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Augmented Reality and Virtual Reality in Education: Public Perspectives, Sentiments, Attitudes, and Discourses

Georgios Lampropoulos [1,2,*], Euclid Keramopoulos [1] Konstantinos Diamantaras [1] and Georgios Evangelidis [3]

[1] Department of Information and Electronic Engineering, International Hellenic University, 57400 Thessaloniki, Greece
[2] School of Humanities, Hellenic Open University, 26335 Patras, Greece
[3] Department of Applied Informatics, University of Macedonia, 54636 Thessaloniki, Greece
* Correspondence: lamprop.geo@gmail.com

Abstract: This study aims to understand the public's perspectives, sentiments, attitudes, and discourses regarding the adoption, integration, and use of augmented reality and virtual reality in education and in general by analyzing social media data. Due to its nature, Twitter was the selected platform. Over 17 million tweets were retrieved from January 2010 to December 2020 and four datasets were created. Two of them referred to the general use of these technologies and two to their educational use. The data was analyzed using text mining, sentiment analysis (e.g., polarity and emotion detection), and topic modeling methods. TextBlob, Word-Emotion Association Lexicon (EmoLex), Valence Aware Dictionary for Sentiment Reasoning (VADER), and Latent Dirichlet Allocation (LDA) were some of the tools used. Based on the results, the majority of the public were positively disposed toward the general and the educational use of both augmented reality and virtual reality and mostly expressed positive emotions (e.g., anticipation, trust, and joy) when referring to them. In total, 11 topics emerged that were related to education, new technologies, digital and social media use, marketing and advertising, the industrial domain, the health domain, gaming, fitness and exercising, devices, the travel and tourism domain, and software development kits. The educational benefits of augmented reality and virtual reality, their ability to enrich both teaching and learning activities, and their role as effective educational means were evident.

Keywords: augmented reality; virtual reality; education; data analysis; sentiment analysis; topic modeling; educational innovation; social media; twitter; educational technology

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1. Introduction

New technological applications are being actively integrated into the education process to accommodate students' diverse learning styles and address educational requirements and demands [1]. Hence, technology-enhanced learning is becoming more popular as it can constitute an integral part of 21st century education [2]. It can enrich traditional education, assist educators, improve education quality, and successfully meet the emerging educational needs [3]. Learners' interests, preferences, capabilities, personality, and knowledge should be taken into account when designing technology-enhanced learning activities [4,5].

The adoption of extended reality technologies, such as augmented reality and virtual reality, in the educational domain is also gaining ground as they provide intriguing experiences through interactive environments [6–9]. These safe and secure environments provide a sense of immersion and are in line with instructional theory [10,11]. Moreover, they affect all human senses, create more motivating and engaging learning activities, promote positive learning behaviors and attitudes, facilitate teaching and learning processes, lead to improved learning outcomes, and enable students to better comprehend learning subjects and hone their skills [12–14]. Thus, immersive technologies can affect learners'

self-regulation, self-efficacy, cognitive load, motivation, embodiment, and interest while also fostering their agency and presence [15].

More empirical studies regarding the use of extended reality technologies in education are being conducted [16,17]. The educational benefits of these technologies have been highlighted in the recent literature and are widely accepted and positively viewed by both students and teachers [8,18–21]. Despite this fact, little is known about the public's perspectives, sentiments, attitudes, and discourses regarding the use of augmented reality and virtual reality in educational contexts as studies focus on specific populations. Due to their nature, social media platforms can be an invaluable tool to comprehend public opinions on different matters [22,23].

Consequently, the main aim of this study is to identify, process, and comprehend public perspectives, sentiments, attitudes, and discourses regarding the adoption and integration of augmented reality and virtual reality in education by analyzing social media data. Particularly, the Twitter platform was selected and over 17 million tweets were retrieved from January 2010 to December 2020. The specific time period was chosen to offer a more coherent and complete overview as well as to present data gathered before the COVID-19 pandemic. The tweets were analyzed using text mining, sentiment analysis, and topic modeling methods. In total, four datasets involving the general and educational use of both augmented reality and virtual reality were created. The research questions (RQ) that guided this research were:

- RQ1: What are the perspectives, sentiments, and attitudes of the public toward augmented reality?
- RQ2: What are the perspectives, sentiments, and attitudes of the public toward the use of augmented reality in education?
- RQ3: What are the perspectives, sentiments, and attitudes of the public toward virtual reality?
- RQ4: What are the perspectives, sentiments, and attitudes of the public toward the use of virtual reality in education?
- RQ5: What are the main discourse topics regarding augmented reality and virtual reality?
- RQ6: How do the results of augmented reality compare to those of virtual reality?

2. Theoretical Background

2.1. Augmented Reality and Virtual Reality

Based on the "reality–virtuality continuum", a mixed reality is in the middle of a spectrum which has a fully virtual environment at one end and the real physical one at the other end [24]. Therefore, a mixed reality environment can take place anywhere between the two ends, and can be characterized as an area in which virtual and physical objects co-exist, interact, and are presented in a unified depiction [25]. Augmented reality is closer to the real environment while virtual reality to the virtual one.

Augmented reality uses technological applications of computer units to enrich users' perceived physical environment with interactive virtual objects and information in real time [26]. As it combines the virtual with the physical environment and due to its interactive and immersive nature, augmented reality can effectively be applied in educational contexts of different levels and subjects [8,27]. Moreover, it can create inclusive learning environments that motivate students, promote an active learning process, and offer education of high quality at anytime and anyplace [3,28]. On the other hand, virtual reality involves computer-generated virtual environments that perceptually surround users and simulate their physical presence within them so that they can be regarded as real [29–31]. Its main characteristics are the sense of presence it provides, the immersion and immediacy it offers, and its ability to actively involve users [32,33]. Due to its nature, virtual reality can create safe and secure learning environments which motivate and engage students while also providing meaningful learning [21,34]. As a result, its integration in educational settings can lead to increased benefits and improved learning outcomes [7,18].

2.2. Social Media

Social media are ruled by hybrid media logic [35], have bottom-up communication, transparency, horizontal knowledge sharing, and personalization at their core, create a sense of belonging and socialization [36–38], and are driven by user-generated and freely shareable content [39]. Additionally, they allow users to interact with others in real time and create a network of relationships within a common information space [40–42]. As a result, they constitute a significant component of everyday life and have drastically changed the way people co-create and share information, communicate, and interact [43].

