Online Learning in 280 Characters: Analysing Public Sentiment on Online Learning During COVID-19

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Abstract: The global COVID-19 pandemic forced a seismic shift towards online learning, replacing conventional in-person education in response to the inherent health risks. This transformation showcased the resilience of educational systems and the transformative potential of technology in breaking geographical barriers and delivering accessible learning opportunities. Despite the pandemic's challenges, it expedited online education developments, heralding a more adaptable, inclusive educational paradigm poised to outlast the pandemic's immediate effects. This study investigates public sentiment and perspectives concerning online learning in Saudi Arabia during the COVID-19 pandemic, using Twitter as a primary data source. By scrutinising tweets and interactions, this study aims to unearth insights into the challenges, advantages, and overall perceptions of online learning amid the pandemic. The analysis of the collected dataset revealed a prevalent negativity at 37.19%, contrasting with 29.37% positive sentiments and 33.43% neutral viewpoints. The primary cause for negative perceptions lies in the difficulties encountered during the shift to online learning, leading to strain on platforms. Nevertheless, positive feedback highlights the efficacy of the online learning system, viewing it as an opportunity for educational development. Neutral tweets often mention platform names, reflecting the nature of the data collected. Key themes in online learning discourse during the pandemic included technological challenges, student engagement, equity, teacher support, and assessment. The study emphasises the potential of Twitter data in identifying obstacles, gauging sentiment, and improving online learning strategies by sharing best practices and tailoring interventions.

Keywords: Sentiment analysis, Online learning, Twitter, COVID-19

1. Introduction

Sentiment analysis has become increasingly important in recent years as the volume of digital data generated by social media, online reviews, and other sources has grown exponentially (Liu, 2012). The ability to analyse this data and extract insights about public sentiment has many applications in areas such as market research, customer feedback analysis (Liu, 2012), brand reputation management, and product development (Dellarocas, Zhang & Awad, 2007). By providing a more nuanced understanding of public opinion, sentiment analysis allows businesses to make data-driven decisions that can improve customer satisfaction, brand perception, and overall business performance. One of the key challenges in sentiment analysis is accurately interpreting short sentences, such as those commonly used on social media platforms like Twitter and Facebook (Pak, & Paroubek, 2010). Global COVID-19 pandemic triggered a significant surge in the adoption of online learning as a response to the disruption of traditional in-person education (UNESCO, 2020). With health concerns rendering physical classrooms unsafe, online learning emerged as a vital alternative, enabling students to continue their education from the safety of their homes (Hodges et al, 2020). This transition highlighted the resilience of educational systems and the transformative power of technology in bridging geographical barriers and providing accessible learning opportunities. Despite the challenges posed by the pandemic, online education advancements were accelerated, leading to a more adaptable and inclusive approach to learning that is expected to endure beyond the pandemic (Darling-Hammond, Hyler, & Gardner, 2020).

This study aims to explore public sentiment and opinions regarding online learning in Saudi Arabia on Twitter during the COVID-19 pandemic. Twitter, as a prominent social media platform, provides a valuable source of real-time data reflecting diverse perspectives on remote education during this unprecedented period. By analysing tweets and interactions, we seek to gain insights into the challenges, benefits, and overall perceptions of online learning during the COVID-19 pandemic. The present study seeks to answer the following questions:

RQ1. How did the sentiment on Twitter towards online learning evolve over the course of the COVID-19 pandemic, and what were the key factors influencing these changes?

RQ2. What were the most frequently discussed topics and issues related to online learning on Twitter during the pandemic?

RQ3. What insights can be gleaned from Twitter data to inform the improvement of online learning strategies and policies for future crises or remote learning scenarios?

