Forecasting And Predictive Analytics

Student Name

Instructor Name

Institution Name

Submission Date

Abstract

Marketing campaign is an important process for improving overall growth and performance of the company as it enables the business to increase its brand awareness and achieve specific goals. The primary aim of this study was to formulate a predictive model using forecasting and predictive analytics to analyse performance of marketing campaigns and establish principal factors that influence their contributions to success and failure. In order to achieve this goal, this study adopted secondary quantitative research with the collected marketing campaign data analysed using R-Studio software through forecasting and predictive analytics. Results from the conducted analysis demonstrated that there is a positive relationship between impressions and clicks, and impressions and engagement scores generated during the marketing campaign process. However, none of these relationships were statistically significant which is an indication that there are other additional factors that influence ability of the adopted marketing campaign method to generate expected results from the targeted customers.

Keywords: marketing campaign, forecasting and predictive analytics

Table of Contents

Abstract....2

List of Figures....4

Introduction....5

Aim and Objectives of the Study....6

Research Aim....6

Research Objectives....6

Literature Review....6

Business Case Study....9

Data Exploration....9

Data Experimentation....9

Data Preparation....9

Data Manipulation....10

Data Analysis-Basic....11

Visualization of Selected Variables for Forecasting....12

Results....15

Classification....15

Linear Regression....15

Evaluation of Forecasting and Predictive Analytics Models....17

Discussion and Conclusion....18

Future Research Directions....20

Limitations of the research....21

Reflect on professional, ethical, and legal issues....21

References....22

List of Figures

Figure 1: Data Preparation..10

Figure 2: Data Summary..11

Figure 3: Descriptive Statistics..12

Figure 4: Plot for Impressions vs. Date...13

Figure 5: Plot for Date vs. Clicks..14

Figure 6: Plot for Date vs. Engagement Score..14

Figure 7: Impression and Clicks Correlation Analysis.................................16

Figure 8: Histogram for Clicks Frequency...16

Figure 9: Impression and Engagement Scores Correlation Analysis...........17

Figure 10: Histogram for Engagement Scores Frequency...........................17

Introduction

Digital marketing tools and social media benefits businesses regardless of size and category; they magnify small and medium enterprises, even those in the construction industry. Firstly, Dwivedi et al. (2021) reported that the Internet and social media can cut media costs by providing an alternative means of communication with an audience to extend the reach but at a more manageable level. According to Rissman et al. (2020), traditional advertisers in the housing and construction industries may spend 6-11% of their annual revenue, as much as Deloitte has witnessed. Still, this number is expected to rise even more, and companies are now increasingly spending up to 60% of their marketing spending on Internet marketing (Leong et al., 2021). The Internet has presented no technical problems that impede the purchase of display ads or paid searches. At the same time, social media marketing has been an avenue in which a company can make great content and share it with its followers.

Moreover, digital marketing helps construction companies gain recognition, spread information about their products and services, and position themselves as key market participants. However, regular sharing of valuable content, including project progress, management advice, interviews with industry professionals, or site life videos, will help a company to establish itself as a reliable source of information within the construction sector. Of utmost importance is the fact that social media network sites promote direct contact with the potential consumer.

Companies can use these platforms to respond to customer queries, conduct knowledge sessions to demonstrate their knowledge and competence and gain the customers' trust through endorsements and positive reviews. Social media can also increase brand equity, which can happen when brand recognition, relationship, and quality are positively altered. In addition, Makridakis et al. (2022) reported that brand equity, which can be defined as the index of brand strength and brand value, will be acquired using social media, which ordinarily will be used to address the track record of the industry, the value that the consumers may generate with the products display and a positive image through community service.

Aim and Objectives of the Study

Research Aim

The primary aim of this study was to formulate a predictive model using forecasting and predictive analytics to analyse performance of marketing campaigns and establish principal factors that influence their contributions to success and failure.

Research Objectives

- To identify the impacts of types of campaigns, characteristics of the target audience and the adopted campaign channels on the rate of conversion, acquisition rate and return on investment.
- To explore the impacts of campaign type on the relationship between impressions and clicks registered during the marketing campaign process.

- To assess the effects of campaign durations on the relationship between impressions and engagement score among the target customers during the marketing campaign.

Literature Review

Social media has the potential to win customers' trust and confidence and provide the industry with a high level of customer experience marred with customer complaints due to the use of social media. Moreover, a recent survey conducted by Evans and Mathur (2018) indicated that many people are involved in the Internet as its users suppose there is a greater need to conduct research after acquiring specific information available for free or paid online. Companies nowadays can outsource very little information about their consumers, such as the market's environment, their rivals and the customers' requirements, much of which comes from social media users. Customers collect and circulate data and opinions through social media sites as active generators of the social media system. On the other hand, research proved that social media user-generated content and electronic word-of-mouth positively affect purchase intention (Leong et al., 2021). The implication for businesses is that interactions may be done all day long on social media lines; how they manage the situation will determine whether they survive in this new era of marketing or not. However, the dawn of this era has made matters tricky or has created issues in designing and implementing successful market strategies. The online market adopts the attributes of customers having more control while firms see direct relationships (Henley et al., 2020). Another point is an increase in channel fragmentation (increasing channel segments carrying fewer people on each compared to channel centres) coupled with the customers' evolving needs (about channel introduction and developed demands).

