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INFOGRAPHICS IN DIGITAL ADS: A/B TESTING FOR CONTENT OPTIMIZATION

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Abstract: *Internet users are bombarded every day with various ads, and they try to block them in all possible ways. If they do not block them, they usually pay little attention to them. Therefore, ads need to be creative and provide as much relevant information as possible about the advertised product or service at a glance in order to lead to conversions. For this purpose, the benefits of infographics can be used very well, in addition to dynamic forms of ads that consist of audio and video elements, especially in a responsive web environment. This type of advertising is also great for posting on social media, where the flow of information and responses is very fast. Infographics actually represent a visual presentation of information through a combination of typography, symbols, pictograms, shapes, and colours and are used to present complex information quickly and clearly. The use of infographics as one of the multimedia elements in digital advertising contributes to the optimization of advertising content, which also contributes to SEO optimization. To investigate the extent to which infographics in digital advertising can contribute to the optimization of advertising content in a responsive web environment, A/B testing of multimedia advertising content presented through infographics and content that contained all relevant information about the advertiser and was not presented in the form of an infographic was conducted on two types of screens. The A/B testing model itself provides the opportunity to maximize conversion rates, but it also provides a significant increase in knowledge about how advertising content is presented. It can also establish a set of optimized practices for multimedia elements of ad content. The proposed testing model provides the perfect opportunity to properly test your ad before launch. The same analogy can be applied to other multimedia elements used to create ads, such as photos, animations, colours, content management system elements, etc.*
The obtained results provide valuable information about infographics possibilities in advertising content optimization in a responsive web environment because they load faster, are suitable for small screens, and do not tire users.

Key words: infographics, digital ads, ads content optimization, responsive web, A/B testing

1. INTRODUCTION

The use of the Internet and social media has changed consumer behavior and the way companies do business. By the early 2020s, more than 4.5 billion people use the Internet, while the number of social media users has surpassed 3.8 billion, and the average Internet user now spends 6 hours and 43 minutes per day online (Dixon, 2022). But 49% of internet users install ad blockers (Dixon, 2022), causing companies to suffer losses and be forced to find more acceptable ways of digital advertising. This opened space for the use of social media, which allows two-way communication. Social and digital marketing offers significant opportunities for businesses through lower costs, improved brand awareness, and increased revenue. However, there are also significant challenges from negative electronic word of mouth and an intrusive and irritating online brand presence.
There is, however, a problem with user attention and retention. Today, the average Internet user is exposed to myriad messages and information throughout the day, and the ability to concentrate is declining. Therefore, effective digital media should be borderless, ubiquitous, creative, personalized, viral, immersive, and data driven.
Considering that 40% of people respond better to visual content than text, it is infographics that enable digital media to convey a message to users in a short period of time. Statistics show that those who publish infographics in their media have 12% more visitors than those who do not. Studies show that 90% of the information that is absorbed on a daily basis is conveyed visually. Infographics are visual content that is easy to adopt. They speak to people with simple images that are easy to read and understand.
Information graphics or infographics are a visual representation of information, data, or knowledge. Such graphics are used when complex information needs to be explained quickly and clearly, such as in signage, maps, journalism, technical writing, and education. They are also used as a tool to facilitate the

process of developing conceptual information. Infographics are visual content that the recipient of the message easily adopts, and on social media, they are shared faster and more frequently than a text post, meaning they go viral more quickly. Infographics also contribute to search engine optimization, but also to brand awareness if the topic of the infographic is related to the company's activity or the company logo is integrated into the infographic.

2. RESEARCH BACKGROUND

Considering the fact that humans are increasingly acquiring information visually, images have recently been used more frequently in visual communication to express views, opinions, feelings, emotions, and moods (Gajarla & Gupta, 2015; Katsurai & Satoh, 2016; Kumar & Garg, 2019). Images are particularly powerful because they are associated with cognition and visual experiences better convey feelings and emotions.

Controlled online experiments are often used to improve website performance by comparing user behavior across different variations of a given website. Although such experiments can have an important impact on the key metrics to be maximized, it is difficult for small websites to use this method because they have few users. Moreover, the variants under consideration increase exponentially with the number of elements that need to be optimized. To solve these problems, an A/B testing method that finds powerful variants with multiple samples is suitable (Iitsuka & Matsuo, 2015).

A/B testing, also known as bucket testing, split testing, or controlled experiments, is a standard method for evaluating user engagement or satisfaction with a new service, feature, or product. It is widely used with online websites, including social networks (Gui et al., 2015; Xu et al., 2015). A/B testing allows a company to evaluate the performance or impact of new features on its website by introducing them to a small subset of visitors (Conti et al., 2018).