It should be mentioned that social media can also be a source of fake news [44–46] or misinformation [47,48]. In many cases, this is caused by bots [49–51]. In addition, there are security and privacy concerns that should be taken into account when using social media [52–54]. As social media are also being used as a marketing and promotional tool, the overlapping of enterprise interest in different areas, including the educational sector, should be considered [55–57]. Despite these facts, the use and analysis of social media data still remain an effective and valid method to comprehend the wisdom of the crowd on specific matters [58,59].

Twitter is one of the main social media platforms that people use to share their opinions and discourse on news, matters, and topics as they occur and due to its nature, it urges them to do so concisely and precisely [60–62]. Additionally, as Twitter significantly affects people's opinions compared to other social media platforms, several studies opt to use it as they deem its data more important [63,64].

3. Materials and Methods

The methodology used followed the one presented in [31]. The steps involved in the methodology are the following: (i) setting up the appropriate data requirements, (ii) identifying, retrieving, and collecting the related data, (iii) processing the retrieved data, (iv) analyzing the data, and (v) visualizing the results.

Specific rules and aims (e.g., time period, sources, keywords, variables, etc.) were set to ensure data accuracy and validity and to provide precise results and outcomes. After testing out several combinations and based on previous studies [8], the keywords used along with the required wildcards to retrieve the 17,278,040 related tweets from January 2010 to December 2020 were:

- For the general use of augmented reality: ("augmented reality" OR #AR OR augmentedreality);
- For the educational use of augmented reality: ("augmented reality" OR #AR OR augmentedreality) AND (learn OR teach OR train OR education OR university OR college OR school OR class OR student OR pupil);
- For the general use of virtual reality: ("virtual reality" OR #VR OR virtualreality);
- For the educational use of virtual reality: ("virtual reality" OR #VR OR virtualreality) AND (learn OR teach OR train OR education OR university OR college OR school OR class OR student OR pupil).

The data retrieval process was followed by data processing, cleaning, and storage. Stop-words, single characters, URLs, and punctuation marks were removed. Besides the hashtags, the text was converted into lower case and abbreviated words were expanded. The final four datasets created were stored in JSON and CSV files. The data was analyzed both on a yearly basis and as a whole. For the analysis of the frequency of words, hashtags, tweets, bigrams, and trigrams, text mining methods were used. To detect the emerging topics discussed, topic modeling methods were applied while sentiment analysis was used for the polarity and emotion detection.

3.1. Sentiment Analysis

Sentiment analysis refers to the computational study of subjective information (e.g., opinions, biases, attitudes), affective states, feelings, and emotions within text data using Natural Language Processing (NLP), text analysis, biometrics, and computational linguis-

tics [31,65,66]. The methods of sentiment analysis can either be machine learning-based, lexicon-based, or hybrid [67] and they can be applied on an aspect, topic, document, or sentence level [68,69].

This study adopted a lexicon-based sentiment analysis approach to detect the emotions and polarity of the tweets. More specifically, TextBlob [70] and Valence Aware Dictionary for Sentiment Reasoning (VADER) [71] were used to conduct the polarity detection while the National Research Council Canada (NRC) Word-Emotion Association Lexicon (EmoLex) [72] was used to detect the emotions within the tweets. Furthermore, the emotions detected are in line with Plutchik's wheel of emotions, which consists of eight basic emotions which are paired, and opposing emotions cannot be felt simultaneously [73]. The pairs of emotions are: (i) surprise and anticipation, (ii) joy and sadness, (iii) fear and anger as well as (iv) acceptance and disgust.

3.2. Topic Modeling

Topic models aim at identifying the underlying topics and affinities within text datasets and provide actionable insights by extracting the intellectual structure, semantics, and hidden variables [74–77]. Moreover, a priori annotations are not required to develop topic models as they constitute unsupervised ubiquitous tools that need only the text datasets and the specific number of topics to be recognized [78–80]. Due to its flexibility and effectiveness, topic modeling is widely used to analyze social media data [81].

The Latent Dirichlet Allocation (LDA) method was selected to create the topic models. LDA is a probabilistic model which analyzes a set of documents, it is one of the most popular methods for topic modeling and has been effectively used to examine Twitter and social media data [82–84]. Particularly, LDA is a three-level hierarchical Bayesian model which can be used on discrete datasets and represents each item as a finite mixture over an underlying set of topics [85].

3.3. Limitations and Challenges

Some limitations to this study that can be mentioned involve the use of only one social media platform and the retrieval of tweets written only in English. Additionally, some data fields could not be analyzed as they are private by default and cannot be retrieved unless users themselves set them to public status. An example of that is the field "country". In this case, although some tweets contained the country, there is no reference to it in this article as even after normalizing the country data, the data did not reflect the actual numbers. Another field that could be of particular interest which was not included in this study for the same reason is the field "occupation". As a result, it was not possible to detect if a specific tweet was related to a particular firm or enterprise and used for promotional or marketing reasons. Thus, we opted to create separate datasets for education which used additional keywords related to the educational sector.

Moreover, due to the nature of the study, some limitations involve the sentiment analysis as some tweets could be referring to a specific experience and not to the technologies themselves. This is a common limitation of similar studies. To address it, the educational datasets were manually filtered to include tweets that were directly related to the use of augmented reality and virtual reality in education. Finally, it is worth noting that the use of social media as a means for promotion and marketing may result in particular users or enterprises expressing intentionally positive or negative perspectives.

4. Results

To address the main research questions and meet the aims of the study, the aforementioned methodology was used to generate four datasets containing data from Twitter. The time period of the search was set from January 2010 to December 2020. This choice was made to include years that were key to the development and adoption of augmented reality and virtual reality, to provide a more coherent and complete overview of their advancement and to present results of data which was gathered before the COVID-19 pandemic.

In total, 17,278,040 tweets were retrieved out of which 6,820,696 were related to augmented reality and 10,457,344 to virtual reality. The datasets generated were separated into (i) general use of augmented reality (6,643,458 tweets), (ii) educational use of augmented reality (177,238 tweets), (iii) general use of virtual reality (10,157,427 tweets), and (iv) educational use of virtual reality (299,917 tweets). The data analysis included text mining, sentiment analysis, and topic modeling. In particular, the frequency of words, hashtags, tweets, bigrams, and trigrams as well as the polarity and sentiment of the tweets were analyzed as a whole and per year. Additionally, the topics emerged were identified. When appropriate, cross-validation was conducted to verify the accuracy of the results.

