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THE POTENTIAL OF ARTIFICIAL INTELLIGENCE (AI) TO IMPROVE ELECTRONIC WORD-OF-MOUTH'S (eWOM) EFFICACY***

Abstract: Internet-mediated online communication, particularly with regard to a product, brand, or organization, is known as electronic word-of-mouth (eWOM). Analyzing this open exchange of opinions and information about a company or product among consumers can be extremely useful for businesses. Opinion mining, (sentiment analysis), is a popular subdomain in Natural language processing (NLP) which allows for transforming qualitative data into quantitative information. The sentiment analysis of eWOM has greatly improved with the advancement of artificial intelligence (AI). Nowadays, computer algorithms can automatically classify the sentiment polarity of digital communication after extracting plain text. Artificial intelligence (AI) has the potential to fundamentally alter how companies assess and use consumer feedback to improve their products and services. In this paper, the authors, by analysing the attitudes of 450 respondents, tried to bring this current topic closer to experts in the field of digital marketing, in order to point out to them all the benefits that the sentiment analysis of consumers with the help of artificial intelligence algorithms can provide. The aim of this study is to indicate that if marketing experts use sentiment analysis supported by artificial intelligence (AI), they will be able to gain deeper insights on their customers and adjust their business strategies accordingly.

Keywords: Artificial Intelligence (AI), Electronic Word-of-Mouth (eWOM), Sentiment Analysis, Natural Language Processing (NLP).

INTRODUCTION

New technologies have opened up a whole new universe of opportunities and unlimited growth possibilities for businesses (Ravić et al. 2022) allowing improvements in corporate efficiency and strengthening relationships with consumers (Papakonstantinidis

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et al. 2021). Among the new technologies, artificial intelligence (AI) and machine learning (ML) certainly stand out by providing marketers with on-demand monitoring, understanding and predicting consumer behavior. Businesses can also use AI tools to automatically generate consumers profiles by classifying their clientele into different groups based on their demographics, behaviors and interests (Kempton 2023).

Consumers exchanging and sharing information about a company or product via social media, mobile communication, and the Internet is known as electronic word-of-mouth (eWOM) (Chu 2021). Social influence, or the process by which people alter their attitudes, behaviors, thoughts, or feelings as a result of connecting with others online, can be facilitated via eWOM (Jobs, Gilfoil 2012). In the context of customer relationship management, social media monitoring is frequently predicated on the valence, i.e., whether electronic word-of-mouth (eWOM) is positive, negative, or neutral. Being confronted with negative reviews while looking for information online can damage the brand's image and lower future sales potential (Kwiatek et al. 2021), thus the goal of the analysis may be to identify negative eWOM and effectively address customer complaints (Van Noort, Willemsen 2012). In sentiment analysis, AI and ML are used to automatically evaluate vast amounts of consumer input to find patterns that suggest a positive or negative valence (AIContentfy 2023). Marketing professionals have long understood that designing marketing communications to emotionally connect with consumers is necessary to bring brands closer to them (Baltezarević, Baltezarević 2023). Managers can learn what customers like and dislike about their products and services by adequately studying what is shared in their written communication (e.g., reviews, tweets, social media posts). An effective, large-scale identification of sentiment allows to pinpoint areas in need of development and make data-driven marketing activities more engaging (Srivastava 2023). Online reviews (also referred to as eWOM) assist consumers in developing trust in a brand and provide credibility to businesses through actual customer feedback (GoSite 2022). According to studies, 95% of consumers read online reviews before making a purchase decision. Importantly, 58% of these individuals are willing to invest extra money in products endorsed by well-reviewed businesses. This suggests that customer opinions are highly important (Srivastava 2023). Here, AI serves as an intelligent tool that helps businesses comprehend their customers' opinions and emotions at scale. AI-based sentiment analysis can also help companies uncover customer trends, and thus allowing to make more informed decisions about strategies for the future. Additionally, it assists companies in developing better customer service strategies which can lead to higher customer satisfaction and loyalty.

Structured and unstructured big data are the two categories that AI handles. Structured data refers to conventional datasets such as demographics, transaction records, and online browsing history. AI is capable of processing this kind of data by performing intricate calculations and delivering precise outcomes instantly. Additionally, structured data is simply arranged in spreadsheets (Kietzmann et al. 2018). Spreadsheets are not a suitable format for presenting the complex, unstructured data that is generated on a regular basis by consumers. Instead, more sophisticated approaches must be used to ensure that the findings are understandable (Sponder, Khan 2018). One of the issues brought on by the increasing volume of data at hand is how to monitor and process it to yield insightful information. Fortunately, real-time management and response to massive volumes of data by service providers is made possible by AI technology, which also automate service interactions. This can therefore result in a personalized experience that customers greatly value (Lemon, Verhoef 2016). There are four types of consumer interaction behaviours: customer-initiated, firm-initiated, collaborative, or passive. Companies can get a competitive edge by gathering and evaluating big data from these four forms of engagement, which increases both the company's and the customer's value at the same time (Kunz et al. 2017).

