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An Analysis of New Visitors' Website Behaviour before & after TV Advertising

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Abstract: This paper explores and analyses the actions of users on an e-commerce website after they have watched TV-advertising. The analysis considers factors such as month, day and time of the website visit. This article utilises visualization tools for the analysis of the frequency ratios (probabilities) of searches, conversions, bookings made by new visitors on the website.

Keywords: TV-advertising, visualization, effectiveness

I. Introduction

TV advertising appears to be an important element in the relationship between manufacturers of goods and services and their customers. The problem of evaluation of the TV-advertising effectiveness is important for many industries, and researchers are developing solutions and approaches for evaluating its effectiveness [1-13, 15-18].

These methods work well in cases when the customer places an order on the phone immediately or shortly after watching the TV-advertising. A different situation is observed when a customer places an order online on the website of the provider of goods or services. In the latter case it is difficult to estimate the effectiveness of the TV-advertising, since there is little confidence that the booking was triggered by the TV-advertisement shown shortly before the booking. Besides, it should be noted that the TV-advertising is generic information pushed towards the customer and it is unclear how it aligns with the customer's needs in a given time and how it impacts the customers' decision-making.

We assume that making a booking as a result of watching TV-advertising is likely to be a probabilistic event and there are a large number of external and internal factors that can influence this process. Accordingly, before deciding on the method for evaluation of TV-advertising effectiveness it is necessary to examine whether this assumption is true. If so, the method for estimating the TV-advertising effectiveness must take into account the factors influencing the probability of the event itself.

This article considers several factors that may affect the action of booking, putting special emphasis on time factors. Furthermore, aiming to identify user behaviour features, which may be useful in choosing the method for estimating the TV-advertising effectiveness, the article analyses the behaviour of users in several market segment. We also visualise the dependencies observed for these segments.

II. Related Work

The analysis of the literature [18, 19, 23] demonstrated that in assessing the TV-advertising effectiveness many existing factors affecting the process of making a booking should be taken into account. They can be divided into three types:

- factors related to the TV-advertising (content; brand; feed; position in video stream - pre-, mid-, post-roll; length);
- factors related to the program where the commercial is placed (type - news, movies, shows; duration; character - entertainment, humour, drama, etc.);
- factors related to the user (location; connection: 2G, 3G, ADSL, Cable, Optic; user characteristics: temperament, demand for the product, money availability, etc). These factors must be taken into account in the selection of the method for the assessment of the effectiveness of TV-advertising. Thus, in [23] it is argued that various capabilities of neural networks can be used for the evaluation of the effectiveness of TV-advertising. The authors suggest an approach that takes into account 13 factors affecting 50 proposed attributes. The effectiveness of the simulated network reached 99%, but it should be noted that this result was obtained from 837 respondents in one place in India.

In [17], the authors identified 11 factors of influence. To assess the effectiveness of TV-advertising, they used correlation analysis. The results were based on the data from 33 video providers for a period of 15 days. Another work [25], used Google Insights tools for search, and analysed the volume of requests for search terms after watching TV-commercials. They demonstrated that watching TV-commercials significantly stimulates the growth of search queries. However, this finding was based on a single event such as the opening of the Vancouver Winter Olympic Games. Among the advantages of this approach, is the opportunity to work with specific geographic regions and time periods. In addition to these methods of evaluation of the TV-advertising effectiveness the following techniques were applied:

- call tracking - tracking users behaviour through the phone number provided in the commercial [10, 22];
- survey following the TV-campaign, in order to determine which TV-commercial affected users and helped them to make the final selection [20];
- analysis of covariance (ANCOVA) [16];
- classic metrics such as the gross rating points (GRPs) [6];
- econometric modeling [7];

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- regression analysis (multiple regression) [7];
- transfer function analysis [7];
- Markov chain Monte Carlo algorithm (MCMC) [4];
- Bayesian analysis [4].

Virtually the entire list of methods used for the study of the time series in marketing is given in [6, 11]. It should be noted that all the above methods show fairly good results, but at the same time, authors either simulate the original data or take a small period of time with the real data. The main issue emerges when applying the models, to a large-scale real data. In this case, the models may not perform well, because they need to be rebuilt according to the specific user behaviour in a specific market and or adjusted to specific influencing factors. In other words, the efficiency of the obtained models on real data still has to be proved.

Therefore, before deciding on the method for the evaluation of the TV-advertising effectiveness in a particular market, it is necessary to understand the behaviour of users and the key factors that lead to the bookings. The main objective of this work is to show that the user behaviour varies across different market segments and depends on temporal factors, such as the month, day, the time of the day running the TV-advertising and the time of the website visit.

