THE ADVANTAGES OF SENTIMENT ANALYSIS DRIVEN BY ARTIFICIAL INTELLIGENCE (AI)[1]

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ABSTRACT
Sentiment analysis is the process of determining the opinion, judgment, or emotion expressed in natural language. This analysis is an effective method for evaluating written or spoken language to identify whether it is positive, negative, or neutral, and to what extent. These days, electronic word-of-mouth, or eWOM, is a common way for customers to publicly share their thoughts about products and services on websites (that provide reviews), social media, and forums. Negative customer sentiment toward a brand or company in the digital sphere can generally have detrimental effects on business. Therefore, in order to solve issues and please customers, it's critical for companies to take specific actions that align with the insights gleaned from sentiment analysis. The development of artificial intelligence (AI) has significantly improved sentiment analysis and it is increasingly becoming an integral part of digital marketing, which can be used to gather information about consumer sentiment towards a brand in a digital environment, on the basis of which strategies can be optimized. However, because artificial intelligence is still a relatively new technology, it struggles to understand texts that contain emojis, photos, hashtags, or other common slang, irony or sarcastic statements used by users in digital environment. Because of these ongoing challenges, AI is yet unable to provide results from sentiment analysis that are accurate enough. However, it won't be long until these techniques improve even further and, as a result, become a crucial part of digital marketing strategies.
Keywords: Sentiment Analysis, Artificial Intelligence (AI), Digital Marketing, Ewom

Introduction
The digital world is gradually surpassing traditional media in terms of shaping social attitudes. Customers can express conflicting viewpoints with others on social networks, as well as satisfy their demands for communication and knowledge (Baltezarević, 2021). Companies can make better business decisions by utilizing artificial intelligence (AI), a technology that can predict based on a large amount of data (Baltezarević, 2023). It is anticipated that these tools will advance much further in the future, with intelligent solutions capable of making quick, effective, autonomous, and innovative predictions based on unstructured input (Safieddine & Baltezarević, 2016). It is anticipated that the overall AI market (including generative AI) will develop at a rate of around 16% per year, reaching a value of US$739 billion by 2030 (Statista, 2023).

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Social networks and mobile technology are the most important channels via which consumers can share information prior to making a purchase (Abedi et al., 2020). Consumers are increasingly relying on social media platforms to guide their purchasing decisions, including information about the brand, the manufacturer's background, and the availability of retailers (Chivandi et al., 2020). Research findings show that 37.6 percent of respondents acknowledge the impact of eWOM had on their decision making (Navarro, 2023).

Differentiating itself from traditional WOM, eWOM allows for instantaneous information sharing via always-available Internet communication channels (Huete-Alcocer, 2017). Effective word-of-mouth (eWOM) is a more trustworthy and approachable information route than traditional advertising, even though it can also have negative effects which include losing credibility and fuelling mistrust among consumers (Reimer & Benkenstein, 2016). With the recent surge of generative AI solutions across various domains previously reserved to human activity, it is inevitable that eWOM will evolve further and include algorithm-to-algorithm recommendations (Buhalis & Sinarta, 2019). In the future, communications developed and disseminated by non-human AI tools that can enhance customer decision-making regarding destinations and activities, will be possible thanks to AI algorithms that can autonomously create and spread language outputs (Williams et al., 2020).

Boyd and Crawford (2012) debate whether collecting and analysing such public data is ethical. The authors argue that the ethical implications of big data are not fully understood, making it difficult for researchers to explain their conduct as ethical merely because the data is available (Boyd & Crawford, 2012). Sentiment analysis can yield quantifiable outcomes, gather information from many sources including blogs, Facebook, and Twitter, and handle business intelligence issues (Kumar & Garg, 2020). This marketing strategy uses human emotions to appeal to consumers. Sentiment analysis shows how a consumer's feelings impact their decision of purchasing a particular product. ML techniques and sentiment analysis may enhance a brand's performance and deliver positive consumer experiences (Liu et al., 2020). Artificial intelligence (AI) sentiment analysis is the process of identifying, extracting, quantifying, and studying affective states and subjective information from text using AI technologies, particularly natural language processing (NLP) (Braoulias, 2024). While there are currently issues with artificial intelligence's ability to analyze consumer sentiment, it is clear that as technology advances, this technique will become an essential component of digital marketing.