In its simplest form, an online A/B test can be treated as a static hypothesis test, where traditional statistical tools such as p-values and power analyze can be applied to help decision makers determine which variant performs better (Ju et al., 2019).

Due to the dynamic environment of today and the increasing number of websites, their assessment and evaluation has also emerged. On the other hand, website users do not like static pages and look for those that can convey more information in less time (Ranjbarfard & Kheiri, 2019). Infographics keep popping up on a variety of websites, so design teams have picked up on the trend of infographics (Albers, 2014) and therefore, in recent years, the use of infographics in digital media has become more popular. Infographics are valued, but only if they are coherently integrated into a story and thus serve an easy-to-understand function, because news consumers actually read infographics regardless of the platform on which the visual is published (de Haan et al., 2018). To this end, the author group (Firmenich et al., 2019) proposed an iterative method supported by a toolkit that allows usability experts to design user tests, run them remotely, analyze the results, and evaluate alternative solutions to usability problems similar to A/B testing. Each solution is created by applying client-side web refactoring, i.e., making changes to the web pages in the client to improve usability. Ranjbarfard & Kheiri (2019) emphasized that infographic is one of the components of website evaluation that has a positive and significant impact on website quality, user satisfaction with the website, and their desire to return to the website.

Fedorchenko & Ponomarenko (2019) tested a number of approaches to website A/B split testing in the context of implementing the company's online digital marketing strategy. They examined the main approaches to implementing A/B split testing as an effective tool for improving conversion of a corporate website using a system structural and comparative analysis. Sinha, Healey & Sengupta (2020) presented an interactive user interface that allows digital marketing professionals to access real-time insights from back-end AI that predicts potential click-through rates for collocated content based on similar past campaigns. Their framework decomposes aspects of previous campaigns into features such as image quality and text readability, which is important for graphic designers and web developers. They have shown that an algorithm with a high predictive value on a historical test set (AUC .80) and using the AI agent's advice can generate content that increases click-through rates by up to 22% on 700 A/B preference tasks given to masters (AMT).

Deng et al. (2017) have sought to accelerate innovation by evaluating ideas quickly and accurately with controlled experiments, also called A/B testing. They introduce A/B testing, share key lessons learned from scaling experiments at Bing to thousands of experiments per year, present real-world examples, and outline promising directions for future work. The tutorial introduces applications of A/B testing in

information retrieval and also discusses the practical and scientific challenges of running experiments on websites and in mobile and desktop apps.
Kumar (2019) emphasized that A/B testing has become the de facto standard for design optimization, helping designers create more effective user experiences by leveraging data. Beyond A/B testing, however, there are other powerful data-driven methods that can link design decisions to desired outcomes. Evaluating data from existing designs can open up a wider space of different solutions to designers than A/B testing. Models such as generative adversarial networks and variational autoencoders can create designs based on high-level constraints or complete them based on partial specifications. This opened a space to develop a model for creating intelligent advertising content, consisting of infographics, in real time. To achieve this, it is necessary to integrate intelligent technologies that work on the principle of ontology and semantic-based information.
Recently, images, infographics, memes, and GIFs have dominated social media feeds. As a result, text posts are pushed into the background. Therefore, an attempt was made to investigate whether there is a difference in social media users' responses when the same message is sent in three different forms. Therefore, multimodal data was used to collect user responses: Text Releases, Image Releases, and Ecology Infographics, which should be analyzed because they have the potential to change, confirm, or evaluate the polarity of sentiment. The model can analyze for each tweet or reaction of a user whether it is positive, negative, or neutral.

3. RESEARCH METHODOLOGY

3.1 Problem formulation

This research is a part of the extensive research within the project “Optimization and personalization of multimedia content using artificial intelligence”.
The main goal of this article was to integrate the idea of A/B testing into the context of testing multimedia elements of websites with digital advertising content to provide a method for improving usability in web and ads development. Web developers and ads designers need various tools to enable optimization and personalization of web and ads content to increase conversion rates. Therefore, the well-known statistical approaches in synergy with artificial intelligence served as a platform for the development of this model.
Considering the above requirements, the methodology of this research is described by formulating problems and testing principles and hypotheses.
This requires creating a model capable of copying the logic of each user step to create real-time intelligent advertising content that reaches users through multimedia channels. To achieve this, the first step is to integrate personalization technologies that work on the principle of ontology and semantic-based information. The sequence diagram will connect the user, the multimedia advertising content and the database through modelling, filtering, and content customization (Figure 1).

