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# Marketing Mix Modeling of Traffic to the Store Under the Covid-19 Crisis

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**Abstract.**
The paper contains the results of marketing mix modeling for Ukrainian retail in conditions of the COVID-19 crisis. The main goals of the research are modeling the level of traffic to the store based on regression analysis and forming appropriate recommendations for media strategy. Estimating the influence of media on business KPI makes a basis for ROI calculations and optimization of budget allocation between communication channels by periods, formats, and optimization of media pressure. Models for offline and online traffic were constructed based on weekly data for 2018-2021 and since 2020 there is a strong impact of COVID-19 on traffic and media response. In 2020 there was a significant drop in offline traffic due to the lockdown, but also there was deferred demand, which was compensating for a part of the traffic. The results show that TV is the main driver for offline traffic and digital - for online, but there are also significant impacts of TV and digital on online and offline traffic, respectively. During the lockdown, the mobility of consumers dropped, that is, a decrease in response from Out of Home advertising; therefore, we need to compensate for this by higher activity in other media channels. Scenario forecasting of different media mix helps to select the most efficient strategy taking into account memory decay of advertising, period of activity, and weekly weights. Marketing mix modeling is an effective tool for business management, as it generates opportunities to improve ROI by more than 15% and ensures the achievement of business goals in the most efficient way.

**Keywords:** marketing mix modeling, COVID-19, ROI, regression analysis, retail, traffic

**jel CLASSIFICATION codes:**

C1, C5, M3.

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## 1. Introduction

Retailers sell goods and provide related services to end customers. In conditions of intensified competition, due to the reduction of effective demand and the presence of a large number of retailers and Internet sellers, it is important to gain a competitive advantage for the company. The development of Ukraine's economy is accompanied by the emergence of new causal links that form and determine the peculiarities of the functioning of retail enterprises. Modern conditions of retail development in Ukraine, characterized by a high level of dynamism and uncertainty of the environment, complex and multifaceted processes, necessitate the diagnosis of a wide range of factors, analysis of their positive or negative impact through modeling key business indicators and effective performance management of retail [1]. Due to the COVID-19 quarantine restrictions in 2020-2021, a significant part of Non-Food retail stores was closed, demand and sales fell sharply, but there was a large-scale jump in online sales, especially in the largest online hypermarkets and marketplaces.

Over the past 10 years, the Ukrainian retail market has undergone many changes. Thus, today the main market share is occupied by large retail chains, virtually displacing local retailers from this niche. However, it should be noted that in general, the popularity of offline retail stores has declined markedly. Currently, more and more consumers prefer to shop online. In addition, the purchase of goods becomes mobile, because more than half of all purchases are made via smartphones [2]. With this in mind, retailers are actively investing in technology to improve brand reputation, customer experience and increase their value to the consumer. Retailers should rely more and more on the omnichannel model of interaction with consumers and finding ways to optimize their media support. In the case of lockdown in the period of the COVID-19 crisis, the mobility and moving around the city of potential consumers significantly dropped, and there is a decrease in media response from advertising, so we need to find effective solutions to compensate for it, ensure a high level of company's readiness to challenges of the external environment [3] and achieve positive dynamics of business indicators.

In order to achieve the strategic goals of a commercial enterprise, it is necessary to apply new approaches to the effective management of retail trade, as one of the main indicators of economic and social development of the state in general and individual enterprises in particular [4]. The practical implementation of modern marketing management mechanisms is the key to both performance and achievement of target strategic vectors of development of retail enterprises. This, in turn, involves modifying the management process in terms of timely identification, diagnosis, prevention of negative impact on the activities of retailers of a wide range of factors [5], preventive measures, expanding incentives for potential consumers through media support and other instruments.

In modern conditions of development of economic systems, especially under the COVID-19 crisis, the management of the enterprise is expedient to carry out on the basis of economic and mathematical models that will allow to investigate dynamics of development of the trade sphere both of Ukraine, its regions, and a certain enterprise. The use of economic and mathematical methods and models will identify trends in the impact of factors on the size of retail turnover of commercial enterprises [6]. Due to the accumulation of significant achievements in the methodology of economic and mathematical modeling, it is necessary to generalize, adapt and implement in the practice of activities of commercial enterprises.

The basis of the marketing management system of the retail business is an organic set of interconnected elements that define the contour of an effective mechanism to stimulate business through advertising, which provides a systematic approach to media strategy development and optimization of marketing investments. The development of an optimal media strategy involves the selection of business-relevant communication channels, their prioritization in accordance with the expected return on marketing/media investment (ROMI), as well as taking into account the marginal utility of each of them, the selection necessary volume of media pressure [7] in general and on the weekly breakpoint. In addition, there is an effective distribution of media investment by placement format (for example, a split between different video durations or between video and display advertising, etc.), by periods during a year, etc.

Business process optimization is becoming one of the most important tasks to maintain the viability of the enterprise. Modeling the marketing activities of a retail business becomes extremely important, especially in times of crisis and periods of strategic surprises, when non-standard management approaches are needed to maintain market presence and maintain consumer value (for example, organizing activities in conditions of COVID-19 pandemic and its recession) [1]. In these circumstances, media activity and any actions of the retailer in relation to the required target level of business indicators should be justified as much as possible, which can be achieved through marketing mix modeling based on in-depth data analysis and comprehensive assessment of various external factors and the internal environment of the enterprise. All solutions must be generated and adapted to ever-changing market conditions [3] and ensure that goals are achieved in the most efficient way.