LITERATURE REVIEW

Any comment (positive or negative) that any prospective, current, or past customer makes online regarding a product or business is referred to as electronic word-of-mouth (eWOM) communication (Hennig-Thurau et al., 2004). There are two types of neutral eWOM. Indifferent Neutral eWOM (INWOM) is the first type that consists solely of product/service details. Pros and negatives information about a product or service are included in the second type of eWOM, known as mixed neutral eWOM (MNWOM) (Tang et al., 2014). MNWOM gives online buyers the chance to compare products based on specific facts about their benefits and drawbacks, as per the opportunity−motivation−ability (OMA) theory. This improved the credibility of online reviews and had a favourable impact on sales (Roy et al., 2018). When neutral eWOM lacks positive as well as negative feedback, consumers' willingness to analyze eWOM falls because they find indifferent communications less intriguing (Tang et al., 2014).

According to the attribution theory (Heider, 1958), consumers will be influenced by an online review of a product if they believe it to be true and reputable and may therefore be linked to the product's actual performance.

Customers will consider a review as prejudiced and refuse to be persuaded by it if they believe the review was influenced by financial gain (Jeong & Koo, 2015). According to the media richness theory, a message's perceived value will increase with accuracy (Kahai & Cooper, 2003). Furthermore, views regarding the objectivity of information have been shown to have a favorable impact on attitudes toward it (Park & Lee, 2008). False information provided to the consumer who adopts the prior review will result in a loss of purchasing intent. Social media provides relatively easy access to information, and users can remain anonymous. This lowers the quality and credibility of social media content. As a result, these two features are crucial in determining the impact of eWOM information (Leong et al., 2022). While some content receives insufficient response, others spread quickly and reach a larger audience (Alboqami et al., 2015). This demonstrated how the impact of information varies from person to person and how different thoughts can be evoked in receivers by the same content (Erkan & Evans, 2018).

eWOM communication has great potential for virality (Baltezarević et al., 2022), however it is the negative eWOM which spreads exponentially through the digital environment and once sent, it is almost impossible to control its spread (Baltezarević & Baltezarević, 2021). An illustrative example is the incident that occurred on July 15, 2017 when a US-based McDonald's employee revealed a food scandal on his personal Twitter account. A man (who goes by the name @nick on Twitter) from Laplace, Louisiana, USA, shared pictures of unclean ice cream machines and other food-making equipment. The pictures also clearly showed that the tray was full of sticky slime and mold, as well as other messes in the kitchen, such as fungus-covered floors. Within minutes, the post had over 10,000 comments and over 15,000 forwards. As a result, McDonald's lost $100 million in market value in just one hour, and its stock dropped 1.3% (Qian & Chen, 2019). On the other hand, according to recent research in the field of customer reviews, an excessively positive review may actually have the opposite effect on sales and behavioural intentions (Kupor & Tormala, 2018). To gain a deeper knowledge of the long-term benefits of eWOM, longitudinal studies measuring its effects on consumer loyalty, brand advocacy, and repeat purchases should be conducted (Emad, 2023).