4.1. General Use of Augmented Reality

According to the results of the word frequency analysis, reality, augmented, ar, vr, and app were the top-5 most commonly used words. Table 1 depicts the top-40 most common words. #AR, #ar, #VR, #AugmentedReality, and #augmentedreality were the top-5 most common hashtags. Table 2 displays the top-40 most commonly used hashtags. The frequency of the annual and monthly tweets is presented in Figure 1. The majority of the tweets were posted in 2017 (14.1%). The frequency of the top-20 most common bigrams and trigrams is showcased in Tables 3 and 4. Regarding the tweet polarity, the results of both TextBlob and VADER (Figures 2–4) showed the majority of tweets were neutral, followed by positive and negative. The majority of tweets did not express a particular emotion (59.58%). Anticipation (16.58%), trust (9.65%), and joy (4.22%) were the most expressed emotions. Figure 5 presents the emotion analysis on a yearly basis.

Table 1. Frequency of the top-40 most common words within the augmented reality tweets.

Word	Freq.	Word	Freq.	Word	Freq.	Word	Freq.
reality	4,346,364	tech	255,979	see	147,720	news	116,313
augmented	4,049,674	ai	245,673	apple	147,355	go	111,963
ar	3,290,094	video	222,395	iphone	144,767	make	110,855
vr	790,815	future	221,923	world	142,387	business	109,236
app	535,416	game	204,320	experience	133,371	next	104,398
via	486,831	iot	193,118	get	124,164	first	102,993
virtual	458,072	google	179,928	digital	119,503	real	100,762
new	393,814	3d	178,210	marketing	117,682	one	100,170
use	249,786	glass	173,213	like	117,677	way	99,163
technology	259,955	mobile	173,036	check	116,395	android	97,611

Table 2. Frequency of the top-40 most common hashtags within the augmented reality tweets.

Hashtag	Freq.	Hashtag	Freq.	Hashtag	Freq.	Hashtag	Freq.
#AR	2,148,784	#MR	83,589	#blurreal	41,253	#marketing	35,311
#ar	864,263	#technology	71,169	#socialmedia	40,170	#layar	35,061
#VR	632,177	#virtualreality	58,102	#MixedReality	39,370	#XR	35,000
#AugmentedReality	552,546	#3D	56,668	#realestate	39,008	#blockchain	33,264
#augmentedreality	316,271	#Ar	53,589	#ML	38,698	#MachineLearning	32,970
#AI	208,732	#Tech	49,588	#social	38,220	#Technology	32,883
#IoT	161,095	#innovation	47,169	#mobile	36,910	#Augmented	32,207
#VirtualReality	130,075	#ARNews	46,296	#ArtificialIntelligence	36,296	#StarWars	29,499
#tech	103,983	#BigData	45,815	#Robotics	35,842	#LittleRock	29,289
#vr	93,960	#edtech	45,138	#jobs	35,678	#Blockchain	29,196

Monthly and annual augmented reality tweets over the years 2010-2020

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
January	31,577	29,458	50,893	57,960	42,817	46,280	61,964	66,599	72,653	47,879	40,161
February	33,897	31,269	54,462	59,603	38,926	51,832	65,657	61,605	70,047	52,493	36,435
March	32,277	44,066	56,046	62,915	46,595	46,376	62,076	76,626	83,921	52,728	34,184
April	26,840	41,262	77,683	53,867	42,710	42,681	50,720	77,521	67,630	45,979	32,325
May	28,141	47,901	64,445	52,966	47,421	44,571	52,016	74,809	63,773	53,036	37,317
June	28,479	41,126	64,799	44,834	39,073	40,157	57,233	81,425	87,709	45,496	34,386
July	29,632	42,428	67,702	39,105	42,269	38,494	99,735	77,799	55,312	43,224	36,306
August	26,944	46,195	52,829	51,070	28,856	32,214	69,311	85,851	57,635	41,530	36,297
September	27,978	42,456	55,913	40,327	33,188	34,585	62,097	90,154	61,692	42,930	33,022
October	29,381	47,164	53,863	44,677	40,056	50,946	68,885	81,844	62,456	43,618	36,958
November	31,215	61,439	65,648	36,923	35,895	48,034	69,479	82,727	52,164	39,864	31,771
December	31,585	44,085	58,440	37,057	33,925	54,422	61,474	80,801	45,187	35,125	28,662
Total	357,946	518,849	722,723	581,304	471,731	530,592	780,647	937,761	780,179	543,902	417,824
Percentage	5.4%	7.8%	10.9%	8.8%	7.1%	8.0%	11.8%	14.1%	11.7%	8.2%	6.3%

Over 90,000
Over 80,000
Over 70,000
Over 60,000
Over 50,000
Over 40,000
Over 0

Figure 1. Monthly and annual augmented reality tweets over the years 2010–2020.

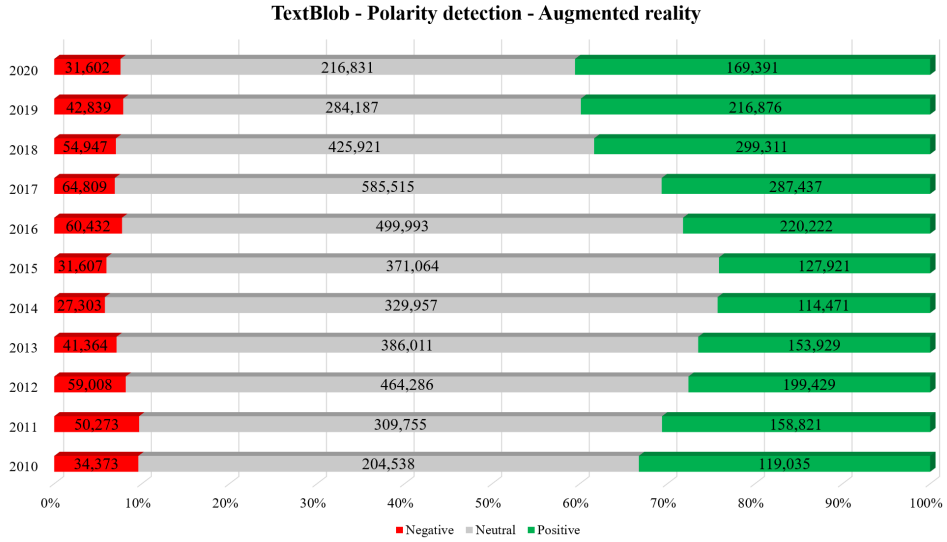

Figure 2. TextBlob polarity detection: Augmented reality dataset.

