Sentiment analysis of electronic word of mouth (E-WoM) on e-learning.

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Chapter 57
Sentiment Analysis of Electronic Word of Mouth (E-WoM) on E-Learning

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ABSTRACT

The proliferation of social media and the internet has given people many opportunities to air their views and to be at liberty to say what they feel without hindrance. This is beneficial to commercial organizations and the general well-being of the populace. However, the cost of this freedom is that spamming is practiced with little or no control. This chapter focuses on the electronic word of mouth (eWOM) of opinion holders and the sentiments expressed in eWOM. One of the areas of life impacted by sentiment is electronic learning because it has become a prevalent mode of learning. The study aims to analyze eWOM on e-learning which can help in identifying learners' sentiments. Findings from three thousand tweets show more neutral sentiments, followed by positive sentiments. Suggestions and recommendations as well as the future directions for sentiment analysis of eWOM on e-learning are also discussed in this chapter.

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INTRODUCTION

Learning enables individuals or systems to undergo changes, thereby improving the efficiency of tasks and activities. The changes in behaviour, attitude, reasoning and general well-being are a result of conscious and unconscious learning. Knowledge acquisition, skill refinement, problem-solving, induction, analogy and discovery are some of the ways by which one can learn. We learn every time, the traditional learning methods are gradually fading away due to the advent of technology. Conventional libraries are dying, as learners seem more comfortable learning with electronic devices and resources. Newspaper vendors are thrown into the labour market because readers are at ease reading news from their mobile devices. Electronic learning(e-learning) has become a more popular method of learning by reason of its accessibility and flexibility. Despite the many advantages of e-learning, this technology still poses some challenges and these challenges are often expressed by users in the form of criticism. These criticisms are mainly escalated through electronic word of mouth (eWOM). The informal communication between people online is known as Electronic Word of Mouth. This informal communication could be through review sites, social media platforms and online forums about products and services. EWOM is a method employed by customers to review products and services and most times without any commercial intent to either promote or discredit them. Sentiment analysis is a method used to find out the emotional tone enunciated in text. According to Rani and Shivaprasad (2019), offline and online purchase decisions are based on eWOM messages, as consumers tend to rely on the opinions of other consumers when making decisions. The application of sentiment analysis to eWOM can help business owners gain significant insights into how customers feel about a particular product or service, which can assist them in identifying areas of improvement and strengthening customer loyalty. Though eWOM is not restricted to textual datasets, our study focuses on textual datasets where the source datasets are aimed at promoting or discrediting e-learning to consumers or potential consumers.

The advent of the internet cum social media has resulted in the exponential dissipation of audio and textual datasets from various sources to diverse destinations contributing to the big data syndrome in cyberspace. While emphasis has been placed on the security of image and textual data, audio data seems less secure. Audio data also contributes immensely to societal ills such as fake news. Oral and textual datasets are prone to sentiments that can cause damage to an individual's and an organization's reputation. This study develops a framework for analysing electronic word of mouth (eWOM) on electronic learning. Three thousand tweets about e-learning were gathered and analysed to find the polarity that impacts e-learning. The chapters are organised as follows; the background of the study, then the concept of eWOM, borders on e-learning and sentiment analysis will be discussed. The next section will practically demonstrate sentiment analysis of the tweets with findings and discussion, and finally, the summary and conclusion are drawn.

BACKGROUND

Electronic Word of Mouth plays a huge part in learning and knowledge acquisition by furnishing learners with access to experiences and feedback of others on social media platforms, and online discussion fora. In the process of learning, the learner acquires knowledge. This acquired knowledge which comprises information, facts, ideas and rules, is used in making informed decisions. Learning is a crucial method of acquiring knowledge, and knowledge is required to drive the nation's socioeconomic life. The ability to obtain, assimilate, and apply the proper knowledge effectively is an essential skill even for the next century. Concurrently, sensitivity to culture and gender differences and the learning needs of the physically challenged have contributed to the rapid growth of e-learning (Tîrziua and Vrabie, 2015). Sentiments are capable of causing damage to a product through eWOM by promoting or devaluing a product to the detriment of the producer. eWOM has been described as consumer communication about a product, service, or company in which sources are perceived as free of commercial influence (Litvin et al., 2008). eWOM has a positive or negative impact on the purchase of a product. It can be unbiased when some sentiments are not attached to such an opinion, thereby promoting sales. In such a case, it can be highly influential in shaping consumer attitudes, behavioural intentions and purchases (Wu and Wang, 2011). In the information superhighway, opinions are often expressed randomly, endangering its core purpose. Electronic word of mouth has altered the buying environment and customers can access the comparative evaluation of product attributes with a single click of a mouse (Varadarajan and Yadav, 2002), causing many internet users to nickname eWOM as the word of 'mouse'. eWOM also affects the learning space, which today is thriving on the backbone of the internet. Electronic learning has been impacted by eWOM through consumer's online communication.

Electronic Word of Mouth (e-WOM)

Word of Mouth (WOM) is personal communication concerning a brand, product, service or organisation. Here, the sender has no commercial intention, and the receiver knows the sender has no such meaning, even when there may be negative or positive emotions in the communication. The purpose is to share or acquire knowledge of the brand, product, service or organisation. Usually, this occurs between friends, relations or acquaintances with some levels of trust and privacy. The message's non-commercial intent builds confidence in the consumers to rely on Word of Mouth (WOM) more than the conventional media, whose sole purpose is to promote or discredit the item communicated. WOM, though a non-marketer-driven form of communication, is one of the oldest methods of advertising products and services of an organisation and perhaps the most efficient method of influencing consumers' decisions. Westbrook (1987) defined WOM as all informal communications aimed at other consumers regarding the possession, use, or characteristics of specific products and services or their sellers. WOM is an all-encompassing communication channel that embraces all forms of business. WOM allows the customer to engage directly with the business and contributes to the business's growth by deciding the quality and quantity of the products through feedback, reviews and suggestions. The consumer contributes to the business by using his words to encourage or discourage potential customers. Consumers regard word of mouth as a more reliable medium than traditional media (Cheung and Thadani, 2012).