III. Methodology

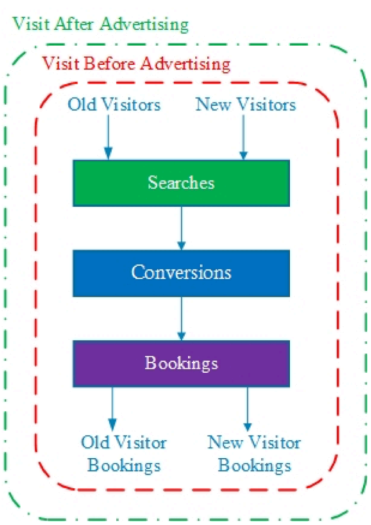

Fig. 1. *The chain of possible actions of the customer when visiting the website*

When visiting a website, the customer first searches for the right product or service. Then, the customer limits themselves to several options, makes some useful leads (in marketing language conversions) and then places the order (booking). Usually these steps can be presented in the form of series-connected units, as shown in Figure 1. Analysing the chain in Figure 1, it should be noted that there are 4 options for customer behaviour on the website:

1) Customer does nothing or leaves the website;
2) Customer performs only search;
3) Customer makes a search and conversion;
4) Customer performs a search, conversion, and a booking;

Despite the fact that not many user behaviour patterns exist, it is difficult to predict how the customer will behave. This process is complicated by the fact that for the customer visiting the website for the first time, there is no historical data that would allow for the predictions. Thus, we differentiate between "New Visitors" (their actions are recorded as "New Visitor Searches", "New Visitor Conversions", and so on) and "Old Visitors" (their actions are recorded as "Old Visitor Searches", "Old Visitor Conversions", and so on).

The behaviour of New Visitors and Old Visitors tends to differ significantly. New Visitors are more focused on the satisfaction of their information interests caused by TV-advertising. Hence, more often the visits of New Visitors do not end up with a booking. Old Visitors are more motivated to make a booking, because they return to the website with a particular aim after a certain period of time. On this basis, attracting New Visitors to the website is one of the important tasks of the TV-advertising. In this paper we examine the behaviour of the New Visitors only, because we believe that the behaviour of these users after watching TV-advertising affects whether they will make a booking immediately, or come back later as Old Visitors.

The time of the website visit also appears important in the analysis. There are only two options: (1) the website visit before the TV-advertising, Before Advertising (it is assumed that the user could have seen the TV-advertising before or that the visit was attributed to another reason) and (2) the website visit after the TV-advertising, After Advertising. We assume that user behavior Before Advertising and After Advertising are different and we consider this assumption in the following analysis.

Aiming to evaluate the degree of the factors' influence, we analysed the behaviour of customers in four markets (denoted to as markets 2, 4, 5 and 6). We used data obtained from an international travelling industry provider. The analysis was conducted on the data sample related to the following periods:

- Market 2: 01/01/2014 to 31/12/2014 - 16,575 visits;
- Market 4: 01/01/2014 to 08/03/2015 - 830,260 visits;
- Market 5: 17/05/2014 to 28/02/2015 - 50,939 visits;
- Market 6: 10/01/2014 to 22/01/2015 - 143,656 visits.

The data for the analysis was structured in the form of a number of searches, conversions and bookings done by the customers during a single visit to the website at a particular time, day and month. The total data sample for each of the markets was limited to the total number of website visits made during the interval of 5 minutes before and after the TV-advertising. The interval of 5 minutes was adopted based on the observations of users' activity for the above markets showing that 95% of user activity falls into this interval, before and after the TV-advertising. It should be noted that in some markets, this interval is set to 15 or even 30 minutes [8, 17, 18].

The analysis of the customer behaviour was conducted in the context of actions performed by the customers during the visit to the website. We addressed the frequency ratio of the following actions conducted Before Advertising, and After Advertising:

- The number of searches in relation to the number of visits by New Visitors

$$S = \frac{\sum New\,Visitor\ Searches}{\sum New\,Visitor\ Count} \tag{1}$$

- The number of conversions in relation to the number of visits made by New Visitors

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$$C = \frac{\sum New\,Visitor\ Conversion\,s}{\sum New\,Visitor\ Count} \quad (2)$$

- The number of bookings in relation to the number of visits made by New Visitors

$$B = \frac{\sum New\,Visitor\ Booking\,s}{\sum New\,Visitor\ Count} \quad (3)$$

Since we consider the frequency ratios, we discuss the probability of certain actions by specific visitors according to the frequency definition of probability [14]. In the reminder of the article the results of the analysis will be presented.