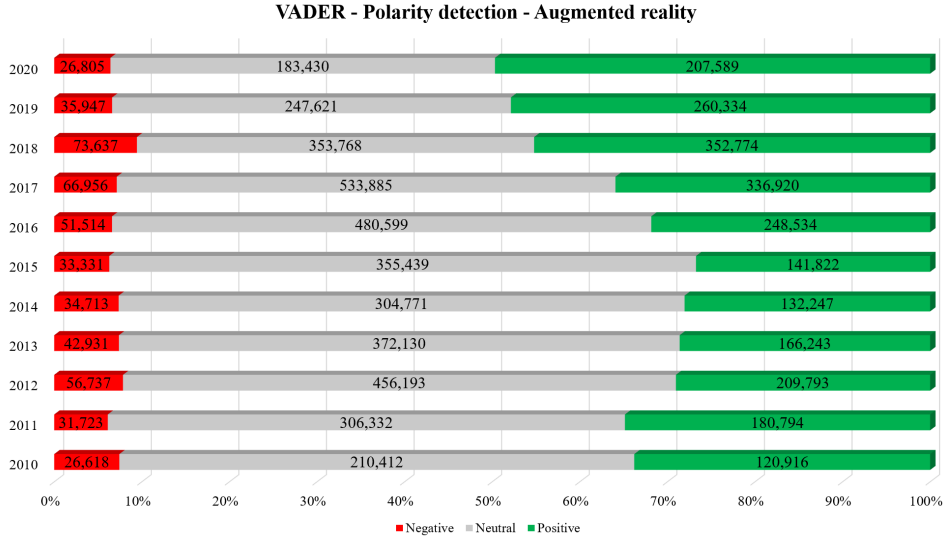

Figure 3. VADER polarity detection: Augmented reality dataset.

Table 3. Frequency of the top-20 most common bigrams within the augmented reality tweets.

Bigram	Freq.	Bigram	Freq.
(augmented, reality)	3,059,128	(new, augmented)	45,453
(ar, vr)	524,877	(reality, apps)	41,722
(reality, app)	135,588	(blurreal, ar)	41,247
(virtual, reality)	117,379	(magic, leap)	39,968
(reality, ar)	71,204	(ai, ar)	39,569
(use, augmented)	79,297	(reality, augmented)	35,123
(reality, glasses)	65,698	(ar, realestate)	34,098
(virtual, augmented)	59,410	(vr, mr)	33,701
(let, us)	58,415	(use, augmented)	33,556
(reality, game)	50,057	(app, augmented)	33,289

Table 4. Frequency of the top-20 most common trigrams within the augmented reality tweets.

Trigram	Freq.	Trigram	Freq.
(augmented, reality, app)	134,397	(reality, augmented, reality)	31,465
(use, augmented, reality)	66,851	(future, augmented, reality)	30,900
(augmented, reality, ar)	65,371	(find, layar, ar)	30,727
(augmented, reality, glasses)	64,975	(augmented, reality, via)	29,238
(virtual, augmented, reality)	57,103	(augmented, reality, headset)	25,980
(augmented, reality, game)	49,209	(augmented, reality, future)	24,508
(new, augmented, reality)	44,534	(augmented, reality, technology)	24,483
(using, augmented, reality)	44,024	(augmented, reality, virtual)	24,142
(augmented, reality, apps)	40,552	(mobile, augmented, reality)	23,067
(app, augmented, reality)	32,852	(virtual, reality, augmented)	22,943

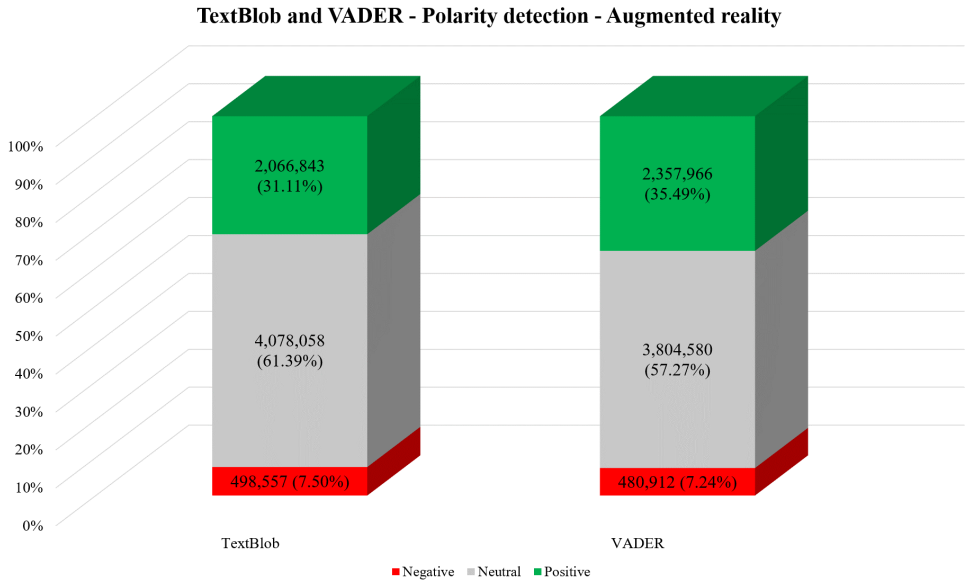

Figure 4. TextBlob and VADER polarity detection: Augmented reality dataset.