Before the advent of the internet cum social media, WOM was a person-to-person affair. Today everyone that can access the internet engages in electronic communication. The internet has revolutionised WOM to what is popularly known as electronic Word of Mouth (eWOM), the online communication between consumers. In Donthu et al (2021), a bibliometric analysis to explore the field of eWOM shows consistent growth in publications, with North America and Europe leading in the research. This trend is attributed to the extent of internet and social network penetration in these two regions. Hennig-Thurau et al. (2004) defined eWOM as any positive or negative review or post by customers about a product or company made available to multiple people and institutions via the internet. The internet came with its attendant challenges, one of which is vulnerability to fake and sentiment-prone information. The numerical strengths of internet users are growing in leaps and bounds every day, and there has been an equally increased number of open platforms such as social networking sites, blogs and online communities (Barreto, 2014). These and many more factors have promoted WOM from its erstwhile status to a fast and efficient means of communicating consumers' feelings about a product to the producer and the consuming communities. With eWOM, customers are at liberty to conduct a comparative evaluation of what they purchase and communicate the evaluation results to other customers and the producers of these products. Sometimes, these evaluations are polluted with sentiments, which can mar the purchasing interest of other customers. With eWOM, marketers and customers can have one-to-many, one-to-one, many-to-many and many-to-one ways of communication (Weisfeld-spotter et al., 2014). According to (Neilson, 2015), 92% of consumers trust communications about a product by fellow consumers above those done by conventional advertisements. EWOM has no barrier of location and time. Most times, eWOM is motivated by product satisfaction, loyalty, trust involvement and incentives (Neumann, 2015).

According to Jan and Bhat (2021), WOM communication happens spontaneously. It vanishes soon as it is uttered, a notion that does not hold in the case of eWOM, which is written and transpires for an indefinite period. Thus, eWOM is persistent and observable. Rani and Shivaprasad (2019) summarised the differences between eWOM and traditional WOM, as shown in Table 1. Conventional mouth word occurs in a face-to-face setting largely among friends and family members, while eWOM occurs virtually using digital platforms, which is extensively diffusive and occurs among people known as well as unknown but may be linked by a common interest or need.

Table 1. Differences between conventional WOM and E-WOM (Huete-Alcocer, 2017)

Features	WOM	eWOM
Medium	Face-to-face, telephone	Social media, discussion forums, blogs, e-tailers, websites
Credibility	The receiver of the information knows the communicator (positive influence on credibility)	Anonymity between the communicator and the receiver of the information (negative influence on credibility)
Privacy	The conversation is private, interpersonal (via dialogues), and conducted in real time	The shared information is not private and, because it is written down, can sometimes be viewed by anyone and at any time
Diffusion speed	Messages spread slowly. Users must be present when the information is being shared	Messages are conveyed more quickly between users and, via the Internet, can be conveyed at any time
Accessibility	Less accessible	Easily accessible
Form of communication	Oral	Written

Traditional word of mouth occurs among close ties wrapped with higher levels of trust. In the case of eWOM, anonymity or false identity raises credibility issues. The issue of false identity fuels the sentiment-prone contents of eWOM. Electronic word of mouth (eWOM) is the dynamic information exchange process for consumers regarding a product, service, brand, or company via the internet (Ismagilova et al., 2017).

Certain factors should be taken into consideration in order for eWOM to be effective and they include:

- **Source of the message:** When a receiver sees a message on a medium, the first thing that goes into his mind is where the message is coming from, that is, who is the author of the message? What is the antecedent of the author? How credible is the author? What is the level of expertise of the author in the context of the message? How trustworthy is the message? If the 'author's real name, geographical location, profession and gender are used, and he is reputable in authoring authentic messages, the receiver will have a high level of trust in such a message. This level of trust will prompt the receiver to share the message among his peers, thereby spreading the eWOM, and this confidence will equally prompt him to adopt the message. Adopting the message means accepting the information in the eWOM. A receiver often checks the social capital of the author; social capital is the resources and outcomes of a network of membership (Nahapiet and Ghoshal, 1998). According to Neumann (2015), a strong social tie between the authors of eWOM and the receiver positively influences the effectiveness of such eWOM by increasing its credibility.

- **Quality of Coverage:** eWOM is well-articulated with the balance of valence (positivity and negativity), emotions, and simple, lucid and concise language that can convince the receiver to adopt such a message. However, the negativity of expression is believed to be more influential and attract more attention than the positivity of a message. Striking a balance between the two for completeness and efficiency is a good practice. Where a message is one-sided, a consumer may sense a bias and feel reluctant to adopt such a message. Suppose the content of what is posted is too voluminous, the receiver will spend so much time trying to understand the contents, so eWOM should be concise and simple. Consumers also visit various sites to compare reviews, and if they are consistent, the effectiveness of such a message is maintained.
- **Format of Communication:** eWOM comes in different formats, such as textual, audio, video, and images, but the textual form of communication is the most popular. According to Townsend and Kahn (2014), consumers perceive the visual presentation format to be faster, easier, and more enjoyable than other communication formats. This, in effect, means that visual communication can influence the effectiveness of eWOM. High-quality pictures can appeal to a consumer in more than a thousand textual formats depicting the same message. On the other hand, a textual message though easier to send, could be challenging to decipher, especially if it is voluminous. There are, however, some messages that the visual format cannot convey, so text or audio becomes unavoidable.
- **The receiver of the message:** Receiving eWOM may not affect the message, but what is done to the received message does. Factors such as the need for the message, the previous idea of the message, the trustworthiness of the message and the receiver's social status contribute to the message's effectiveness. If what is received does not appeal to the 'receiver's needs and he believes and trusts the authenticity of the source of the message, the receiver may leave such a message on the shelf. Prior knowledge of the received message could help in deciding on the message's usage/ adoption or discarding. The social capital of the receiver of the message and other demographic factors such as age, gender, level of literacy, religion, culture etc., can also affect the status of the message after receipt.

Electronic word of mouth has tremendously influenced the socio-economic lives of people and organizations. The following are some of the ways this has happened:

- **Promotion of Social Interaction:** According to the Kemp (2023), 60% of the world's population uses social media which is about 4.76 billion social media users around the world. Social media has helped to promote social interaction with active users expressing their views and opinions on several issues with no commercial intent. People's confidence in expression and their social capital is enhanced; likewise, their attitudes, purchase intention and purchase decisions. Conventional Business-to-Customer (B2C) and Customer-to-Customer (C2C) communication are rapidly phasing out. Buzz marketing, viral marketing and content marketing strategies are now in vogue (Bowen and Gordon, 2014). Before, consumers trusted communications from friends and family members to aid them in purchasing a product, but today, they look to online information about such a product. In the process, social interaction is enhanced (Nieto et al., 2014). Zhang et al (2021) investigated the impact of interpersonal closeness (IC) and social status (SS) on eWOM effectiveness. Findings show that both IC and SS can interact to positively influence purchase intention, with a review valence moderating the impact. The implication is that firms promoting their products on semi-closed social media such as WeChat, used in the study, need to pay more attention to interpersonal relationships in such a platform.