2. Literature Review

2.1 Sentiment Analysis

Sentiment analysis, also known as opinion mining, is a process that uses natural language processing, text analysis, and computational linguistics to identify and extract subjective information from text (Young, 2018). It involves analysing the emotional tone or attitude expressed in a piece of text, such as a tweet, review, or news article, and determining whether the sentiment expressed is positive, negative, or neutral (Pang, & Lee, 2012). Sentiment analysis is widely used in various fields, including marketing, customer service, and social media analysis (Liu, 2012), to understand public opinion, identify trends, and make data-driven decisions. One of the most important benefits of sentiment analysis is the ability to analyse people's feedback from various sources, such as social media, reviews, and surveys. By using sentiment analysis, businesses can gain a deeper understanding of customer sentiment and identify areas for improvement. This is particularly helpful for businesses looking to improve their customer service, product offerings, or overall customer experience (Liu, 2012). Sentiment analysis can also be used to monitor brand reputation by tracking the sentiment around the brand (Alsuhaibani, 2018; Pang et al, 2009), identifying any negative sentiment and taking appropriate action to address any issues that may be affecting their reputation. This is especially important in industries where customer trust is crucial, such as healthcare, finance, and technology. By monitoring brand reputation, businesses can stay ahead of the curve and proactively address any issues that may arise. In addition to customer feedback analysis and brand reputation management (Cambria et al, 2014), sentiment analysis can be used to improve marketing and advertising efforts by analysing the sentiment of social media posts. This can help businesses target specific demographics or improve their overall marketing strategy. Sentiment analysis can also be used for competitive analysis by monitoring sentiment around competitors, identifying where they can differentiate themselves and gain a competitive advantage (Dellarocas et al, 2007). Overall, sentiment analysis is an essential tool that can provide valuable insights into public opinion and help businesses make data-driven decisions that can improve customer satisfaction, brand reputation, and overall business performance.

2.2 Online Learning During COVID-19

Online learning pertains to the dissemination of educational materials and teaching via the internet. This mode enables students to enrol in courses and attain qualifications from remote locations, eliminating the necessity for physical attendance at educational institutions. Diverse in its manifestations, online learning encompasses web-centric classes, virtual conferencing, and autonomous learning modules (Singh & Thurman). The global education landscape has been profoundly transformed by the far-reaching impacts of the COVID-19 pandemic, leading to the rapid and widespread adoption of online learning as a critical response (UNESCO. 2020). Facing unprecedented challenges, educational institutions around the world have rapidly shifted from traditional classroom settings to online learning environments (Hodges et al, 2020). This transformation necessitated the creative use of digital technologies, online platforms, and virtual collaboration tools to ensure uninterrupted access to education and maintain educational continuity. The experience of online learning during the COVID-19 pandemic has not only highlighted the resilience of educational systems, but also demonstrated the remarkable adaptability and resourcefulness of both teachers and students (Means et al, 2010). Through effective integration of technology and adoption of online learning, educational institutions have succeeded in providing comprehensive and flexible education, transcending geographical boundaries, and enabling learners to participate in engaging and interactive virtual learning experiences (United Nations, 2020). This transformative approach to education has not only mitigated the disruptions caused by the pandemic but has also accelerated the exploration and implementation of innovative pedagogical practices (Bozkurt et al, 2020), which will continue to shape the future of education beyond the current crisis. The shift to online education amid the pandemic had positive effects, notably increasing enrolment in distance learning courses (Abdelwahed et al, 2023; Zhou, 2024). However, the setup differs between temporary measures and established distance learning programs at universities. Before the pandemic, there were existing online degree programs, but the situation accelerated growth. Data shows a significant rise in registrations, in 2016, there were 21 million registered students on online learning platforms, a number that increased annually by about 7 million over the next two years. However, the pandemic significantly boosted these numbers, with registrations almost tripling in 2020 to 71 million and reaching 92 million in 2021. Course enrolments for online learning also experienced dramatic increases. Pre-pandemic growth was overshadowed by substantial spikes during the pandemic, with enrolment numbers doubling in 2020 and growing by 32% in 2021, culminating in a peak of 189 million enrolments (Zhou, 2024). In the aftermath of the COVID-19 pandemic, online learning has become deeply integrated into Saudi Arabia's educational landscape, offering both students and educators a versatile platform for remote instruction and collaboration. The adoption of online learning tools and platforms continues to expand, facilitating greater flexibility in learning schedules and enhancing access to educational resources across the country (Madani et al, 2023). Many educational institutions in Saudi Arabia have seamlessly integrated virtual classrooms into their curriculum, allowing students to participate in live lectures, discussions, and collaborative projects from the comfort of their homes (Abdelwahed et al, 2023).