Emotion frequency based on the most intense emotion of each augmented reality tweet for each year over the years 2010-2020

	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation	Neutral
2010	21,665	32,215	10,860	2633	2323	4650	14,430	63,764	205,406
2011	35,817	41,792	16,918	3379	3893	3172	15,290	84,295	314,293
2012	21,161	71,930	20,593	7542	5279	5321	34,118	111,268	445,511
2013	17,705	47,668	16,889	5623	4275	5360	28,147	81,570	374,067
2014	14,872	36,383	14,598	2986	4038	2969	15,747	62,168	317,970
2015	15,898	44,345	15,552	3005	2872	3768	18,462	63,797	362,893
2016	25,315	67,918	30,841	8867	5236	6041	29,497	115,395	491,537
2017	34,564	86,982	37,259	9240	7122	5568	34,674	169,504	552,848
2018	39,995	91,920	31,386	8387	5601	5831	27,115	153,720	416,224
2019	29,919	65,457	23,207	7187	4564	4848	29,842	111,489	267,389
2020	23,758	54,740	17,632	4091	3862	3688	15,748	84,550	209,755
Total	280,669	641,350	235,735	62,940	49,065	51,216	263,070	1,101,520	3,957,893
Percentage	4.22%	9.65%	3.55%	0.95%	0.74%	0.77%	3.96%	16.58%	59.58%

Figure 5. Emotion frequency based on the most intense emotion of each augmented reality tweet for each year over the years 2010–2020.

4.2. Educational Use of Augmented Reality

The results of the frequency analysis of the words are presented in Table 5 while for the hashtags in Table 6. Reality, augmented, ar, education, and learn were the top-5 most common world while the top-5 most commonly used hashtags were #AR, #VR, #AugmentedReality, #education, and #edtech. Figure 6 displays the annual and monthly tweet frequency with 2018 (19.7%) being the year with the most relevant tweets. The top-20 most frequently used bigrams and trigrams are presented in Tables 7 and 8, respectively. Using TextBlob, the polarity analysis revealed that most tweets were neutral (50.86%), followed by positive (42.42%) and negative (6.72%). When using VADER, the polarity analysis revealed that the majority of tweets were positive (49.44%), followed by neutral (46.43%) and negative (4.13%). The detailed results of the polarity analysis are presented in Figures 7–9. Most tweets expressed anticipation (22.95%), trust (17.86%), and joy (8.14%) while the majority of them were neutral, without expressing any emotion in particular (41.96%). The detailed emotion analysis is displayed for each year in Figure 10.

Table 5. Frequency of the top-40 most common words within the tweets of the educational augmented reality dataset.

Word	Freq.	Word	Freq.	Word	Freq.	Word	Freq.
reality	143,343	app	16,522	ai	8999	game	5146
augmented	125,452	technology	16,007	teach	8971	classroom	5085
ar	88,735	student	13,908	future	7783	business	4958
education	64,831	new	12,904	way	7506	iot	4934
learn	52,990	learning	12,724	experience	7240	innovation	4775
vr	38,182	via	12,338	help	6591	digital	4677
virtual	25,030	class	10,088	more	5646	elearning	4656
use	23,737	tech	9962	video	5578	world	4629
school	17,889	university	9147	kid	5466	tool	4513
edtech	16,902	train	9083	3d	5369	college	4401

Table 6. Frequency of the top-40 most common hashtags within the tweets of the educational augmented reality dataset.

Hashtag	Freq.	Hashtag	Freq.	Hashtag	Freq.	Hashtag	Freq.
#AR	68,038	#tech	4144	#XR	2537	#BigData	1413
#VR	31,051	#IoT	4102	#STEM	2382	#school	1314
#AugmentedReality	24,298	#technology	4101	#learning	2333	#ArtificialIntelligence	1211
#education	20,548	#elearning	3792	#innovation	2299	#teaching	1201
#edtech	13,283	#vr	3596	#3D	2125	#ai	1172
#augmentedreality	11,933	#MR	3578	#mlearning	1993	#marketing	1162
#ar	9694	#edchat	3342	#k12	1776	#UX	1033
#Education	8256	#EdTech	3049	#Tech	1733	#healthcare	1026
#VirtualReality	7636	#virtualreality	3023	#Technology	1637	#art	1021
#AI	7266	#ARVRinEDU	2756	#MixedReality	1611	#MachineLearning	1011

Monthly and annual tweets of the educational augmented reality dataset over the years 2010-2020

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
January	180	297	903	1062	471	488	613	1760	3062	2549	2353
February	261	365	715	1114	502	1263	843	1291	2809	2595	2388
March	278	1661	567	850	594	755	1346	1599	3585	2770	1986
April	247	413	899	705	950	859	859	1606	3197	2658	1925
May	227	418	497	892	1002	588	872	1650	2962	2672	1989
June	218	430	645	1050	663	698	1144	1544	2915	2606	2234
July	287	271	530	918	657	725	1602	1965	2586	2631	2137
August	178	448	673	743	390	671	1569	1886	2722	2477	2107
September	297	315	1693	1057	438	546	1418	2267	3147	2469	1853
October	244	475	1093	790	570	913	3447	2413	3117	2549	2323
November	285	568	878	688	678	949	2765	2709	2656	2338	2180
December	185	456	928	611	436	649	1197	2311	2132	2088	1835
Total	2887	6117	10,021	10,480	7351	9104	17,675	23,001	34,890	30,402	25,310
Percentage	1.6%	3.5%	5.7%	5.9%	4.1%	5.1%	10.0%	13.0%	19.7%	17.2%	14.3%

Over 3000
Over 2500
Over 2000
Over 1500
Over 1000
Over 500
Over 0

Figure 6. Monthly and annual tweets of the educational augmented reality dataset over the years 2010–2020.

Table 7. Frequency of the top-20 most common bigrams within the tweets of the educational augmented reality dataset.

Bigram	Freq.	Bigram	Freq.
(augmented, reality)	85,330	(education, edtech)	2702
(ar, vr)	25,742	(learn, augmented)	2364
(reality, education)	10,717	(learn, ar)	2082
(use, augmented)	9387	(augmentedreality, ar)	2053
(virtual, reality)	6970	(education, ar)	1943
(reality, app)	5783	(reality, augmented)	1912
(learn, consultants)	3884	(reality, teach)	1889
(ar, education)	3027	(reality, learn)	1882
(virtual, augmented)	2878	(future, education)	1880
(reality, ar)	2849	(teach, kids)	1687

Table 8. Frequency of the top-20 most common trigrams within the tweets of the educational augmented reality dataset.