- **Marketing:** eWOM is especially used in marketing to promote sales of products and services. This is done mainly via social media platforms. However, some customers take advantage of this development, necessitating large organisations to create websites where customers can leave comments and share their opinions about the business products and services (Vallejo et al., 2015). This way, such organisations are gaining control of eWOM that goes to their websites by filtering some dangerous ones capable of damaging their reputations. According to Racherla et al. (2012), online product reviews are reported to be nearly 12 times more trusted by consumers than 'sellers' advertisements. This has led to an increase in the adoption of eWOM by consumers. eWOM can have both negative and positive effects on marketing. It can increase or reduce sales due to comments made by a customer and adopted by another. Consumers often get affected by more emotional expressions, whether positive or negative (Yin et al., 2014). According to (Verma and Jadav, 2021), There has been a paradigm shift in marketing communication channels in recent years. Marketing-sponsored communication channels are replaced with customer-to-customer social network channels. Products and services are under the stringent vigil of consumers. The consumers are sharing their product and service experiences in virtual communities that have no geographical boundary.
- **Academic Research:** One of the most important needs of research is data, yet data gathering has been challenging for researchers. Undertaking research becomes a herculean task without data. To make up for this, some researchers generate and falsify data for their study resulting in outputs that end up on the shelf. eWOM is capable of closing this gap as researchers can gather data from research participants through eWOM on social media. The data used for this research was collected through eWOM on Twitter. Burgees et al. (2015) used eWOM to investigate adopting consumer-generated media (CGM) strategies in small to medium tourism enterprises. Abdullah et al. (2021) used eWOM to investigate the factors influencing visual eWOM on restaurant experience. Post reviews through eWOM were used to find out who posts, why, where and what by vacationers (Bronner and Hoog, 2008). eWOM was the data source (Johan et al., 2021), where respondents' interest in generating eWOM through social media channels was discovered.
- **Decision Support:** The manager of an organisation needs the opinion of his customers to decide on the quality and quantity of a product and services rendered by the organisation. Such opinion should be unbiased, devoid of commercial intent, and could be obtained through eWOM. Market survey on a product through eWOM helps in decision-making. Apart from assisting organisations in taking decisions, eWOM can also assist individuals (customers/consumers) in making decisions concerning their purchases. eWOM from consumers on a particular drug in the form of tes-

timony on the drug has helped customers decide to buy such drugs to enjoy the same benefits. The same goes for other products and services. In a study conducted by Dwityas et al. (2021) on the use of e-wallet applications by Indonesian customers, it was shown that the eWOM variable alone had a significant influence of 39.5% on the purchasing decision-making process using the LinkAja application, while the other factors combined had the remaining 60.5%. Consumers' behaviour is tilted toward the internet, as customers are wont to turn to the social media platform to find out what people say about a product/service before buying. If the response is averagely positive, then the eWOM is adopted, thus supporting decision-making.

- **Increased healthy competition:** No doubt, some people could be reckless in putting up comments about a product/service of an organisation. Consumers search for information about a product/service before making a purchase decision. Manufacturers and service providers would not want information detrimental to their sales posted. This has resulted in healthy competition to improve the provision of service. A study carried out by Abdullah (2016) showed that 20% of participants posted their eWOM to promote the company they commented on. With the proliferation of eWOM in the cyber-space, no organisation wants a negative comment, so everyone is on its toes to satisfy the customers/consumers in service delivery. This has fostered competition with the attendant growth in health services. The adoption of eWOM makes consumers feel a sense of belonging when they realize that their opinions are considered in improving the quality of a product, they are patronizing. According to (Lee et al., 2011), eWOM is increasingly changing everyday life and the relationship between customers and businesses. eWOM is one of the determining forces in influencing attitudes towards a product, stimulating purchase intention and encouraging product purchase (Cheung and Thadani, 2012).

Despite the widespread acceptability of eWOM, it is not without some challenges and some of the challenges are:

- **False Identity/Anonymity:** Some opinion holders do not want their identity disclosed. They either tag their opinions with a fake identity and location or leave it without identification. Irrespective of the valance of such an opinion, the issue of trust and credibility goes with it. This often hinders the adoption of such eWOM. According to Rani and Sivaprasad (2019), eWOM generally comes from anonymous consumers, which gives the scope to be skeptical about credibility compared to WOM. They then suggested an 'authors' ranking system to improve the trustworthiness in eWOM. A key feature of social media is that it enables anyone from anywhere in the world to freely express their views and opinions without disclosing his/her identity and without the fear of undesirable consequences. These opinions are thus highly valuable. However, this anonymity also comes with a price. It allows people with hidden agendas or malicious intentions to work the system to give people the impression that they are independent members of the public and post fake opinions to promote or discredit target products, services, organisations, or individuals without disclosing their true intentions, or the person or organisation that they are secretly working. Such individuals are called opinion spammers, and their activities are called opinion spamming (Jindal and Liu, 2006).
- **Emotional expression:** The effectiveness of eWOM is influenced by the magnitude of emotions expressed in the message. Opinion holders communicate their messages based on the circumstances, mood and sometimes their relationship with the organisation they are commenting on.

Some eWOMs are not based on reasoning and cognition but intuitive feelings. These emotions are sometimes embellished with sentiments capable of tilting the message towards a particular direction that may be beneficial or detrimental to the health of a product or service. Consumers often get more affected by emotional expression, whether positive or negative (Yin et al., 2014).

