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Sentiment Analysis With Transformers Applied to Education: Systematic Review

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Abstract

Sentiment analysis, empowered by artificial intelligence, can play a critical role in assessing the impact of cultural factors on the advancement of Open Science and artificial intelligence. Additionally, it can offer valuable insights into the open data gathered within educational contexts. This article presents a systematic review of the use of Transformers models in sentiment analysis in education. A systematic review approach was used to analyze 41 articles from recognized digital databases. The results of the review provide a comprehensive understanding of previous research related to the use of Transformers models in education for the task of sentiment analysis, their benefits, challenges, as well as future areas of research that can lay the foundation for a more sustainable and effective education system.

Keywords

Artificial Intelligence, Natural Language Processing, Sentiment Analysis in Education, Transformers, Systematic Review.

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I. Introduction

Sentiment analysis, also known as opinion mining, is one of the most well-known tasks of Natural Language Processing (hereinafter, NLP). This task identifies how sentiments are expressed in words, sentences, or writings toward a particular topic [1]. In essence, it involves finding out the attitudes, opinions, preferences, and sentiments of users by researching, analyzing, and mining subjective texts [2]. In educational environments, students' emotions play a crucial role in the learning process because they can enhance or undermine their ability to learn or remember what they have learned [3]. Opinion mining is a multidisciplinary field that can be applied to different educational domain challenges, such as course evaluation, understanding student participation, educational infrastructure constraints, and educational policy decision-making [4]. In this sense, when information is extracted from reviews left by students, it can improve teaching and learning practices [5]. Yan et al. [6] and Du [7] conducted studies to analyze student feedback, revealing several critical factors that influence student satisfaction in virtual learning environments. These factors include course content, technical elements, difficulty level, instructor proficiency, video resources, course organization, and workload.

Culture is transmitted between generations through text, images, audio, video, or traditions that generate collective memory [8], [9]. Sentiment analysis is an emerging tool for analyzing cultural phenomena. Culturally, language choice affects moral decisions, suggesting the importance of language in message transmission [10]. Similarly, Lennox et al. [11] consider that sentiment analyses culturally provide better data to address the human side of conservation. In this sense, the opinion or behavior of humans in relation to certain topics of interest varies according to how feelings are expressed, perceived, and interpreted in different cultures. In fact, culture greatly influences social behavior, communication, cognitive processes, and pedagogical technology [12]. Therefore, sentiment analysis can be crucial in determining the influence of culture on Open Science and artificial intelligence, providing a solid understanding of the open data collected in educational environments and contexts.

In 2017, a new Transformers architecture was proposed, applying parallel computing and transfer learning with a self-attention mechanism [13]. This architecture is simple and has shown that it was possible to design this type of network with good results in NLP tasks such as sentiment analysis with a set of multiple sequential attention layers [14]. Nowadays, there is little research that mentions Transformers architecture in a systematic literature review (SLR) on sentiment analysis applied to education. Previous reviews of the literature identified machine learning techniques and algorithms that are prevalent in sentiment analysis in education. A study by Oghu et al. [15] examined 59 relevant papers and the authors identified five common techniques that are mainly investigated for sentiment analysis in education and the prevailing supervised machine learning algorithms. Shaik et al. [16] conducted research on sentiment analysis using educational data and found that educational institutions have invested heavily in creating sentiment analysis tools and applications based on student opinion analysis. In the paper, the authors explored the challenges of sentiment analysis, such as multipolarity, polysemy, negation words, and opinion spam detection. These two studies only

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mention Transformers models without expanding their scope of application.

Given the lack of a literature review on the current state of the art of sentiment analysis with Transformers architecture in education, it is important to establish the current state of the art of this topic and determine how it can influence culture and Open Science. Additionally, it is also important to determine challenges and future applications that can improve the educational field. This research seeks to address the following research questions (RQ).

- RQ1: What is the current state of the art in sentiment analysis research with Transformers applied to education?
- RQ2: What are the main benefits of applying sentiment analysis with Transformers in education?
- RQ3: What are the main challenges in applying sentiment analysis with Transformers in education?
- RQ4: What are the possible future areas of research around sentiment analysis with Transformers in education?

This paper presents a systematic review of sentiment analysis with the Transformers architecture in the educational setting. The main aim of this investigation is to analyze and present a general summary of research related to this topic. This is necessary to provide updates on the state of the art, identify well-researched areas, reveal lagging areas that need further research, and understand the main trends in this field. Finally, to provide a useful summary of current knowledge in a field of study, and, consequently, possible research directions.

II. Overview of Transformers Technology

Although the human-machine interaction may seem simple in theory, it is complex and difficult in practice. In fact, deep learning models have addressed challenges in NLP tasks that present significant results [17]. However, in 2017 the NLP field was revolutionized with the origin of the Transformers models. Transformers have a deep learning architecture that differentiates the importance of each input sequence based on an attention mechanism. Therefore, words are detected by this mechanism, which means that the data are not necessarily processed in an ordered way. Furthermore, the architecture is based on an encoder-decoder structure. The encoder layer processes the input layer by layer, while the decoder layer does the same in the opposite direction [13]. Thus, the encoder layer encodes the input, while the self-attention mechanism assigns weights to each input according to its relevance [13], [18]. Due to the attentional mechanisms, Transformers allow for greater parallelization during training and can be trained faster, improving their performance on NLP tasks. However, the main disadvantage of the Transformers architecture is the high computational cost when training and testing models.

