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IMPORTANCE OF EMOTIONS IN ADVERTISING: ASSESSMENT OF DIFFERENCES IN EMOTION LEVELS BETWEEN ADVERTISING TEXT CREATED BY COPYWRITERS AND AI IN THE PHARMACEUTICAL INDUSTRY

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Summary

Emotions are an important element of advertising and have a decisive influence on its effectiveness. The aim of the presented article is to assess the differences in the level of emotions present in advertising texts created by a copywriter and a text generator based on artificial intelligence (AI). Sentiment analysis performed through the IBM Watson NLU application was used to assess emotions. This study provides information on the emotions present in radio advertisements for pharmaceuticals, and enables the identification of differences between human and AI generated text sources. The results show that ads from both sources have a similar emotional level, with the exception of the category "disgust", which in this situation can be used as an indicator of the origin of the ads. The results described refer only to radio advertisements for pharmaceuticals. At the end of the article, recommendations for business are formulated and directions for future research are indicated.

Keywords: emotions, artificial intelligence, text generators, radio ads

Klasyfikacja JEL: M3, O320, O330

Introduction

Advertising is a communication tool between businesses and customers. It serves as the main method to generate sales and it is therefore crucial to create advertising content that will resonate with potential customers. Advertising messages are delivered through a variety of methods such as visual aids, text, speech and sounds. However, underpinning all advertisement media are emotions, as they are the primary source of influence over customer decisions. These emotions are tailored to maximize advertisement effectiveness according to the sector and advertising channel. Consequently, embedded emotional metadata greatly influences ad quality.

To measure which emotions and to what extent are present in the text, sentiment analysis (SA) can be used as it focuses on identifying, quantifying, extracting, and studying affective states and subjective information in analyzed text (Patil, Parekh, Tejaswini, Patil, Ospanova, 2022). SA commonly focuses on assessing individual scores for six or eight basic emotions (depending on the SA model) which include the following: joy, anger, fear, trust, surprise, sadness, disgust, and anticipation). Furthermore, it provides information about the sentiment of text – measured with an overall score in a range from -1 to 1 (negative (-1), neutral (0), positive (1)). In this research paper, we propose a new approach to creating advertisements based on emotions present in the text as well as compare text created by artificial intelligence text generators and copywriters. The results of this analysis will help answer the question of how well-developed the text generator http://rytr.me is and whether it can mimic copywriters on the basis of emotions contained within text.

SA is solely an appropriate tool to assess text and cannot process emotions and sentiment conveyed through other means of advertising such as graphic content or music. Therefore, to reliably utilize SA, we focus exclusively on advertisements that deliver advertising messages only through text (transcribed audio).

Our aim is to assess the difference between the marketing text of pharmaceutical advertisements created by a copywriter and artificial intelligence (AI) with the use of natural language processing (NLP) and sentimental analysis (SA). Assessing text quality and origin is crucial, especially when considering using AI-generated text for marketing purposes. This research focuses solely on sentiment analysis of pharmaceutical advertisements; therefore the results apply specifically to this sector. To accomplish the stated goals, we use natural language understanding (NLU) and NLP software. In the case of this research, we utilize IBM NLU to extract metadata and meaning from text through the use of deep learning algorithms.

A major focus within the advertising research sector is analysis on discrete emotions and how they influence advertising outcomes. One example is analysis of fear language which incites fear in targeted individuals with the advertisement commonly offering solutions to ameliorate the cause (Rossiter, Thornton, 2004). Guilt is another extensively studied discrete emotion and has been shown to significantly impact donation-related behavior. For instance, advertisements that incite a feeling of guilt and focus on egoistic higher perks for the giver rather than the receiver are more effective (Changa, 2014).

Emotions such as anger and sadness are similarly the topics of marketing research. For example, Rucker and Petty find that customer emotion impacts their receptivity to different marketing designs. Customers who were influenced by sad emotions were more receptive to passive marketing, and those influenced by angry emotions were more receptive to active marketing (Rucker, Petty, 2004). Consequently, emotions present in advertising language can have a large effect on how receptive customers are to the advertising campaign as a whole.

