect on retention ($\beta = -0.092332$, $t = 4.362472$) and was supported.

Table 5 Path Coefficients and Hypothesis Testing for Customer Retention

Hypothesis	Relationship	Coefficient	t-value	Supported
H6	Loyalty -> Retention	-0.092332	4.362472*	Yes

Table 6 presents the results of the hypothesis testing for brand loyalty. H1 proposes that there is a positive relationship between strong brand image and loyalty ($\beta = 0.355312$, $t = 5.493750$) and was supported. H2 proposes that trust in the operator has a positive effect on loyalty ($\beta = 0.042262$, $t = 2.088868$) and was accepted. H3 proposes that perceived psychological cost has a positive effect on loyalty (β = 0.042262, t = 1.019922) and was not supported. H4 proposes that perceived value has a positive effect on loyalty (β = -0.000041, t = 0.000796) and was not supported.

Table 6 Path Coefficients and Hypothesis Testing for Brand Loyalty

Hypothesis	Relationship	Coefficient	t-value	Supported
H1	Brand_Image -> Loyalty	0.355312	5.493750*	Yes
H2	Trust -> Loyalty	0.042262	2.088868*	Yes
H3	Psychological_Cost -> Loyalty	0.042262	1.019922	No
H4	Perceived_Value -> Loyalty	-0.000041	0.000796	No

5. Discussion and conclusion

The main objective of this study was to explore the effect of brand loyalty on churn and retention in the Turkish mobile telecommunication market. There are several findings as follows. First, the structural churn model predicts 69%, meaning that the latent variable of brand loyalty moderately explains 69% of the variance in the customer churn endogenous latent variable. Findings suggest that brand loyalty does not significantly influence churn. Second, the structural retention model predicts 92%, which means that the latent variable of brand loyalty substantially explains 92% of the variance in the customer retention endogenous latent variable. Brand loyalty is a core driver of retention in the Turkish mobile telecommunication industry. Thus a subscriber's retention intention is related to the level of their loyalty towards their service provider. Drawing from the literature review, previous studies in the mobile telecommunication industry also found the influence of loyalty on customer retention (Ahn et al. 2006; Gerpott et al. 2001; Keramati & Ardabili 2011).

5.1 Theoretical implications

This study adds an important theoretical contribution by offering empirical evidence for the significant influence of loyalty on customer retention. Additionally, this research empirically provides the main components of loyalty in the Turkish mobile telecommunication sector. The finding reveals a positive correlation between trust, image, and brand loyalty. Subscribers' loyalty to their mobile operator is most strongly influenced by brand image and is in parallel with previous studies (Kim & Yoon, 2004; Turnbull et al., 2000). Trust construct was found to be the second critical component of loyalty in the Turkish mobile telecommunication sector, which is in parallel with the results of earlier research (Aydin & Ozer, 2005; Lee et al., 2001).

5.2 Managerial implications

The analysis of this research has multiple implications based on a managerial perspective. First, Turkish mobile operators above all else, should maximize brand loyalty to enhance customer retention. Loyalty alone cannot establish customer retention. Mobile operators also need to focus on customer satisfaction. Loyal and satisfied customers generate positive WOM between people they know and turn subscribers' friends and families into new customers. Secondly, according to the study's findings, the factors significantly affecting brand loyalty appear to be brand image and trust. Brand image can be enhanced through continuous advertising and public relations activities, as well as the use of societal marketing including corporate social responsibility. In addition, mobile operators should build trust with their customers. Building trust is not an easy process, but gaining subscribers' trust can be built by providing great customer service.

5.3 Limitations and directions for future research

This research, as with any other research, has several limitations. Consumer segmentation is the first limitation of this study. Along with brand loyalty, it is crucial to involve different consumer segmentations such as psychographic and behavioral as well as generational segmentation to examine the effect of different consumer segments on churn and retention. Moreover, a more in-depth analysis of the demographic characteristics of the subscribers is required for a better prediction of churn, semi-churn, and retention. Another limitation is related to sampling. This current study used a non-probability sampling and it was tested in Turkey. Respondents were mainly located in Istanbul, Izmir, and Ankara. Considering the entire population of Turkey, this research does not reflect the entire population of Turkey and it is necessary to include other cities in Turkey. Furthermore, the characteristics of the population in Turkey may be different than other populations in other countries. The last limitation is that this research only investigated brand loyalty constructs concerning churn and retention, future research should consider adding other antecedents of churn and retention (e.g. customer satisfaction and switching barriers).

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