Successful companies should not only come up with a breath of commodities and services but also argue to themselves in case their current channels will continue to evolve as well as have to puzzle over in case they face a broadened view of distribution strength, which is particularly relevant to the much talked about channels evolution. Research conducted by Javaid et al. (2022) indicated that the analysis has shown, too, that as technology takes away jobs, companies strive to build these new systems as fast as possible so that they can function again with new thinking, new strategies. Modern marketing strategies need this foresight, which considers emerging trends and new disruptors, willingness to test new marketing approaches, and a marketing approach that goes through many layers to meet the customer's needs (Evans and Mathur, 2018). It creates another challenge: hiring competent professionals to fulfil the paramount marketing positions in many organizations remains challenging as more companies try to differentiate themselves from the competition through marketing (Leong et al., 2021). One of the most annoying factors for businesses is the need for more professionals who are well-versed in marketing strategies in social media, big data, artificial intelligence, digital media.

Furthermore, Leppäniemi and Karjaluoto (2020) reported that this kind of people tends to focus on trendy, hi-tech employers who offer good benefits to attract them other than large companies, leaving small firms usually with no qualified employees. Organizational problems could hinder firms, and with managerial inflexibility, catering for these questions may be challenging. In other words, they could be very good at different marketing skills, and others still need to gain this former ability, which may no longer be relevant, preventing new ideas from development either. Consequently, they have yet to try and test or explore several marketing avenues, resulting in inefficient expenditures (Constantinescu, 2019). The analogous problem arises between the businesses that need more time to analyze their marketing campaigns. Consequently, they need to catch up in the mechanism of their marketing strategies, which would be more fruitful (de Ruyter et al., 2022). The situation has changed dramatically since the appearance of many new players who need more time to digest and analyze the available data and determine the right strategy. Circumstances make it difficult for companies – and, again, smaller businesses – to cope with the new reality of a constantly evolving world where breakthroughs in technology and internet marketing occur almost daily. According to Henley et al. (2020), in the wake of these resource- and technology-based constitutionality matters, firms are consequently compelled to embark on adopting the most novel and technologically advanced marketing tools to boost brand awareness, target new demographics, interact with emerging customers and eventually climb the market ladder.

Business Case Study

The Marketing Campaign Performance Dataset included in this analysis presents valuable information about the efficiency of different marketing approaches. Precisely, the dataset provides detailed description of the performance metrics, target audience, duration, channels used, in addition to other factors that influence overall success of a marketing campaign process. Therefore, marketers and data analysts are able to use this data to develop an in-depth understanding of different factors that influence marketing campaign success. The dataset serves as an important source for marketing research, data-driven decision-making process.

Data Exploration

In the exploration of the marketing campaign data for forecasting, emphasis was placed on the adoption of forecasting and predictive analytics techniques. Precisely, this process was initiated by comprehensive assessment of the quality of data, such as handling the missing values, performing appropriate transformations in addition to the identification of outliers. Furthermore, different techniques such as data loading and attachment, and application of different functions such as head(), str(), and summary() in R programming environment was very essential at this stage. Different text preprocessing techniques were then applied to prepare the collected data for further analysis, these include removal of special characters and conversion to lowercase.

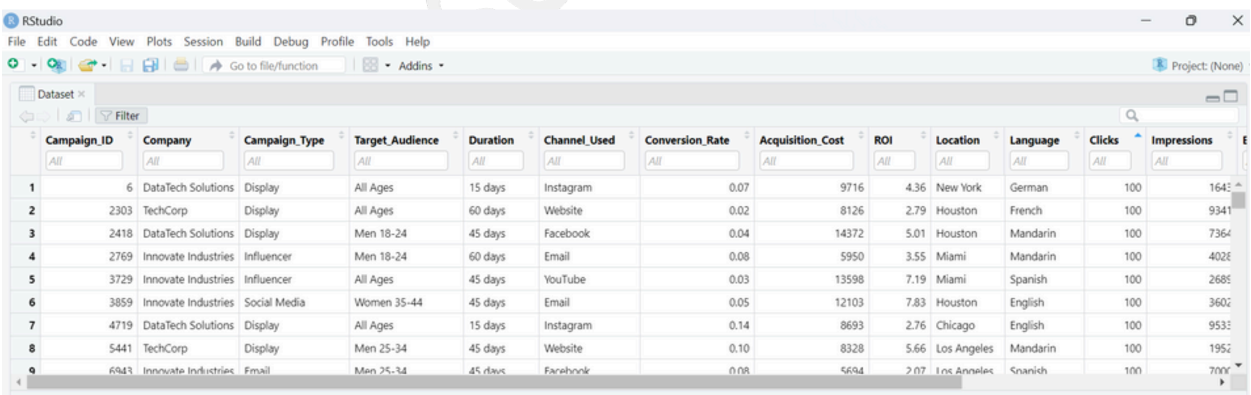
Data Experimentation

Data Preparation

During the data preparation process, the identified dataset was cleaned and transformed to improve its integrity and quality prior to the actual analysis. The missing values were removed using na.omit() function. Furthermore, all the selected variables from the dataset were standardized in order to facilitate effective comparison as well as interpretation across the different features of the datasets. The following R codes were used for the data preparation process.