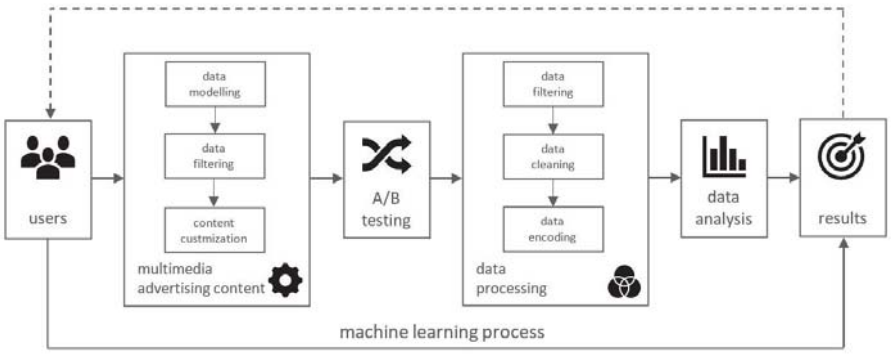

Figure 1: Sequence diagram (Source: own)

Conducting A/B test on ads, regularly can bring in more targeted leads by doing what works and changing what does not.
A/B testing or split testing is a method of comparing two versions of a web page or some parts or elements to see which performs better. This is an experiment in which two or more variants are randomly

shown to different segments of users at the same time and statistical analysis is used to determine which variant better meets the conversion goal. A web page is changed to a second version of the same web page. Half of the visitors are shown the original version of the web page (the so-called control) and the other half are shown the changed version of the web page (the variant).
For this purpose, the infographic was singled out as a key visual structural element. The test was conducted in three iterations, in combinations of text and image, text and infographic, image and infographic (Figure 2).

Figure 2: Tested information carriers

3.2. Testing principle and hypothesis

Statistically, the AB test is an example of a test of a statistical hypothesis, a procedure in which a hypothesis is made about the relationship between two data sets and these data sets are compared to determine whether or not a statistically significant relationship exists. For this purpose, the z-test, t-test, chi-square test, or Fisher's exact test can be used. In this work, the z-test with two proportions was used. A z-test is a statistical test used to determine if the means of two populations differ when the variances are known, and the sample size is large. It is assumed that the test statistic is normally distributed, and interfering parameters such as standard deviation should be known in order to perform an accurate z-test. The observed *z-score* is a number that indicates how many standard deviations above or below the population mean a value derived from a z-test is.

$$z = \frac{(\widehat{p_1} - \widehat{p_2}) - (p_1 - p_2)}{\sqrt{\frac{p_1(1-p_1)}{n_1} - \frac{p_2(1-p_2)}{n_2}}} \quad (1)$$

The hypothesis:

H0: There is no significant difference between two conversion rates from two group of samples ($p_1 = p_2$).
H1: There is significant difference between two conversion rates from two group of samples ($p_1 \neq p_2$).

H0 is rejected if *z-statistic* from this formula is higher than standard *z-score* with degree of freedom ($n_1 + n_2 - 2$) or *p-value* is smaller than significance level ($\alpha = 0.05$).
To test the hypothesis, two experimental plants described above were created and operated for 21 days.

4. RESULTS AND DISCUSSION

In this section, the main results of the study are presented. The results are presented in tables. The first experimental unit consists of text and image as carriers of information. The first website with digital ads is a control website named A that contains text, and the second website is a variant named B that contains an image as an information carrier.
The conversion rates and the standard error rate are calculated and presented in Table 1. Conversion rate is the percentage of users on a website who take act beyond simply viewing content or visiting the website as a result of subtle or direct prompts from marketers, advertisers, and content creators. A good conversion rate is above 10%, with some companies achieving an average of 11.45%. Both of tested web pages have below average conversion rates.

Table 1: Visits and Conversion rates from each variant, variants' conversation rates and standard error text/image

A/B test	Users	Conversions	Conversion rate	Standard error
A Text	4110	264	6.42%	0.0317%
B Image	4216	377	8.97%	0.0054%

Based on the inputs, the estimated confidence interval that the value is statistically significant is determined based on *z-score* confidence intervals for 90% and 95% conversion rate limits. These are then used to test the *p-value* against the confidence intervals (Table 2).

Table 2: Significance levels based on inputs, text/image

A/B test	90% Conversion Rate Limits		95% Conversion Rate Limits	
	From	To	From	To
A Text	3.98%	6.29%	3.22%	5.19%
B Image	7.78%	8.53%	7.05%	8.82%

In the third step, the *z-score* and *p-value* are calculated. The results show that the hypothesis H0 is rejected because the *p-value* is less than 0.05. This means that the test is statistically significant and web page B with the variable font file performs better than web page A. In other words, version B converts 39.75% better than version A (Table 3).