IV. RESULTS

Fig. 2 represents the results of a general comparison of the behaviour of new visitors in markets 2, 4, 5 and 6. For every market, the left column represents the behaviour of visitors, who visited the website before the TV-advertising, right column - the behaviour of visitors, who visited the website after the TV-advertising. The colour of each bar represents the fulfilment of actions on the website, namely across markets 2, 4, 5 and 6:

- Blue – probability of search;
- Red – probability of conversion;

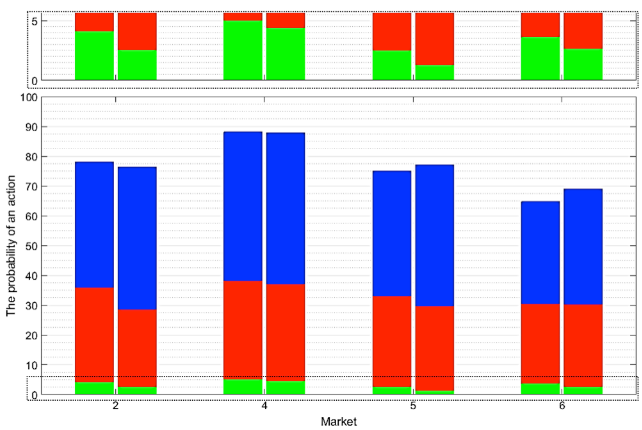

Fig. 2. *Total visualization of visitors' behaviour in the markets*

- Green – probability of booking.

Since one of the main goals of any travel provider is to increase booking rates, the charts given below show an additional rectangular area of frequency ratios of bookings as a scaled version of the whole actions on the website for a better comparison. Thus, Figure 2 shows the following:

Market 2. Out of the visitors, who made a visit to the website before TV-advertising, 78.1% conducted search (the probability of making a search is 0.781), 35.7% made conversion (the probability of making a conversion is 0.357) and 4.1% made booking (the probability of making a booking is 0.041). Out of the visitors, who visited the website after the TV-advertising, 76.3% conducted search (0.763), 28.5% made a conversion (0.285) and 2.5% made a booking (0.025).

Market 4. Out of the visitors, who made a visit to the website before TV-advertising, 88.2% conducted search (0.882), 38.1% made conversion (0.381) and 5% made booking (0.05). Out of the visitors, who visited website after TV-advertising, 87.8% conducted search (0.878), 35.8% made conversion (0.358) and 4.4% made booking (0.044).

Market 5. Out of the visitors, who made a visit to the website before TV-advertising, 75% conducted search (0.75), 32.9% made conversion (0.329) and 2.5% made booking (0.025). Out of the visitors, who visited website after TV-advertising, 77.2% conducted search (0.772), 29.6% made conversion (0.296) and 1.3% made booking (0.013).

Market 6. Out of the visitors, who made a visit to the website before TV-advertising, 64.7% conducted search (0.647), 30.4% made conversion (0.304) and 3.6% made booking (0.036). Out of the visitors, who visited website after TV-advertising, 68.9% conducted search (0.689), 30.1% made conversion (0.301) and 2.6% made booking (0.026).

Based on the analysis of the frequency ratios (for all four markets) is seen that visitors who make a visit before TV-advertising, make more actions than those who came to the website after TV-advertising, that is, they do more conversions and bookings. This finding can be explained primarily by the fact that visitors who came to the website before TV-advertising largely aimed at a specific result, in this case, to make a booking. This fact is well evident in Figures for market 5 and 6, where visitors conduct fewer search queries (75% of search queries performed before TV-advertising compared to 77.2% after TV-advertising in market 5 and 64.7% of search queries performed before TV-advertising to 68.9 % after TV-advertising in market 6) before they made the conversions and bookings. In other words, they presumable have already made the decision to purchase and were just looking for the most suitable option.

It should also be noted that when considering not the probabilities but the actual number of website visits, searches, conversions and bookings made before and after the TV-advertising (see Table 1), there is an increase in each of the indicators after the TV-ad. This means that the TV-advertising works and attracts more customers to the website. At the same time there is a probability decrease due to the significant growth in the number of visits in relation to other indicators. This important trade-off should be considered in the further analysis.

TABLE I
THE VALUES OF VISITS, SEARCHES, CONVERSIONS AND BOOKING IN DIFFERENT MARKETS

	Visits	Searches	Conversions	Bookings
Market 2				
Before Ad	51188	39979	18290	2084
After Ad	125387	95727	35721	3152
Market 4				
Before Ad	321392	283399	122468	16054
After Ad	508868	446700	187354	22273
Market 5				
Before Ad	7232	5423	2378	180
After Ad	43707	33727	12936	553
Market 6				
Before Ad	32653	50440	15316	1819
After Ad	93216	64239	28053	2432

Based on Figure 2, the most efficient market in terms of making bookings is Market 4, where the probability of booking is 0.05 and 0.044 before and after TV-advertising respectively (or 5 and 4.4%). Markets 2, 6 and 5 with respective values of the frequency ratio follow Market 4. If we consider these values in terms of the actual number of bookings, i.e., in market 4 – 16,054 bookings per 321,392 visits before TV-advertising and 22,273 bookings per 508,868 visits after TV-advertising, and predict the future behavior of users in these markets in terms of the probability of booking, we must choose a method that might work with a small number of positive events. Let us further examine how the frequency of visitors' actions changes as a function of the month of year (see Figures 3 – 6).