Trigram	Freq.	Trigram	Freq.
(augmented, reality, education)	9713	(augmented, reality, learn)	1713
(use, augmented, reality)	8940	(augmented, reality, tool)	1422
(augmented, reality, app)	3651	(augmented, reality, experiments)	1421
(augmented, reality, ar)	2693	(reality, experiments, education)	1386
(virtual, augmented, reality)	2692	(change, med, school)	1349
(learn, augmented, reality)	2316	(totally, change, med)	1347
(augmented, reality, apps)	1931	(reality, tool, could)	1322
(reality, augmented, reality)	1851	(introduction, augmented, reality)	1201
(augmented, reality, teach)	1848	(augmented, reality, web)	1143
(virtual, reality, augmented)	1762	(reality, teach, kids)	1107

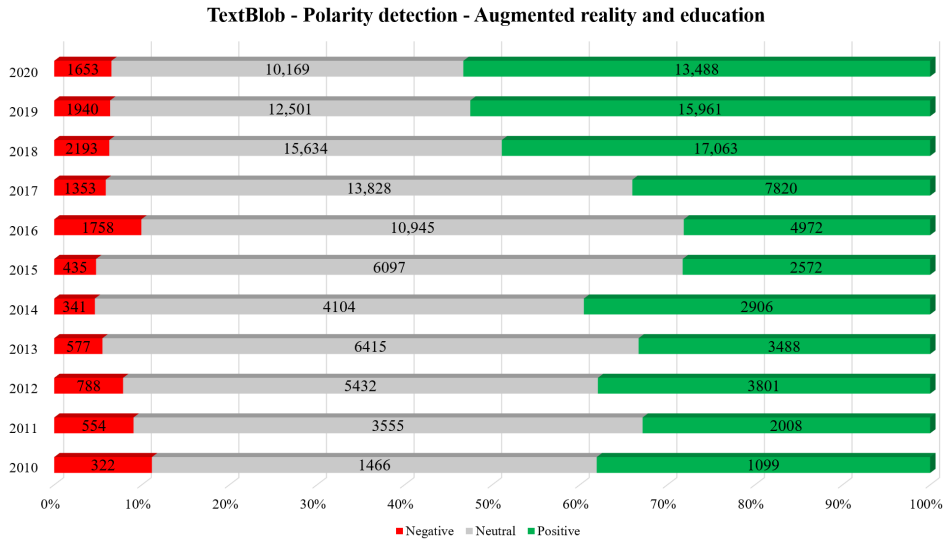

Figure 7. TextBlob polarity detection: Educational augmented reality dataset.

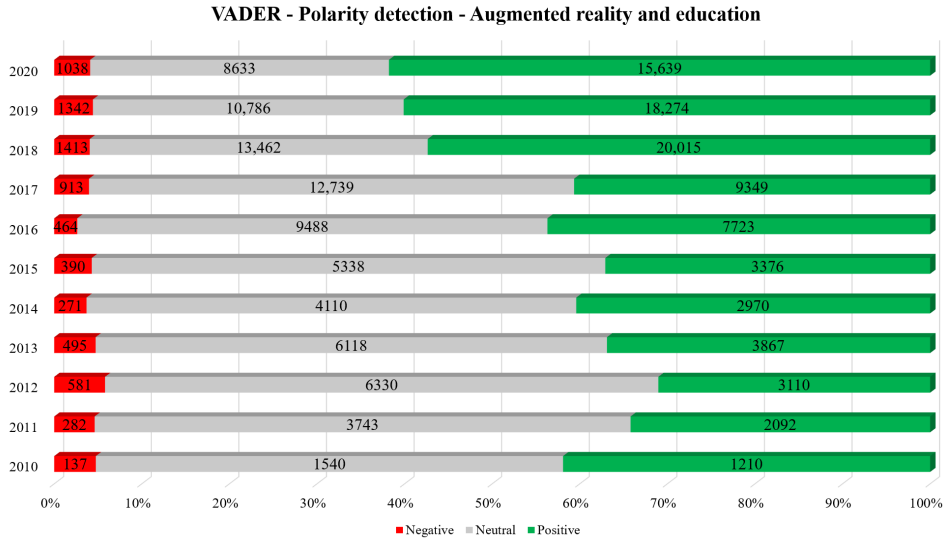

Figure 8. VADER polarity detection: Educational augmented reality dataset.

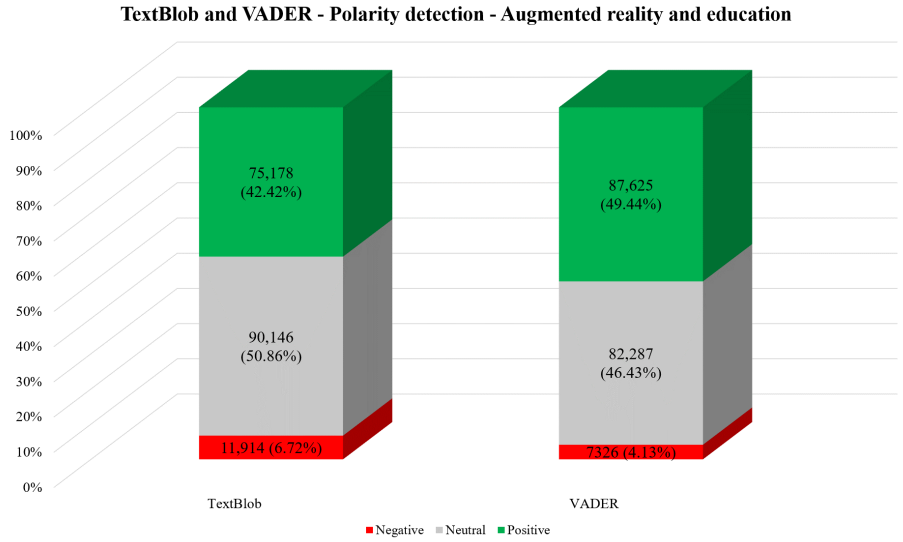

Figure 9. TextBlob and VADER polarity detection: Educational augmented reality dataset.

Emotion frequency based on the most intense emotion of each tweet of the educational augmented reality dataset for each year over the years 2010-2020

	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation	Neutral
2010	184	403	85	15	14	16	43	713	1414
2011	315	1015	74	51	23	27	148	2202	2262
2012	608	1541	419	32	67	61	300	3352	3641
2013	918	1700	619	88	63	44	211	1864	4973
2014	407	1489	254	49	39	40	125	1512	3436
2015	451	1440	318	28	19	39	86	1638	5085
2016	2978	1915	1805	99	47	90	246	3310	7185
2017	1309	3047	757	147	59	111	656	4437	12,478
2018	2795	6961	1366	351	241	254	1027	7960	13,935
2019	2357	6516	1021	386	226	226	1000	7429	11,241
2020	2111	5621	1195	293	260	222	632	6256	8720
Total	14,433	31,648	7913	1539	1058	1130	4474	40,673	74,370
Percentage	8.14%	17.86%	4.46%	0.87%	0.60%	0.64%	2.52%	22.95%	41.96%

Figure 10. Emotion frequency based on the most intense emotion of each tweet of the educational augmented reality dataset for each year over the years 2010–2020.