The competitive environment in this market segment is quite complex, which requires companies to find ways to improve their marketing activities. In today's competitive environment, economic entities are continuously improving their activities, developing opportunities, optimizing and formalizing business processes to maintain long-term competitiveness. Modeling of business indicators of the enterprise is the basis for intellectual analysis and information processing, which is necessary for making complex management decisions with the greatest efficiency [5]. The aim of the article is to model the marketing mix impact on traffic for one of the leading Ukrainian companies in the field of non-food retail under the COVID-19 crisis, to form recommendations based on it to optimize media strategy and ensure effective business growth in the future.

## 2. Literature Review

Advertising activity and its impact on consumer demand are given considerable attention in the scientific literature, where the model of marketing response emerged as the dominant analytical structure. In recent years, the basic structure of the model has developed in different directions. One of them is the inclusion of paid, owned and earned media to encourage offline and online ways to purchase. Cain (2021) [8] mentioned that no one development or model effectively provides a fully holistic view of the role of advertising. He proposes a practical modeling system for marketing practitioners with a solid economic and statistical basis for the short-term and long-term effects of advertising.

Marketing communication is one of the most important activities that businesses rely on to satisfy the desires of consumers, raise awareness of the company's products or services and, consequently, increase sales. The study by Mensah et al. (2021) [9] establishes the impact of marketing communication on consumer purchasing behavior in developing countries. All hypotheses were tested using the method of structural equations modeling. The results show that the evaluated marketing communication strategies have a positive and significant impact on consumer buying behavior.

The effectiveness of marketing strategy is a function of a dynamic interactive process that includes internal resources of the firm, environmental factors and the actions of competitors. Liu (2021) [10] shows, that, following the impact of COVID-19, the new digital marketing platform will become more active for implementation. Modern marketing relies on digital technology to analyze the overall effectiveness of a marketing campaign and help develop future strategies and decisions.

The availability of timely information about future customer needs is a key factor in the success of any business. To maximize the profit, the business needs to understand demand signals, manage them, and shape future demand, using price, sales, promotion and other economic tools to meet customer needs. The study by Kumar et al. (2020) [11] aims to explore the contribution of promotional marketing activities, historical demand and other factors to forecasting and developing of the system based on fuzzy classifiers driven by big data that can shape, perceive and respond to real customer requirements. This method wins in terms of optimality, efficiency and other statistical indicators.

The services sector is growing all over the world. At the present stage of development, traditional retail stores have significantly reduced their popularity. Due to the growing number of modern stores, they are attracting more and more people to visit their stores and use their services, because modern stores are better suited to people's lifestyles. Chantayarkul et al. (2020) [12] developed the GREAT model, which will increase the competitiveness of stores by forming their systematization and greater efficiency. Using such a model will help you get a better idea of business operations and conduct business with clear instructions and procedures. In addition, this model can help identify weaknesses and strengthen strengths to survive the era of digital transformation.

With the rapid development of computer technology and e-commerce, the concept of consumer activity has changed greatly. The e-commerce market is growing exponentially in terms of both business and data. A significant number of companies rely on their sites to attract new customers while retaining current ones. E-commerce websites give consumers flexibility in time, price and location when shopping [13]. Online stores have become increasingly popular [14]. The classic marketing complex, consisting of product, price, place and promotion (4P), determines important aspects of the consumer's journey to purchase and factors of choice. The study by Sriram et al. (2019) [13] is an attempt to find the impact of e-marketing on the loyalty and popularity of e-commerce sites. Survey data were analyzed by structural equations modeling using the least squares method. The results show that the popularity of the brand was significantly influenced by product characteristics and effective intelligent promotion methods. Brand popularity has an impact on brand loyalty in the e-commerce marketing space.

For online trading platforms such as Amazon, a robust system for analyzing online shopping behavior allows them to better understand consumer psychology and then develop better business strategies to increase sales. The Shi article (2021) [14] focuses on factors that can influence visitor intent based on a set of online shopping intentions that consists of aggregated pageview data during a visit session along with other user information. Using descriptive statistical analysis, Shi finds that variables such as time spent and page values are positively correlated with intent to purchase, while variables, including bounce rate and rate of return, are negatively correlated with intent to purchase. Three models of forecasting the intentions of online shopping are based on the corresponding classical models of machine learning (logistic regression, decision tree and random forest). As a result, the random forest works best in predicting the behavior of online shoppers regarding the intention to make a purchase, with an accuracy of 87.5-89.5% in the training or test sample.

With the gradual disappearance of third-party cookies and advertiser IDs, marketers are becoming increasingly limited in their ability to measure the effectiveness of their marketing initiatives. Standard attribution models are currently based on user-level data to establish individual relationships between customer interactions and conversion goals. However, as access to user-level data becomes more difficult, marketers will have to use alternative ways to measure the effectiveness of their marketing efforts [15], including modeling the marketing mix through regression analysis. As we mentioned in our previous research [16], marketing mix modeling is a convenient and flexible tool for marketing management, as it allows to develop the optimal combination of factors to achieve short-term and long-term business goals through the management of key influencing factors. Model's support helps to achieve the necessary business results by the minimum budget or higher business results by the current existing budget.