Culture influences the mechanism of cognitive stereotyping, which leads to the classification and judgment of oneself and others based on personality traits and likeness, hence altering trust, credibility, attitudes, and behaviours. People from various cultures use different messages and channels to communicate (Kale, 1991). In low-context societies (such as the United States), users join social networks to manage superficial impressions and casual interactions, whereas in high-context cultures (such as Korea), the motivations are cantered on the desire to create long-term relationships and define one's group identity (Pentina et al., 2015). Individualism promotes positive word-of-mouth (WOM) to out-groups (weak connections), but masculinity increases WOM sharing with in-groups (strong ties). Uncertainty avoidance is negatively associated with in-group (strong-tie) WOM. Customers in high uncertainty-avoidance cultures were also less likely to complain or spread negative word-of-mouth (Liu et al., 2001). Individualistic consumers share more information than collectivistic consumers because individualistic societies value the expression of diverse viewpoints, whereas collectivistic cultures prioritize harmony preservation, hierarchy respect, and group face-saving (Cheong & Mohammed-Baksh, 2020). As a result, collectivistic societies express viewpoints less frequently in order to avoid challenging other members of the group. These results were consistent across both the horizontal and vertical dimensions of individualism (Choi & Kim, 2019).

While Western consumers (analytical thinking style) tend to view an object as independent of its context and are therefore likely to evaluate a service or product without external influences, East Asians (holistic thinking style) are more likely to be influenced by their surroundings and peripheral cues, such as prior eWOM (Kim et al., 2018). Perceived usefulness is negatively impacted by cultural distance. Reviews are seen as being more useful when they are produced by consumers who come from similar cultural backgrounds because they are assumed to share comparable preferences and attitudes. People from high uncertainty avoidance cultures are often more receptive to information from unknown sources, which is often the case with eWOM, in terms of trust because uncertainty avoidance is linked to risk aversion (Kim et al., 2018). The connection between indulgence and review rate was discovered to be favorable because people in indulgent societies have a more positive mindset, which makes them feel more optimistic and more inclined to remember happy emotions (Stamolampros et al., 2019). Individuals from constrained societies, on the other hand, are less optimistic, less likely to recall pleasurable emotions, and gloomier (Mariani et al., 2019). Masculinity is found to be adversely associated with the review rate, since masculine consumers are less tolerant of service failures and believe they have the capacity to confront service providers about the disappointing experience (Torres et al., 2014). Furthermore, uncertainty avoidance was found to have a negative impact on the review rate because customers with higher uncertainty avoidance are more risk-averse and hence search for product and service qualities, resulting in higher expectations (Litvin, 2019).

When consumers evaluate eWOM information that combines text and visuals, it yields far greater results in terms of message quality, credibility, product interest, and purchasing intention. Similar results imply that buyers are more motivated to make a purchase when presented with text and visual information rather than text alone (Lee & Tussyadiah, 2010). Businesses can respond to customer eWOM more quickly by using machine learning (ML) techniques to analyse vast amounts of online comments. These techniques offer faster and better insights into customer comments and reactions (Pantano et al., 2019). Social media serves as a repository for eWOM, allowing people to freely communicate their opinions and feelings without fear of intimidation. 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 analyze 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). The global revenue from the natural language processing (NLP) market is expected to grow rapidly over the next few years. This market is expected to be over 14 times larger in 2025 than it was in 2017, growing from roughly 3 billion USD in 2017 to more than 43 billion in 2025. NLP, which relies on computer science and computational linguistics among other areas, aims to bridge the gap between human communication and computer understanding (Thormundsson, 2022).

Sentiment analysis may collect data from multiple sources, such as Twitter, Facebook, and blogs, produce measurable results, and address corporate intelligence concerns. The sentiment analysis effectively detects grammatically correct material, and does not include slang, colloquial language, odd acronyms, or misspelled words (Kumar & Garg, 2020). Sentiment analysis builds a model that can identify and extract opinions from eWOM and gather attribute expressions such as the topic of discussion (positive, negative, or neutral), the opinion's polarity, and the opinion holder.

Opinion is subjective, but factual information is objective. Opinions are statements made by individuals conveying their thoughts, emotions, and evaluation of a topic or interest (Obot et al., 2025). After extracting the plain text, computer algorithms can automatically classify the sentiment polarity of social media communications. Two major categories can be used to classify sentiment analysis algorithms: a) Lexicon-based: This method uses a pre-compiled list of emotive phrases to fit the message. A knowledge base with textual components labeled with sentiments is called an emotion lexicon. They make use of lexical resources such as word banks, lexicons, and ontologies. b) AI-based: This method employs ML for determining sentiment. Using algorithms that can learn from data, the ML approach makes use of document similarities across text messages (Rajan, 2024).