- **Source of the message:** The person that authors eWOM is the source of the message; that person represents the opinion holder. The challenge usually seen from the source of eWOM is that the source may lack the expertise and knowledge of the subject he is communicating on. For instance, someone who is positively or negatively communicating on e-learning and has never attended any e-learning classes or taught an e-learning class is doing so based on rumours or what he has read about the learning method. Though such an author tags his message with his identity, the message could be biased without depth. The receiver of such a message could be misled into taking a wrong decision by adopting or rejecting the eWOM. eWOM can also suffer from trustability which, according to Saremi (2014), represents the level of trust in which a receiver identifies a message. If a receiver doubts the trustworthiness of the source of eWOM, such a message suffers from further sharing and adaptability.
- **Privacy concern:** Privacy of information concerns anyone who communicates with another. Everyone is careful not to disclose what he would not want to another person. Hallam and Zanella (2017) describe the gap between privacy concerns and self-disclosure behaviour as a privacy paradox. According to Pasternak et al. (2017), 'consumers' privacy concerns may be an internal psychological barrier to eWOM's behaviour on Facebook. Because of the openness of Facebook pages, individuals tend to be more cautious when they present their messages (Park and Kim, 2020). A study by Park and Kim (2020) shows that privacy concerns are negatively related, while privacy protection is positively related to eWOM. They defined privacy concern as the 'user's feeling of anxiety about unwanted and unintended exposure of their personal information, while privacy protection is defined as the 'users' behaviour to restrict the information they share through their profile. Their findings show that privacy concerns inhibit people from creating eWOM on Facebook while privacy protection aid in increasing eWOM's creation. Overall, this indicates that inadequate privacy could hinder someone from posting eWOM, but the less privacy is emphasised, the more accessibility is achieved.

ELECTRONIC LEARNING

Learning is the process of enabling a system to undergo a change in performing a task better than what it did previously. There are many learning methods, including self-learning and learning with an instructor, where the instructor could be a friend, parent, a relation or a professional teacher. These forms of learning are commonly referred to as traditional learning. The end product of learning is knowledge. According to Dermol (2013), there is a relatively strong relationship between knowledge creation and the occurrence of cognitive and behavioural changes in an organization. Knowledge creation contributes to the quality of products and services, intensive use of technologies, labour productivity, better communication within an organization higher employee satisfaction.

Today, the advancement in technology, principally information technology, has given rise to technology-enhanced learning called electronic learning (e-Learning). In traditional learning, the physical presence of both the learner and the instructor is needed in a physical location (classroom) for learning to occur.

This is in contrast to e-learning, where the learner does not need the physical presence of the instructor but digital materials and internet connectivity. Unlike traditional learning, which is rigid in location and time, e-learning has the flexibility of location and time. In the Canadian Council on Learning's report, e-learning is defined as "*the development of knowledge and skills through the use of information and communication technologies (ICTs), particularly to support interactions for learning – interactions with content, with learning activities and tools, and with other people*" (Abrami et al., 2008).

Various applications, learning methods and processes are used for e-Learning (Rossi, 2009). E-learning encompasses more than offering online courses it includes using multimedia technology and the internet for course delivery independent of location and increases learning quality by providing access to facilities and services for exchanges and collaboration (Oblinger and Hawkins, 2005).

The gap between learning and working is narrowing based on the ubiquitous nature of e-learning, making resources and services available to learners in real time while working. There are diverse ways of classifying e-learning: computer-based and internet-based e-learning. Computer-based is mostly the use of a full range of hardware and software that are available for information and communication technology which supports computer-managed instructions and computer-assisted learning. While internet-based learning extends computer-based learning to include making content available on the internet. Algahtani (2011) describes fully online e-Learning as synchronous and asynchronous learning methods, including delivery of contents via the Internet, Intranet, Extranet, satellite broadcast, audio-video tape, interactive TV and CD-ROM (Kaplan-Leierson, 2006). Synchronous allows online access between learners and instructors and other learners via the internet simultaneously with the use of tools such as video conferences and chat rooms, while asynchronous also allows discussions with instructors and learners, but at different times. Some of the learning methods of e-learning are shown in Table 2. Oye et al (2012) list e-learning tools to include curriculum, digital library and knowledge representation. The curriculum tool comprises the materials selected and organised to facilitate class activities such as the progress of learning and self-test. Digital library tool focuses on storing and retrieving information to aid a learner in effortlessly searching and locating needed information.

Table 2. e-learning Methods

Methods	Description
Virtual Classroom	Allows the learners to meet online in a designated video call session to share interactive learning activities and enable active participation in the process. This method is instructor-led training or lectures, and learners join the virtual classroom regardless of location and participate simultaneously.
Online learning	This is a synchronous method of learning that takes place via the WEB. Although the teacher is at the other end, there is no physical interaction between the instructor and the learner. Learning materials may be left for the learner to learn independently, and most progress is tracked. Online learning content includes slide-based courses, interactive quizzes, video courses and tutorials, simulations, podcasts, and e-books. Learners can access these materials on their PCs, laptops, tablets, and mobile devices.
Hybrid or blended learning	The hybrid learning method combines both online and face-to-face learning. The delivery of course materials and explanations is shared between the traditional learning method and the e-learning method. It grants learners online access to learning materials to study at their pace and includes meetings for discussions and mentoring. This method is agile and comprehensive addressing various learning styles and needs.
Mobile learning	M-learning involves using mobile, portable devices to deliver online learning content to learners. The content is digital, which can convert into HTML5 format, delivered in smaller portions and can adjust properly to various screen sizes. The method is convenient, engaging, and future-oriented, however very distractive, requiring reliable devices and a stable internet connection.

In knowledge representation, a learner is supported to visually review, capture and develop knowledge using such a knowledge representation tool (Thomson and Cooke, 2000). There are various advantages of e-learning which include flexibility in time and space, enhanced efficacy of knowledge and qualification through access to multiple resources, provides opportunities to relate with other learners, cost-effectiveness, taking into consideration the individual learner and allows self-pacing. However, there are also some downsides to e-learning.

There are various challenges to e-Learning. Some of these challenges include location, culture and belief specific. The challenges of e-learning are varied to both the students and the instructors; such challenges include low-quality internet services and an increased workload to fore students (Maatuk et al., 2022). In a study by Shahmoradi et al. (2018), 40% of participants reported poor access to the e-learning platform as the main challenge of e-learning. This is in addition to culture and skills. The challenges of e-learning are also discussed in (Khan, 2020; Tawafak et al., 2019; Ilie and Frăsineanu, 2019). Some of the challenges are shown in Table 3.