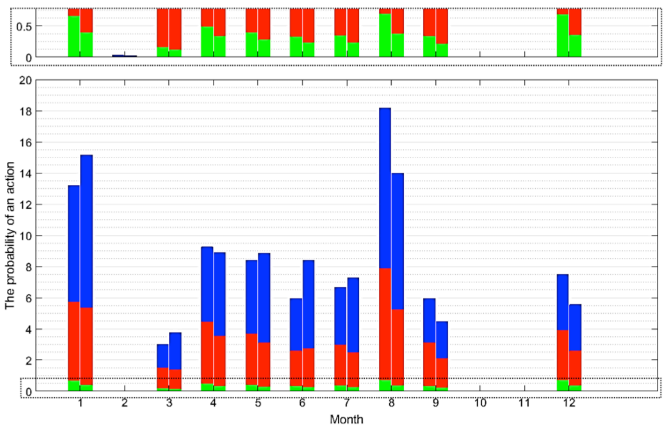

Fig. 3. *The behaviour of visitors in Market 2 per months*

Market 2. As seen in Figure 3 the TV-advertising campaign on the market 2 was run during all the months except for February, October and November. The best month was August, with the probability of making bookings was 0.007 (0.7%) before TV-advertising and 0.004 (0.4%) after the TV-advertising. December and January followed months with the probability of making booking 0.007 and 0.0065 (0.7% and 0.65%) before TV-advertising and 0.003 and 0.0039 (0.3% and 0.39%) after TV-advertising. All the remaining months do not show explicit dynamics, frequency ratio were comparable.

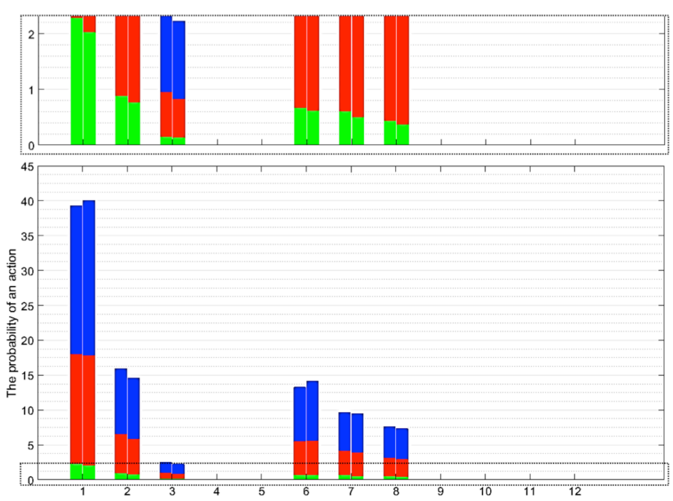

Fig. 4. *The behaviour of visitors in Market 4 per months*

Market 4. As seen in Figure 4 TV-advertising campaign for Market 4 targeted only 6 months: January, February, March, June, July and August. The best performance was observed in January, with the probability of making booking 0.022 (2.2%) before TV-advertising and 0.02 (2%) after TV-advertising. Then follows February, with the probability of booking 0.009 (0.9%) before TV-advertising and 0.008 (0.8%) after TV-advertising. All the remaining months (except for March) show no explicit dynamics and the frequency ratio values are comparable. Notable March demonstrate the worst performance and the reasons for this should be further investigated.

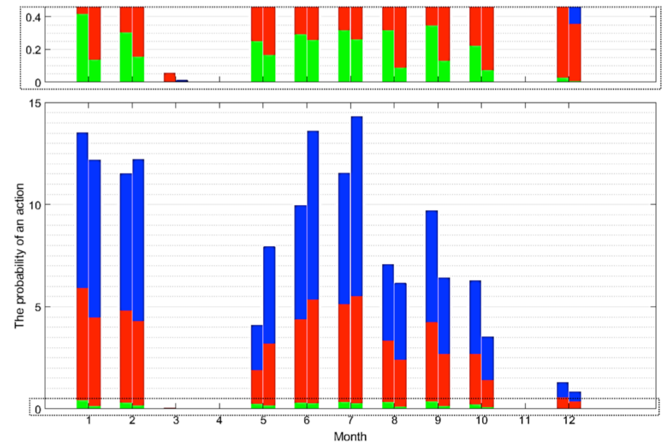

Fig. 5. *The behaviour of visitors in Market 5 per months*

Market 5. As seen in Figure 5, the TV-advertising campaign in Market 5 was run during all the months except for March, April and November. The peculiarity of this market is in the fact that the values of booking frequency distributions before and after TV-advertising are consistently high across different months, which is a contrast case to other markets. The best performance indicators (effectiveness) before TV-advertising are seen in January and September, when the likelihood of booking is 0.0041 (0.41%) and 0.0034 (0.34%) respectively. The best performance after the TV-advertising are observed in June and July, where the likelihood of booking is 0.0025 (0.25%) and 0.0026 (0.26%), respectively. All the remaining months did not show explicit dynamics, frequency ratio values remain comparable.