#Remove observations with missing values

#Standardize variables



	Campaign_ID	Company	Campaign_Type	Target_Audience	Duration	Channel_Used	Conversion_Rate	Acquisition_Cost	ROI	Location	Language	Clicks	Impressions
1	6	DataTech Solutions	Display	All Ages	15 days	Instagram	0.07	9716	4.36	New York	German	100	164
2	2303	TechCorp	Display	All Ages	60 days	Website	0.02	8126	2.79	Houston	French	100	9341
3	2418	DataTech Solutions	Display	Men 18-24	45 days	Facebook	0.04	14372	5.01	Houston	Mandarin	100	736
4	2769	Innovate Industries	Influencer	Men 18-24	60 days	Email	0.08	5950	3.55	Miami	Mandarin	100	402
5	3729	Innovate Industries	Influencer	All Ages	45 days	YouTube	0.03	13598	7.19	Miami	Spanish	100	268
6	3859	Innovate Industries	Social Media	Women 35-44	45 days	Email	0.05	12103	7.83	Houston	English	100	360
7	4719	DataTech Solutions	Display	All Ages	15 days	Instagram	0.14	8693	2.76	Chicago	English	100	953
8	5441	TechCorp	Display	Men 25-34	45 days	Website	0.10	8328	5.66	Los Angeles	Mandarin	100	195
9	6943	Innovate Industries	Email	Men 25-34	45 days	Facebook	0.08	5694	2.07	Los Angeles	Spanish	100	700

Showing 1 to 9 of 200,000 entries, 16 total columns

Figure 1: Data Preparation

Data Manipulation

Filtering and aggregating approaches were applied in order to extract most appropriate information from the dataset for forecasting and predictive modeling. Precisely, the filtered data included only those with information relevant to the marketing campaign analytics. The aggregation process was conducted to summarize data from the dataset based on their predefined groups or variables. Reported findings are shown in the Figure 2 below. The following R codes were applied:

#Filter data

#Aggregate data

```
> summary(Dataset)
  Campaign_ID        Company           Campaign_Type      Target_Audience       Duration
 Min.   :     1   Length:200000      Length:200000      Length:200000      Length:200000
 1st Qu.: 50001   Class :character   Class :character   Class :character   Class :character
 Median :100001   Mode  :character   Mode  :character   Mode  :character   Mode  :character
 Mean   :100001
 3rd Qu.:150000
 Max.   :200000
 Channel_Used       Conversion_Rate   Acquisition_Cost       ROI            Location
 Length:200000      Min.   :0.01000   Min.   : 5000    Min.   :2.000   Length:200000
 Class :character   1st Qu.:0.05000   1st Qu.: 8740    1st Qu.:3.500   Class :character
 Mode  :character   Median :0.08000   Median :12496    Median :5.010   Mode  :character
                    Mean   :0.08007   Mean   :12504    Mean   :5.002
                    3rd Qu.:0.12000   3rd Qu.:16264    3rd Qu.:6.510
                    Max.   :0.15000   Max.   :20000    Max.   :8.000
   Language             Clicks         Impressions     Engagement_Score Customer_Segment
 Length:200000      Min.   : 100.0   Min.   : 1000   Min.   : 1.000   Length:200000
 Class :character   1st Qu.: 325.0   1st Qu.: 3266   1st Qu.: 3.000   Class :character
 Mode  :character   Median : 550.0   Median : 5518   Median : 5.000   Mode  :character
                    Mean   : 549.8   Mean   : 5507   Mean   : 5.495
                    3rd Qu.: 775.0   3rd Qu.: 7753   3rd Qu.: 8.000
                    Max.   :1000.0   Max.   :10000   Max.   :10.000
      Date
 Min.   :2021-01-01 00:00:00.0
 1st Qu.:2021-04-02 00:00:00.0
 Median :2021-07-02 00:00:00.0
 Mean   :2021-07-01 23:35:09.5
 3rd Qu.:2021-10-01 00:00:00.0
 Max.   :2021-12-31 00:00:00.0
```

Figure 2: Data Summary

Data Analysis-Basic

Both descriptive statistics and correlation analyses were performed on the R-studio to determine the direction of relationships between the variables in the dataset allowing for effective forecasting and predictive analytics. Precisely, the conducted descriptive statistics provided in-depth information about the tendency, dispersion, and distribution of variables.

On the other hand, correlation analysis assessed the direction and strength of relationship between the included variables. Results are reported in the Figure 3. The following R codes were applied at this stage:

#Attach (Dataset)

#Library(fBasics)

#Summary (Campaign_Type)

#Summary (Conversion_Rate)