4.3. General Use of Virtual Reality

Based on the word frequency analysis, reality, virtual, vr, ar, via were the top-5 most commonly used words. In Table 9, the top-40 most common words are presented. The hashtag frequency analysis revealed #VR, #VirtualReality, #vr, #virtualreality, and #AR as the top-5 most common hashtags. The top-40 most commonly used hashtags are displayed in Table 10. Figure 11 presents the annual and monthly frequency of the relevant tweets. The year with the most tweets was 2016 (27.3%). Tables 11 and 12 depict the frequency of the top-20 most common bigrams and trigrams respectively. The polarity analysis using TextBlob revealed the majority of tweets were neutral (56.38%), followed by positive (34.35%) and negative (9.27%) while the results of VADER also showcased that most of the tweets were neutral (53.51%), followed by positive (37.91%) and negative (8.58%). Figures 12–14 present the polarity of the tweets for each year and tool. Most tweets expressed anticipation (18.75%), trust (9.03%), and anger (4.51%) while the majority of them were neutral (55.56%). The emotion analysis is depicted for each year in Figure 15.

Table 9. Frequency of the top-40 most common words within the virtual reality tweets.

Word	Freq.	Word	Freq.	Word	Freq.	Word	Freq.
reality	6,891,651	tech	458,588	youtube	245,198	htc	192,938
virtual	6,776,767	3d	413,478	get	244,590	facebook	185,227
vr	5,792,465	experience	404,629	rift	226,343	time	182,484
ar	741,303	technology	370,107	like	218,515	next	179,254
via	686,991	augmented	370,834	vive	215,830	one	178,856
new	642,332	future	318,930	first	215,393	using	178,252
oculus	593,164	ai	296,717	iot	207,227	check	178,092
headset	557,119	gaming	292,711	make	204,167	real	174,467
game	525,340	google	274,487	news	201,863	could	171,022
video	458,588	world	250,911	see	196,718	help	158,504

Table 10. Frequency of the top-40 most common hashtags within the virtual reality tweets.

Hashtag	Freq.	Hashtag	Freq.	Hashtag	Freq.	Hashtag	Freq.
#VR	3,802,049	#gamedev	116,208	#oculus	67,717	#Technology	49,462
#VirtualReality	962,281	#3D	112,055	#edtech	66,858	#blockchain	46,388
#vr	869,986	#Oculus	105,903	#Gaming	63,442	#Blockchain	45,690
#virtualreality	693,700	#technology	105,146	#OculusRift	62,363	#news	44,708
#AR	615,182	#gaming	99,185	#innovation	62,320	#PSVR	44,591
#AI	244,152	#ar	86,645	#oculusrift	60,668	#XR	40,870
#tech	201,637	#indiedev	79,976	#htcvive	56,655	#marketing	40,582
#IoT	168,825	#MR	78,569	#HTCVive	52,607	#MixedReality	39,230
#blurreal	140,928	#Tech	76,105	#augmentedreality	51,899	#vive	37,919
#AugmentedReality	131,402	#BigData	68,587	#ML	50,836	#virtual	37,814

Table 11. Frequency of the top-20 most common bigrams within the virtual reality tweets.

Bigram	Freq.	Bigram	Freq.
(virtual, reality)	4,757,432	(youtube, video)	90,142
(vr, ar)	531,535	(liked, youtube)	88,401
(vr, virtualreality)	316,262	(3d, vr)	87,600
(reality, headset)	234,978	(let, us)	81,171
(oculus, rift)	189,975	(vr, virtual)	74,716
(virtualreality, vr)	145,937	(reality, experience)	72,097
(vr, headset)	117,740	(new, virtual)	67,640
(augmented, reality)	115,053	(reality, game)	58,105
(reality, vr)	101,034	(vr, tech)	56,944
(use, virtual)	98,290	(oculus, vr)	56,069

Table 12. Frequency of the top-20 most common trigrams within the virtual reality tweets.

Trigram	Freq.	Trigram	Freq.
(virtual, reality, headset)	231,622	(virtual, reality, via)	47,828
(use, virtual, reality)	95,902	(augmented, virtual, reality)	45,616
(virtual, reality, vr)	91,366	(3d, virtual, reality)	41,961
(liked, youtube, video)	87,992	(future, virtual, reality)	38,682
(virtual, reality, experience)	71,045	(virtual, reality, video)	38,072
(vr, virtual, reality)	67,669	(virtual, reality, gaming)	37,078
(new, virtual, reality)	65,221	(virtual, reality, games)	33,789
(virtual, reality, game)	57,091	(first, virtual, reality)	33,210
(virtual, reality, headsets)	54,287	(virtual, reality, glasses)	33,054
(virtual, reality, technology)	49,989	(virtual, reality, 3d)	32,894

Monthly and annual virtual reality tweets over the years 2010-2020

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
January	2937	3658	7117	11,564	19,029	76,274	244,897	209,490	146,716	90,773	73,063
February	2498	4023	7683	9812	15,041	72,363	232,195	189,816	128,992	77,630	72,719
March	2972	4903	7603	12,875	84,451	110,872	266,674	200,377	144,091	86,693	81,074
April	3109	5222	7038	14,333	32,068	69,937	249,449	178,164	126,238	82,706	72,547
May	4437	5858	7899	10,790	41,368	99,795	246,417	173,528	124,783	79,506	74,607
June	2854	5858	11,410	13,674	38,254	123,798	250,290	168,700	115,188	71,098	64,888
July	2681	5687	10,385	12,514	34,882	124,323	198,902	152,273	109,733	70,444	65,501
August	3504	4713	11,044	12,625	30,666	89,008	212,081	154,431	104,350	66,867	65,758
September	2230	5005	7285	14,281	51,959	129,618	199,342	148,236	106,189	68,674	65,985
October	2457	4537	6373	14,028	37,003	142,159	255,597	183,500	104,645	74,202	72,892
November	2763	4369	8053	14,151	45,912	160,933	210,384	163,646	92,101	72,001	60,276
December	3163	4074	6644	16,983	42,818	177,214	209,287	145,131	83,266	62,642	56,361
Total	35,605	57,907	98,534	157,630	473,451	1,376,294	2,775,515	2,067,292	1,386,292	903,236	825,671
Percentage	0.4%	0.6%	1.0%	1.6%	4.7%	13.5%	27.3%	20.4%	13.6%	8.9%	8.1%

Over 250,000
Over 200,000
Over 150,000
Over 100,000
Over 75,000
Over 50,000
Over 0

Figure 11. Monthly and annual virtual reality tweets over the years 2010–2020.