Kamena (2021) [15] suggests methods for attributing inference attribution as a potential alternative or complementary approach to user-level attribution methods, and a review of old marketing techniques, such as media mix models, to address future changes in the marketing data ecosystem.

There are many media channels that can be used by retailers and e-commerce companies to increase business profitability. However, the use of any media is usually associated with an investment in selected communication channels. From the point of view of the business, it is necessary to evaluate the possible results of these investments (determine the ROMI) to select the most effective media mix. Because customers don't usually buy when they first visit a store, it's important to monitor their customer journey and evaluate the value of certain interactions. The purpose of the Kakalejčík et al. article (2021) [17] is an analysis of data from selected advertising companies using Markov chains based on data on online shopping and customer behavior. The Markov model was found to reduce the estimate assigned to channels that are fundamental to last-click heuristic models and to give more weight to channels that prefer first-click models or linear heuristic models.

Understanding customer behavior plays a significant role in marketing. Modeling customer behavior allows you to effectively segment the market and effectively develop a marketing mix. Existing customer decision-making models are ill-suited to uncertain, inaccurate real-world situations, and there is a need to develop a new conceptual and quantitative model [18].

The development of computer software and machine learning methods has improved the methodology of assessment through modeling and forecasting of economic values. New machine learning methods, such as tree-based regression models, have been proposed as an alternative to linear regression for predicting economic values based on auxiliary variables, as these algorithms are able to handle abnormalities and nonlinearities of data. However, regression trees are usually estimated based on independent rather than spatially correlated data. The quantile regression forest algorithm was used by Cordoba et al. (2021) [19] to provide a regression model to predict and estimate the uncertainty associated with the predictions derived from the model. The study of Yan et al. (2022) [20] offers a novel least squares twin support vector regression method based on a reliable $L_1$-norm distance to alleviate the negative effect of traffic data with outliers.

Legendre et al. (2020) [21] investigate the effectiveness of the experience of interaction with the brand on the formation of the memory of visitors and their intention to return using the method of partial least squares - modeling of structural equations. The results show that the experience of interacting with an individual's brand can help them to become more involved and find meaningful experiences, as well as to form a greater willingness to keep memories of the event. Forming a memory based on brand experience can help predict the positive behavior of visitors after future experiences. Marketing managers and decision-makers need to build a strong brand experience focused on combining sensory, emotional, intellectual and behavioral messages related to greater brand awareness and memory formation.

The study by Dash et al. (2019) [22] offers a marketing response model that includes a linear model with all possible interaction effects. The customer's request as his reaction was accepted as a dependent variable. Independent variables were the costs of advertising in various media. The results of the model provide a measurement of the effectiveness of each of the media, as well as the interaction between them.

The study by Kusumawati et al. (2021) [23] focuses on the analysis of the impact of marketing, culture and experience on purchasing intentions and purchasing decisions based on theories of consumer behavior - the theory of reasonable action and the theory of planned behavior. The study found that price, distribution, and physical evidence influence purchase intentions, while product and advertising influence purchase decisions. Kengpol et al. (2022) [24] showed that marketing mix has a direct impact on consumer behavior.

The study by Issock et al. (2021) [25] showed that the impact of the marketing mix depends on the stage of change at which the target audience is. Thus, the results show that the elements of the marketing complex significantly affect the intention to act, when the target audience is in the stages of reflection and preparation.

It is well known that customer behavior can affect the distribution of new products, business development and, consequently, the profits of firms. Therefore, firms must consider the strategic behavior of customers to make their marketing decisions [26].

An important marketing challenge is understanding the impact of different marketing efforts on sales and profits. The results of Chenavaz et al. (2020) research [27] reveal the lucrative potential of a business that manages a more complex marketing mix. Woodley (2021) [28] presents the State Space model for estimating the effects of individual channels, using aggregate sales or response data for all channels. The proposed structure allows you to change the effects of transfer between marketing channels. In addition, the proposed structure allows different rates of decay in different marketing channels, so paves the way for more comprehensive optimization of the marketing complex.

Despite the significant scientific achievements of scientists, many issues of media strategy optimization remain unclear, in particular, the effectiveness of media channels, calculation of ROI for retail categories, prioritization and redistribution of activity by periods during the year, taking into account seasonal ROMI and so on. The COVID-19 pandemic has challenged all business owners to support their businesses and find ways to overcome uncertainty.

## 3. Methodology

The main goals of the study are to realize marketing mix modeling, estimate the media efficiency by media channels and analyze the main changes in the period of the COVID-19 crisis. It will help to find effective conclusions for the media strategy of one of the key retailers in the non-food segment in Ukraine.

The theoretical and methodological basis of the study were the works of leading domestic and foreign economists, whose works reflected the concept of modeling economic processes and, in particular, marketing. In the research abstract-logical and mathematical methods of forecasting were used; economic and statistical methods of data processing to identify the state of marketing in the retail industry under the COVID-19 crisis.

To achieve this goal the system analysis and general scientific methods were used. The key group is methods of multicriteria analysis and modeling - econometric modeling - for understanding and quantifying the impact of marketing mix complex, competitor's activity and external factors about market conditions on traffic to the online and offline stores, respectively, of one of the Ukrainian retail enterprises based on regression analysis, as well as the recommendations formation for improvement the efficiency of company's media strategy and optimizing the business KPIs.