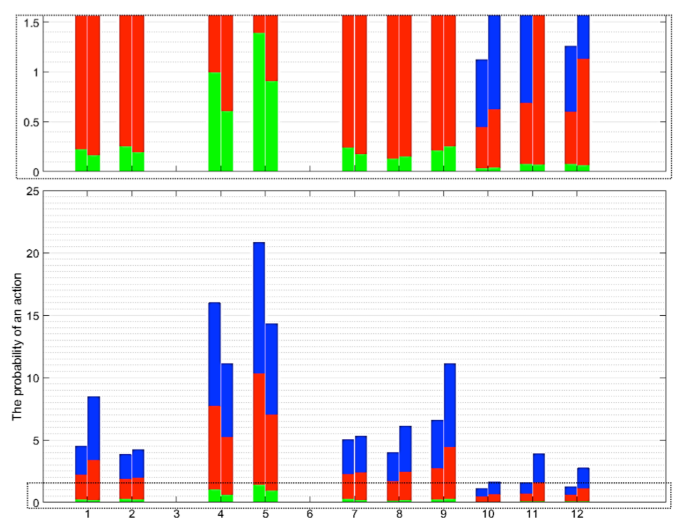

Fig. 6. *The behaviour of visitors in Market 6 per months*

Market 6. As seen in Figure 6 TV-advertising campaign in the Market 6 was run during all months except for March and June. The best performing month is May, with the probability of making booking 0.013 (1.3%) before TV-advertising and 0.0091 (0.9%) after the TV-ad. Then comes April, with the probability of booking 0.0099 (0.99%) before TV-advertising and 0.006 (0.6%) after the TV-ad. All the remaining months except for October, November and December do not show explicit dynamics, and frequency ratio values are comparable. October, November and December demonstrated the worst performance.

The analysis of the impact of month on visitors' behaviour shows that the overall probability of making booking in the tested markets varies across many months of the TV-advertising campaign. In other words, the issue of seasonality is quite acute. For each market there are 1-2 months, when the performance indicators or visitors' behaviour is higher than the rest. Generally, the high indicators are observed during the winter holidays, December-January for market 2, January-February for markets 4 and 5, as well as during periods of individual performance for each market, August for market 2, August-September for market 5 and April-May for market 6. In addition, there are also differences in the behavior of users who came to website before and after TV-advertisement.

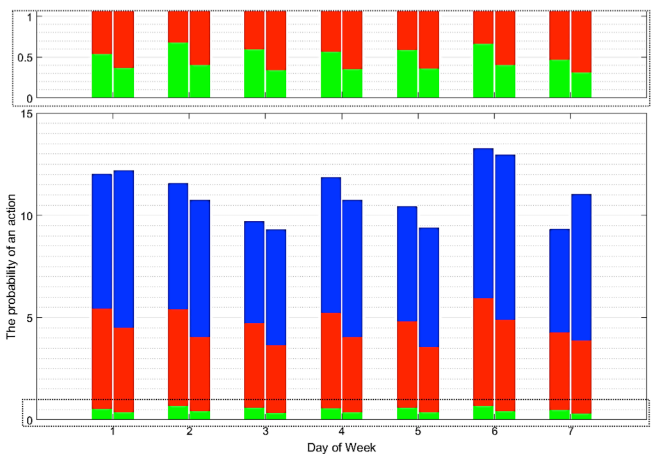

Fig. 7. *The behaviour of visitors in Market 2 per days of the week*

Let us further examine how the frequency performance of visitors' actions varies across the days of week (see Figures 7 – 10).

Market 2. As seen in Figure 7 the probability of certain actions is evenly distributed over the days of the week, with no apparent dominance of a particular weekday. High probability of making booking is captured on Tuesday and Saturday, respectively, 0.0068 and 0.0068 (or 0.68%) before TV-advertising and 0.004 and 0,004 (0.4%) after the TV-advertising.

Market 4. As seen in Figure 8 the probability of certain actions is evenly distributed from Monday to Friday, with no apparent dominance of a particular weekday. The advertising campaign target mainly weekdays. High probability of making booking is observed on Tuesday and Wednesday, respectively, 0.01 and 0.01 (or 1%) before TV-advertising and 0.0092 and 0.0092 (0.92%) after TV-advertising. Very little activity is observed on Saturday and Sunday.