2.3 Related Studies

A recent study by Muhammad et al (2021) argued that the COVID-19 pandemic has greatly impacted the online education system, leading to concerns from stakeholders such as parents, teachers, and students. This study investigates the effectiveness of online education by analysing stakeholder sentiment using social media data. The dataset used was obtained from the Twitter API, and various text preprocessing methods were used to clean the tweets. Machine learning algorithms were used to classify positive, negative and neutral reviews. Synthetic Minority Over-sampling Technique (SMOTE), Decision Tree (DT) and Support Vector Machine (SVM) are classification algorithms, Random Forest (RF) is an ensemble learning method, and Valence Aware Dictionary for Sentiment Reasoning (VADER) and lexical resource for sentiment analysis (SentiWordNet) are sentiment analysis tools used in this study. The results show that data normalisation with SMOTE enhances classification accuracy, with DT, SVM, and RF performing well. VADER and SentiWordNet techniques were used to compare performance, with TextBlob showing superior results for data annotation. Furthermore, deep learning models have been found to perform better due to the smaller size of the dataset. When modelling the topic using LSA, concerns emerged regarding uncertainty surrounding the opening date of institutions and the lack of technical skills in rural areas.

Another study by AL-Rubaie et al (2016) focused on the design and implementation of Arabic text classification of the opinions of students at King Abdulaziz University. This study employed algorithms such as SVM and NB (Naive Bayes is a probabilistic machine learning algorithm based on Bayes' theorem). Their analysis showed promising results with students' online comments, revealing that their texts were more traditional and that local Saudi dialects were used more frequently in comments than Modern Standard Arabic (MSA). The best accuracy was achieved by SVM with n-gram feature and class neutral. Future work plans include analysing structured data on the whiteboard and creating a semantic diagram to understand students' behaviours while studying.

A recent study by Zuhri & Aznan (2022) conducted a sentiment analysis about e-learning using Twitter data, focusing on SVM as the most accurate algorithm. SVM achieved a higher accuracy compared to the Linear Regression (LR) algorithm by 3%. However, more research is needed to understand which parameter tuning will lead to better classification results, as the only parameter that was tuned in this project was parameter C (The C parameter tells the SVM optimisation how much a user wants to avoid misclassifying each training example) with different values.

This paper addresses a significant gap in the literature on online learning during the COVID-19 pandemic, namely focusing on Saudi content. While previous studies have explored sentiment analysis and online learning, there remains a lack of comprehensive research that specifically investigates public sentiment and opinions regarding online learning in Saudi Arabia, especially using Twitter data. The distinctive cultural, social, and educational context of Saudi Arabia may significantly influence experiences and perceptions of online learning in this specific setting. Understanding public sentiment and opinions specific to Saudi Arabia is crucial to developing tailored strategies and policies to promote online learning in this country. By examining Twitter data, this paper aims to fill this gap by providing insights into the challenges, benefits, and public perceptions of online learning during the pandemic in Saudi Arabia.