Moreover, as neuroscience in the previous decade advanced it is used in the advertising industry to create tailored ads. Tools such as opinion mining, sentiment analysis, and emotion understanding made it possible to create smart and contextual ads. These tools are especially useful due to real-time feedback for ad effectiveness and the capability to forecast advertising results (Sanchez-Nunez, Cobo, Heras-Pedrosa, Palaez, Herrera-Vidma, 2020).

1. Research questions and hypothesis

In this research, we ask the following question: Are AI-generated advertisements as effective as copywriter-produced ones? We chose the emotional score of the text as an indicator of similarity between the two advertisement types. Emotional scores are statistical measures produced by the Watson NLU algorithm and indicate the level of expression of the particular emotion in the text (see Methodology section for a detailed discussion). Our assumption is that if AI-generated ads have an identical or similar emotional score to copywriter-generated advertisement, then both advertisements will be equally effective in marketing a product. This assumption is based on the empirically validated importance of emotions in marketing and their dominant influence on consumer purchase decisions (Mizerski, White, 1986; Taylor, 2000; O'Shaughnessy, O'Shaughnessy, 2002; Falkowski, Tyszka, 2009).

We can formalize our research question as the following hypothesis:

H1: The emotional score in the text does not differ between AI-generated and copywriter-produced advertisements.

In addition, we determine which emotions are most frequently represented in pharmaceutical advertising. Specifically,, we examine which emotions have the greatest expression in the ad's text and whether there is an interaction effect between the emotional score and the advertisement type. We can express those presumptions as the following hypotheses:

H2: All emotions have the same emotional score.

H3: There is an interaction effect between the advertisement type and the emotional score in the text.

Hypotheses 2 and 3 do not affect our main hypothesis (H1), but only deepen our understanding of the phenomenon of emotions in pharmaceutical advertising and how these emotions are generated by artificial intelligence.

We use natural language understanding (NLU) and natural language processing (NLP) software to identify the sentiment and emotions present in advertisement text. We chose IBM Watson NLU as the emotional analysis tool to both extract sentiment metadata and categorize the emotions. The ability to extract sentiment and emotions from data is based on research such as the NRC Emotion Lexicon (Mohammad, Turney, 2013). The NRC emotion categories are frequently used in the computer science field to analyze online text such as Facebook posts (Farnadi et al, 2014). IBM Watson utilizes the NRC emotion categories allowing easier comparison and interpretation. We use statistics to analyze the Watson NLU output to determine characteristics and differences in the advertisements. Due to all analyzed text being transcribed audio pharmaceutical advertisements, we limit our conclusions to this advertising space.

2. Sector selection and data collection

We analyze the pharmaceutical industry advertising sector primarily due to its specific characteristics. Within advertising, each sector has its own specific advertising language and emotions. For example, gastronomy advertisements commonly use words that emphasize pleasure, smells, and tastes (Kusumasondjaja, Tjiptono 2019). Pharmaceutical advertisements differ from many other advertisements as they are subject to greater regulation and oversight. They consequently strike a delicate balance of being creative and yet adhering to pharmaceutical advertising regulations. However, they are also extremely varied, with pharmaceuticals serving very different purposes from ameliorating hormonal symptoms to increasing hair growth. Consequently, pharmaceutical advertisements are potentially more difficult for machine learning algorithms to mimic. We therefore choose to examine the effectiveness of generated ads within this sector.

During primary research, we found that pharmaceutical audio advertising was more accessible for text extraction. Even in audio advertising, other sounds such as music or background sound effects can convey emotions. Examples include the sound of a sizzling hamburger or sea gulls on a beach. However, we found that pharmaceutical audio advertising less frequently utilized background sounds other than music. It was therefore comparatively easier to analyze these advertisements.