LITERATURE REVIEW

Electronic word-of-mouth (eWOM) refers to any non-commercial, online, and personal dissemination of information about a product or company that makes use of both mass and personal communication channels (Donthu et al. 2021). Any favourable or negative comment made by present, potential, or past customers about a good, service, business, or brand on the Internet is referred to as eWOM behaviour (Hennig-Thurau et al. 2004). The key benefits of utilizing eWOM in marketing are its capacity to produce an effective message and connect in a broad spectrum of consumer markets (Xu, Lee 2020). In the last several years manager have realized how critical it is to promote and use eWOM to enhance their reputations and brand recognition while simultaneously increasing demand from customers (Chae et al. 2017). Companies regularly employ incentives to encourage customers to discuss their product and service experiences. It is also possible to view this practice as a type of social exchange (Garnefeld et al. 2020). When people share their WOM, they will expect people to interact with them. It could be complaining together or discussing ideas (Luo et al. 2020). The emotions conveyed in online reviews and the perception of those reviews' usefulness in supporting decision-making are significantly correlated (Ahmad, Laroche 2015). Different negative emotions' effects on post-purchase product evaluation are taken into account in some studies. When consumers experience a feeling of regret, for instance, they assess the product more calmly and sensibly, but when they are frustrated or other negative emotions strike, they may make impulsive decisions (Zeelenberg, Pieters 2007).

Sentiment analysis stands for recognizing the valence (emotional polarity) of a text. Natural language processing (NLP) is significantly impacted by research in sentiment analysis. Because social, political, economics, and management sciences are all affected by people's opinions, these fields may also be impacted (Liu 2012). The goal of NLP is to teach computers how to comprehend and analyse text similarly to humans. With the advent of chatbots like ChatGPT, the field has received a lot of interest recently. However, the field encompasses much more than just chatbots, with examples including translating text from one language to another, summarizing enormous quantities of text into a few lines, and transferring information from databases to human language (Cofino et al. 2024). Hartmann et al. outline three primary methods employed in marketing research for sentiment analysis: (1) lexicons, (2) traditional machine learning, and (3) transfer learning, highlighting two significant methodological shifts. Initially, research moved from manual lexicons to automated machine learning techniques, which utilize sparse, high-dimensional "bag-of-words" features for training. The subsequent shift involved the adoption of transfer learning, which employs low-dimensional, dense embeddings from texts (Hartmann et al. 2023). These embeddings are generated through artificial neural networks pre-trained on large-scale open-domain text data (Hartmann et al. 2021).

Lexicons are simple and widely used in applied research; they assign a positive or negative sentiment to each word or phrase in a dictionary without requiring labelled data, relying on frequency counts of these words to classify documents (Hansen et al. 2018). Conversely, traditional machine learning methods, like support vector machines and random forests (Matalon et al. 2021), require labelled training data and use a supervised learning approach to automatically detect sentiment-based associations in text. The progression of text representation methods has significantly evolved, moving from the bag-of-words model to more advanced word embedding techniques, such as GloVe and Word2Vec. These advanced methods, developed by Pennington et al., are capable of capturing semantic relationships between words, offering a deeper understanding of language nuances (Pennington et al. 2014). The advent of transfer learning brought also context-dependent embeddings, as described by Vaswani et al. (Vaswani et al. 2017). These embeddings provide a richer interpretation of words by considering their specific contextual usage. Trained on extensive text corpora, these models foster a more holistic grasp of language and sentiment, proving particularly effective in sentiment analysis tasks when fine-tuned with labelled data. The introduction of models like BERT (Bidirectional Encoder Representations from Transformers) marked a significant milestone in this journey. The model, a ground-breaking approach in natural language processing, was introduced by Devlin et al. in their 2018 paper titled "BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding". This model marked a significant advancement due to its bidirectional understanding of context in text, setting new standards in various NLP tasks. BERT's effectiveness stems from its transformer architecture, which allows comprehensive contextual analysis by examining words both before and after a given word in a sentence (Devlin et al. 2019).