In the educational field, Transformers have been applied in some NLP tasks to contribute to teaching and learning processes by automating repetitive tasks. For example, different models have been applied to the automatic grading of essays [19], the automatic grading of multiple-choice tests [20], and even the automatic grading of short answers [21]. Text generation is another task that has been applied in the educational domain for the automatic summarization of high-quality texts [22] or for creating story endings [23]. This task has also been related to the paraphrasing of original texts with different expressions [24]. Finally, models have also been used to create multiple-choice questions for assessments [25] or to automatically classify the students' responses for further evaluation [26], [27]. These studies suggest that the application of natural language processing can contribute to Open Science by ensuring that scientific knowledge is accessible and that the production of that knowledge itself is inclusive, efficient, equitable, and sustainable.

Sentiment analysis, often referred to as opinion mining, is one of the most widely used NLP applications for identifying human intentions based on opinions [16]. While these terms are commonly used interchangeably in the academic literature, they are not synonymous. However, for the purposes of this article, they will be treated as such. Chats, remarks, opinions, or comments with emotional valuations are part of public opinion on the Internet. In general, any kind of topic is discussed on social networks, forums, news, or other types of digital spaces. In recent years, Transformers models have been applied for sentiment classification [28]. Additionally, an enormous amount of text data often needs to be automatically reviewed, classified, and filtered malicious categories such as hate speech, fake news, or spam [16]. In this case, efficient emotion recognition has aroused great research interest in presenting methodological proposals that focus on stable and accurate results [29], or frameworks specialized in optimizing tasks [30]. Similarly, other research focused on the quality of the explanatory text to improve user confidence and satisfaction by generating recommendations [31] and a public opinion sentiment analysis method to improve the efficiency of sentiment trend analysis [32].

It is important to consider in sentiment analysis the recognition of textual emotion because information may be limited or ambiguous. Different approaches have been proposed for identifying emotions. Ekman et al. [33] indicated the existence of six emotions: happiness, sadness, anger, fear, disgust, and surprise. Izard et al. [34] considered twelve emotions: interest, joy, surprise, sadness, anger, disgust, contempt, self-hostility, fear, shame, shyness, and guilt. However, Ekman's approach is one of the most widely applied approaches in natural language processing. Additionally, Bruna et al. [35] established categorical emotion models in which the textual recognition of emotions is based on the idea of discrete emotion theory, in which the categorical classification is simpler and consists of deciding whether the emotion is positive or negative. In general, to evaluate emotion, lexicons with appropriate emotional content are used, or a classifier is trained with a well-annotated database indicating the nature of the emotions.

Currently, different models based on the Transformers architecture can be found such as BERT (Bidirectional Encoder Representations from Transformers) [36], RoBERTa [37], AlBERT [38], XLNet [39], DistilBERT [40], Reformer [41], GPT-2 [42] and GPT-3 [43]. One of the models that has achieved excellent results in the NLP field is BERT with its respective variants [44], [45]. This model is present in most research aimed at classifying opinion aspect sequences [46], [47], high-quality word detection [48], and significant feature detection for classifying fake news and real news [49], [50]. Therefore, studies have focused on improving the performance [51], [52], stability [53], [54], efficiency [18], [55] and robustness against missing data [56] - [58] of Transformers models intended for sentiment classification. Finally, automatic term extraction is an important task in sentiment analysis, this is the case for a text in which keywords are identified to improve sentiment prediction [56].

III. Methodology

Systematic reviews of the literature are classified into domain-based reviews, theory-based reviews, and method-based reviews [59]. The methodological approach taken in this study is Callahan´s method [60] and this method belongs to the category of domain-based reviews. Callahan´s guidelines consist of a systematic literature review with the 6W framework (Who, When, Where, hoW, What, and Why). Therefore, this paper applied Callahan´s method to present a review of existing literature on the use of sentiment analysis in education with Transformers and the key information on the method is summarized in Table I.

TABLE I. Key Information for the Systematic Literature Review Adapted From Callahan's 6W Framework [60]

Who conducted the review?	The authors of this paper
When were the data collected?	From October 2023 to December 2023
Where were the data collected?	Six electronic databases (Scopus, ScienceDirect, IEEE Xplore, SpringerLink, Taylor & Francis, and MDPI) were searched for articles in peer-reviewed, scholarly journals and conferences
How were the data found?	The identification of literature relevant to the topic involves considering research questions that establish a search for articles on uses, benefits, challenges, or future applications of the Transformers architecture in sentiment analysis in the field of education. Subsequently, Keywords extracted from research questions are given below: "education", "student", "MOOC", "learning", "teaching", "sentiment analysis", "opinion mining", "Transformer" and "pretrain model". The search strings were then defined to be used in the bibliographic databases of Scopus, ScienceDirect, IEEE Xplore, SpringerLink, Taylor & Francis, and MDPI
What was found?	A final data set of 41 articles
Why were certain works included?	Search words found in title, abstract, or keywords; English; explicitly on sentiment analysis applied in education with Transformers models.

A. Data Collection

Data for this study were collected between October and December 2023. To establish the search interval, the emergence of Transformers in 2017 was taken as a reference [13]. Consequently, the research was restricted to literature published from 2017 to December 2023. Data included literature that met the following selection criteria: published journal or conference written in English, mention of sentiment analysis with Transformers applied to education in title, abstract, or keywords.

A pilot search in Scopus showed that a search using the term "sentiment analysis" would yield more than 42.954 articles. In contrast, a more specific search with Boolean operators was performed including title, abstract, and keywords. Therefore, the search keywords were "sentiment" AND "analysis", AND "transformers", AND "education". In this case, there were six publications returned. It was therefore determined that the first search led to many publications that referred to an unmanageable number of articles, and the second search was evidently too restrictive. As a result, the data were collected in two phases, a process illustrated in Fig. 1.