Table 3. Challenges of e-Learning

Challenges	Description
Distraction	A physical teacher has to organise the class and influence the learners from distractions and interruptions from outside interference. This is not so in an e-learning environment where a learner is on his own, learns at his own pace, and in a different location.
Time consumption	Lack of concentration due to distractions can cause undue delay in the understanding process. This will necessitate a lack of motivation and more time for engagement to learn and understand.
Access	The quality of internet connectivity available to learners varies based on location, and some locations may not be conducive to learning. This may have adversely affected learning outputs and passion for learning.
Attitudes	Many learners and instructors still perceive e-learning as inferior to face-to-face learning. This negative attitude has affected the enthusiasm for learning via e-learning platforms.
Contents	Most of the contents of e-learning are developed to suit the developer's culture, religion and locality without recourse to learners from different cultures, religions and localities. A learner who is very conscious of his locality can be put off if the contents are in contrast to these parameters.
Evaluation of the Learner:	The methods used in evaluating what is learned leave room for cheating, and where security measures are put in place to avert this, the cost becomes prohibitive. E-learning may also be subject to privacy, plagiarism and cheating.
Communication	Absence of vital personal interactions between learners and instructors and also among different learners
Discipline	E-learning may be appropriate for social sciences and humanities. However, scientific fields that require hands-on practical experiences may be difficult to study through e-learning.

SENTIMENT ANALYSIS

The sentiment is an expressed opinion prompted by one's feelings. Expressing 'one's sentiments is a natural phenomenon and has been going on throughout human existence. Before 2000, sentiment analysis was not a research area, but with the proliferation of the internet and many social networking sites, what was expressed among a few peers is now discussed in the global village. There is a large volume of opinions on a particular subject or product on social media. Social media is a reservoir of eWOM where individuals, without fear of intimidation, express their feelings; pour out their emotions and sentiments. Research in sentiment analysis has an important impact on natural language processing (NLP). It may also have an impact on management sciences, political science, economics, and social sciences, as they are all affected by people's opinions (Liu, 2012).

Sentiment analysis, also called opinion mining, is applied in decision-making to enhance manufacturing, marketing, public administration, healthcare etc. Organizations no longer need to conduct opinion polls, market surveys and the like to gather people's opinions because such information is readily available on the web. Nowadays, it is common to find a 'consumer's product being displayed on social media, and the public's opinion is sought about such a product. The same goes for a public figure to be appointed or elected. The public space is inundated with people's opinions on a product's choice, which are expressed with diverse sentiments. Distilling these opinions from the avalanche of information available on the web has become a task for information scientists.

Sentiment analysis creates a model that can detect and extract opinions from eWOM and extract attribute expressions such as the subject matter being talked about (negative or positive or neutral), opinion (polarity) and the person that expressed the opinion (opinion holder). Factual information is objective, while opinion is subjective. Opinions are expressions from people expressing their sentiments, feelings and appraisal on a subject matter or interest. Sentiment analysis can be modelled to classify sentences in a text as either subjective or objective in what is termed subjectivity classification. Polarity classification is the classification of a sentence expressing a positive, negative or neutral opinion about a specific issue.

The opinion could be direct or indirect, comparative and explicit or implicit. In direct opinion, the opinion holder gives an exact opinion about an entity. For instance, in the statement: *"The students of A-Z College are unruly"*, here, the entity is the behaviour of students of A-Z College, expressed precisely without involving another entity (sub-entity). In indirect opinion, the exact opinion of the opinion holder is not expressed on the entity, but its effects on the sub-entity are addressed. For example, the sentence "*The behaviour of A-Z students is shown in the performance of their final examination results*". This indirectly gives an adverse opinion or sentiment about the behaviour of A-Z students. In this case, the entity is the student's behaviour, and the aspect or sub-entity is their performance in the final examination results. Direct and indirect opinions are called regular opinions. In a comparative opinion, an entity is compared with another entity while expressing an opinion using a relative or superlative adjective. For instance, students in A-Z College are more unruly than those in ABC College.

The explicit opinion is concerned with an opinion expressed in the subjective statement, while the implicit opinion is an opinion expressed in an objective statement. Each of these can be regular or comparative. A comparative opinion expresses a relation of similarities or differences between two or more entities and/or a preference of the opinion holder based on some shared aspects of the entities (Jindal and Liu, 2006). The sentence: "*Yesterday's service was amazing*" is an explicit opinion. The sentence: "*A-Z College is nearer than ABC College*" is an implicit comparative opinion. "*The road between A-Z College and ABC College is not motorable*" is an implicit statement. Explicit opinions are more accessible to detect and classify than implicit opinions (Liu, 2012). An objective statement expresses a fact about an object or an event, while a subjective statement expresses personal feelings, beliefs or views about an object or an event. Example: the statement "*This is a beautiful house*" is a subjective statement. The statement "*The house is located at No. 7 Obo Road*" is an objective statement. The different scopes of sentiment analysis are presented in Table 4.

Sentiment analysis are not without challenges and some of these challenges that militate the proper analysis of sentiments include:

Table 4. Scopes of sentiment analysis

Scope	Explanation
Document-level:	Here sentiments are extracted within a document, in this level, the opinion of the entire product is reviewed. The assumption is that each document discusses the opinion of an entity, such as a product. The task is to classify whether a whole document expresses a positive or negative sentiment (Turney, 2002). A document that compares two or more entities is not treated at a document level.
Sentence level:	At the sentence level, sentiments are extracted sentence by sentence, and concentration is on the opinion (positive or negative) expressed in each sentence of a document.
Sub-sentence level:	Here a sub-sentence is analysed to get sentiments before proceeding to another sub-sentence within the sentence.
Aspect or Entity level:	At this level, sentiments about entities and their aspect (if any) as the target are established. For example, the sentence "*The behaviour of A-Z students is shown in the poor performance of their final examination results*." The target, the final examination results, is the aspect of the entity and behaviour of students. The aspect level performs a finer-grained analysis. According to Liu (2012), this level of analysis aims to discover sentiments on entities and/or their aspects. Another example is the statement: "*The students at ABC College are neatly dressed, but they are rude*". Here, the students (entity) with two aspects of dressing and behaviour are evaluated with positive sentiments expressed about dressing and negative ones about behaviour. At the aspect or entity level, the unstructured document is converted into a structured document, where an entity is extracted from the document, and each entity has some properties or what is termed an aspect here.