Opinion mining, another name for sentiment analysis, has grown in popularity as a method for converting primarily qualitative data into quantitative information. Its goal is to ascertain the sentiment (an attitude, opinion, or judgment motivated by feeling) of the writer or speaker of a text. Sentiment analysis software scores on a spectrum from negative to positive, depending on the scale it chooses to employ (Turney 2002). With sentiment as a multifaceted entity, marketers will gain more understanding of their consumers (Chapman 2019). AI can effectively be used to identify the sentiment of eWOM (Rajan 2024). Sentiment analysis is an NLP technique that involves mining text sources and abstract data for subjective information. The objective is emotion categorization so that user input can be categorized as positive or negative. For example, the word "wonderful" had a positive connotation, but, when paired with a negative word, like "not," the meaning can shift significantly. Emotion classification has been applied to examine product reviews, movies, and accommodations (Patil, Chandrashekar 2022). Tracking and responding to relevant eWOM is crucial for preserving, extending, and enhancing a brand's reputation as well as its customer relationships (Coombs 2002). AI-based methods, in contrast to lexicon-based, rely on ML algorithms instead of manually generated rules. Lexicon-based systems are not very effective since social media users communicate in non-standard languages. Thus, one of the key advantages of AI-based methods is their ability to produce correct results (Rajan 2024).

Because users of social media typically write informally and utilize slang and colloquial language, it can be challenging to analyse user sentiment. A lot of acronyms, pictures, hashtags, and emojis are commonly utilized in the millions of messages that users create online every second. Predefined symbol and emoji mapping allows to work around such problems. Using their equivalent meanings found in the Unicode Common Locale Data Repository (CLDR), popular emojis used in sentiment analysis can be converted into plain text. Being the largest and most comprehensive standard collection of locale data accessible, CLDR offers essential building blocks for software that supports the languages spoken throughout the world (Cldr.unicode 2023). Once emotions have been identified, AI chatbots and virtual assistants can analyse client sentiment throughout chats and adjust responses accordingly. For example, if a client shows frustration in their comments, an AI-powered chatbot can be trained to respond with empathy and understanding, suggesting solutions that are consistent with the identified sentiment (Lumoa 2024).

AI sentiment analysis tools use ML and NLP to conduct in-depth text analyses. It indicates that the more online mentions are studied, the more reliable the results will be. Sentiment analysis tools enable businesses to assess their customers' feelings regarding a brand, product, or service in real-time. Brand24, Clarabridge, Repustate, OpenText, ParallelDots stand out among the most famous AI sentiment analysis tools (Rogalski 2023). Businesses may rapidly and effectively evaluate massive volumes of consumer feedback and obtain insightful knowledge about customer sentiment by utilizing these tools and platforms. Additionally, they may use these data to boost customer satisfaction, develop their products and services, and obtain a competitive advantage in their market (AIContentfy 2023). However, these tools are still in their early stages of development, and errors are common. AI sentiment analysis techniques do not perform well when someone is being sarcastic or simply joking about a brand on social media and utilizing words with negative meanings, but complete expressions aren't always negative when the entire context is considered (Rogalski 2023).

THEORETICAL FOUNDATION AND HYPOTHESES

Sentiment analysis of eWOM is sometimes difficult, because people don't write formally and use slang and personal language. Emojis, acronyms, photos and hashtags are frequently used in the millions of messages generated by consumers in the online environment every second. Predefined symbol and emoji mapping allows to work around such problems. The original context and sentiment are conveyed even though the converted plain text may not be a coherent statement. This may serve as a vector input for ML algorithms (Rajan 2024).

We hypothesize that:

H1: If people use emojis, acronyms, photos, hashtags and don't write in a formally manner, then eWOM sentiment analysis is much more difficult to achieve.

The sentiment polarity of social media communications can be automatically classified by computer algorithms once the plain text has been extracted. Sentiment analysis algorithms could be broadly categorized into two categories: a) Lexicon-based: This method matches the message with a pre-compiled list of emotive terms. An emotion lexicon is a knowledge repository that contains textual elements labelled with sentiments. They rely on lexical resources like ontologies, lexicons, and word banks. b) AI-based: ML algorithms are used by AI-based methods to determine the sentiment. Through the use of document similarity across text messages, the ML employs algorithms that may learn from data. AI-based methods, in contrast to lexicon-based, rely on ML algorithms instead of manually generated rules. Lexicon-based systems are not very effective since social media users communicate in non-standard languages. Thus, one of the key advantages of AI-based methods is their ability to produce correct results (Rajan 2024).

We hypothesize that:

H2: If marketing experts choose AI-based methods for eWOM sentiment analysis, the results are more likely to be accurate than those obtained with Lexicon-based methods.

Sentiment analysis plays a major role in business intelligence since it helps to better understand customer behaviour and feedback, which improves prediction and decision-making. Business intelligence relies heavily on sentimental analysis because it facilitates a better understanding of customer behaviour and feedback, which enhances prediction and decision-making (Singh et al. 2016).

We hypothesize that:

H3: If business intelligence relies heavily on sentimental analysis, the better it will understand consumer behavior and feedback and thus improve predictions and decision-making.