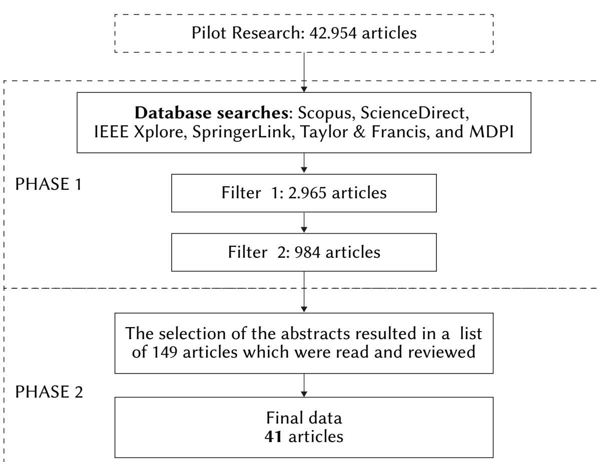

Fig. 1. Overview of the search and review process.

B. The First Search Phase

Education is a vast field and covers different topics. Sentiment analysis can also be referred to as opinion mining. Due to this situation, synonyms and other useful keywords were used for advanced search. This is presented in Table II.

TABLE II. Keywords With Their Respective Synonyms

Keyword	Synonym
Sentiment analysis	opinion mining
Transformers	pretrain model
Education	training instruction teaching learning academic learning study tutoring e-learning

The next step was to apply some of the synonyms in searches with Boolean operators OR and AND. However, the first results were associated with other types of research. For example, the term "learning" was associated with the term "machine learning", which refers to models other than Transformers, but is equally related to the field of artificial intelligence. In this case, it was decided to keep the term "Transformer" or "pretrain model" and thus limit somewhat the inclusion of other types of research. One situation that could be observed in the development of the advanced search was that some studies were left out by not considering the words associated with the analysis of student sentiment or the analysis of online course comments. Therefore, to minimize the risk of omitting relevant publications, the searches were customized to include useful words such as "student" and "MOOC". Next, Table III shows the keywords and Boolean operators applied in the advanced search of this first phase. The database search engines used were Scopus, ScienceDirect, IEEE Xplore, SpringerLink, Taylor & Francis, and MDPI. In this case, publications were extracted in the form of research articles, and the search was performed on titles, abstracts, and keywords.

In Table III, a "filter 1" column is displayed, which corresponds to the application of the advanced search with 2.965 results. In this first filter, some considerations were taken into account. For example, the search words changed in two cases in the ScienceDirect database where the word "academic" was not included because the database limited the number of words. Therefore, tests were carried out to verify that removing a word did not alter the search result set. The second case was in the MDPI database where the search was changed because the results became restrictive as more words were added. Therefore, the search was continued with "sentiment analysis" OR "opinion mining". Finally, filter 2 considered only English-language open-access articles published between 2017 and 2023, obtaining 984 results in this first phase.

C. The Second Search Phase

In the second phase of the process, the 984 articles derived from the initial phase were reviewed. The review of the abstracts was based on the following inclusion and exclusion criteria.

1. Inclusion Criteria

Articles that (a) focused exclusively on sentiment analysis applied to education using the Transformers architecture and (b) were original, peer-reviewed publications in open-access journals or conferences, were included.

TABLE III. Advanced Database Search

Database	Advanced Search	Returned Articles	
		Filter 1	Filter 2
IEEE Xplore	"All Metadata": education OR "All Metadata": student OR "All Metadata": MOOC OR "All Metadata": learning OR "All Metadata": academic OR "All "Metadata": teaching) AND ("All Metadata": "sentiment analysis" OR "All Metadata": "opinion mining") AND ("All Metadata": "Transformer" OR "All Metadata": "pretrain model"	603	80
ScienceDirect	(education OR student OR MOOC OR learning OR teaching) AND ("sentiment analysis" OR "opinion mining") AND ("Transformer" OR "pretrain model")	63	25
Scopus	(education OR student OR "MOOC" OR learning OR academic OR teaching) AND ("sentiment analysis" OR "opinion mining") AND ("Transformer" OR "pretrain model")	838	255
SpringerLink	("education" OR "student" OR MOOC OR "learning" OR "academic" OR "teaching") AND ("sentiment analysis" OR "opinion mining") AND ("Transformer" OR "pretrain model")	970	217
Taylor and Francis Online	("education" OR "student" OR MOOC OR "learning" OR "academic" OR "teaching") AND ("sentiment analysis" OR "opinion mining") AND ("Transformer" OR "pretrain model")	100	43
MDPI	("sentiment analysis" OR "opinion mining")	391	364
TOTAL		**2.965**	**984**

2. Exclusion Criteria

Articles that (a) were not related to the Transformers architecture, (b) did not apply the Transformers architecture in the educational setting, and (c) only showed the performance results of Transformers models, were excluded. In addition, non-journal or non-conference peer-reviewed articles were also excluded.

The evaluation of the abstracts led to the identification of a list of 149 articles which were subjected to a thorough reading and detailed review.

As a result, articles were selected that demonstrated the practical value of analyzing feelings using Transformer models in education, with the aim of understanding how this technology is being implemented in the field and what it contributes. Subsequently, the articles that deviated from the scope of the research were excluded, resulting in a final list of 41 selected articles.

IV. Results

This section presents the results obtained in the present work. The 41 articles were classified into three categories. Category A corresponds to the research that collected the analysis data in online educational environments. Category B has the works that collected the analysis data from social networks or platforms such as Google Play, and category C finds the articles that obtained the analysis data from different media such as audio or surveys. After ranking the 41 items, the percentages occupied by each of the labeled categories were: category A (46%), category B (32%), and category C (22%). The coding scheme was employed to obtain information from the studies, based on Table IV.