We chose audio transmitted advertisements as they maximize the usefulness of textual analysis. As mentioned above, advertisements evoke emotion through methods other than spoken text. Specifically, we want to avoid advertisements that rely on visual stimuli. This is because visual ads likely convey some part of their message through means other than text such as pictures, videos, emoticons, and infographics. By using such ads, we miss much of the emotional data. Consequently, we focus exclusively on audio advertising as the spoken text should contain most if not all of the advertising contents.

Due to most radio advertisements being stored as audio files, we found no substantial databases that include written transcripts of recent radio advertisements. We therefore source our textual data from audio files that we selected and then transcribed. We use Google Cloud's Speech-To-Text transcription tool to transcribe the advertisements from audio to written text.

We source the audio advertisements from adsspot.me, a website archive of ads that offers search filters and downloadable MP3 files. We selected the 'audio' media type, the 'health & pharmaceuticals' industry, and manually selected pharmaceutical ads. We chose nine advertisements that broadly represented different branches of the pharmaceutical industry including painkillers, supplements for nicotine withdrawal, medication addressing thyroid cancer, hormone medication, and anti-inflammatory medicine. All advertisements are around one minute in length and were downloaded as MP3 files.

We set the Google Speech-To-Text language to 'American English' and the transcription model to 'phone call'. We chose these settings as the language of the audio ads was primarily American English and because the 'phone call' model most closely matched the source. We manually corrected the transcribed texts to exactly match the audio.

In addition to the nine unique audio advertisements, we also generated nine marketing texts using the artificial intelligence software http://rytr.me (Rytr). After obtaining nine audio transcriptions from Google Cloud, we manually selected a set of keywords from each advertisement transcript. These keywords were inputted into Rytr to serve as a foundation for generating advertisements describing the same products using AI. While the keywords were manually selected, they follow a standardized method. We selected: the product name, key features, and the problem is solved. By inputting these specifications, the program generates text similar to real audio advertisements. The Rytr product is designed to generate text for commercial use and is intended to be utilized in the manner described above. We adjusted Rytr's settings and generated nine text ads, each using the keywords from a corresponding audio ad. In total, we analyze eighteen text examples.

Rytr is an artificial intelligence program capable of generating different types of high-quality text according to specified inputs and criteria. We chose 'American English' and 'enthusiastic tone' for the language and tone of the generated advertisements. We chose the language to match that of the audio ads and selected the 'enthusiastic tone' from the 20+ available options as it was the most applicable to advertising. We set the creativity level to 'high' and did not select a copywriting framework. We generated output until it was the same length as the transcribed texts from the audio advertisements.

3. Sentiment analysis methods

We conduct sentiment and emotional analysis on the advertisements using IBM's Watson NLU product. We chose this program since Watson NLU was recently shown to be more accurate than its competitors from Amazon, Google, and Microsoft (Ermakova et al, 2021). Furthermore, Watson is easy to use and replicate, allowing for excellent analysis.

Watson's Sentiment feature analyzes text and returns the overall sentiment on a scale of -1 to 1. Scores between –1 and 0 represent negative sentiment and scores between 0 and 1 indicate positive sentiment. Scores at or around 0 represent neutral sentiment. The closer the score is to –1 or 1, the more strongly the positive or negative sentiment is expressed.

We similarly utilize Watson's Emotion feature to analyze the emotions contained in the advertisement texts. Watson's Emotion feature outputs five sentiment confidence scores for the five NCR emotion categories of sadness, joy, fear, disgust, and anger. Each score ranges from 0 and 1. A higher score indicates that the emotion is more likely to be conveyed in the text. A score of 0 indicates that the emotion is not expressed in the text and a 1 indicates that the emotion is strongly expressed (see Natural Language Understanding - IBM Cloud API Docs, 2022).