METHODOLOGY AND RESULTS

Sample and Procedures

The data were forwarded via e-mail to students and teaching staff of faculties located in the territory of the Republic of Serbia. All participants were informed in advance about the confidentiality of the collected material, with the explanation that the survey would only be used for academic research. A total of 475 questionnaires were collected, of which 25 questionnaires were excluded due to incomplete data. The final sample included 450 questionnaires with a response rate of 100%, whose dimension is a confirmation of the satisfactory reliability of the study (Bakker et al. 2012).

The sample was predominantly male (62,00%), M=1,38, SD=.486; mostly respondents aged 26-35 years (33,3%), M=2.58, SD=1.232. Master's level of education prevails (35,8%), M=2.99, SD=.944.

Variable Measurement

To determine the attitudes of respondents to the statements contained in the questionnaire the variables were measured with a five-point Likert scale ranging from "1" (I do not agree at all) to "5" (I completely agree). Out of a total of 17 statements contained in the questionnaire, 6 statements were used to check the validity of the set hypotheses:

H1: If people use emojis, acronyms, photos, hashtags and don't write in a formally manner, then eWOM sentiment analysis is much more difficult to achieve.

To test the validity of H1, we analyzed:

Statement 1. Do you agree with the statement that people use emojis, acronyms, photos, hashtags and do not write in a formal way?

Statement 2. Do you agree with the statement that eWOM sentiment analysis is made easier if they write in a formal way?

H2: If marketing experts choose AI-based methods for eWOM sentiment analysis, the results are more likely to be accurate than those obtained with Lexicon-based methods.

To test the validity of H2, we analyzed:

Statement 3. Do you agree with the statement that marketing experts are applying AI-based methods to eWOM sentiment analysis?

Statement 4. Do you agree with the statement that Lexicon-based methods are less reliable?

To test the validity of H3, we analyzed:

H3: If business intelligence relies heavily on sentimental analysis, the better it will understand consumer behavior and feedback and thus improve predictions and decision-making.

Statement 5. Do you agree with the statement that business intelligence relies heavily on sentiment analysis to understand consumers and gain feedback?

Statement 6. Do you agree with the statement that sentimental analysis contributes to improving and predicting decisions?

We tested the internal consistency of the selected subscale with the help of Crombach alpha. Cronbach's coefficient alpha α=.835 with standardization α=.820 shows a high value of internal agreement of the scale and confirms that the variables are well chosen. The result obtained by testing the selected subscale for testing the set hypotheses α=.807 with standardization α=.803 also shows a high value of internal consistency of the scale. Given that the subscale has a small number of variable values tested (less than 10), in this case, we tested 6 variables, the recommendation is to calculate the mean correlation values between each pair of values. The optimal mean value of the correlation between pairs of values on the scale is between 0.2 and 0.4 (Briggs, Cheek 1986).

Table 1. Mean subscale correlations

Item Statistics			
	Mean	Std. Deviation	N
P1	3.45	1.102	450
P2	3.37	1.251	450
P3	2.82	1.176	450
P4	3.06	1.329	450
P5	2.95	1.330	450
P6	2.82	1.242	450

Table 1 shows that the mean value of the correlation ranges from 2.82 to 3.45, which proves the internal agreement.

Research results

Testing H1: If people use emojis, acronyms, photos, hashtags and don't write in a formally manner, then eWOM sentiment analysis is much more difficult to achieve:

Table 2. Results of the chi-square test for H1.

Chi-Square Tests			
	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	355.146a	16	.000
Likelihood Ratio	295.049	16	.000
Linear-by-Linear Association	40.408	1	.000
N of Valid Cases	450		

a. 3 cells (12.0%) have expected count less than 5. The minimum expected count is 4.09.

Table 3. Symmetric Measures for H1.

Symmetric Measures					
		Value	Asymp. Std. Errora	Approx. Tb	Approx. Sig.
Ordinal by Ordinal	Gamma	.403	.056	6.678	.000
	Spearman Correlation	.336	.049	7.561	.000c
Interval by Interval	Pearson's R	.300	.051	6.656	.000c
N of Valid Cases		450			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

The relationship between these variables is statistically significant, $\chi^2(16,1) = 355.146^a$, $p<0.01$. Spearman's rank correlation coefficient rho= .336 and Pearson's correlation r= .300 indicates positive moderate correlation. A gamma coefficient of .403 indicates that knowing the level of acceptance of the first statement improves the prediction of acceptance of the second statement by 40.3%. The hypothesis H1 is confirmed.

Testing H2: If marketing experts choose AI-based methods for eWOM sentiment analysis, the results are more likely to be accurate than those obtained with Lexicon-based methods.

Table 4. Results of the chi-square test for H2.

Chi-Square Tests			
	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	258.608a	16	.000
Likelihood Ratio	197.597	16	.000
Linear-by-Linear Association	70.877	1	.000
N of Valid Cases	450		

a. 2 cells (8.0%) have expected count less than 5. The minimum expected count is 3.76.