Market 5. As seen in Figure 9 the probability of certain actions is not evenly distributed over the days of week, with a

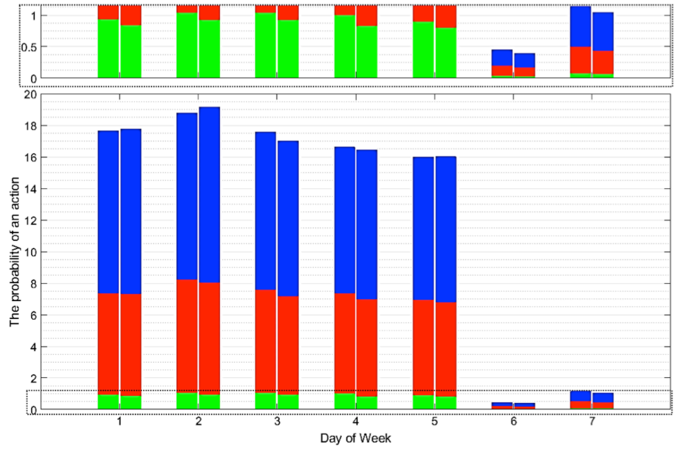

Fig.8. *The behaviour of visitors in Market 4 per days of the week*

clear dominance of performance indicators obtained on Sunday. High probability of making booking is observed on Tuesday and Sunday, respectively, 0.0053 and 0.0057 (0.53% and 0.57%) before TV-advertising and 0.0018 and 0.0033 (0.18% and 0.33 %) after TV-advertising.

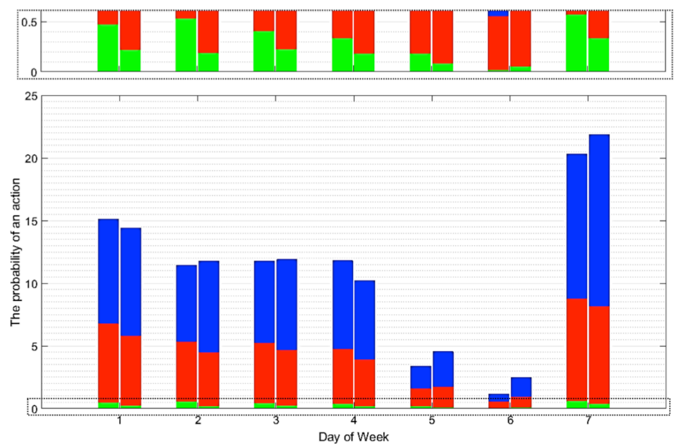

Fig. 9. *The behaviour of visitors in Market 5 per days of the week*

Market 6. As seen in Figure 10 the probability of certain actions is evenly distributed over the days of the week, with a clear dominance of Tuesday and Wednesday, as per the number of searches and conversions performed. High probability of making booking is observed on Tuesday and Wednesday, respectively, 0.0061 and 0.0063 (0.61% and 0.633%) before TV-advertising and 0.0046 and 0.0044 (0.46% and 0.44%) after TV-advertising.

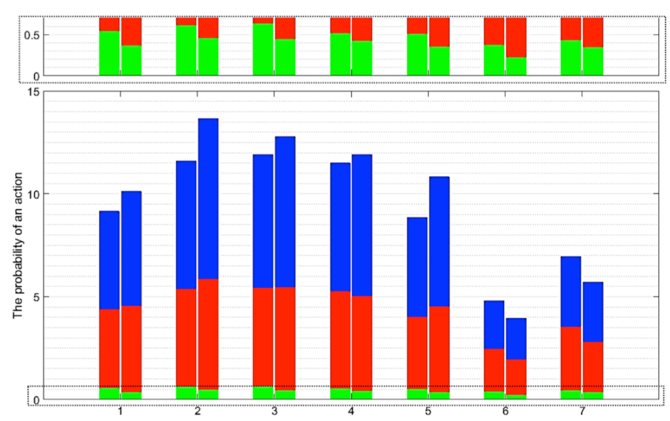

Fig. 10. *The behaviour of visitors in Market 6 per days of the week*

The analysis of the impact of a particular day of the week on visitors' behaviour signposts that in general the probability of booking in the tested markets is distributed quite evenly across all days of the week, but for all markets Tuesday is the day achieving the best performance. The high performance of other days, i.e., Wednesday, Saturday, and Sunday, is typical only for specific markets. There are also differences observed in the behavior of users before and after TV-ad. Let us lastly examine how the performance of the actions made by visitors depends on the time of their website visit (Figures 11 - 14).