#basicStats(data.frame(Conversion_Rate,Acquisition_Cost,ROI,Clicks,Impressions,Engagement_Score))

```
> options(scipen = 999)
> options(scipen = 999)
> basicStats(data.frame(Conversion_Rate,Acquisition_Cost,ROI,Clicks,Impressions,Engagement_Score))
            Conversion_Rate  Acquisition_Cost          ROI          Clicks
nobs          200000.000000     200000.000000  200000.000000   200000.000000
NAs                0.000000          0.000000       0.000000        0.000000
Minimum            0.010000       5000.000000       2.000000      100.000000
Maximum            0.150000      20000.000000       8.000000     1000.000000
1. Quartile        0.050000       8739.750000       3.500000      325.000000
3. Quartile        0.120000      16264.000000       6.510000      775.000000
Mean               0.080070      12504.393040       5.002438      549.772030
Median             0.080000      12496.500000       5.010000      550.000000
Sum            16013.930000 2500878608.000000 1000487.570000 109954406.000000
SE Mean            0.000091          9.699313       0.003878        0.581420
LCL Mean           0.079892      12485.382621       4.994836      548.632460
UCL Mean           0.080248      12523.403459       5.010039      550.911600
Variance           0.001648   18815333.704718       3.008450    67609.909369
Stdev              0.040602       4337.664545       1.734488      260.019056
Skewness          -0.003411          0.001846      -0.005043        0.001423
Kurtosis          -1.177330         -1.203020      -1.203389       -1.199918
                 Impressions  Engagement_Score
nobs           200000.000000     200000.000000
NAs                 0.000000          0.000000
Minimum          1000.000000          1.000000
Maximum         10000.000000         10.000000
1. Quartile      3266.000000          3.000000
3. Quartile      7753.000000          8.000000
Mean             5507.301520          5.494710
Median           5517.500000          5.000000
Sum        1101460304.000000    1098942.000000
SE Mean             5.806765          0.006423
LCL Mean         5495.920401          5.482121
UCL Mean         5518.682639          5.507299
Variance      6743704.121216          8.251723
Stdev            2596.864286          2.872581
Skewness           -0.004118          0.002551
Kurtosis           -1.195519         -1.225538
```

Figure 3: Descriptive Statistics

Visualization of Selected Variables for Forecasting

The selected variables from the dataset were then visualized using plots and charts in order to gain in-depth information about the trends and relevant patterns for forecasting in the marketing campaign domain. Precisely, the visualization process at this stage provided a graphical representation of data, relationships between the variables as well as the trends overtime. Results are reported in the Figure 4, 5 and 6 below. The following r codes were used for creating visualization using ggplot2:

```
#library(ggplot2)
#ggplot(Dataset,aes(x=Date,y=Impressions))+geom_line()
#ggplot(Dataset,aes(x=Date,y=Clicks))+geom_line()
#ggplot(Dataset,aes(x=Date,y=Engagement_Score))+geom_line()
```

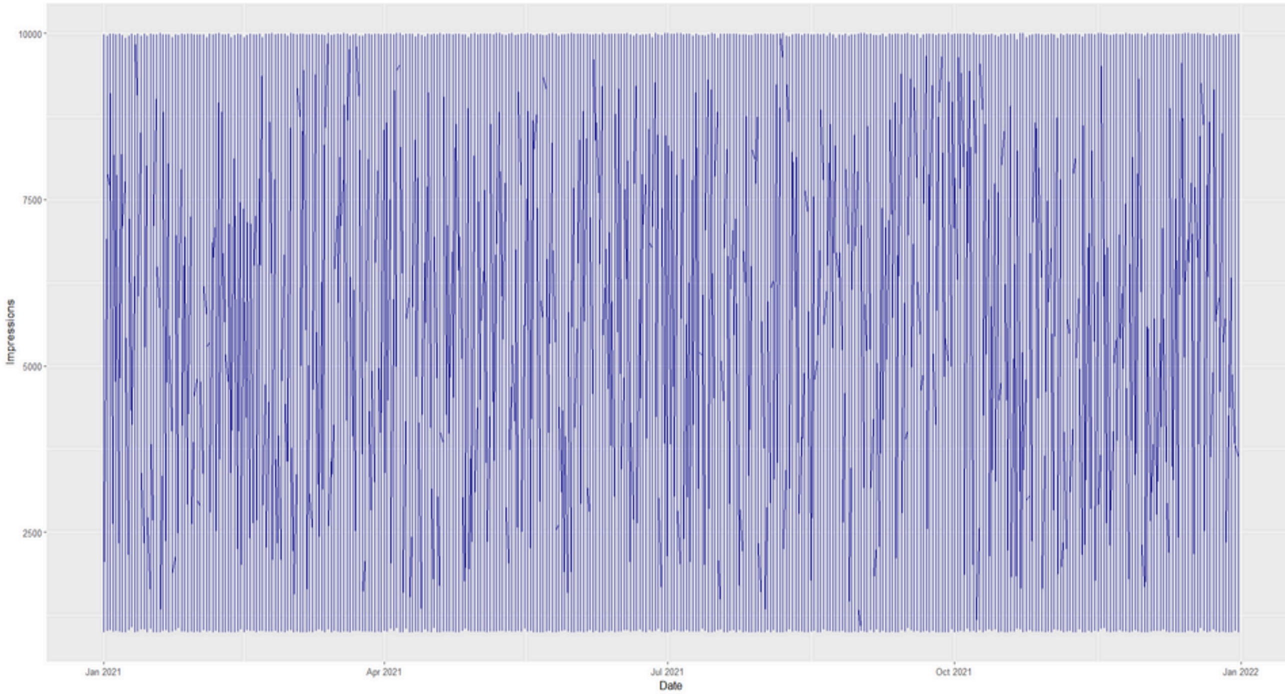


Figure 4: Plot for Impressions vs. Date

Results reported in the Figure 4 above shows that impressions generated by the adopted marketing campaign approach significantly increased with time. This is an indication that the positive effects of the adopted marketing campaign could not be experienced at early stages of the campaign.