To achieve this goal were used regression analysis and economic and mathematical modeling (based on machine learning technologies, in particular, a multiple regression) of the dependence of traffic to the store on such factors as: seasonality (*Additive_seasonality*), the infection rate for COVID-19 and its lag effect for estimation of deferred demand (*Covid_19*), number of stores in the retail network (*Stores_number*), number of cities of presence (*Cities_number*), number of personal mailings by CRM base (*E-mail* and *Viber*), brand awareness, brand's and its competitors' media activity in all communication channels (television *(TV)*, digital (*Digital_display* and *Digital_video*), out of home (*OOH*), radio and press), number of a loyalty card (*Card_number*), quality indicators of opened or closed stores (*Stores_quality*) and others. All factors were selected by analysis of correlation with traffic level and analysis of the significance of these correlations.

We have collected data on all necessary indicators presented above for the period from 2017 to 2021 in a weekly breakdown. Business data were collected from the internal database with business indicators. Media activity data were collected from the monitoring system by Nielsen Ukraine by SQL requests and marketing data (for example, the infection rate for COVID-19) were collected from open-source. Due to confidentiality, all data in the article will be unified and indexed from 0 to 1. All data were collected in an Excel file, which was integrated into R-Studio software for modeling. There are business data from the internal database (strictly confidential), data about media activity and consumer behavior, as well as open data about macroeconomic and category situations.

The process of data mining and modeling consists of data collection and importing all relevant variables into the software, performing some data preparation and descriptive analysis (correlation matrix and significance of correlations, sales funnel analysis, data visualization), marketing mix models construction, model's testing and interpretation. The final stage is model deployment in real business application.

For each traffic, we will construct the multiple regression models, which look like this:

$Traffic = Constant + Additive\_seasonality + e*Covid\_19 + a_1*Stores\_number + a_2*Cities\_number + a_3*Stores\_quality + a_4*E\text{-}mail + a_5*Viber + a_6*Card\_number + (a_7*Adstock(TV_1) + a_8*Adstock(TV_2) + \ldots + a_n*Adstock(TVn) + d_1*Adstock(OOH) + d_2*Adstock(Radio) + c_1*Adstock(Digital\_video) + c_2*Adstock(Digital\_display) + b_1*Adstock(TV\_Competitor_1) + \ldots + b_m*Adstock(TV\_Competitor_m) + f_3*Adstock(OOH\_competitor_m) + f_4*Adstock(Radio\_competitor_m) + f_1*Adstock(Digital\_video\_competitor_m) + f_2*Adstock(Digital\_display\_competitor_m)) * Media\_efficiency\_index$,

where *Adstock* is the instant, prolonged, and lagged effect of advertising activity on consumer purchase behavior, which indicates the influence of all media activity (in TRPs) during a time. For example, *Adstock* for Digital activity will be calculated like this:

$Adstock(Digital_t) = Digital_t + a*Adstock(Digital_{t-1})$.

For the constructed multiple regression (econometric) models for offline and online traffic on a national scale and for main regions separately, which were estimated by the method of least squares using R-Studio software, the main hypotheses about the adequacy of the models, the significance of the coefficients for all factors, the presence of heteroskedasticity and autocorrelation were tested.

All constructed models undergo quality testing by following main criteria:

1. less than 10% for average error and at least 90% for accuracy;
2. quality of the model by the coefficient of determination $R^2$, which describes the understanding of the dynamics of traffic data due to significant influencing factors at the level of at least 80%;
3. assessment of the contribution of key factors with a probability of 95% (checking of t-statistics and f-statistics with a 95% of confidence level for probability).

In the current crisis, the importance of marketing modeling is growing and is that first, it is necessary on mathematical models, and then in the current market conditions to find the optimization ways for marketing activity of the company in the market, fight with competitors and capture the market and attract new consumers.

Estimation of the influence of marketing factors, comparison of such impact by media channels in terms of efficiency help to form recommendations for media strategy and media budget allocation, prioritize media channels by advertising activity and by the level of media pressure. Such recommendations, as a result, help to increase ROMI (return on media/marketing investments). Scenario forecasting of the different media mix, architecture of media campaigns helps to select the most efficient strategy taking into account memory decay of advertising message, period of activity, and weekly weights.

The marketing mix modeling was deployed taking into account the results of the analysis of consumer journey and consumer behavior after contacts with media channels. There are two alternatives for the transition from awareness and interest to visits. The first one is offline traffic and the second is online traffic, but a lot of people switch between these sales channels. For example, the first visit is online with goals to find product, checking information, availability of products, the next one may be an offline visit and purchase, so there is a growing need to make a ROPO analysis and estimate the real influence of different media channels on business performance.

## 4. Marketing Mix Modeling Results

One of the Ukrainian non-food retailers in recent years has a significant media activity, which has a strong influence on business results. The average growth rate for traffic is about 3-5% and 3-4% for turnover. Online traffic is growing more quickly due to high Internet penetration in Ukraine and online shopping trend. An important part of business growth is increasing sales, which can be achieved by attracting new traffic and maintaining a high level of conversion rate from traffic to purchases. The current media mix of this company mainly consists of TV and Digital. Out of home advertising and Radio are used as additional communication channels with a low share in a budget split of media investment.