Table 5. Symmetric Measures for H2.

Symmetric Measures					
		Value	Asymp. Std. Errora	Approx. Tb	Approx. Sig.
Ordinal by Ordinal	Gamma	.430	.050	8.043	.000
	Spearman Correlation	.391	.047	8.978	.000c
Interval by Interval	Pearson's R	.397	.046	9.164	.000c
N of Valid Cases		450			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

The relationship between these variables is statistically significant, $\chi^2(16,1)=258.608^a$, $p<0.01$. Spearman's rank correlation coefficient rho= .391 and Pearson's correlation r= .397 indicates positive moderate correlation. A gamma coefficient of .430 indicates that knowing the level of acceptance of the first statement improves the prediction of acceptance of the second statement by 43.0%. The hypothesis H2 is confirmed.

Testing H3: If business intelligence relies heavily on sentimental analysis, the better it will understand consumer behaviour and feedback and thus improve predictions and decision-making.

Table 6. Results of the chi-square test for H3.

Chi-Square Tests			
	Value	Df	Asymp. Sig. (2-sided)
Pearson Chi-Square	168.000[a]	16	.000
Likelihood Ratio	165.987	16	.000
Linear-by-Linear Association	74.433	1	.000
N of Valid Cases	450		

a. 3 cells (12.0%) have expected count less than 5. The minimum expected count is 2.76.

Table 7. Symmetric Measures for H3.

Symmetric Measures					
		Value	Asymp. Std. Error[a]	Approx. T[b]	Approx. Sig.
Ordinal by Ordinal	Gamma	.440	.045	9.283	.000
	Spearman Correlation	.408	.043	9.450	.000[c]
Interval by Interval	Pearson's R	.407	.043	9.435	.000[c]
N of Valid Cases		450			

a. Not assuming the null hypothesis.

b. Using the asymptotic standard error assuming the null hypothesis.

c. Based on normal approximation.

The relationship between these variables is statistically significant, $\chi^2(16,1)$ =168.000[a], $p<0.01$. Spearman's rank correlation coefficient rho= .408 and Pearson's correlation r= .407 indicates positive moderate correlation. A gamma coefficient of .440 indicates that knowing the level of acceptance of the first statement improves the prediction of acceptance of the second statement by 44.0%. The hypothesis H3 is confirmed.

CONCLUSION

Electronic word-of-mouth (eWOM) refers to any statement, positive or negative, made by prospective, current, or former customers about an organization or product that is made available online and accessible to a broad audience. Online reviews, consumer-to-consumer knowledge sharing, buzz, online recommendations, and online opinions are some of the terms used to describe it. Because eWOM shares real experiences and offers unbiased opinions, consumers consider it as more trustworthy and persuasive than advertisements from companies, which can appear to be dishonest. Due to its ability to raise awareness, attitude, and consideration of products and services, eWOM has a significant positive (or negative) influence on consumer behaviour. Additionally, eWOM might indirectly impact social processes by influencing how customers seek for and evaluate information. Companies that use social media anticipate favourable comments from customers on these platforms. Reviews enable the company to engage with potential customers, shape their attitudes, increase brand exposure, and facilitate customer feedback.

Artificial intelligence (AI) is the capacity of computers to carry out tasks requiring intellect comparable to that of humans, such as learning, designing, critical thinking, and creative problem-solving. To create strong customer interactions, companies are now integrating eWOM and AI into their operations. A common use of AI in marketing is the use of digital assistants, which are tools that mimic human speech and communicate with users through a digital interface. Their value lies in their high scalability and capacity to provide regular customer support to a large number of clients at once. The basic concept behind the adoption of intelligent agents is that they can improve customer experience and outcome in conjunction with a business. AI has the potential to transform marketing interactions with clients by generating novel forms of social connection that evoke a sense of being accompanied by another person. Research on the effects of AI and AI-enabled assistants is, however, still in its infancy and is not very extensive.

Considerable insight may be gained into the variables that impact key strategic objectives, like customer involvement and engagement, likelihood of purchase, and trolling behaviours, through AI-powered eWOM sentiment analysis. By utilizing AI in sentiment analysis, organizations may instantly gain valuable insights from large amounts of customer data by automatically interpreting the emotional tone encoded in customer remarks. In public forums where people can freely express their thoughts, customer messages are frequently accompanied by images, emoticons, and other elements to evoke a more profound emotion or viewpoint from the user. Sentiment polarity of textual data is the outcome of analysis expressed in terms of a numerical value produced by the algebraic sum of opinions contained in each sentence, document, or communication. It can be classified as positive, negative, or neutral. High-level algorithms enable ML, a component of AI, to process massive volumes of data and generate predictions. More specifically, ML employs algorithms that may learn from data by analysing document similarities between text messages.