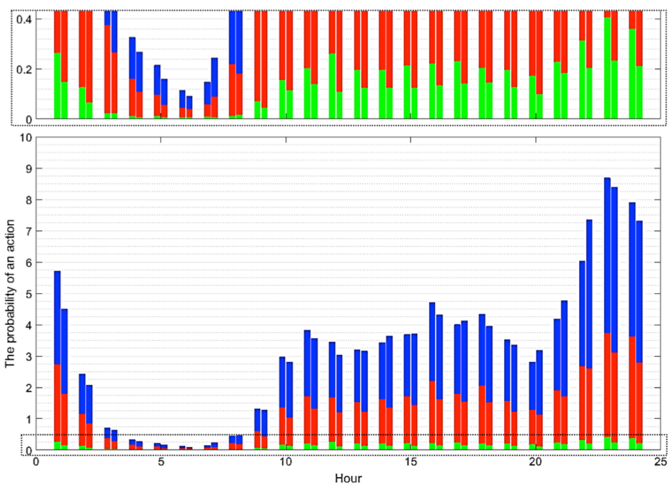

Fig. 11. *The behaviour of visitors in Market 2 per the time of the website visit*

Market 2. As can be seen in Figure 11 the probability of certain actions in this market is not evenly distributed by the time of the visit to the website. The lack of the visitors' activity between 4:00 to 8:00 is noticeable. Starting from 9:00 the activity of visitors steadily increases and from 10:00 to 21:00 remains largely unchanged. The probability of booking thus ranges from 0.09% to 0.26%. The peak period of visitors' activity is from 22:00 to 24:00; the probability of booking during these hours grows and ranges from 0.2% to 0.4%. The peak probability of making the booking is observed from 23:00 to 00:00 and comprises up to 0.4% before TV-advertising and 0.23% after the TV-ad. Then, starting from 01:00 there is a gradual decline in activity of visitors to close to zero values at 06:00.

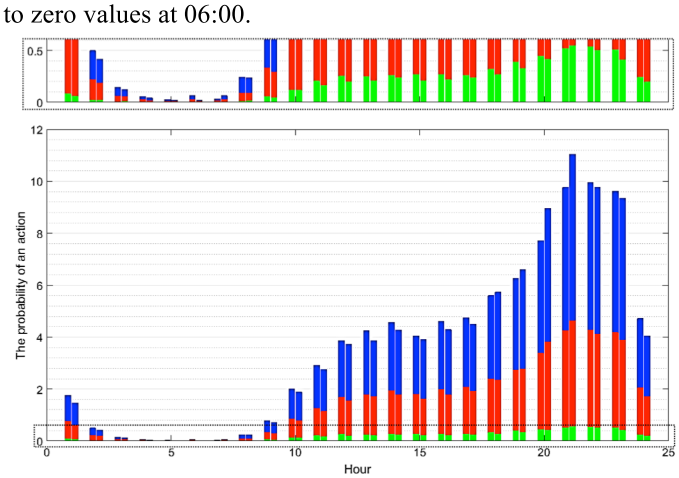

Fig. 12. *The behaviour of visitors in Market 4 per the time of the website visit*

Market 4. As seen from Figure 12 the probability of certain activities is not evenly distributed by the time of the visit to the website. The virtual absence of visitors' activity can be traced from 2:00 to 8:00. Starting from 9:00 visitors' activity increases and in the period from 10:00 to 24:00 stays at a high level. The probability of booking ranges from 0.04% to 0.54%. The peak period for this market is from 21:00 to 23:00, when the likelihood of booking significantly increases and ranges from 0.41% to 0.54%. Top probability of booking is traced at 21:00 and constitutes 0.51% before TV-advertising and 0.54% after the TV-ad. It should be noted that this is the only case where the likelihood of booking after TV-advertising is higher than before. Then starting at 00:00 there is a sharp decline in visitors' activity to close to zero values at 04:00 and 05:00.

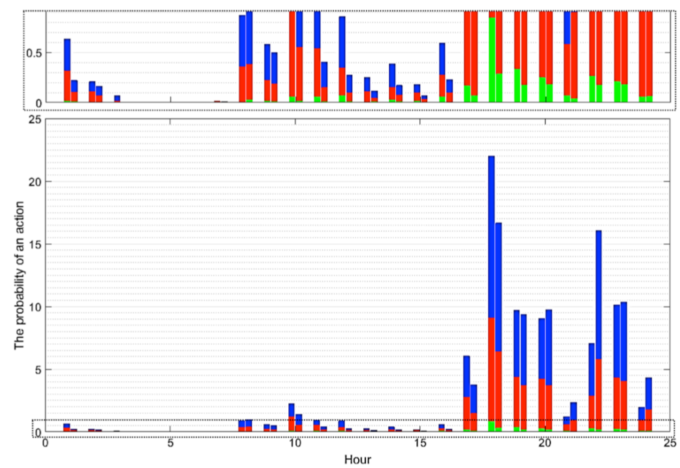

Fig. 13. *The behaviour of visitors in Market 5 per the time of the website visit*