- **Summarization:** Opinions are subjective. An opinion from a single opinion holder is not enough for analysis. Opinions from many holders are needed in most applications for better output and this shows that a summary of opinions is desired.
- **Sarcasm:** The use of irony to mock or convey contempt with a meaning of a word opposite to what is stated in the sentence is an issue in sentiment analysis. Sarcasm is an expression where the literal meaning is opposite to the intended purpose. Example: After a meal that a particular customer does not like and his opinion is sought, the person replies, "*it's great!*". There is no negative term in the expression; meanwhile, the customer did not like the meal and will never return to the restaurant. This is a difficult situation to deal with, except the context, the opinion holder, the language etc., are well understood.
- **Unstructured datasets:** Most opinions are in the form of unstructured datasets and require extra effort to transform into structured datasets.
- **Synonymy and polysemy:** Synonymy and polysemy issues are challenges on sentiment analysis and opinion mining problems. Suppose an opinion holder uses a term similar in meaning to a term not found in the analyst lexicon. In that case, analysis becomes difficult, or the results of the analysis may not be accurate.
- **The ambiguity of words:** Words with very different meanings could also pose a problem in trying to analyse sentiments. According to (Kautish and Kaur, 2017), the ambiguity of words may be a vast issue that, nonetheless, is to be resolved through automatic summarization.
- **Sentiment lexicon:** Sentiment or opinion words are words used to express negative or positive sentiments. Such terms include good, bad, ugly, beautiful, great, wonderful, awesome, scary, awkward, scanty etc. There are also sentiment or opinion phrases such as "*it is awesome; weather is clement; nasty environment*". A list of such words and phrases is called a sentiment lexicon or opinion lexicon. A sentiment lexicon is necessary but not sufficient for sentiment analysis (Liu,

2012). A positive or negative sentiment may have different meanings depending on its context. Sometimes, the fact that there is a sentiment word in a statement does not connote any sentiment. Example "*It is good to go*". "*If I am sound, I will come and see you tomorrow*". Here the opinion words "good" and "sound" do not portray any sentiment; though "*good*" is a sentiment word, "*sound*" is a context-dependent sentiment word. Many sentences without sentiment words can also imply opinions. For example, the statement, "*He uses a lot of water to wash his car*", denotes water wastage in washing, yet there is no sentiment word in the sentence. This lexicon helps in analyses but is also a challenge in the study.

The process of identifying sentiments in a corpus is summarized in the following steps (Farhadloo and Rolland, 2013).

- **Extract all the opinionated fragments:** The first step involves categorizing a corpus into subjective and objective fragments, known as subjectivity classification (Wiebe and Riloff, 2005). The challenge here is that some subjective statements may not necessarily connote opinion, while some objective ideas do. For example, the sentence "I think he stepped out not too long ago", though subjective, does not carry any positive or negative opinion. In the statement, "*The building collapsed after a week*", an implicit negative sentiment of the poor nature of the building, which did not last more than a week, is embedded. Part of speech (POS) tagging algorithms based on terms definitions and the relationship of the term with adjacent and related phrases and words are also used to mark a word in a corpus. These marked words are used to determine sentiments aside from the sentient lexicons. Overall, a text classified as subjective has a higher likelihood of being an opinionated corpus than a text classified as objective.
- **Identify the sentiments of each opinionated fragment:** Two classification schemes known as supervised and unsupervised learning are used for the classification to identify opinions in a corpus.
- **Supervised learning classification:** The supervised learning method involves binary classifying positive and negative sentiments. In a review where numeric values are assigned, such as in a Likert scale of 1-5, with 1-2 representing negative sentiment, 4-5 representing positive and three neutral, the classification is easier. Sentiment lexicons are evaluated in a corpus using machine learning algorithms such as SVM, Naïve Bayes, Random Forest etc. Various methods used in the evaluation include POS tagging, sentiment words or phrases, terms frequency, rules of opinions, sentiment shifters etc. Tripathya et al. (2015) used naïve Bayes and SVM to classify sentiments of movie review datasets. The results of the findings show maximum accuracy of 90% for Bayes naïve and 94% for SVM. Tripathy and Rath (2017) used SVM, Random Forest, Linear Discriminant Analysis (LDA) and Naïve Bayes to classify some corpus gathered from the WEB. The results showed Random Forest performing better than the other three classifiers. In Priyavrat and Singh (2017), SVM, Naïve Bayes, Decision Tree and Neural Networks were employed to classify datasets mined from the WEB, with results showing the superiority of SVM over other classifiers.
- **Unsupervised Learning classification:** The unsupervised learning method involves identifying the extreme sentiment lexicon word or phrase in a corpus and finding the degree of similarity between the extreme words and the unknown word/phrase. For example, if the word "Large" is opinionated as a positive and the word "Small" as negative. The semantic similarity of prominent with the other similar sentiment word up to the word "small". In this case, large and big will have the same degree of similarity; likewise, small and little, but large and medium will differ. The

aggregate opinion of each of the polarities is then calculated to find where the sentiment is tilted to. Pointwise mutual Information (PMI), POS, and semantic similarity measures are some other methods employed in the unsupervised classification of sentiments. Hu et al. (2013) modelled sentiment analysis for emotional signals from social media datasets. The new method used recorded an improvement of 21.4% over the 17.9% earlier recorded by the previous method.

Generally, e-Learning, sentiment analysis and eWOM are related concepts. e-Learning involves the interactions between instructors and learners through e-learning platforms, discussion forums and other social media platforms, and these platforms generate huge volumes of eWOM with users sharing experiences, opinions and feedback. The application of sentiment analysis on e-learning data to figure out the emotional tones of users can provide insight onto the learning experience of users and identify areas where improvements are needed.

SOLUTIONS AND RECOMMENDATIONS

This section presents some possible solutions and recommendations for sentiment analysis of eWOM on e-learning.

The learning experience of users can be personalized by using sentiment analysis to track users' attitudes and emotions. The impact of contextual and cultural factors should be considered to ensure accurate sentiment interpretations because different contexts and cultures may influence how users of an e-learning platform express their sentiments. Encouraging users to share recommendations and honest feedback can help to increase visibility as well as improve the reputation of e-learning platforms. Ethical issues and privacy concerns should be clearly addressed through the development of clear guidelines and policies for collecting, storing and analyzing eWOM data.