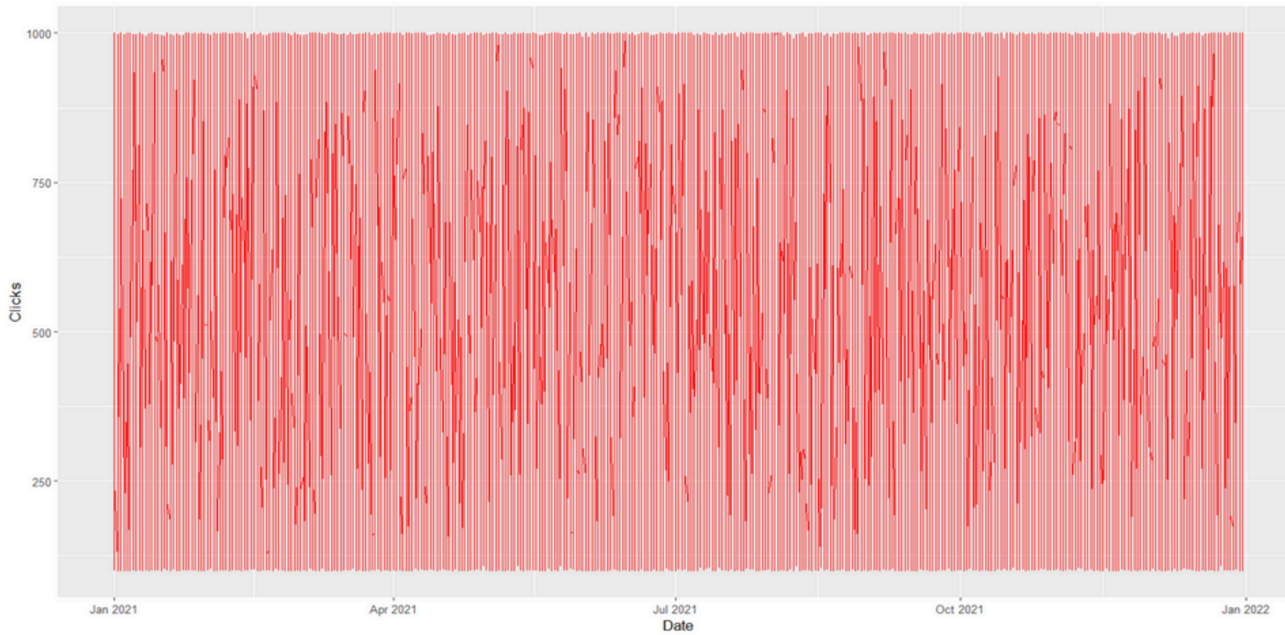


Figure 5: Plot for Date vs. Clicks

Results reported in the Figure 5 above shows that the relationship between campaign data and clicks significantly varied. Precisely, the results demonstrated that the number of clicks significantly increased with time.

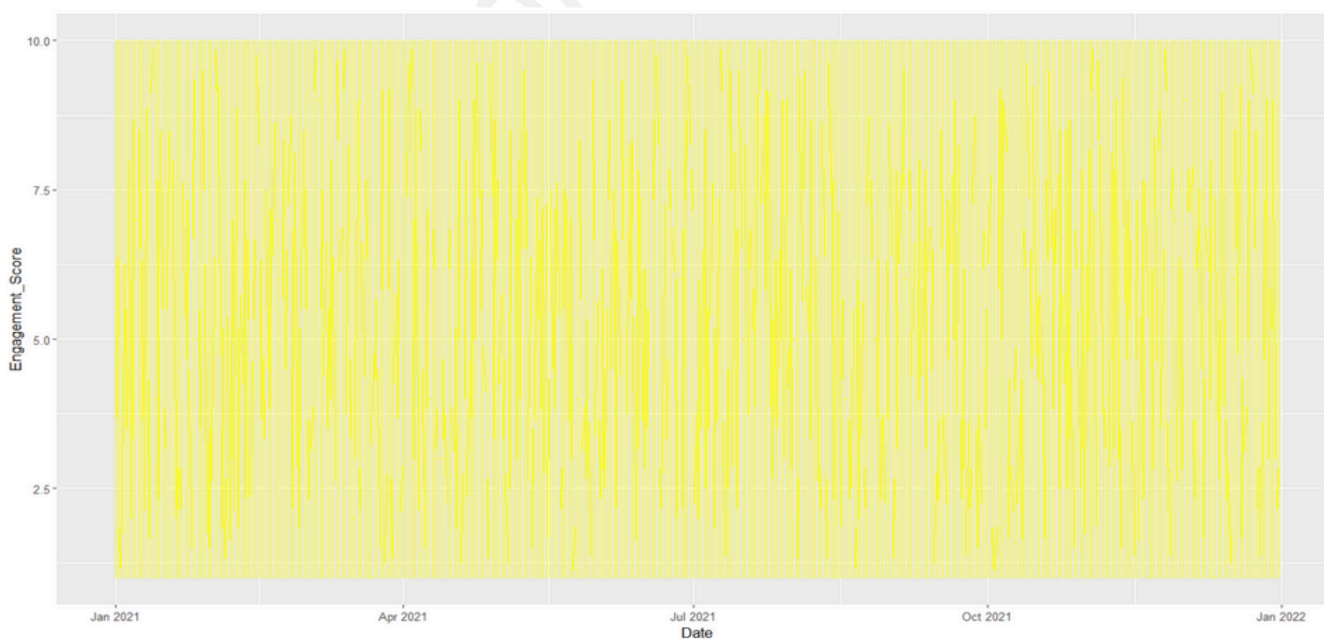


Figure 6: Plot for Date vs. Engagement Score

Results reported in the Figure 6 shows that the volume of engagement scores varied depending on time when the campaign was conducted. Therefore, there is need for the companies conducting the marketing campaign to understand the specific dates or time when engagement scores among the customers are high for positive results to be registered.