TABLE IV. Categories and Items Included in the Coding Scheme of This Systematic Review

Coding Domine	Items
Source information	Year of publication Author
Study Quality	Source of data
Setting characteristics	Research objective Data collection spaces

The results obtained provide a comprehensive overview of the evolution and trends in sentiment analysis research with Transformers in education. It is important to emphasize that the presented works start from the year 2019. These findings may be associated with the scientific publication cycle, wherein the research process, from conceptualization to publication, takes time. Therefore, many projects could have begun in the years preceding 2019, but their results were disclosed in conferences or scientific journals in that specific year. In the following sections, the papers will be presented according to the established categories, and different research based on Transformers models will be exposed considering that each of them has its respective scope according to the objective set. The compilation of all studies can be visualized in Table V.

A. Data Extracted From Online Educational Environments

The first section will examine research works that have collected opinions, comments, chats, or reviews left by students in online educational environments, in such a way that they go through a sentiment analysis process that contributes to improving the educational processes of teaching and learning. A growing body of literature has investigated e-learning, a teaching and learning system based on the use of Information and Communication Technologies (ICT) [61]. More recent attention has focused on applying a Transformer-based model that performs automatic sentiment prediction. Therefore, it is important to mention research that as a result evaluates the accuracy of a model, other research that develops a deep analysis of emotions, and more findings that are related to educational improvement.

In recent years, there has been an increasing amount of literature on Massive Open Online Courses (MOOCs). One of the most well-known teaching systems is a type of online course designed to be accessible to many participants around the world. According to Zhou et al. [62] reviews left by students in these courses are taken to accurately classify each of them or to evaluate the quality of the courses according to the sentiments detected. This view is supported by Yan et al. [63] and Du [7], who in their research extracted reviews posted by students on MOOC courses and determined that course content, technical content, degree of difficulty, teaching staff level, video provided, course schedule, and homework load are the main factors affecting student satisfaction in these virtual learning environments. Together, these studies show that these factors help to identify deficiencies in the course to act and improve the quality of the course. Moreover, Jatain et al. [64] analyzed student feedback from Coursera to capture aspects that influence the popularity of the course, although the study focused on assessing the pressure on the BERT model´s prediction of sentiment.

The authors of two studies [65], [66] conducted a sentiment analysis of MOOC course reviews to compare Transformers models with other deep learning methods emphasizing the superior performance of models such as BERT or RoBERTa. Similarly, Marfani et al. [67] analyzed four Coursera courses and extracted opinions and comments from students for sentiment analysis to help identify their shortcomings and improve their courses. In the case of this research, the aim was to find the model that worked best to identify the key aspects of sentiment classification by basing the experiments on real student data. The accuracy rate obtained in this research with BERT was outstanding. A broader perspective was adopted by Pan et al. [68] who applied the BERT model. In this case, after the classification of feelings from the comments left by the students, the results obtained were analyzed in depth. Therefore, it was determined that academic emotions improved significantly in the first and second periods of the course and tended to be stable in the second and third periods of the course. In the same vein, a pre-trained ALBERT model was also applied to extract key information from comments left in MOOCs courses and it was determined that the model overcame the problem of the traditional sentiment analysis method that cannot distinguish the different meanings of the same word in different contexts [69]. Research has also proposed new models according to language needs. Conversely, Min et al. [70] proposed in their work to extract reviews of Chinese online courses using an ALBERT model by analyzing a small amount of labeled data to choose courses with better reviews.

In addition to reviews posted on MOOCs, forums are one of the means of communication between teachers and students, although it is difficult to distinguish messages that require prompt intervention considering a priority level. In this sense, sentiment analysis helps teachers prioritize responses to questions left on forums promptly [71]. Liu et al. [72] collected 8.867 student posts in a forum and identified the interactive relationship between emotional and cognitive engagement in students' learning process. In other words, positive or confusing emotions have been determined to contribute more to high-level cognition than negative emotions. Cognitive screening was also conducted in MOOCs to identify unlabeled messages from two MOOC courses and determine the cognitive presence of learners. These results provide valuable information on the effectiveness of pre-training in large-scale multidisciplinary discussion data [73]. These articles reveal the relationship between cognitive aspects and the opinions left in the forums.

Recently, researchers have paid attention to more sentiments. As is the case of Alkaabi et al. [75] who used messages left on online learning platforms to classify students' emotions as positive, negative, or neutral. They then managed to extract dominant negative sentiments such as anger, disgust, fear, and sadness from students. In this sense, chats between teachers and students have also made it possible to analyze feelings on these platforms to help teachers improve their teaching methods [79]. In these works, the pre-trained BERT model was applied to perform sentiment classification, achieving high accuracy in emotion prediction.

So far, all research has presented data collected exclusively from MOOCs. However, studies have been written that perform sentiment analysis with multimodal data that are taken from MOOCs and other different educational spaces. In a sentiment analysis, Qu et al. [74] classified student behavioral data collected from the course evaluation system and the academic management system, including textual information from students' comments on the course. Another author, Dyulicheva [77], investigated mathematics MOOCs and student reviews. In sentiment analysis, deep learning was applied to identify some clusters of various negative emotions related to students past bad mathematics experiences. As a result, students' emotional states associated with math phobia represent substantial barriers to learning mathematics and acquiring basic mathematical skills. Together, these studies outline the high performance of the Transformer BERT model with multimodal data.