Building a sentiment analysis model tailored to the specific context of e-learning, involving technical terms and specialized languages to train relevant datasets that replicate the features of e-learning settings is one way of achieving an accurate model. We present the sentiment analysis of eWOM from tweets using the popular Python libraries in Google Colab to analyse and visualize the subjectivity and polarity associated with the tweets. The process involved is clearly outlined below.

Firstly, important libraries were imported in google collab before adding the Twitter API credentials by creating the authentication object and setting the access token and access token secret before creating the API object. These steps authenticate our account to the Twitter API before access to the tweets can be granted. Table 5 shows some of the sample tweets from the dataset, and the entire dataset is shown in the link in Appendix 1b.

The data set extracted for this sentiment analysis consists of about 3000 tweets (records) on "eLearning", which contained countless contents that do not contribute to the sentiment of the user; therefore, the tweets were first pre-processed. According to Jianqiang and Xiaolin (2017), preprocessing involves the removal of stop words, URLs, special symbols and usernames. The removal of hyperlinks, leading and trailing whitespaces and special characters during preprocessing reduces the noise in textual data. Duplicate tweets (rows) were also removed, and the cleaned dataset, as shown in Appendix 1b, was used in the sentiment analysis. In order to get accurate subjectivity and polarity classification of the tweets, a Python library (2 & 3) for processing textual data (Diyasa et al., 2021), known as TextBlob, was used. According to Gujjar and HR (2021), TextBlob is an API offered by the python library to accomplish

Table 5. Sample tweets

What a pleasure it was to catch up with @eLearning_Laura this afternoon to plan out my Local Leader work for this year. She even helped me find a brilliant activity for cross-curricular day ðŸ™ŒðŸ™Œ#ntlt #edutwitter #computing #localleader #ict
RT @CAAWO1: Sign up for our free e-learning course to learn all about #animalwelfare; what it is, what it means and how you can bring aboutâ€¦
RT @serveleadchange: Great timing for this tweet from @ReadSpeaker as we are about to participate in #Convergence2022 with @ ATLEAlberta inâ€¦
Hi friends, As I'm launching my own app, I'm introducing my first Online Course for Kids in Grades 4 - 10. âœ ï¸ Just Learn from Home via the simple app at a convenient time âœ ï¸ Certified trainer âœ ï¸ Digital Board teaching âœ ï¸ Free Demo available #OnlineCourse #LearnfromHome #elearning https://t.co/0hbEfW5cIr
RT @74WTungsteno: Covering theory is delightful for algebraic topologists https://t.co/bOpkMQ91xx #math #science #iteachmath #mtbos #visualâ€¦
RT @svekisl: #LEARN #EDUCATION Save time learn How to Setup a localhost machine in minutes #FREE #COURSE #FREE #code #elearning #LAURENCESâ€¦
Surprise! Elearning can change your life! Are you ready, online #students? https://t.co/TSQotA6ac6
#eLearning simulations ðŸ'©ðŸ »â€ ðŸ'» engage employees by providing them with immersive # experiences in imitated versions of real-life environments.
RT @CAAWO1: Sign up for our free e-learning course to learn all about #animalwelfare; what it is, what it means and how you can bring aboutâ€¦
RT @CoSpaces_Edu: Psssst, CoSpacers! Here's your first look at what's coming soon! ðŸ˜Ž We'll be adding a 360Â° images Library that makes creatâ€¦
Great timing for this tweet from @ReadSpeaker as we are about to participate in #Convergence2022 with @ATLEAlberta in #RedDeer! #elearning #accessibility #inclusion #UDL https://t.co/RrpXEQfsuW
Planning to create learner-centric eLearning? Then #instructionaldesign strategies are all you need. Explore popular Instructional design strategies in our eBook â€˜Instructional Design Strategies to Design Engaging #eLearning Coursesâ€™. https://t.co/zQuIsZP0r6 https://t.co/B87cSvmKZM
#LEARN #EDUCATION Save time learn How to Setup a localhost machine in minutes #FREE #COURSE #FREE #code #elearning #LAURENCESVEKIS #academy #course https://t.co/foL3eBcTaR

certain natural language processing tasks. During the subjectivity detection, the tweets were classified into subjective and objective tweets before the polarity detection, which classified the subjective tweets into positive, negative and neutral tweets. The sentiment analysis results are shown in the charts below, with Figure 1 depicting the polarity and subjectivity of the tweets. The tweets were labelled as negative, positive and Neutral with the polarity of (polarity<0), (polarity>0) and (polarity=0), respectively. Figure 2 shows the number of positive, negative and neutral tweets from the sensitivity analysis. The figure shows more neutral tweets followed by positive tweets with a small number of negative tweets.

FUTURE RESEARCH DIRECTION

The application of sentiment analysis and eWOM to e-learning by practitioner and researchers have increased significantly in recent years and in some possible future directions.

Sentiment analysis algorithms face some challenges in correctly detecting the sentiments expressed by users in texts, especially in the context of e-learning where language can be technical. Future research could focus on building robust sentiment analysis models that can efficiently consider contextual factors in e-learning.