Results

Classification

First, three models were fitted in order to predict whether type of campaign adopted had higher or lower impression levels among the target customers. Thereafter, model train control analysis was conducted as an approach for ensuring that all the models were equality included in the analysis. Each model was trained using cross-validation. Furthermore, the optimal model was used for developing predictions on the data. In the present analysis, confusion matrix was applied in order to evaluate each classification model as well as to develop a strong comparison between the performances of the models using balanced accuracy.

Linear Regression

A linear regression analysis was performed in order to assess the factors which influenced the effectiveness of marketing campaign approach adopted by different companies. Precisely, the primary objective of the conducted linear regression was to assess whether clicks, impressions and engagement scores were influenced by the type of marketing approach adopted.

First, the linear regression analysis was conducted to model the relationship between impressions and clicks, with the clicks being the outcome or dependent variable. A correlation analysis between Impressions and Clicks was conducted with the results showing that true correlation is not equal to 0; with a p-value of 0.9882 as shown in the Figure 7 and 8 below.

```
> cor(Impressions, Clicks)
[1] 3.306901e-05
> cor.test(Impressions,Clicks)

        Pearson's product-moment correlation

data:  Impressions and Clicks
t = 0.014789, df = 199998, p-value = 0.9882
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.004349549  0.004415686
sample estimates:
         cor
3.306901e-05
```

Figure 7: Impression and Clicks Correlation Analysis

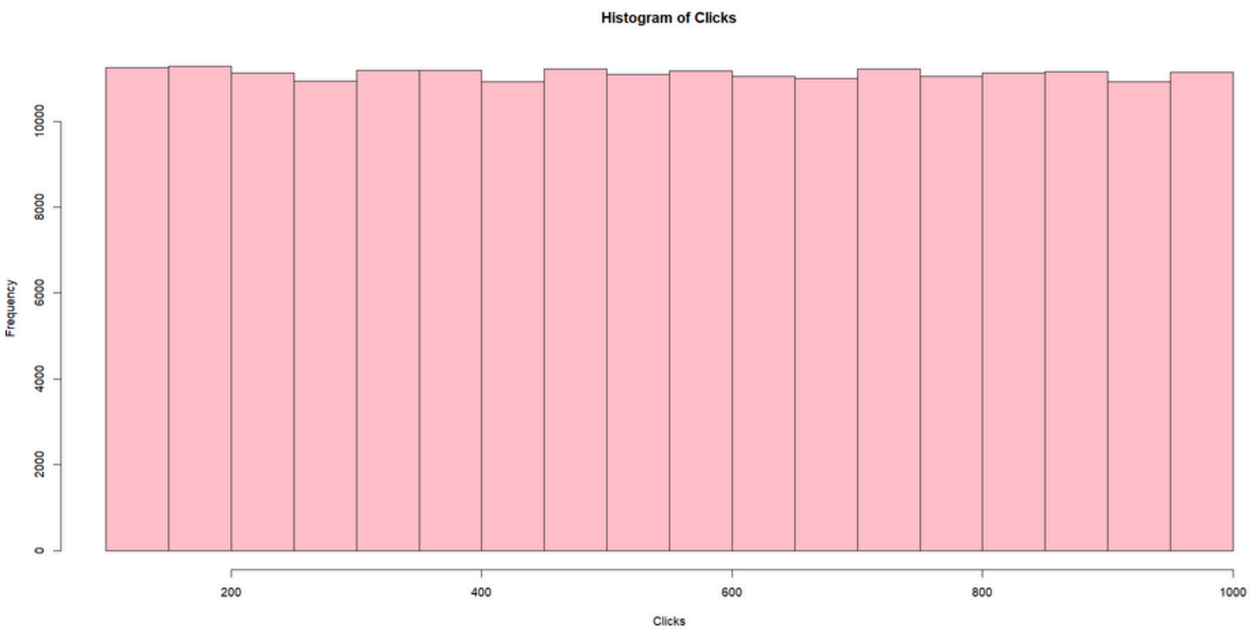


Figure 8: Histogram for Clicks Frequency

Secondly, regression analysis was conducted to model the relationship between impressions and engagement scores. The reported results from this conducted analysis are presented in the Figure 9 and 10 below. The conducted correlation analysis established that there is no significant relationship between impressions and engagement scores, with a p-value of 0.1754.

```
> cor.test(Impressions,Engagement_Score)

        Pearson's product-moment correlation

data:  Impressions and Engagement_Score
t = 1.3549, df = 199998, p-value = 0.1754
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 -0.001352922  0.007412233
sample estimates:
        cor
0.003029714
```