An interesting aspect of the research focused on sentiment analysis in this category is proposals with new models based on Transformers. For example, BERT model can be modified or fine-tuned to train it with different data. More recent attention has focused on comparing Transformer models and determining their performance. In this sense, among studies that compared Transformers models with other machine learning models, the superiority of Transformers models in sentiment analysis prediction was highlighted due to the inherent ability to capture complex patterns and long-range relationships in text sequences.

Overall, these studies indicate that sentiment analysis focused on the educational field can improve the teaching and learning process, especially on online learning platforms. One possible implication of this is that there is great value in the information found in learning systems because it is objective and didactic data that are useful for school management and can improve course development. Students' academic emotions are important for academic performance and contribute greatly to educational success because they generate new problem-solving proposals that manifest themselves in online educational environments.

B. Data Extracted From Social Media

The second section will examine research that has collected feedback left by students outside of online educational environments, such as social networks or other platforms. More recent attention has focused on social networks because they have a large and diverse population, so people can express their opinions on any topic daily. Collectively, comments are open to all audiences, and students use this medium to express feelings or opinions also in an educational context [88]. Some studies analyze comments on topics that can influence students' decision-making for their vocational training. For example, Fouad et al. [91] used more than 250.000 tweets in sentiment analysis with the BERT model to analyze perceptions of women in STEM (Science, Technology, Engineering, and Mathematics) fields. Many of the opinions were positive about women's entry into these fields, and consequently, in this sentiment analysis, it was determined that the positive aspects may encourage women to enroll in higher education careers related to them. Another study also analyzed around 3.542 Reddit forum posts about the Radiology career with the RoBERTa Transformer and the perception of the Radiology career was positive for the students [82]. Considering both results, the mostly positive comments may encourage students to make enrollment decisions.

However, in contrast to earlier findings, there have been several studies that reveal critical opinions about educational topics. The research by Zhou and Mou [86] found that the expectations associated with online learners are difficult to meet, as they expect students to be self-disciplined and self-regulated. It is expressed that students must stare at the screen for a long time due to long online sessions; this situation was associated with keywords such as "drowsy" and "anxious" in the sentiment classification. In the same vein, another study analyzed student tweets, in which it was found that students may suffer from stress in this modality [83]. There is no doubt that online education is an omnipresent force that can meet emergent needs during unexpected events to provide continuity in education, but studies have also exposed critical views. Therefore, the authors mention the need to diversify online teaching and learning activities to maximize student attention. Prasad et al. [80] address the challenge of manually annotating large volumes of data, they proposed a machine learning method that uses the sentiment 140 dataset as a training set to automate the process of tagging student tweets on social networks. They conclude that this method can be effectively applied to label any qualitative data.

TABLE V. The Use of Transformers in Sentiment Analysis in Education

S/N	Article Title	Authors	Publication Year	Category
1	Sentiment Analysis of MOOC Reviews Based On Capsule Network [69]	Liu et al.	2021	A
2	A Shallow BERT-CNN Model for Sentiment Analysis on MOOCs Comments [65]	Li et al.	2019	A
3	Analysis of Learners' Sentiments on MOOC Forums using Natural Language Processing Techniques [67]	Marfani et al.	2022	A
4	Can We Predict Student Performance Based on Tabular and Textual Data? [74]	Qu et al.	2022	A
5	Online Course Quality Evaluation Based on BERT [62]	Zhou et al.	2020	A
6	Bi-GRU Urgent Classification for MOOC Discussion Forums Based on BERT [71]	Khodeir	2021	A
7	MOOC-BERT: Automatically Identifying Learner Cognitive Presence From MOOC Discussion Data [73]	Liu et al.	2023	A
8	An exploration of the causal factors making an online course content popular & engaging [64]	Jatain et al.	2023	A
9	Automated detection of emotional and cognitive engagement in MOOC discussions to predict learning achievement [72]	Liu et al.	2022	A
10	Deep learning for opinion mining and topic classification of course reviews [66]	Koufakou	2023	A
11	Sentiment Analysis and Topic Mining Using a Novel Deep Attention-Based Parallel Dual-Channel Model for Online Course Reviews [63]	Yan et al.	2023	A
12	Detecting Emotions behind the Screen [75]	Alkaabi et al.	2022	A
13	Cross-Domain Polarity Models to Evaluate User eXperience in E-learning [76]	Sanchis-Font et al.	2021	A
14	Learning Analytics in MOOCs as an Instrument for Measuring Math Anxiety [77]	Dyulicheva	2021	A
15	A Small amount of Labeled Data Chinese Online Course Review Target Extraction via ALBERT-IDCNN-CRF Model [70]	Min et al.	2020	A
16	Case Study: Predicting Students Objectivity in Self-evaluation Responses Using Bert Single-Label and Multi-Label Fine-Tuned Deep-Learning Models [78]	Nikolovski Vlatko and Kitanovs	2020	A
17	Sentiment Analysis of Comment Texts on Online Courses Based on Hierarchical Attention Mechanism [79]	Su et al.	2023	A
18	Research on the factors influencing the learner satisfaction of MOOCs [7]	Du	2023	A
19	Are students happier the more they learn? – Research on the influence of course progress on academic emotion in online learning [68]	Pan et al.	2022	A
20	Supervised Sentiment Analysis of Indirect Qualitative Student Feedback for Unbiased Opinion Mining [80]	Prasad et al.	2023	B
21	Sentiment Analysis of Students' Feedback on E-Learning Using a Hybrid Fuzzy Model [81]	Alzaid et al.	2023	B
22	Broadening the Understanding of Medical Students' Discussion of Radiology Online: A Social Listening Study of Reddit [82]	Hameed et al.	2023	B
23	Sentiment Analysis of Stress Among the Students Amidst the Covid Pandemic Using Global Tweets [83]	Jyothsna et al.	2023	B
24	Sentiment Analysis of Tweets on Online Education during COVID-19 [84]	Yldrm Elif and Yazgan	2023	B
25	Sentiment Analysis and Topic Modeling on Tweets about Online Education during COVID-19 [85]	Mujahid et al.	2021	B
26	Tracking public opinion about online education over COVID-19 in China [86]	Zhou et al.	2022	B
27	The Ivory Tower Lost: How College Students Respond Differently than the General Public to the COVID-19 Pandemic [87]	Duong et al.	2020	B
28	Research on the Method of Identifying Students' Online Emotion Based on ALBERT [88]	Ren et al.	2021	B
29	Sentiment Analysis of Code-mixed Social Media Data on Philippine UAQTE using Fine-tuned mBERT Model [89]	Maceda et al.	2023	B
30	Analysing user reviews of interactive educational apps: a sentiment analysis approach [90]	Mondal et al.	2022	B
31	Sentiment Analysis for Women in STEM using Twitter and Transfer Learning Models [91]	Fouad et al.	2023	B
32	Students' preferences with university teaching practices: analysis of testimonials with artificial intelligence [92]	Álvarez-Álvarez et al.	2023	B
33	A Multi-Modal Convolutional Neural Network Model for Intelligent Analysis of the Influence of Music Genres on Children's Emotions [93]	Qian and Chen	2022	C
34	Unlocking the opportunities through ChatGPT Tool towards ameliorating the education system [94]	Javaid et al.	2023	C
35	Sentiment Analysis of Using ChatGPT in Education [95]	Tubishat et al.	2023	C
36	Online teaching emotion analysis based on GRU and nonlinear transformer algorithm [96]	Ding	2023	C
37	Arabic Sentiment Analysis for Student Evaluation using Machine Learning and the AraBERT Transformer [97]	Munshi et al.	2023	C
38	Analysis of the Sentiment in the Evaluation Texts of University Students by Means of the Concept of Flexible Management [98]	Zhu	2023	C
39	Aspect and Sentiment Classification Mechanisms of Student After-Class Self-Evaluated Comments: Investigation on Nonsense Data, Feature Extraction, and Classification Models [99]	Chou et al.	2023	C
40	Multilabel Classification of Student Feedback Data Using BERT and Machine Learning Methods [100]	Setiawan et al.	2023	C
41	Towards Application of Speech Analysis in Predicting Learners' Performance [101]	Chowdary Attota et al.	2022	C