3. Methodology

3.1 Data Collection

The dataset utilised in this study pertains to the domain of online learning in Saudi Arabia during the COVID-19 pandemic. This data was sourced from Kaggle, a prominent online community platform catering to data science and machine learning enthusiasts (Kaggle, 2023). Kaggle served as a valuable resource, providing access to a diverse collection of datasets and supplementary materials essential for the successful execution of this research project. Data acquisition occurred over the time-frame spanning from September 2 to September 17, 2020, encompassing the initial two weeks of the academic year. It is important to note that none of the tweets included in our analysis were duplicated from the same individual within the specified timeframe. Each tweet was treated as a unique data point, contributing to the overall breadth and diversity of the dataset. The dataset was meticulously compiled from four trending hashtags in Saudi Arabia about online learning and COVID-19. These hashtags encompass a total of 1676 records consisting of text Tweets in Arabic, all of which share the same geographic location of Saudi Arabia. These records were structured into 10 distinct data columns, enhancing the richness and depth of the dataset for comprehensive analysis. The first hashtag is #وزارة_التعليم translates to Ministry of Education in English and it is commonly used to discuss news, updates, and initiatives related to the Ministry of Education in Saudi Arabia. The second hashtag is #تعليم_عن_بعد translates to online learning and it is associated with discussions, resources, and experiences related to remote or online education. It became particularly prominent during the COVID-19 pandemic. The third hashtag is #عين which translates to Ain which is the official platform that the Ministry of Education in Saudi Arabia launched during COVID-19 for online education. The fourth hashtag is #تيمز which is related to Microsoft Teams which was highly used by students in their online education and discussion. These hashtags primarily pertain to school pupils rather than university students. Consequently, we expect the data to reflect the opinions of parents of pupils regarding the online learning experience.

3.2 Data Cleaning

Prior to analysing the data, we performed a thorough data cleaning process to ensure the accuracy and reliability of our findings. This involved removing columns that were deemed irrelevant to our research objectives, such as retweet count, hashtags, and the time of a tweet. In addition, we restored words with repeated letters to their original form, such as "خيررر" to "خير". Furthermore, we removed Arabic diacritics, such as “قّ”, which can appear above or below Arabic letters, to standardise the text and facilitate analysis. For example, "سيّء" was changed back to "سيء". These data cleaning steps were imperative in preparing a high-quality dataset for our research.

3.3 Data Analysis

The data for this study was analysed manually by three researchers who are fluent Arabic speakers. A codebook, containing the three primary emotion dimensions (Table 1) was developed prior to the commencement of coding work. After each coder had completed the analysis of 200 tweets, an interceding reliability check was applied to ensure consistency between the three coders. The test revealed positive results, with an Average Pairwise Percent Agreement of 90.452%, Fleiss' Kappa coefficient of 0.853, and an Observed Agreement of 0.905. Subsequently, the analysis was applied to the whole dataset (1676 tweets).

Table 1: Sentiment Codebook

ID	Code	Definition	Example
0	Neutral	The tweet's content doesn't give a feeling of negativity or positivity.	“لكل تجربة مشاكل ولكن اذا فيه حلول يمكن تجاوز المشاكل” (Every experience has problems, but if there are solutions, the problems can be overcome)
1	Negative	The tweet's content gives a feeling of negativity.	“التعليم الالكتروني غير مجدي وغير نافع” (online learning is useless and ineffective)
2	Positive	The tweet's content gives a feeling of positivity.	“ منصة مدرستي يقدم من خلالها جهود عظيمة للامانه يعيش أبناؤنا تجربة تقنيه تعليميه فريدة ومستمتعين فيها جدا” (Madrasati platform is a great platform. Our children live a unique educational technology experience and enjoy it very much)

4. Findings

As illustrated in Figure 1, it is evident that opinions regarding online learning in Saudi Arabia are predominantly negative. The negative sentiment represents 37.19% of the opinions, while the positive sentiment accounts for 29.37%. The remaining 33.43% of opinions were deemed neutral which was interesting. An explanation of this will be presented in the following sections. One of the key reasons behind the negative sentiment is attributed to difficulties faced during the transition to online learning, which resulted in significant strain on the platforms. Consequently, people formed a negative perception at the outset. However, we also discovered positive opinions that praised the effectiveness of the online learning system in Saudi Arabia. Additionally, some individuals initially held neutral opinions but acknowledged the potential for rapid advancements in the field of online learning within the country.