Table 3: Z-score, p-value and significance, text/image

A/B test	z-score	p-value	Significant	Improvement
A Text	3.912	0.0043	yes	-
B Image	5.638	0.0007	yes	39.75%

On the same principle the second experimental unit are created, but the first website i.e., control website named A contains text, and the second website i.e., variant website named B and contains an infographic as an information carrier.
The conversion rates and standard level of error are calculated and for the second experiment unit and presented in Table 4. Tested web page A have below average conversion rate (5.73%), and tested web page B achieved an average rate of 10.67%.

Table 4: Visits and Conversion rates from each variant, variants' conversation rates and standard error text/infographic

A/B test	Users	Conversions	Conversion rate	Standard error
A Text	3261	187	5.73%	0.0007%
B Infographic	3887	415	10.67%	0.0012%

Table 5 shows the estimated confidence interval that the value is statistically significant based on *z-score* confidence intervals for 90% and 95% conversion rate limits, which in turn are used to test the *p-value* against the confidence intervals.

Table 5: Significance levels based on inputs, text/infographic

A/B test	90% Conversion Rate Limits		95% Conversion Rate Limits	
	From	To	From	To
A Text	2.16%	4.09%	3.73%	4.58%
B Infographic	8.38%	9.12%	7.82%	8.59%

Finally, Table 6 shows the *z-score* and *p-value* for the second experimental unit. Hypothesis H0 is again rejected because the *p-value* is less than 0.05. This means that the test is statistically significant and web page B with has better conversion results than web page A. In this case, version B converts 42.70% better than version A.

Table 6: Z-score, p-value, significance and improvement, text/infographic

A/B test	Z-score	p-value	Significant	Improvement
A Text	3.912	0.0078	yes	-
B Infographic	5.223	0.0001	yes	42.70%

On the same principle and the third experimental unit are created, but the first website i.e., control website named A contains image, and the second website i.e., variant website named B and contains an infographic as an information carrier.
The conversion rates and standard level of error are calculated and for the second experiment unit and presented in Table 7. The tested website A and the third time have a below average conversion rate (8.78%), and the tested website B achieved a borderline average rate of 9.95%.

Table 7: Visits and Conversion rates from each variant, variants' conversation rates and standard error image/infographic

A/B test	Users	Conversions	Conversion rate	Standard error
A Image	4008	352	8.78%	0.0061%
B Infographic	4492	447	9.95%	0.0293%

Table 8 shows the estimated confidence interval that the value is statistically significant based on *z-score* confidence intervals for 90% and 95% conversion rate limits, which in turn are used to test the *p-value* against the confidence intervals.

Table 8: Significance levels based on inputs, image/infographic

A/B test	90% Conversion Rate Limits		95% Conversion Rate Limits	
	From	To	From	To
A Image	4.98%	6.12%	5.19%	7.03%
B Infographic	7.43%	8.17%	6.92%	8.76%

And finally, Table 9 shows the *z-score* and *p-value* for the second experimental unit. The hypothesis H0 is again rejected because the *p-value* is less than 0.05. This means that the test is statistically significant and web page B has better conversion results than web page A. In this case, version B converts 27.01% better than version A.

Table 9: Z-score, p-value, significance and improvement, image/infographic

A/B test	Z-score	p-value	Significant	Improvement
A Image	6.217	0.0056	yes	-
B Infographic	2.911	0.0009	yes	27.01%

5. CONCLUSIONS

Interaction between users and websites requires intelligent systems for clusters of similar data that can be used to optimize and customize content for each user. Therefore, it is necessary to know the capabilities of font files to increase the loading time of web pages. The results presented in this paper show that images achieve a better conversion rate than text in digital ads and that infographics achieve better conversions than text and images. This is the expected result, as an infographic combines text and images in an easy-to-read format.

Although the websites from all three experimental units had below-average results for text, this test was not related to the design and appeal of the digital ads, but to the use of a specific information carrier. The model of A/B testing not only provides the opportunity to maximize conversion rates, but also to significantly increase knowledge about how web pages are presented. It can also determine a set of optimized practices for multimedia elements of advertising content.
The proposed testing model provides the perfect opportunity to thoroughly test the web design before launching the website. The same analogy can be used for other elements of the website such as photos, animations, colors, content management system elements, etc. Another test such as the t-test, chi-square test, or Fisher's exact test can be used to verify the results. If a large number of elements are changed on the web, a cluster analysis can also be performed.

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