Turning to the opinions of students on the topic of the pandemic on social media, Duong et al. [87] in their research analyzed 73.787 tweets from 12.776 university Twitter followers, and only tweets related to the pandemic were considered. They found that university students were significantly more negative due to the spread of COVID-19 and were observed with racist comments toward the Asian community. It is important to mention that in this study the data were collected in the year 2020 during the pandemic, which is why these results were observed. In the same vein, Mujahid et al. developed two studies focusing on sentiment analysis of students' emotions about the pandemic using e-learning Twitter data [85] and distance education data to classify sentiments into positive, negative, and neutral [84].

Studies on sentiment analysis have also focused on languages other than English. For example, a topic of interest to students is access to universities in the Philippines. In this case, around 13.332 student comments were collected on Twitter, Facebook, and YouTube. Then the multilingual Bidirectional Encoder Representations from Transformers (mBERT) model was applied, achieving 80% accuracy, and determining that students view third-level education positively but also revealed concerns about delays in grants or alleged misuse of funds [89]. Additionally, a study analyzing the sentiment of student comments on e-learning in Saudi Arabia found that comments were ambiguous, and opinions were unclear [81]. This study suggests that the opinion of a personal text differs depending on the context or setting in which it is expressed, and in social networks, informal language can also be a drawback when analyzing sentiment. These findings contribute to the understanding that the application of Transformers models extends to other languages while maintaining strong performance in sentiment prediction.

On the other hand, it is feasible to analyze the public opinion of students themselves on platforms such as the Google Play Store. Mondal et al. [90] analyzed over one million reviews of 800 Augmented Reality (AR) and Virtual Reality (VR) apps with an educational focus. The results suggested that educational applications that did not incorporate AR or VR received higher user satisfaction than applications that incorporated these technologies. In the same way, the study by Sanchis et al. [76] analyzed users' feelings based on preferences, behaviors, and achievements before, during, and after interaction with virtual learning environments. Likewise, Nikolovski et al. dealt with student opinions about teachers obtained objectively for further analysis using these educational software [78]. These results could emphasize categorizing user opinions within a technological environment and hold great potential for guiding educational software developers in refining the design of programs, applications, or virtual learning platforms. By gaining insights into user sentiments, developers can better align their innovations with the specific functionalities desired by users.

These investigations agree with the findings of other studies located in the first section, in which opinions or comments allow valuable information to be extracted and thus take action. Likewise, some studies [80], [81] expressed the belief that one of the drawbacks detected in this research is the lack of context in opinion detection, as it decreases the likelihood of correct sentiment detection, due to the use of jargon, youth code, or various forms of expression used by students. Therefore, pre-processing and cleaning the data contributes to a better sentiment classification process with Transformers models. Sentiment analysis with Transformers in different languages is still scarce, and the application of Transformers in research focuses on fitting pre-trained models and evaluating their behavior in terms of performance metrics.