The main goal of the research is the construction of marketing mix models for developing of effective media strategy, which can help to increase traffic to the stores and, as a result, the turnover and company's profit. To achieve this goal, we implement a Data Mining process, that allows us to explore in detail the existing problem and find effective business and media solutions through marketing mix modeling of online and offline traffic, respectively. A regression model for each target metrics is a convenient tool for assessing the influence of various internal and external factors on business results. We can estimate brand drivers (for example, marketing factors (penetration, level of store's network, pricing strategy, price promo, etc.), brand's media support, competitor's media activity, macroeconomic external factors (GDP, exchange rate, inflation, consumer's income, average salary, etc.), weather and so on), quantify their individual and synergistic effects, make comparisons between them and realize scenario forecasting for key business metrics.

As a result, we construct qualitative models to determine the impact of factors and make conclusions and recommendations. The average model error was within 5-6% for traffic (offline traffic on a national scale, online traffic on a national scale, offline traffic for key regions, respectively) on a weekly basis and up to 9% on a daily forecasting. The indicator of model quality $R^2$ was from 91% to 97%, which shows the high quality of estimated models and their practical relevance and value for real business application.

We estimated the influence of key factors that determine the traffic level to non-food stores in Ukraine: base level, seasonality, level of development of store's network and consumer's base, dynamics of a number of loyalty cards; advertising activity of the brand and its competitors by media channels, different creatives, video durations, etc.

Media activity provides a significant share of offline traffic - about 16%, an increase in the number of loyalty cards and e-mails, Viber mailing for the CRM base is around 7%. The seasonality contribution is 27%, and the impact of other organic factors is about 57% for the whole period of analysis. The competitor's media activity has a low negative impact. Competitors on average led to a loss of 5-7% of traffic in 2017-2021.

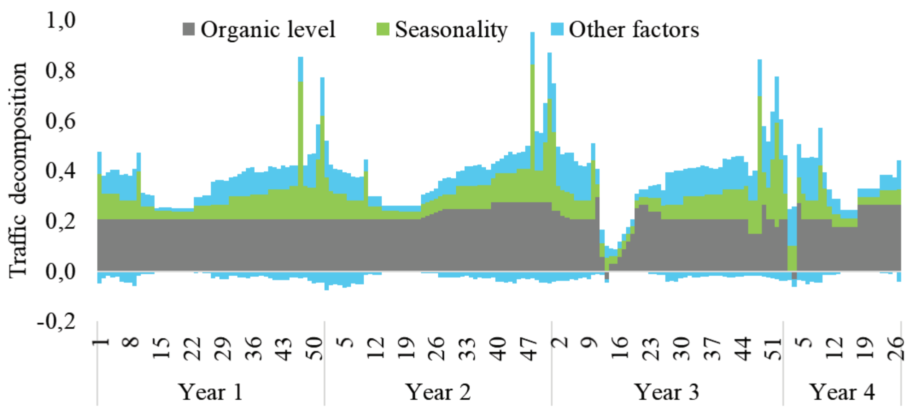
The contribution of media changed during 2017-2021 from 13% to 20% due to changes in media mix (higher or lower share of Radio and Out of Home advertising, different split between TV and Digital, different split by video durations and by digital instruments) and due to different allocation of media activity by periods during a year (high and low season).

Non-media factors are uncontrollable in the short-term period and include organic level (baseline), seasonality, a network of stores and client's base (number of clients, which make purchases regularly and have their own loyalty cards).

The organic level (baseline and expansion of network) generates about 57-64% of traffic to the stores. It includes: brand awareness, the volume of the client base and its expansion, the level of the store's network and its expansion, the level of work with the client base through e-mail and Viber mailings, image and perception of the retailer, previous experience with the company (quality of service, quality of products, etc.), the impact of COVID-19 crisis and lockdown in Ukraine, other factors that can't be quantified and digitized.

Significant seasonality is relevant for this retail subcategory. Consumer demand is growing significantly in the second half of the year. The contribution of seasonality was determined in the model as additive seasonality on a monthly basis. The dynamics of seasonality are the same for both offline and online traffic. Black Friday, Eve of New Year are the highest sales periods during the year.

The seasonal component is one of the key factors, that determine consumer activity throughout the year (Figure 1). The period from January to March and from August to December is the highest period of business activity and, as a result, is a period with traffic growth. The contribution of seasonal fluctuations to traffic varies from 8% to 41% during the year on a monthly basis.



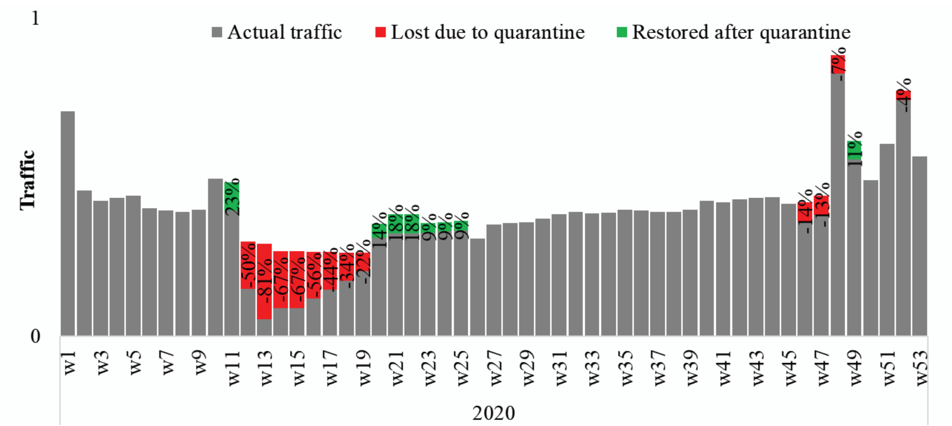

.Source: authors' own work based on data of the retail company

**Figure** 1: Decomposition of Model for Offline Traffic.

So, after the determination of weekly seasonality through marketing mix modeling, we may highlight the periods of a high level of consumers activity and periods for strengthening of media pressure. There are periods of New Year and Christmas, Saint Valentine's Day, Woman's Day, period of Back-to-School Period (from August to October) and Black Friday.