IBM Watson's proprietary pre-built classification model constructs the sentiment and emotional scores (see IBM Cloud Docs, 2022). We use these sentiment and emotional confidence scores to analyze the overall advertising samples. These scores allow us to compare the language expression of audio advertisements to their generated peers.

4. Results

The results of the sentiment analysis are presented in Table 1. It contains emotional scores for a given emotion in a given advertisement text. From the analysis of averages, it is simple to observe that individual emotions differ in their emotional score. Sadness and joy have the highest scores in all texts, regardless of the advertisement type. The standard deviations for these emotions are also significantly higher than for other emotions, suggesting a large dispersion between advertisements.

Table 1. Sentiment analysis

	Sadness		Joy		Fear		Disgust		Anger	
Ad	**Real**	**Comp.**	**Real**	**Comp.**	**Real**	**Comp.**	**Real**	**Comp.**	**Real**	**Comp.**
1	44,35	25,74	19,48	17,16	15,64	22,05	3,08	2,53	8,36	8,95
2	46,2	46,98	10,83	16,57	15,84	5,89	2,82	3,35	5,95	6,66
3	38,89	18,74	28,38	76,53	9,52	6,87	5,12	2,8	9,16	1,26
4	36,53	24,3	33,14	45,99	11,13	2,81	3,08	1,81	12,91	11,77
5	21,13	54,99	43,34	33,06	12,9	6,25	2,94	1,17	8,36	2,98
6	35,32	52,55	34,85	11,41	7,37	8,2	5	1,37	4,92	10,47
7	33,46	35,42	28,06	21,8	14,19	17,35	4,35	0,83	11,05	6,3
8	28,29	37,74	41,73	27,96	12,49	10,66	3,66	1,1	9,2	7,21
9	29,8	32,65	30,05	40,41	10,1	7,4	3,83	2,51	9,69	7,08
Mean	34,89	36,57	29,98	32,32	12,13	9,72	3,76	1,94	8,84	6,96
SD	7,88	12,78	10,21	20,16	2,86	6,14	0,88	0,89	2,41	3,32
Range	25,07	36,25	32,51	65,12	8,47	19,24	2,30	2,52	7,99	10,51

In order to understand the statistical relationships presented in Table 1., we perform a two-way analysis of variance using the robust non-parametric method proposed by Wilcox and implemented in the WRS2 package in R (2020). From the results shown in Figure 1., it is clear that the differences between computer-generated and copyrighter-produced advertisements are small. Indeed, ANOVA indicates no significant statistical difference between the advertisement type and emotional score ($F(1) = 0,41$, $p = 0,5225$, $\eta = 0,00$), which is consistent with our first hypothesis. In contrast, ANOVA shows significant differences between the emotional score and the emotion type ($F(4) = 22,52$, $p < 0,001$, $\eta = 0,71$). From Figure 1., we can observe that sadness and joy have greater expression in the text of pharmaceutical advertisement. This leads us to reject our second hypothesis. Our last hypothesis about an interaction effect between the advertisement type and the emotion type cannot be supported ($Chisq(4) = 0,7332$, $p = 0,7332$, $\eta = 0,00$). Both AI-generated and copyrighted-produced ads emphasize sadness and joy as the dominant emotions in the advertisement text and potentially most likely to influence consumer decisions (Figure 2).

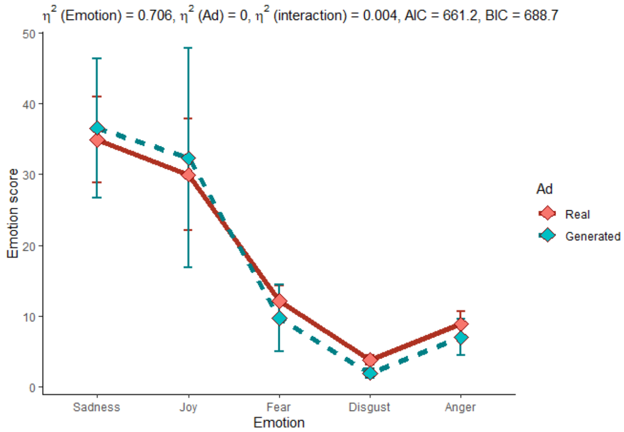

Figure 1. Emocional differences between computer-generated and copyrighter-produced advertisements