Our empirical findings confirm that: Sentiment analysis is easier to achieve if people write in a formal way and avoid using emojis, acronyms, photos and hashtags; That marketer who choose AI-based methods for eWOM sentiment analysis can expect results to be more accurate than those obtained with Lexicon-based methods. If business intelligence is heavily focused on sentiment analysis, a better understanding of consumer behavior and feedback will be provided, thereby improving forecasting and decision-making.

Companies employ AI to gather user information from eWOM to boost customer lifetime value and user experience. Thanks to AI, marketers can now individually tailor their marketing mix for each and every customer by storing and analysing data about them on an unprecedented scale. However, AI still has its limits. It is not yet developed enough to completely replace humans or offer completely accurate forecasts. AI's inability to properly handle sarcasm, empathy, and sudden phrases in text is one of the primary issues. Refining the hardware and software that will further advance the AI requires additional time. On the other hand, the inability of AI systems to comprehend linguistic subtleties and context can result in erroneous sentiment analysis. It might be difficult for algorithms to understand text correctly when the same words have various meanings in different circumstances. Unfortunately, there are still not enough studies in the scientific literature that would more precisely show the benefits of using AI-based approaches for eWOM sentiment analysis. It is a suggestion to all experts in this field to deal more seriously with this phenomenon, because shortly language creation and interpretation capabilities will be at an even higher level because of models like GPT-3. This means that human emotion and context may be effortlessly captured by sentiment analysis algorithms, leading to more accurate and complex sentiment predictions.

REFERENCES

Ahmad, Laroche 2015: Shimi Ahmad, Michel Laroche. "How do expressed emotions affect the helpfulness of a product review? Evidence from reviews using latent semantic analysis", *International Journal of Electronic Commerce, 20*(1), 76-111.

AIContentfy 2023: AIContentfy. "The role of AI in content sentiment analysis for customer feedback." [Online] https://aicontentfy.com/en/blog/role-of-ai-in-content-sentiment-analysis-for-customer-feedback (Accessed: 18.07.2024).

Bakker, Tims, Derks 2012: Arnold Bakker, Maria Tims, Daantje Derks. "Proactive personality and job performance: The role of job crafting and work engagement", *Human Relations, 65*(10), 1359–1378.

Baltezarević, Baltezarević 2023: Ivana Baltezarević, Radoslav Baltezarević. "Negative effects of humor in marketing communications", *Trendovi u poslovanju, 11*(2), 101-106.

Briggs, Cheek 1986: Stephen Briggs, Jonathan Cheek. "The role of factor analysis in the development and evaluation of personality scales", *Journal of personality, 54*(1), 106-148.

Chae, Stephen, Bart, Yao 2017: Inyoung Chae, Andrew Stephen, Yakov Bart, Dai Yao. "Spillover effects in seeded word-of-mouth marketing campaigns", *Marketing Science, 36*(1), 89–104.

Chapman 2019: Chris Chapman. "Mind Your Text in Marketing Practice", *Journal of Marketing, 84*(1), 26-31.

Chu 2021: Shu-Chuan Chu. "Electronic Word-of-Mouth (eWOM)". [Online] https://www.oxfordbibliographies.com/display/document/obo-9780199756841/obo-9780199756841-0267.xml (Accessed: 18.07.2024).

Cldr.unicode 2023: Cldr.unicode. "Unicode CLDR Project". [Online] https://cldr.unicode.org/ (Accessed: 17.07.2024.)

Cofino, Escorial, Lou, Enquilino 2024: Chester Cofino, Ryan Escorial, Debbie Lou Enquilino, Benjamin Alijado. "A Literature Review on Natural Language Processing (NLP) in Aiding Industry to Progress", *International Journal of Engineering Trends and Technology, 72*(2), 41- 46.

Coombs 2002: Timothy Coombs. "Assessing online issue threats: Issue contagions and their effect on issue prioritisation", *Journal of Public Affairs, 2*(4), 215–229.

Devlin, Chang, Lee, Toutanova 2019: Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova. "BERT: Pre-training of deep bidirectional transformers for language understanding", *arXiv preprint* arXiv:1810.04805, https://arxiv.org/abs/1810.04805.

Donthu, Kumar, Pandey, Pandey, Mishra 2021: Naveen Donthu, Satish Kumar, Neeraj Pandey, Nitesh Pandey, Akanksha Mishra. "Mapping the electronic word-of-mouth (eWOM) research: A systematic review and bibliometric analysis", *Journal of Business Research, 135*, 758-773.

Garnefeld, Helm, Grötschel 2020: Ina Garnefeld, Sabrina Helm, Ann-Kathrin Grötschel. „May we buy your love? Psychological effects of incentives on writing likelihood and valence of online product reviews", *Electronic Markets, 30*(4), 805–820.