COVID-19 has a significant negative impact on organic levels of offline traffic, but the consumer has almost restored their consumer behavior. Some level of consumer's demand was deferred from the period of lockdown to the next periods. A sharp decline in target audience mobility and income of the population has led to a significant reduction in the offline traffic since the $12^{th}$ week of 2020, but after the quarantine restrictions are canceled, consumer activity is gradually recovering, partially compensating for the loss of lockdowns. So, in the period of lockdown offline traffic lost up to 81%, but after canceled of main restrictions there is additional growth of traffic by 18% on a national scale. In general, there are drops in offline traffic, but this deferred demand compensates for some level of traffic (Figure 2). The impact of COVID-19 on online traffic is quite lower, than on offline traffic.

A brand's media activity and the advertising activity of its competitors are the next groups of factors. There are managed in a short-term period.




.Source: authors' own work based on data of the retail company

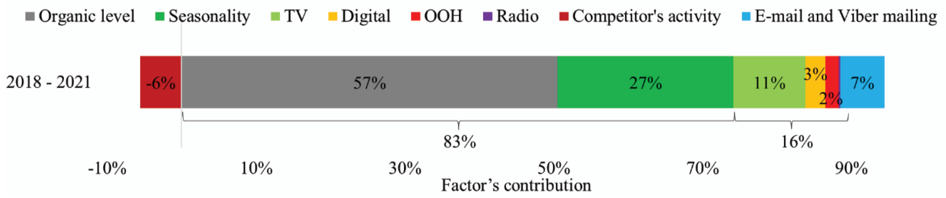
**Figure** 2: Model Decomposition for 2020 and Contribution of COVID-19 and Lockdowns on Offline Traffic.

The increase in the number of loyalty cards and work with them through e-mail and Viber mailing are one of the key instruments that help to increase the brand attractiveness among the target audience. The contribution of these factors to traffic increased from 4% in 2018 to 10% in 2021 due to the growth of the pressure and improvement of loyalty to the brand.

Advertising activities are key levers of influence on traffic in a short-term scale. Brand's advertising activity generates from 9% to 20% of traffic, while competitor's activity leads to loss from 2% to 7%. The fluctuation of media activity contribution by different periods and its growing in previous years are driven by both increased pressure and increased returns on media activity. There is incremental traffic growth by media activity as the contribution of competitor's media support is quite low. From 4% to 17% of traffic to the store is a clear incremental effect in 2017-2021.

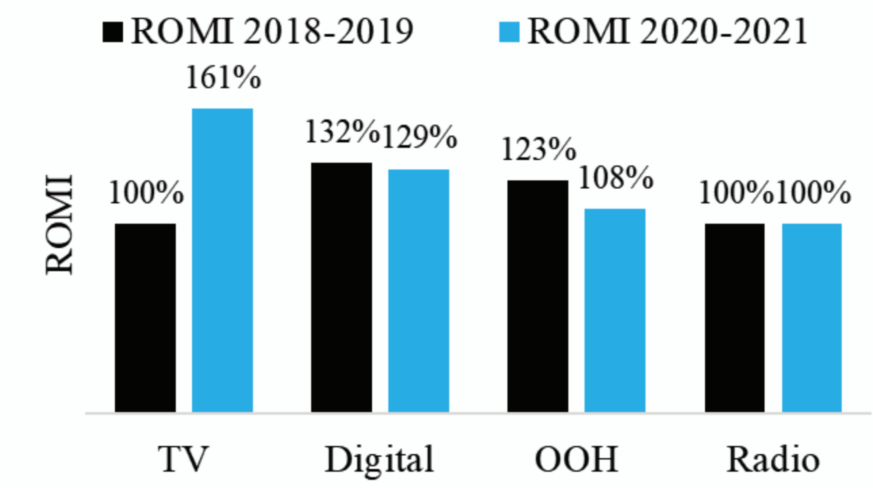
Television is a main driver of traffic with 11% of the contribution in 2018-2021 (Figure 3). The impact of other media channels is around 5% for the analyzed period. The contribution of digital activity is 3%, and the impact of out of home advertising is 2% in 2018-2021 years.

In 2020-2021 the impact of media activity increased to 18%, where 14% was generated by TV and about 4% by non-TV channels. The contribution of OOH dropped from 4% to 0,5% due to decreasing in the volume of media activity and a drop in media response as a result of the lockdown in the period of COVID-19 and a drop in business activity of the target audience in this period. The impact of digital activity is stable during this period, but there is significant growth in the impact of TV support. So, the contribution increased from 11% to 14% with a similar level of media investment. In this case, there are a growth in return on investment and a growth of media efficiency as a result of changes in a split of formats (Figure 4).