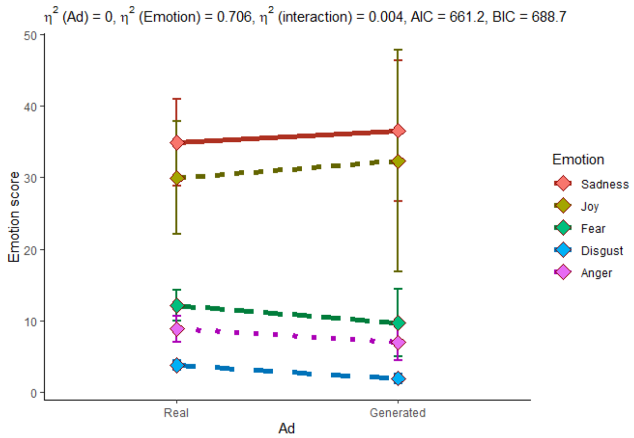

Figure 2. Group differences emocjional between computer-generated and copyrighter-produced advertisements

However, comparing the average emotional scores between AI-generated and copywriter-produced ads only partially answers our research question. By comparing the averages, we find advertisements do not differ on the aggregate emotional score. From Table 1, however, we can perceive that there is a large variance in the similarity between AI-generated and copywriter-produced advertisements. For example, ad no. 1 has a high similarity for the emotional of anger (the emotional score is 8,36 and 8,95 for the copywriter and computer-generated ads respectively). The ad no. 3, however, has a very low similarity for joy (28,38 vs. 76,53). We therefore require a measure that can quantify the similarity between the advertisements for each of the 5 emotions. Cosine similarity (CS) provides a solution. For our dataset, cosine similarity ranges from 0 to 1, where the higher the value, the greater the similarity between the advertisements. The cosine similarities are presented in Table 2.

Table 2. Sentiment analysis - cosine similarities

Emotion	Sadness	Joy	Fear	Disgust	Anger
Cosine similarity (unstandardized)	0,9039257	0,8499858	0,8930435	0,8823236	0,890459
Cosine similarity (standardized)	0,69135	0,5718766	0,8539535	0,9962885	0,9348577

The similarity between computer-generated and copywriter-produced advertisements is quite high. The greatest similarity was achieved by sadness, and the lowest by joy (although still a very high similarity). However, cosine similarity is not a standardized measure and calculates the similarity only for the given emotion while ignoring the values for other emotions. For example, from Table 1, we can see that the absolute difference in an emotional score for disgust is much smaller than the absolute difference for joy (the largest difference for disgust is for the ad no. 6 and equals 3,63 points, while the largest difference for joy is for the ad number 3 and equals 48,15 points). We therefore standardize the results to account for differences in absolute levels of expression for the given emotion. The cosine similarity for the standardized emotional scores significantly decreased for sadness and joy, and increased for disgust. Although sadness and joy have a significantly lower similarity compared to emotions like disgust and anger, their similarity is still large. The decrease in cosine similarity values can also be partially explained by a higher emotional score of these emotions and their higher variance (see means and standard deviations in Table 1).

5. Conclusions

Based on the above results, we can draw two main conclusions:

– AI-generated advertisements are not significantly different from copyrighter-produced ads, when it relating to emotional scores.
– Sadness and joy are emotions with the highest emotional score in the text of pharmaceutical ads.

If we accept our assumption that the emotional score in the advertisement text determines the effectiveness of the marketing message, then we can assume equivalence between AI-generated and copywriter-produced ads. This is a significant conclusion in several respects.