GoSite 2022: GoSite. "6 Undeniable Benefits of Online Reviews." [Online] https://www.gosite.com/blog/6-undeniable-benefits-of-online-reviews. (Accessed: 16.07.2024).

Hansen, Kupfer, Hennig-Thurau 2018: Nele Hansen, Ann-Kristin Kupfer, Thorsten Hennig-Thurau. "Brand crises in the digital age: The short- and long-term effects of social media firestorms on consumers and brands", *International Journal of Research in Marketing*, 35 (4), pp. 557-574.

Hartmann, Heitmann, Siebert, Netzer 2021: Jochen Hartmann, Mark Heitmann, Christian Siebert, Oded Netzer. "The power of brand selfies", *Journal of Marketing Research*, 58 (6), pp. 1159-1177.

Hartmann, Heitmann, Siebert, Schamp 2023: Jochen Hartmann, Mark Heitmann, Christian Siebert, Christina Schamp. "More than a Feeling: Accuracy and Application of Sentiment Analysis", *International Journal of Research in Marketing,* Volume 40, Issue 1, pp.75-87.

Hennig-Thurau, Gwinner, Walsh, Gremler 2004: Thorsten Hennig-Thurau, Kevin Gwinner, Gianfranco Walsh, Dwayne Gremler. "Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet?", *Journal of Interactive Marketing, 18*(1), 38–52.

Jobs, Gilfoil 2012: Charles Jobs, David Gilfoil. "Less is more for online marcom in emerging markets: linking hofstede's cultural dimensions and higher relative preferences for microblogging in developing nations", *Academy of Marketing Studies Journal, 16*(2), 79-96.

Kempton 2023: Beth Kempton. "How Is AI Used in Business? 10 Ways It Can Help." [Online] https://www.upwork.com/resources/how-is-ai-used-in-business (Accessed: 15.07.2024).

Kietzmann, Paschen, Treen 2018: Jan Kietzmann, Jeannette Paschen, Emily Rea Treen. "Artificial intelligence in advertising: How marketers can leverage artificial intelligence along the customer journey", *Journal of Advertising Research, 58*(3), 263-267.

Kunz, Aksoy, Bart, Heinonen, Ordenes, Kabadayi, Sigala, Diaz, Theodoulidis 2017: Werner Kunz, Lerzan Aksoy, Yakov Bart, Kristina Heinonen, Villarroel Ordenes, Sertan Kabadayi, Marriana Sigala, David Diaz, Babis Theodoulidis. "Customer engagement in a Big Data world", *Journal of Services Marketing, 31*(2), 161–171.

Kwiatek, Baltezarević, Papakonstantinidis 2021: Piotr Kwiatek, Radoslav Baltezarević, Stavros Papakonstantinidis. "The impact of credibility of influencers recommendations on social media on consumers behavior towards brands", *Informatologia, 54*(3-4), 181-196.

Lemon, Verhoef 2016: Katherine Lemon, Peter Verhoef. "Understanding customer experience throughout the customer journey", *Journal of Marketing, 80*(6), 69–96.

Liu 2012: Bing Liu. *"Sentiment Analysis and Opinion Mining"*. Morgan & Claypool Publishers.

Lumoa 2024: Lumoa. "5 Creative Ways to Use AI for Sentiment Analysis." [Online] https://www.lumoa.me/blog/5-creative-ways-to-use-ai-for-sentiment-analysis/ (Accessed: 15.07.2024.)

Luo, Chen, Chea 2020: Margaret Meiling Luo, Min Wen Chen, Sophea Chea. "Facebook ewom marketing strategy: a social support theory perspective", *People: International Journal of Social Sciences*, *6*(01), 501–511.

Matalon, Magdaci, Almozlino, Yamin 2021: Yogev Matalon, Ofir Magdaci, Adam Almozlino, Dan Yamin. "Using sentiment analysis to predict opinion inversion in Tweets of political communication", *Scientific Reports*, 11 (1), p. 7250

Pennington, Socher, Manning 2014: Jeffrey Pennington, Richard Socher, Christopher Manning. "*GloVe: Global vectors for word representation*". In Proceedings of the 2014 Conference on EMNLP Doha, Qatar (pp. 1532–1543).

Papakonstantinidis, Kwiatek, Baltezarević 2021: Stavros Papakonstantinidis, Piotr Kwiatek, Radoslav Baltezarević. "The impact of relationship quality and self-service technology on company performance", *Polish Journal of Management Studies*, *23*(1), 315-326.

Patil, Chandrashekar 2022: Rajashekhargouda Patil, Chandrashekar, N.S. "Sentimental Analysis on Amazon Reviews Using Machine Learning." In Karuppusamy, P., García Márquez, F.P., & Nguyen, T.N., (Eds.). *Ubiquitous Intelligent Systems* (pp. 467–477). Springer Nature Singapore: Singapore.