Figure 9: Impression and Engagement Scores Correlation Analysis

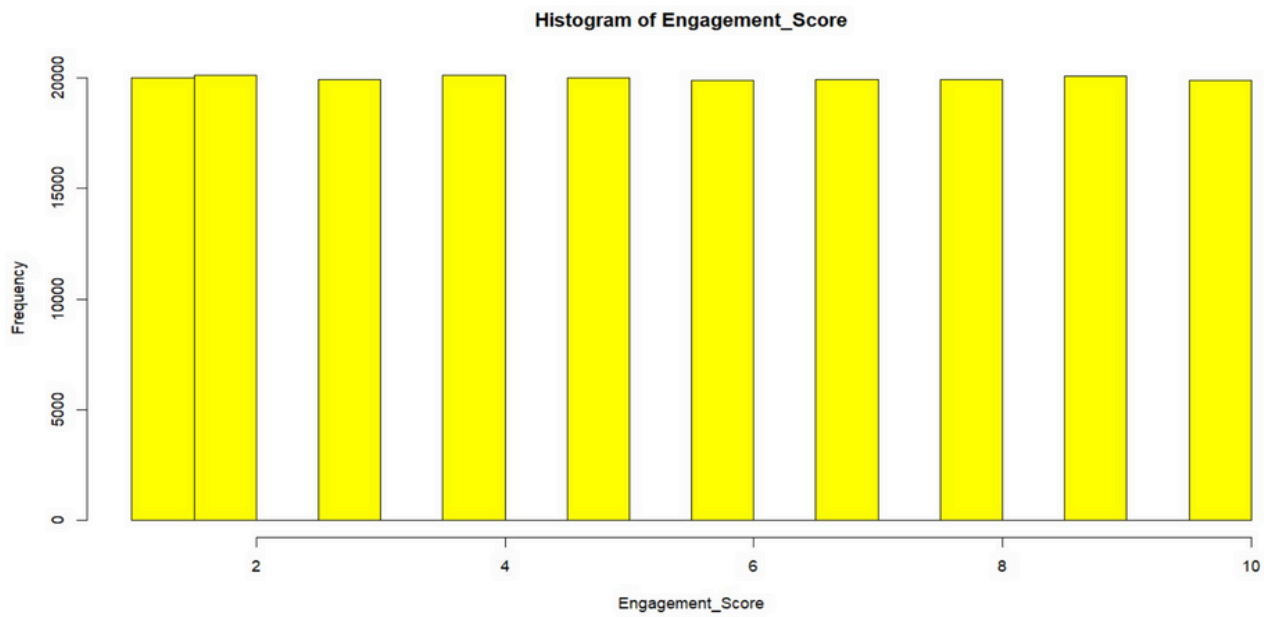


Figure 10: Histogram for Engagement Scores Frequency

Evaluation of Forecasting and Predictive Analytics Models

The evaluation of forecasting and predictive analytics models provides valuable insights into the effectiveness of different marketing campaign approaches that were adopted in this study. Through in-depth analysis of relationships between different variables such as impressions and clicks as influenced by campaign method, and relationship between impressions and engagement scores as influenced by the duration of conducting the campaign, it was easier to effectively determine the impacts of different modelling approaches. The conducted linear regression analysis demonstrated that there is a positive correlation between impressions produced by the marketing campaign approach used and the final clicks received from the target customers. Nonetheless, this relationship was not statistically significant as the p-value>0.05. This is an indication that ability of the target customers to click on the marketing campaign products shared to them may be influenced by other factors apart from the marketing campaign method adopted.

Furthermore, the conducted analysis demonstrated that the duration of marketing campaign significantly impacted the relationship between generated impressions and engagement scores. Nonetheless, the reported p-value was greater than 0.05 which is an indication that the relationship was not statistically significant. Therefore, this was an indication that the relationship between impressions and reported engagement scores among the customers was influenced by other factors apart from the duration of the campaign.

Discussion and Conclusion

The first objective of this study was to identify the impacts of types of campaigns, characteristics of the target audience and the adopted campaign channels on the rate of conversion, acquisition rate and return on investment. The conducted analysis revealed that these factors play a central role in influencing the effectiveness of adopted marketing campaign. Previous research studies by Dwivedi et al. (2021) and Javaid et al. (2022) have concentrated on examining the impact of different campaign types, attributes of target audience segments, and the campaign channels on the marketing effectiveness indicators. However, this research sought to refrain from a singular focus on any of these three factors while the role that they play, either individually or in unison, towards enhancing conversion rates, acquisition rates, and ROI will be examined here. Although there are some investigations that focus on the two-injection method to evaluate the interaction between two factors, such as the studies by Alghamdi and Agag (2024) and Leppäniemi and Karjaluoto (2020), the type of the campaign and its audience characteristics analysing all three factors comprehensively has not been investigated as extensively. In line with this objective, it is anticipated that the results of this study will corroborate the current literature on the subject that effective and carefully crafted campaigns that target a particular segment of consumers through the suitable channels should result in higher conversion rates, higher rate of acquisition.

The second objective of this study was to explore the impacts of campaign type on the relationship between impressions and clicks registered during the marketing campaign process. Based on the reported findings, it can be noted that the type of marketing campaign adopted has significant impacts on the relationship between the generated impressions and clicks. In the field of marketing, it is already known that there is a direct relationship between the number of aired impressions (exposures) and the number of clicks (user responses). However, these findings are contrary to those reported in the previous analysis by Constantinescu (2019) which established that the moderating role of marketing campaign type with the respect to the campaign type has not yet been explored in the literature comprehensively. This research question intends to know if the closeness or distance in the degree of interaction depends on the type of campaign. Earlier studies have virtually confined themselves to the general disposition-impressions-clicks nexus without taking into account the possibility of a moderation by type of campaign (Henley et al., 2020). The result of this analysis could indicate whether some types of campaigns are better at converting impressions to clicks and why this might be so, by relevance and topicality and other factors that can influence creative and likelihood of click through.