C. Data Extracted From Different Educational Spaces.

This section presents different scenarios that have been collected for sentiment analysis. For example, Setiawan et al. [100] collected student feedback from the comments left by students in mentoring sessions with their tutors. This study aimed to find out the students' queries for the university departments to provide answers to ensure satisfactory delivery of services to the students. Therefore, the BERT model was applied to classify students' comments in mentoring sessions as positive or negative, achieving an accuracy of 82% [100]. A broader perspective has been adopted by Zhu [98] who used university students' teaching evaluation texts for a sentiment analysis based on BERT. The objective of this study was to understand and more accurately analyze the teaching evaluation texts of university students by applying sentiment analysis to explore the deep semantic information of the texts.

On the other hand, in the study by Munshi et al. [97] a dataset was created from student surveys. At the end of the manual collection, 1.044 student responses were obtained, reaching 3.472 comments related to preferences about a subject. In this data analysis, a BERT-based model called AraBERT was applied to classify feelings into positive, negative, and neutral, achieving an accuracy of 82%. Similarly, in another investigation [99], students were asked to write their self-assessed comments in a system after each class. In total, 1.640 anonymous comments were collected. The applied model was BERT, with an accuracy of 93%, and the classification was made into three categories: positive, negative, and neutral. An interesting aspect of this study is that for the classification of the three categories mentioned above, seven aspects: interest, gain, positivity, speed, difficulty, teacher in general, and others were applied. Chowdary Attota et al. [101] collected students' moods through audio recordings in class while discussing the course topic in teams. Pre-trained models with transformational linguistic models were applied for automated audio data transcription and conversion achieving high accuracy in predicting students' scores. One of the characteristics of audio is that it can be adopted as additional information, as it is closely associated with text, and the characteristics of changes in sound pulses can be used in the fine classification of emotions. For example, the influence of musical genres on children's emotional intelligence is one of the topics of impact. Qian et al. [93] applied a neural network based on BERT to extract features and analyze emotions in such a way that it was shown to work effectively in the accuracy of musical genre classification tasks based on children's emotions. However, it is difficult for these methods to effectively capture the actual information of the different modalities. Therefore, for the task of the influence of music genres on children's emotions, the BERT transformer was proposed to extract audio-video features and effectively improve the accuracy of sentiment classification tasks.

For sentiment analysis Ding [96] uses students' auditory input, facial expression, and textual data to propose a cross-modal Transformer algorithm to improve information processing. The work is conceived as an innovative idea by using a visual Transformer to achieve accurate and efficient learner emotion analysis in an online teaching context. Achieving an accuracy of 84%. Emotion analysis in this context is crucial for understanding and improving the learning experience and in the evaluation of student engagement in educational courses.

A recent phenomenon is ChatGPT, a conversational artificial intelligence interface chatbot developed by OpenAI. It is being considered as one of the most advanced artificial intelligence applications. ChatGPT is a revolutionary tool that answers questions about almost anything available in the digital environment and can help the state create and implement an impartial and fair curriculum. If properly implemented, it could serve as a bridge to ease the pressure on a stressed education system. Spontaneous student opinions on a particular topic reveal significant data, such as in the case of university teaching practices, where a linguistic model based on AI Generative Pre-trained Transformer-3 (GPT-3) was applied. Sentiment analysis showed that students prefer clear teaching practices where ideas and activities are presented unambiguously and based on interaction between teachers and students and among students themselves [92].

A study of 11.830 tweets about the use of the new ChatGPT technology revealed that opinions on the application of ChatGPT in education show that many tweets are positive or neutral, with a small percentage expressing negative sentiments [95]. It is important to mention that this article was initially thought to belong to category B because the data was collected from a social network. However, after further analysis of its content, it was decided to categorize it in section C as a new scenario. However, there are some concerns about the application in educational settings due to issues such as the deception, honesty, and truthfulness of ChatGPT [94].

V. Discussion

The purpose of this study was to conduct a systematic review of the literature on sentiment analysis with Transformers models applied to education to gain a better understanding of its status, how can influence culture, Open Science and the development of artificial intelligence, together with its benefits, challenges, and future work. Four broad research questions were specified in the Introduction section which are now addressed.

RQ1 investigated the current state of the art in sentiment analysis with Transformers applied to education. To answer this question, 41 published research articles were examined. The first finding reveals that most studies focus on the sentiment analysis of data collected from online educational platforms. For example, comments [62], messages left on the forums [71], or MOOC chat messages [79] were analyzed. Another scenario from which data were collected was social networks, especially comments on Twitter [87], Facebook, and YouTube [89]. In addition, comments from forums, such as Reddit [82]. Finally, data were taken from environments other than those mentioned above, such as comments left in university departments [100] or surveys given to students to determine their opinions [97]. Therefore, the articles were classified into three categories. Category A corresponds to articles that used data collected from online educational platforms. This category represents 46% of the reviewed studies and deals with sentiment analysis applied in virtual educational environments to improve teaching and learning processes. Category B corresponds to articles that used data collected from social networks with 32% of the studies and reflects sentiment analysis of opinions that students leave on social networks. Finally, category C, with 22% of the studies, groups studies that use data that has been taken from surveys, or opinions of new trends in sentiment analysis with audio [101] and new technologies such as ChatGPT [95].