Rajan 2024: Victor Rajan. "Sentiment Analysis of Social Media Using Artificial Intelligence." In J. Li (Ed.), *Advances in Sentiment Analysis - Techniques, Applications, and Challenges*. IntechOpen. doi: 10.5772/intechopen.113092

Ravić, Baltezarević, Radić 2022: Nenad Ravić, Radoslav Baltezarević, Nikola Radić. „Istraživanje upotrebe digitalnog marketinga u malim i srednjim preduzećima u Republici Srbiji", *Megatrend revija*, *19*(2), 1-12.

Rogalski 2023: Kuba Rogalski. "The 14 Best AI Sentiment Analysis Tools [2024]." [Online] https://brand24.com/blog/best-sentiment-analysis-tools/ (Accessed: 19.07.2024.)

Singh, Kushwaha, Vyas 2016: Bharat Singh, Nidhi Kushwaha, Om Prakash Vyas. "An interpretation of sentiment analysis for enrichment of Business Intelligence." In *Proceedings of the 2016 IEEE Region 10 Conference (TENCON)*, (pp. 18–23). Institute of Electrical and Electronics Engineers.

Sponder, Khan 2018: Marshall Sponder, Gohar F. Khan. "Digital Analytics for Marketing. Routledge." New York.

Srivastava 2023: Sudeep Srivastava. "Harnessing the Power of AI Sentiment Analysis – 10 Benefits and Use Cases for Businesses." [Online] https://appinventiv.com/blog/ai-sentiment-analysis-in-business/ (Accessed: 20.07.2024).

Turney 2002: Peter Turney. "Thumbs up or thumbs down?: semantic orientation applied to unsupervised classification of reviews". In *Proceedings of the 40th annual meeting on association for computational linguistics* (pp. 417-424). Association for Computational Linguistics.

Van Noort, Willemsen 2012: Guda Van Noort, Lotte Willemsen. "Online damage control: The effects of proactive versus reactive webcare interventions in consumer-generated and brand-generated platforms", *Journal of Interactive Marketing, 26*(3), 131–140.

Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, Kaiser, Polosukhin 2017: Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan Gomez, Lukasz Kaiser, Illia Polosukhin. "*Attention is all you need*". In Proceedings of the 31st Conference on Neural Information Processing Systems Long Beach, USA.

Xu, Lee 2020: Xun Xu, Chien Lee. "Utilizing the platform economy effect through EWOM: Does the platform matter?", *International Journal of Production Economics, 227*, 107663.

Zeelenberg, Pieters 2007: Marcel Zeelenberg, Rik Pieters. "A theory of regret regulation 1.0", *Journal of Consumer psychology, 17*(1), 3-18.

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Пиотр Б. КВИАТЕК

ПОТЕНЦИЈАЛ ВЕШТАЧКЕ ИНТЕЛИГЕНЦИЈЕ (АИ) ДА ПОБОЉША ЕФИКАСНОСТ ЕЛЕКТРОНСКЕ УСМЕНЕ ПРЕДАЈЕ (EWOM)

Резиме

Интернет посредована онлајн комуникација, посебно у вези са производом, брендом или организацијом, позната је као електронска усмена предаја (eWOM). Анализа ове отворене размене мишљења и информација о компанији или производу међу потрошачима може бити изузетно корисна за предузећа. Прикупљање мишљења (анализа сентимената) је популаран поддомен у обради природног језика (NLP) који омогућава трансформацију квалитативних података у квантитативне информације. Анализа сентимента eWOM-а се значајно побољшала са напретком вештачке интелигенције (АИ). Данас компјутерски алгоритми могу аутоматски да класификују поларитет сентимента дигиталне комуникације након издвајања обичног текста. Вештачка интелигенција (АИ) има потенцијал да суштински промени начин на који компаније процењују и користе повратне информације потрошача за побољшање својих производа и услуга. У овом раду аутори су, анализирајући ставове 450 испитаника, покушали да ову актуелну тему приближе стручњацима из области дигиталног маркетинга, како би им указали на све предности које анализа сентимента потрошача уз помоћ алгоритама вештачке интелигенције може да обезбеди. Циљ ове студије је да укаже на то да ако маркетиншки стручњаци користе анализу сентимената подржану вештачком интелигенцијом (АИ), могу стећи дубљи увид у своје клијенте и да у складу са тим прилагоде своје пословне стратегије.

Кључне речи: вештачка интелигенција (АИ), електронска усмена предаја (eWOM), анализа сентимената, обрада природног језика (NLP).

Рад је предат 17. септембра 2024. године, а након мишљења рецензената, одлуком одговорног уредника *Баштине*, одобрен за штампу.