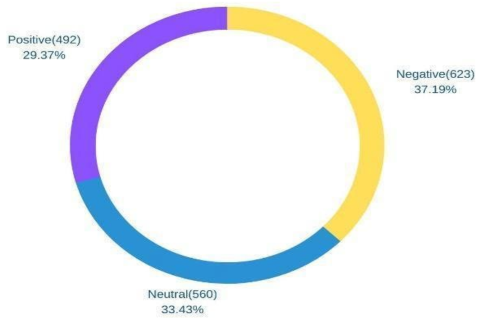

Figure 1: Tweets distribution over categories

From Figure 2, we can observe that the words “عين” ,‘‘مدرستي‘‘ and “منصه”, are repeated in the neutral code. These are the names of the platforms for online learning in Saudi Arabia and this is the reason they appear in this code, as well as in other codes. It is noteworthy that the neutral code appears more frequently than the positive, with the neutral accounting for 33.43% and the positive for 29.37%. This can be attributed to the fact that the existing data included some tweets such as news, advertisements, or responses to tweets. For example, consider the following sentence “ لا يوجد فشل تعطل المنصة لا يعني توقف العملية التعليمية يوجد برنامج التيمز و قنوات عين كبدائل للمنصة”. The code for this sentence is neutral because it emphasises that even if the educational platform experiences technical issues or malfunctions, the educational process itself should not come to a halt because there are alternative tools like Microsoft Teams “التيمز” and “Ain” channels “عين” available to continue the educational activities. It underscores the importance of adaptability and resourcefulness in ensuring that education continues despite challenges.

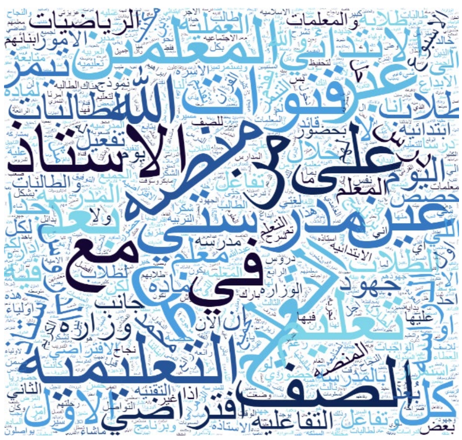

Figure 2: Neutral word cloud[1]

[1] Word cloud translation: Teachers, Education, Students, Platform, Madrasity platform, Class, Virtual, Ain platform, Ministry, Education, Channels, Mathematics, Primary school, Teams, Online, Sessions and Interactive.

Figure 3 illustrates that this code contains numerous positive Arabic words such as "شكراً" and "بارك", which respectively mean 'thanks' and 'blessing'. The reason for its recurrence is people's praise for the online learning platform and their belief in the success of their education or the education of their children despite the pandemic. They perceive it as an opportunity for the development of education in general in Saudi Arabia. For example, consider the following statement " المنصة شيء جميل ولله الحمد وتساعدنا على الاستمرار بالتعلم رغم الظروف لذلك شكرًا على الجهود". In this example, the student is a positive example who praises the mechanism of online learning, describing it as a wonderful solution for the continuation of education and expressing gratitude for the efforts made for education.