RQ2 explored the advantages of employing sentiment analysis using transformers in the realm of education. Initially, the main findings from scrutinized research studies underscored the superior performance of transformer models compared to other categories of machine learning or deep learning technologies, achieving a sentiment prediction accuracy of over 90% [99]. The direct merit lies in the ability of the models to enhance the likelihood of accurate sentiment predictions. Upon closer examination of the literature, one notable advantage emerged: the objectivity of the data used for sentiment analysis because there are two main approaches to obtaining student feedback: the direct approach and the indirect approach. In the direct approach, opinions are collected through the distribution of questionnaires and the subsequent collection of responses [97]. However, this method has limitations as it does not reveal the true experience of students and there is a possibility of bias in the collection and evaluation of questionnaires. To overcome these limitations, an indirect approach can be adopted, where social media posts serve as a source for collecting students' opinions, as students are active on social media and use social media to express their opinions through posts. This objectivity is derived from the source platforms, where students freely express their opinions without external pressures, allowing genuine feelings, perceptions, and opinions to be identified [80]. Furthermore, the investigations revealed multiple benefits derived from the application of sentiment analysis in educational settings. Notably, the methodology facilitates the detection of students' needs, thereby contributing to the enhancement of course quality, refinement of the teaching system, and diversification of instructional materials within online education environments. Consequently, this contributes to heightened satisfaction among students engaging in virtual courses. Indeed, certain studies even delved into the examination of students' phobias, shedding light on issues that warrant attention. In summary, the overarching goal of conducting sentiment analysis is to leverage students' feedback for the continual improvement of educational quality.

RQ3 covered the key challenges in applying sentiment analysis with Transformers in education. There are students with different cultural backgrounds, and identifying online learning environments that respect the particularities of international students is a great challenge [102]. Language is one of the necessary elements for sentiment analysis that reflects culture [103]. First, research on sentiment analysis in online learning environments has predominantly focused on the English language, as it is a language with many available resources, such as reference datasets, annotated corpora, and sentiment lexicons [104], [105]. However, Deriu et al. [106] reported that sentiment analysis methods developed for single-language texts could not be replicated for novel or multilingual texts. In addition, the English language and its common terms and understanding are causing problems for Open Science. For this reason, studies on sentiment analysis in educational settings have also focused on languages other than English. Munshi et al. [97] propose the AraBERT multilingual model based on Arabic, a morphologically rich language with multiple dialects. Similarly, data collected from online educational environments can be multilingual and multicultural, such as those of the Chinese language [70] or Filipino lexicons [89].

Another challenge reflected in the educational context is the concern regarding the use of new artificial intelligence technologies, where sentiment analysis may encounter negative views regarding ethics and dishonesty. Javaid et al. [94] argue that the use of ChatGPT and other linguistic models raises crucial ethical questions about their effects on society. However, there are areas of research to apply new technologies so that students can easily understand and communicate in other languages [94]. At present, the results confirm that ChatGPT is widely used in education [95]. Therefore, new technologies can be used as tools to help students create relevant content on a specific topic. It can also be used to provide students with feedback to help them improve their knowledge based on their moods. This could help ensure that students receive the right amount of challenge and material that is interesting and relevant.

Regarding the Transformer models applied in the research field, the challenge lies in the quality of the training dataset, as the aim is to avoid biased data due to different linguistic and cultural contexts [80]. Therefore, the suggested strategy is to improve the pre-processing stage for correct sentiment analysis. Another aspect is the large number of parameters, which leads to a time-consuming training process [69]. As an alternative, model compression was proposed as far as possible to reduce this time. However, the training process results in high computational costs.

RQ4 addressed the identification of future areas of research. At the end of this systematic literature review, it was determined that there are few studies on sentiment analysis related to culture. The method applied to analyze learner comments left on MOOCs is based on applying the lexicon in a single language [65]. In the work of Marfani et al. [67] about 10.000 reviews from the Coursera platform were analyzed, and data processing was performed in a single language without considering cultural aspects. Considering these works, there is a research space for sentiment analysis with artificial intelligence that includes the opinions of online learning environments of learners from different cultures and nationalities.

Furthermore, it is recommended to give students control over their learning processes by offering multiple cultural options in MOOCs [107]. This recommendation is related to UNESCO [108] recommendation on Open Science by stating that multilingual scientific knowledge should be openly available, accessible, and reusable. Future research should focus on understanding learners' perceptions of open access to multilingual resources in online or distance learning environments. Understanding cultural differences can improve teaching and learning processes to provide quality and culturally sensitive education [102].

VI. Conclusions, Limitations, and Future Works

In recent years, sentiment analysis has been a breakthrough in the field of natural language processing. This paper presents a literature review on sentiment analysis research utilizing Transformers deep learning models. The scope of the research was limited to the educational field and the 6W systematic review method was used to analyze 41 articles from well-known digital databases such as Scopus, ScienceDirect, IEEE Xplore, SpringerLink, Taylor & Francis, and MDPI. The results explain the current state of knowledge on sentiment analysis with Transformers in education and identify the benefits and challenges of use. Furthermore, future areas of research for this modern AI technology and findings in terms of its implications were identified.

The present study achieved significant results in sentiment analysis within the education domain using Transformer models. However, a notable limitation was the difficulty in accessing and consulting relevant databases to filter studies specifically related to the topic. This challenge hindered the refinement of search processes and the identification of precise findings pertinent to this research.

This study has identified the advantages and challenges of using sentiment analysis in educational settings with Transformers. Therefore, future research directions in sentiment analysis applied to the sustainability of education could focus on refining specialized models, integrating multimodal data, assessing the long-term impact of Open Science initiatives, developing specific metrics, actively involving the educational community, creating interactive tools, applying to distance learning environments, and emphasizing inclusion and cultural diversity. In essence, the integration of sentiment analysis with AI technologies heralds a paradigm shift in educational research and practice, empowering stakeholders to forge a more responsive, empathetic, and student-centric educational landscape. As stride steadfastly into the digital age, the synergy between AI and education promises to redefine the contours of teaching and learning, ushering in an era of unprecedented innovation and transformation.

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