.Source: authors' own work based on data of the retail company

**Figure** 3: Decomposition of The Model and Factor's Contribution into Offline Traffic for 2018-2021.




.Source: authors' own work based on data of the retail company

**Figure** 4: Index of ROMI for 2018-2021 (Data Indexed due to Confidentiality).

TV and Digital provide the largest share of both offline and online traffic and have the highest ROMI for this brand on the retail market. We recommend to strengthen the media mix with OOH as regional media and radio as additional media to increase the frequency of contacts.

The impact of the advertising activity to traffic also has fluctuations during the year from 1% to 34% on a monthly basis. The seasonal media response index was estimated by multiplicative seasonality for all advertising factors. Response from advertising activity depends on the seasonality of demand, consumer's business activity during this period, advertising pressure, creative's quality, performance of each media formats, which will be analyzed in details further.

We recommend a continuity presence during the year, but there are periods with different priorities for more effective distribution of media budgets during the year. So, according to the seasonality of traffic and the cost of media placement on TV, we estimate the seasonal ROI for advertising activity, which determines the period for strengthening of media activity and a period for low media pressure.

The period of the first quarter (Q1) and the $3^{rd}$-$4^{th}$ quarters (Q3-Q4) are the main periods of consumer's demand for this category, which determine the highest response from advertising activity. Our recommendation is strengthening of advertising pressure during this period. During a period of lower consumer's activity ($2^{nd}$ quarter – Q2), it is relevant to realize minimal advertising activity as a result of low media efficiency and taking into account that some competitors also reduce their media support in this period of previous years.

Different videos by durations have different efficiency due to diverse messages and diverse quality of contact with potential consumers. Short video durations have the highest media efficiency in a short-term period. The efficiency of the video length is determined by the forgetting of the message (its memory decay indicator) and the level of instant response. According to memory decay, we recommend to realize constant presence during the season with up to 1-2 weeks break between flights, which helps to optimize the architecture of campaigns. After two weeks of break the advertising response (*AdStock*) becomes a minimal.

The specifics of each video lengths leads to different effectiveness of media activity. We recommend to use the mix of long and short video durations to achieve goals for traffic growth in the short-term and long-term periods. Longer videos we need to realize for image campaigns to build loyalty and long-term traffic growth. Short videos are recommended to use for promo campaigns with maximization of frequency of contacts with the target audience for short-term traffic growth throughout the year.

Regular change of creative materials (their rotation) and simultaneous use of different videos help to minimize the wear-out effect of the advertising message and deliver a relevant message to the potential consumers, but also it is necessary to build a single story and brand's image. Advertising activity increases the attractiveness of the store among potential consumers, which converts into traffic and sales.

The Internet is a communication channel number two in the media split. It has a lower impact on offline traffic and works more for the online stores. Media has a significant influence on both offline and online sales: traffic to a website is an indicator of an instant response to media activity, as consumer's need more time to visit offline stores and, as a result, there is also a delay in the effect of media support.

In 2020, due to advertising activity, the company managed to attract additionally +32% of online traffic. TV and Digital have the highest contribution: 19% and 12% respectively. Other communication channels generated up to 1% of online traffic. There is a synergy of

TV and Digital activity on sales channels: online media influence offline traffic and offline activity has a significant impact on online traffic. Digital generates additional reach of the target audience and it is relevant to optimize placement in terms of the optimal and effective cumulative reach of TV and Digital. Video formats are more effective for offline traffic compared to display advertising, but display ads are more effective format for online traffic due to the specifics of the consumer journey. The activity of competitors has a higher impact on online traffic vs on offline traffic: -8% vs -6%, respectively.

Out of home (OOH) and radio advertising activity are effective tools for additional coverage of the target audience, that help to increase business results. Competitor's environment uses this media to work with their potential consumers, but there is decreasing of media presence due to the strengthening of more effective TV and Digital and changes in consumer's behavior and consumer's journey in a period of the COVID-19 crisis and after the pandemic. Reduction of competitor's activity helps to be more visible and, as a result, increases the media response.

On a national scale, the impact of OOH activity is quite low as out of home advertising is a regional media, effect from what is different for each region. So, we built additional regional econometric models for the main regions to form a regional media strategy and control the traffic at the regional scale.

OOH activity is a relevant effective media for regional support of offline stores on the retail market. Based on constructed regression models for two key cities, we estimated, that the impact of out of home activity into offline traffic is 1-2% vs less than 0.5% in national traffic in general. It is relevant to use reach-building solutions for the whole of Ukraine and additional pressure in key regions of presence by OOH, because they have a high potential for business growth.

## 5. Conclusions and Recommendations

We determined and estimated the influence of each communication channels on online and offline traffic (on a national and regional scale). Television provides the largest share of traffic – from 12% to 19%, which varies by key target metrics and has the highest ROI among media channels. TV also has the highest potential for optimization through necessary changes in the media mix by video lengths, formats, and periods of placement. Digital is communication channel number two by its contribution to traffic – from 3%-5% for offline traffic to 12% for online traffic. OOH is a good tool for regional media support and its impact for main regions is 1-2% for offline traffic. Radio activity leads to additional demand in the period of high sales season (up to 10% in the period of advertising campaigns). Our recommendation is to continue media activity taking into account all learnings from marketing mix modeling.

Optimization of media plans after marketing mix modeling realization helps to achieve the growth of general traffic level by 4%, traffic, which was generated by media – by 44%, so we have improvement of media efficiency by 40%. The construction of the model and their regular support enable to maximize the impact of each media channel, which ultimately allows to achieve the higher business KPIs by the current existing marketing budget. ROI optimization is by 40%.