First, artificial intelligence can replicate emotions at a human level. This means that modern text generators can produce texts with equivalent emotional expression to human-created texts. This ability can prove extremely useful for marketers planning to increase the effectiveness of their strategies by enriching text with desired emotions.

Second, using AI-generated advertisement can significantly reduce the cost of marketing campaigns. Small and medium-sized businesses that cannot afford to hire professional marketers can take advantage of much cheaper, AI driven methods of generating ads. All that is needed is to purchase AI software and be able to launch marketing campaigns on social media with great efficiency. Further improvement and popularization of these algorithms can help significantly increase the competitiveness of small and medium-size businesses.

Third, and perhaps most important, the equivalence of AI-generated and human-created advertisement creates new opportunities to run massive advertising campaigns in which thousands of generated ads are distributed across different mass media. This method could prove extremely useful when combined with a strategy of marketing personalization. One can easily imagine a situation where there are two algorithms: one algorithm determines a user's characteristics, preferences and needs e.g., using data from their social profile (see Kosinski, 2013 and Youyou, 2015 for examples of such algorithms), and the second algorithm generates an ad for this user, based on data collected by the first algorithm. The result of such algorithm cooperation would be a full personalization of advertising for the user. Everyone would receive an AI-generated advertisement that would match their financial situation, social group, preferences, desires, personality, and emotional needs. Such a vision may seem like science-fiction, but such algorithms already exist (see Matz, 2017) and one only needs to adapt them to the needs of their marketing strategy.

6. Limitations and future research

This study has two major limitations:
- Use of only radio advertisements
- Use of only pharmaceutical advertisements

Radio ads are only one form of advertisement. Although radio is still extremely common, its popularity among younger generations is declining (Global World Index, 2020). Radio advertising does not include the visual aspect, making it naturally less sophisticated than television or social media advertising. Future research should focus not only on text generation methods but also on images and videos. There are already algorithms capable of creating advanced images and videos e.g., Generative Adversarial Network (GAN) or Neural Style Transfer (NST). Using these algorithms to generate advertisements has not yet been fully explored and is an area for potential research.

The use of only pharmaceutical advertisements is also a limitation. We showed the dominant role of sadness and joy in the advertisement text, but it may be just a characteristic of pharmaceutical advertising. It is necessary to further compare different types of advertisements e.g., car ads, travel agency ads or even election ads. Comparing a larger group of advertising mediums will provide us with more information about the role of particular emotions in marketing and fully confirm our belief in the ability of artificial intelligence to create an effective marketing message.

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ZNACZENIE EMOCJI W REKLAMIE. OCENA RÓŻNIC W POZIOMIE EMOCJI MIĘDZY TEKSTAMI REKLAMOWYMI TWORZONYMI PRZEZ COPYWRITE-RÓW A AI W BRANŻY FARMACEUTYCZNEJ

Streszczenie

Emocje są ważnym elementem reklamy i mają decydujący wpływ na jej skuteczność. Celem prezentowanego artykułu jest ocena różnic w poziomie emocji obecnych w tekstach reklamowych tworzonych przez copywritera i generator tekstów oparty na sztucznej inteligencji (AI). Do oceny emocji wykorzystano analizę sentymentu przeprowadzoną za pomocą aplikacji IBM Watson NLU. Badanie dostarcza informacji na temat emocji obecnych w reklamach radiowych produktów farmaceutycznych, a także umożliwia identyfikację różnic pomiędzy źródłami tekstowymi generowanymi przez człowieka i AI. Wyniki pokazują, że reklamy z obu źródeł mają podobny poziom emocjonalny, z wyjątkiem kategorii "obrzydzenie", która w tej sytuacji może być wykorzystana jako wskaźnik pochodzenia reklamy. Opisane wyniki odnoszą się tylko do radiowych reklam farmaceutyków. Na końcu artykułu sformułowano zalecenia dla biznesu oraz wskazano kierunki przyszłych badań.

Słowa kluczowe: emocje, sztuczna inteligencja, generatory tekstu, reklamy radiowe

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