Figure 1. Subjectivity and polarity of e-learning tweets

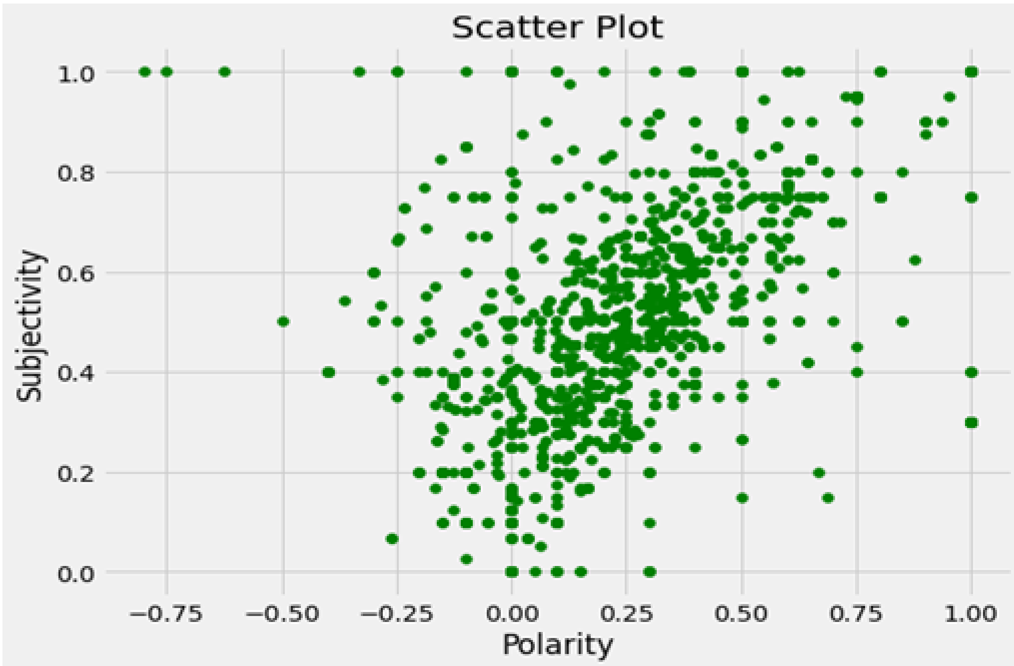
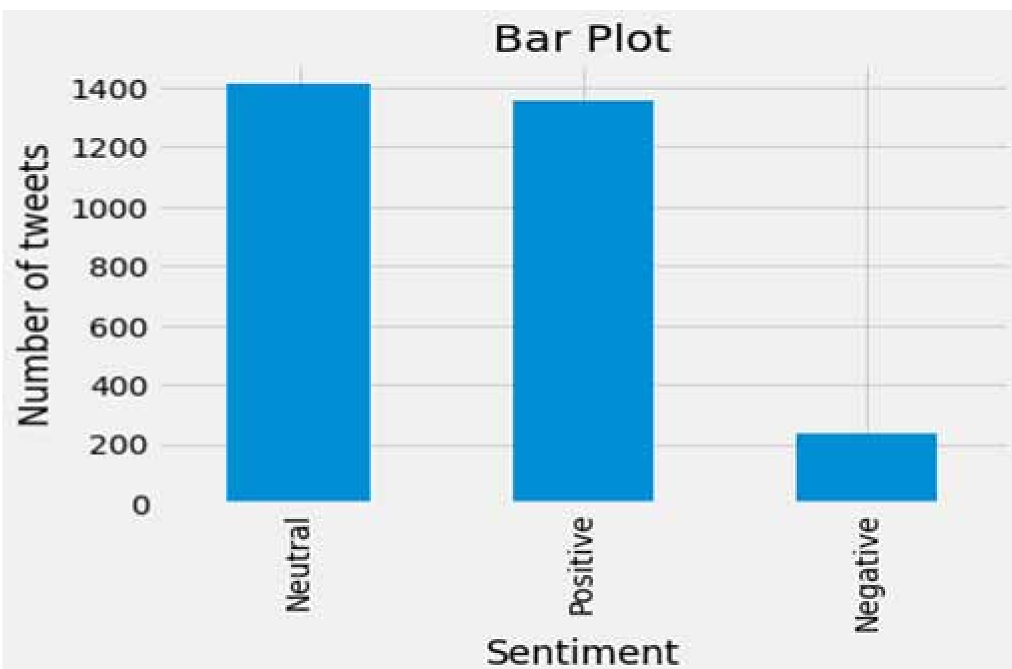


Figure 2. Sensitivity analysis of e-learning tweets



Cultural differences can significantly affect how users express their sentiments, therefore developing a model trained on a particular culture may not be applicable to users from a different culture. Future research could consider developing models with cross-cultural efficacy for diverse user backgrounds.

Future research could consider the combination of sentiment analysis and other data analytics techniques such as machine learning and social network analysis to improve the understanding of users' experiences and behaviours in e-learning.

CONCLUSION

Electronic word of mouth has become the most popular method of promoting or discrediting an organization's products and services. The reason behind this is the explosion of information occasioned by the rise in global technology, where the world is becoming a miniature community. Learning is also a pastime due to the same technology; learning and working are done seamlessly. Everyone wants to learn and acquire knowledge and skills with the knowledge economy. Despite this, e-learning is not without some pitfalls and criticisms. The application of sentiment analysis and eWOM to e-learning involves analyzing sentiments expressed in reviews and feedback about e-learning experiences, which can assist stakeholders in identifying certain factors that influence users' behaviour and attitude. Certain solutions and recommendations are building an accurate sentiment analysis model; with the considerations of contextual and cultural factors; encouraging honest feedback; personalizing users' experiences and addressing privacy concerns and ethical issues. In this work, 3000 tweets were gathered and pre-processed. The sentiment analysis of the tweets revealed that most tweets expressed neutral sentiments about e-learning, followed by positive sentiments, while only a few tweets expressed negative sentiments. With this result, sentiment analysis of eWOM on e-learning can provide valuable insights into users' experiences and attitudes and can help decision-makers to improve the effectiveness and usability of e-learning platforms. Future research directions in this area could include building accurate sentiment analysis models, integrating sentiment analysis with other analytics techniques and investigating cross-cultural differences in sentiment expression in e-learning.

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KEY TERMS AND DEFINITIONS

Electronic Learning (E-Learning): The process of learning using electronic gadgets and internet connectivity such as radio, mobile phone, laptops, PDAs, internet etc., where the physical teacher is not needed and can be taken irrespective of location and time.

Electronic Word of Mouth (e-WOM): Is communication that expresses sentiments about a product or service of an organisation through the internet without commercial intent.

Learning: Is the process of enabling a system to undergo a change in performing a task better than what it did previously.

Opinions: Are expressions from people expressing their sentiments, feelings and appraisal on a subject matter or topic of interest.

Sentiment Analysis: Is the process of identifying and clustering positive and negative opinions about a product or service of an organisation using a computational intelligence method.

Supervised Learning: In supervised learning, the classification of inputs is done with recourse to the desired response of the system. It is the desired response that supervises the learning and acts as a "teacher" by comparing the results of computation with the desired output.

Unsupervised Learning: In unsupervised learning, the system is provided with the inputs without desired outputs. The system then decides what features of the inputs to use in grouping the inputs by self-organising the inputs according to these features.

Word of Mouth (WOM): Is personal communication concerning a brand, product, service or organisation where the sender has no commercial intention, and the receiver knows the sender has no such intention, too, even when there may be negative or positive emotion in the communication.