Using methods like surveys, sentiment analysis, ethnographic research, or even cutting-edge new technologies to gather information that can be evaluated on the efficacy of human and machine collaboration, leaders can observe and gain insight about how AI and human collaboration's function (Cantrel et al., 2022). Because sarcasm is nuanced, context-dependent, and variable, it can be difficult to handle in sentiment analysis. Sarcasm functions covertly in language, making it challenging to recognize and understand in a variety of linguistic situations and styles. Accurate detection depends on context, which includes tone and speaker purpose. Sarcasm frequently combines negative and positive emotions into a single sentence, making the classification of sentiments difficult (Rahma et al., 2023). Because it requires human judgment that is nuanced, annotating datasets for sarcasm is complex (Islam et al., 2024). Sentiment analysis with AI has a bright future ahead of it. News articles can reveal hidden layers of feeling thanks to Natural Language Processing (NLP), which can interpret language's finer points. But as we move forward, let's not lose sight of the fact that the combination of AI innovation and human ingenuity is the real success factor. It is not only necessary, but also a decision to strike a healthy balance between utilizing AI's capabilities and maintaining the core of human knowledge. Sentiment analysis is a testament to the opportunities that arise when we use technology as a partner in our search for deeper knowledge rather than as a substitute in the dynamic dance between humans and machines (Tripathi, 2024).

CONCLUSION

AI facilitates and monitors user interactions on social media platforms. In addition, AI-based solutions can locate, attract and retain loyal customers on social media. Thanks to these technologies, consumers have the opportunity to discover more about products, which could potentially have a favourable impact on their purchasing behaviour. AI technologies improve user experience and boost confidence, contentment, and understanding, as well. Negative eWOM, on the other hand, can have a detrimental impact on performance, growth, and company image when it comes from dissatisfied consumers.

Companies utilize AI to collect data from a variety of sources, including social media, chatbots, location-based ads, emails, and websites, to generate a significant amount of digital information known as big data. This technology is transforming the way that consumers and providers interact by altering the way that purchases are made online. Companies employ AI in a variety of ways, including enabling customers to make knowledgeable decisions, augmenting the customer experience, increasing organizational effectiveness, encouraging ongoing collaboration and communication with stakeholders, and upgrading customer service procedures and product quality. AI is used to obtain demographic information from publicly available profile photos, comments and likes or dislikes.

Because AI offers solutions in predictive marketing analytics and automated information research, it can lessen the workload of sales staff members responsible for assessing the vast amounts of data provided by social media. AI systems that can independently recognize and assess patterns in written text or speech have been made possible by ML algorithms trained on massive amounts of data. AI systems can evaluate interactions with outputs to design future outcomes and automatically assess user engagement with content. Shortly, AI word-of-mouth (aWOM), or communications developed and disseminated by non-human AI tools that can enhance customer decision-making, may be possible because to the recent development of AI algorithms that can autonomously create and spread language outputs. Today, artificial intelligence and natural language processing are used in the manner of AI sentiment analysis to determine the emotional undertone of the content. As a result, businesses are better able to comprehend the sentiments, views, and feelings associated with their brands when they are mentioned, reviewed, or written about online. Sorting the sentiment into three categories positive, negative, and neutral is the main objective. More sophisticated algorithms, however, are able to recognize particular feelings, like joy, rage, or grief. Customer service and market research use this technology extensively to determine what the general public thinks about specific products, services, or subjects. Though this technology is still in its infancy, in order for this strategy to function flawlessly and raise the bar for digital marketing effectiveness, and offer more accurate data, there are a number of impediments that must be removed.

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