Advertising activity helps to maintain permanent communication with potential consumers and achieve the traffic growth by 5-10% per year. Estimation of the impact of different media and marketing factors makes it possible to optimize media strategy and media tactics (media mix and advertising investment distribution by different formats, periods, etc.).

Key learnings and conclusions from marketing mix modeling for traffic to the stores are:

1. Television is the main media channel that leads to the growth of traffic (both offline and online) and has the highest ROMI in 2020-2021. During the COVID-19 crisis, the media response from TV activity significantly growth due to increased TV viewing and reduced mobility of consumers outside the home. The efficiency of TV activity varies during the year: the highest response is in Q1 and Q3-Q4.

2. Video formats with different durations perform different business and media tasks: short video has a higher response to traffic. Regular rotation of the videos minimizes the wear-out effect of the advertising message and maintains a competitive advantage. The effectiveness of media support decreases within 1-2 weeks: permanent support is needed.

3. Digital activity generates additional offline/online traffic and is the channel number two in the media mix with significant potential for strengthening. The media response from Digital activity is unchanged during the COVID-19 crisis.

4. Out of home and radio advertising lead to increasing of media contact's frequency and attracting a new audience to online and offline retail stores. OOH advertising has a significant drop in media response during the COVID-19 pandemic due to reduced mobility of consumers, so we need to compensate for this decrease by others media channels to maintain business results.

5. Competitor advertising activity has a low negative influence on offline traffic. During the main holidays and sales periods, the category also drives consumer's

demand for all category players. So, our recommendation is to realize a strategy of optimal target audience reach.

We formed recommendations to achieve maximal efficiency from media strategy. The main ones are:

1. Continuity presence with optimization of general target audience reach with the achievement of competitive share of voice (SOV) in all communication channels.
2. Realize the main advertising activity on TV and Digital in the period from Q3 to Q1 and reduce activity from the second half of March to the end of June (only maintaining campaigns).
3. Optimize the reach of the target audience on holidays without overspending. It is not relevant to achieve leading SOV during this period.
4. Concentration of video formats on TV and Digital during the year. It is relevant to expand media presence in digital, OOH and radio to build a wide coverage of the target audience, to achieve an additional frequency of contact with the potential consumers.
5. Maximization of advertising with short lengths of the videos, that help to increase traffic in the short term, but it is relevant to add image communication with longer videos for the long-term growth of online and offline traffic.
6. It is necessary to adapt the media mix in the future period of COVID-19 restrictions or similar market conditions, reduce the pressure in ineffective media channels and increase in communication channels with higher efficiency.

Marketing mix modeling is an effective tool for business management, as it generates the opportunities to quantify the impact of each factor on traffic and sales, estimate their optimal mix for the achievement of business KPIs and improvements the company's position on the market, effective marketing or media budgets allocation and scenario forecasting. Regular model support makes it possible to increase the return on each factor, improve ROMI. Marketing mix modeling creates the basis for making effective marketing solutions and forming an effective business development strategy. In the case of regular support of marketing mix modeling projects for the company, we may to determine business tasks depending on different time intervals.

We ensure the achievement of business goals in the most efficient way due to the realization of marketing mix modeling. Econometric modeling and deeper data analysis implementation have a significant economic effect on business performance as help to optimize media efficiency and increase ROMI by up to 40% for this Ukrainian company on the non-food retail market. The results of the research can be used for all enterprises in the retail category (food and non-food) both in Ukraine and abroad.

Marketing mix modeling approaches can be used to solving actual business and economics problems, which are related to the influence of marketing mix elements and other market conditions, so the results correspond to the continuing process of marketing methodology development and research can be used to further development of mathematical methodology in marketing and its application to solve current tasks of the global marketing.

To expand this scientific research in the future, it is planned to delve into regional analytics and modeling for all regions of business presence to cluster cities and optimize regional marketing strategy, as well as continue research on the effectiveness of creative materials and advertising messages on traffic and sales for various categories of products to find additional hidden solutions and increase business efficiency in the future.

# Appendix

Table 1: Technical Characteristics of Constructed Model.

| Indicator | Coefficient | Stand. Error | t-statistics | P-value |
|---|---|---|---|---|
| Constant | 3004,37 | 51,45 | 58,39 | 0,0 |
| Additive_seasonality | 1,08 | 0,06 | 16,92 | 0,0 |
| Covid_19 | 1,06 | 0,10 | 10,97 | 0,0 |
| E-mail and Viber | 10,46 | 3,16 | 3,31 | 0,0 |
| TV1 | 128,33 | 0,61 | 210,38 | 0,0 |
| TV2 | 110,62 | 0,85 | 130,14 | 0,0 |
| TV3 | 275,68 | 2,33 | 118,32 | 0,0 |
| Digital_video | 76,27 | 10,10 | 7,55 | 0,0 |
| Digital_display | 48,61 | 7,25 | 6,70 | 0,0 |
| OOH | 42,74 | 3,02 | 14,15 | 0,0 |
| Radio | 28,61 | 0,37 | 77,32 | 0,0 |
| Competitors | -5,93 | 0,12 | -49,42 | 0,0 |
| Multiple / Adjusted $R^2$ | 0,91 / 0,90 | F-statistics | 368,32 | P-value 0,0 |

Source: authors' own work based on data of the retail company.

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