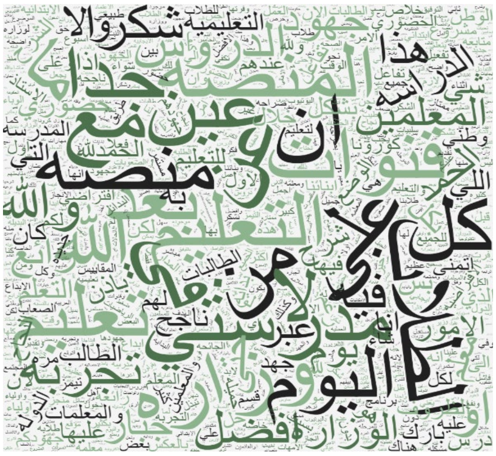

Figure 3: Positive word cloud[2]

In this code, we observe a strong connection between the tweets and their authors. We found that students are usually the main contributors to the tweets in this code. As previously mentioned, the launch of the online learning platform posed significant challenges initially due to server overload and other issues. Students who embarked on online learning found it challenging to adjust to a new system and continued to express a desire to return to in-person study, to which they were accustomed. In this specific example " التعليم عن بعد غير ناجح وخصوصا للابتدائي والمنصه قاصره ولا تفيد والمعلومه لا تصل للطالب بالشكل السليم ولا تستطيع متابعه الطلاب ومتابعه تعلمهم", we classified it as negative because the tweeter appears to lack confidence in the overall success of education, especially for children. They mentioned a lack of a suitable platform and the inability to easily access it to monitor their child's learning.

Figure 4: Negative word cloud[3]

[2] Word cloud translation: Successful, Amazing, Honestly, Awesome, Interactive, Efforts, Thanks, Indeed, Nature, Better, Experience, Beautiful, Creativity, Alternatives, Explanation, Activation and Successfully.

[3] Word cloud translation: Failure, No, Very, Platform, We are tired, Education, Nothing, Hopefully, Not enough, Problems, Pressure, Without and Worse.

5. Discussion and Conclusion

This study contributes to understanding how the COVID-19 outbreak in Saudi Arabia has impacted individuals' attitudes toward online learning. Initially, the COVID-19 pandemic elicited mixed reactions on Twitter regarding online learning. Some expressed enthusiasm, while others expressed concerns about technological difficulties and a lack of in-person interaction. The most frequently discussed topics on Twitter regarding online learning during the pandemic included technological difficulties, student engagement, equity and access, teacher support and professional development, and assessment and evaluation. By identifying these obstacles, tracking sentiment and feedback, sharing best practices, including stakeholders, and focusing interventions on specific needs, insights from Twitter data could potentially enhance online learning strategies. The results will highlight opportunities for improvement in distance learning techniques and policies, as well as insights into the evolution of sentiment and significant influencing variables. The study underscores the critical role sentiment analysis plays in influencing instructional strategies and crisis-related decision-making. The findings of this study can aid policymakers and educational institutions in improving current distant learning opportunities and planning for potential future online learning scenarios.

To advance the scholarly conversation, there is a pressing need to scrutinize the effectiveness of targeted interventions aimed at mitigating technological difficulties, enhancing student engagement, promoting equity, bolstering teacher support, and refining assessment practices. This necessitates rigorous empirical inquiry to assess the impact of such interventions on the overall online learning experience. Furthermore, employing complementary qualitative research methodologies alongside quantitative analyses is imperative to gain a comprehensive understanding of the experiential nuances shaping attitudes toward online learning. Future research endeavours could benefit from incorporating qualitative data and engaging a broader spectrum of stakeholders, including educators, examiners, students, and parents, to provide a more nuanced understanding of online learning. Additionally, researchers should consider undertaking cross-cultural studies to discern variations in online learning perceptions across diverse demographic and regional contexts, thereby contributing to a broader understanding of global implications. Strategic policy analyses, coupled with collaborative efforts involving stakeholders, are pivotal for the development of effective strategies that respond to the identified challenges. While the inclusion of emojis could offer an interesting avenue for extending our research in future studies, it is essential to note the scope and limitations of our current analysis. Despite not incorporating emojis in this iteration of our research, we acknowledge the potential value of exploring their role in sentiment analysis and its implications for understanding online discourse more comprehensively. The absence of emojis in this study is due to having them discarded from the dataset when it was initially retrieved from Kaggle.

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