The third objective of this study was to assess the effects of campaign durations on the relationship between impressions and engagement score among the target customers during the marketing campaign. The reported findings showed that the relationship between impressions and engagement score is influenced by campaign durations, but the relationship was not statically significant. Engagement rates are normally the measures that reflect the overall degree of consumer interest and activity regarding a specific advertisement (Evans & Mathur, 2018). To sum this up, while many previous studies focused on the effects of campaign duration on impression and engagement scores, the effect of impressions on engagement scores has not drawn massive research measurements. Based on this idea, the current study therefore seeks to find out whether campaigns of shorter duration have similar impressions engagement relationship to those that span for a longer period (Leong et al., 2021). Such insights may imply decaying effectiveness over time, which might require either a change in the campaign or the need to shift to a new campaign altogether or an indication of the desired duration exposure level. Therefore, this objective is important in helping the research present profound information on best practices in managing extended times of a campaign as well as the highs and lows of engagement all through the campaign period. **Future Research Directions**

Findings of this research can inform additional investigation in the following aspects. In future research future investigations could examine how particular campaign variables might influence particular industry segments or merchandise classifications. When researching, potential topics for further analysis could involve assessing the effectiveness of new forms of marketing communication, including influencer marketing and social commerce, on campaign outcomes. Other important sources of literature could be the longitudinal studies of the impact of campaign strategies involving customer loyalty, brand equity over long-term periods. In addition, integrating best practices of data analysis like the use of machine learning or even predictive modeling in a campaign can help make more accurate and reliable the results on how the campaign will be.

Limitations of the research

Although this study was designed to yield maximal amounts of information about the specific research questions, several limitations should be noted. The study employs only data from a specific set of marketing campaigns; therefore, the findings could prescribe a limited applicability in equal marketing campaigns in other settings or industries. Further, the study relies on the quantitative measures; thus, the possibility of ignoring the quality characteristics affecting its performance cannot be ruled out. Also, there is a high possibility of obsolescing of some results in light of the continuing enhancement of marketing practices and consumer behaviours it may be advisable to do the study periodically. Last but not least, the factors which may limit the validity of researched questions, include the quality and quantity of data, occurrence of biases or inaccuracies in the work. **Reflect on professional, ethical, and legal issues**

Many times, the marketing campaigns require collation and use personal data, thereby giving rise to ethic and legal implications regarding privacy and protection of such data. It is important for researchers to review the legal guidelines including GDPR and other guidelines set by various industries as they conduct their studies and seek participants' consent. However, ethical concerns arise when the audience is chosen to fit a certain category or when material is chosen to persuade the audience using forceful tactics. Pursuing the given goals, it is vital to remain as transparent and responsibly market products and services as possible to evade possible negative reactions and legal consequences. In addition, there are specific guidelines which should be followed by the researchers, for example, the later should be free of any bias when studying; they should also not engage in any activity that may cause conflict of interest while doing research.

References

Alghamdi, O., & Agag, G. (2024). Competitive advantage: A longitudinal analysis of the roles of data-driven innovation capabilities, marketing agility, and market turbulence. *Journal of Retailing and Consumer Services*, 76(3), 903-909.

Constantinescu, M., Orindaru, A., Pachitanu, A., Rosca, L., Caescu, S. C., & Orzan, M. C. (2019). Attitude evaluation on using the neuromarketing approach in social media: Matching company's purposes and consumer's benefits for sustainable business growth. *Sustainability*, 11(24), 7094-7099.

de Ruyter, K., Keeling, D. I., Plangger, K., Montecchi, M., Scott, M. L., & Dahl, D. W. (2022). Reimagining marketing strategy: driving the debate on grand challenges. *Journal of the Academy of Marketing Science*, **50**(1), 13-21.

Dwivedi, Y. K., Ismagilova, E., Hughes, D. L., Carlson, J., Filieri, R., Jacobson, J., ... & Wang, Y. (2021). Setting the future of digital and social media marketing research: Perspectives and research propositions. *International journal of information management*, 59(1), 23–37.

Evans, J. R., & Mathur, A. (2018). The value of online surveys: A look back and a look ahead. *Internet research*, 28(4), 854-887.

Henley, N., Raffin, S., & Caemmerer, B. (2020). The application of marketing principles to a social marketing campaign. *Marketing Intelligence & Planning*, 29(7), 697-706.

Javaid, M., Haleem, A., Singh, R. P., Suman, R., & Gonzalez, E. S. (2022). Understanding the adoption of Industry 4.0 technologies in improving environmental sustainability. *Sustainable Operations and Computers*, 3(4), 203-217.

Leong, C. M., Loi, A. M. W., & Woon, S. (2022). The influence of social media eWOM information on purchase intention. *Journal of Marketing Analytics*, 14(4), 1-13.

Leppäniemi, M., & Karjaluoto, H. (2020). Mobile marketing: From marketing strategy to mobile marketing campaign implementation. *International Journal of Mobile Marketing*, 3(1), 180-189.

Makridakis, S., Fry, C., Petropoulos, F., & Spiliotis, E. (2022). The future of forecasting competitions: Design attributes and principles. *INFORMS Journal on Data Science*, 1(1), 96-113.

Rissman, J., Bataille, C., Masanet, E., Aden, N., Morrow III, W. R., Zhou, N., & Helseth, J. (2020). Technologies and policies to decarbonize global industry: Review and assessment of mitigation drivers through 2070. *Applied energy*, 12 (7), 190-199.