Market 5. As can be seen in Figure 13 the probability of certain actions in this is unevenly distributed by the time of the visit to website. The virtual absence of visitors' activity can be traced for the period from 01:00 to 16:00. Starting from 17:00 visitors' activity increases, and in the period from 17:00 to 20:00 and then from 21:00 to 22:00 remains practically at the same level, with the probability of booking ranging from 0.05% to 0.84%. The peak periods for this market are from 18:00 to 20:00, when the likelihood of booking ranges from 0.17% to 0.84%. Top probability of booking is observed at 18:00 and constitutes 0.84% before TV-advertising and 0.28% after the TV-ad. Starting from 01:00 there is a sharp decline in activity of visitors, to close to zero values between 3:00 and 07:00.

Market 6. As can be seen in Figure 14 the probability of certain actions in the market 6 is not uniformly distributed by the time of the visit to the website. The virtual absence of visitors' activity can be traced from 5:00 to 7:00. Starting from 8:00 visitors' activity increases, and during the period from 8:00 to 03:00 stays at about the same level, with the probability of booking ranging from 0.02% to 0.32%. The peak period for this market is from 12:00 to 15:00, when the probability of booking ranging from 0.27% to 0.32% before TV-advertising and from 0.18% to 0.24% after TV-ad. High probability of booking is observed from 13:00 to 14:00 and make up 0.32% before TV-advertising at 14:00 and 0.24% after TV-advertising at 13:00. It should be noted that in this market visitors' activity is observed almost during the whole day. In the period from 05:00 to 07:00 there is a decline in

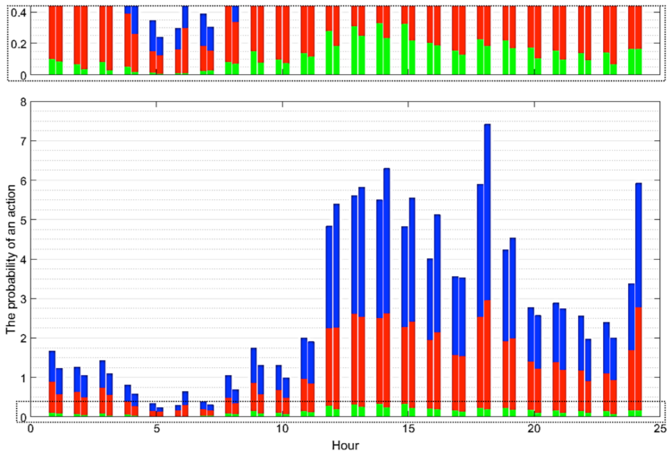

Fig. 14. *The behaviour of visitors in Market 6 per the time of the website visit*

activity of visitors that reach to values of 0.01% at 6:00 before TV-advertising and 0.006% at 5:00 after TV-advertising.

From the analysis of the effect of the time of the website visit on the visitor's behaviour, it follows that in general the probability of booking for the tested markets is distributed quite unevenly across the times of the day when the TV-advertising campaign is running. In addition, for each market there are three time-ranges for visitors' activities, namely:

- effective - usually at least one hour, when the performance indicators, or visitors' behaviour is the most active;

- stable - time interval when visitors' activity is at about the same level for each market;

- non-effective - time interval when the performance, or the behaviour of visitors is reduced to close to zero values.

V. Conclusion

Summarising the above analysis of the effectiveness of TV-advertising, we can conclude the following:

- the data visualization approach employed in this analysis demonstrated that the time factors are important when choosing a method for estimating the effectiveness of TV-advertising in a particular market. These must be taken into account, as there are certain hours, days and months when the effectiveness of TV-advertising in terms of the numbers of bookings is particularly high or low;

- users' behavior in different markets demonstrated notable differences, meaning the models that describe the behavior of visitors, resulting from the evaluation of the TV-advertising effectiveness for different markets, may vary depending on both the time factors and the individual characteristics of the markets and the users;

- the probability of booking (as an indicator of efficiency) is generally quite small and ranges from 0.025 to 0.05, or respectively 2.5% and 5% of visitors who make booking. When it comes to choice of a method for predicting visitors' behaviour, we need a method that is sufficiently sensitive to the small number of positive booking actions;

- the probability of booking by visitor before the TV-advertising is higher than afterwards. The moment of the visit to the website before or after TV-advertising can be used as implicit indicator of the intentions of the visitor. This indicator allows investigating the booking depending on the time of the visit (provided that the analysis was carried out in 5 minute interval before and after TV-advertising);

- current findings are applicable only for the travel industry and represent a solid result for user's behaviour in relation to TV-advertising. Research finding were not compared across industries and cannot be applied to explain user's behaviour after and before TV-advertisement in other domain.

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