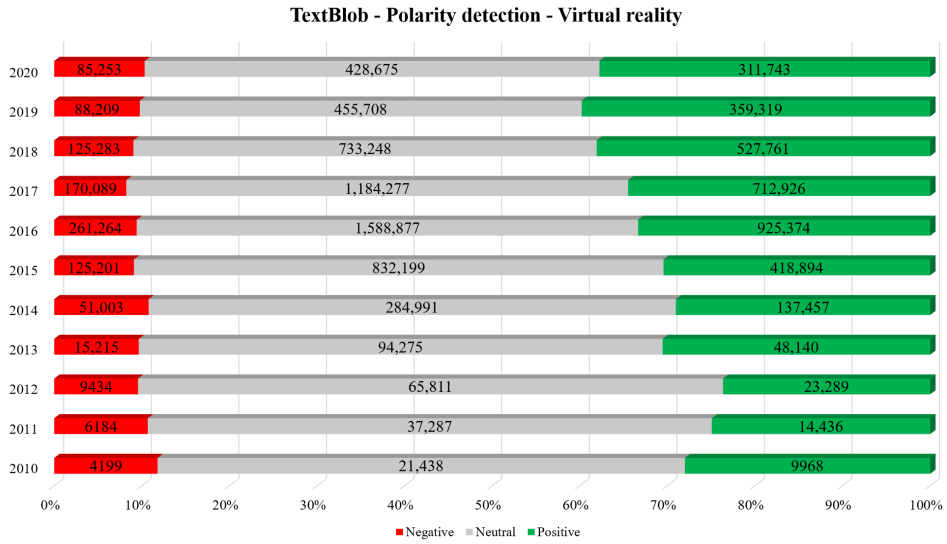

Figure 12. TextBlob polarity detection: Virtual reality dataset.

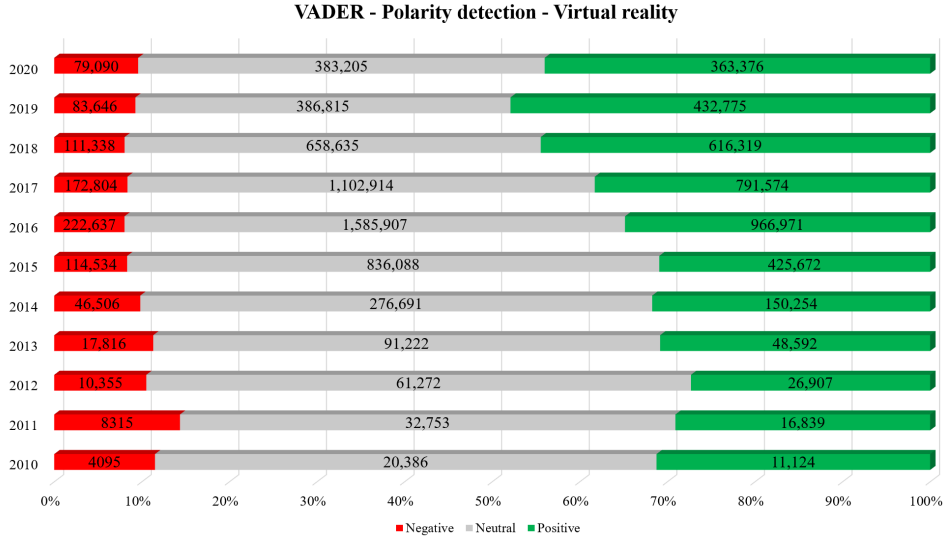

Figure 13. VADER polarity detection: Virtual reality dataset.

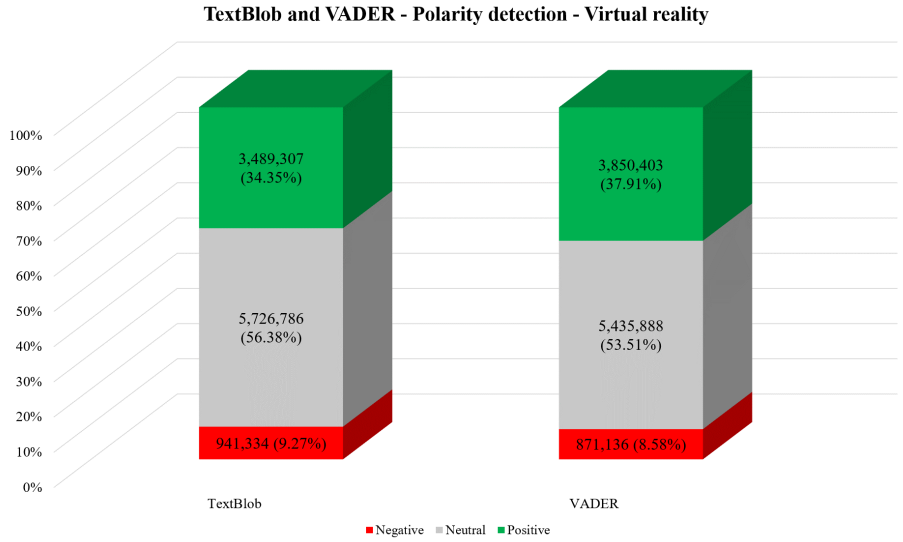

Figure 14. TextBlob and VADER polarity detection: Virtual reality dataset.

Emotion frequency based on the most intense emotion of each virtual reality tweet for each year over the years 2010-2020

	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation	Neutral
2010	1407	3685	1389	781	583	335	1806	4513	21,106
2011	1960	6666	3946	555	593	632	2653	7501	33,401
2012	2809	7767	3513	622	1075	2602	4489	10,802	64,855
2013	7490	13,851	5390	6082	1093	2050	7188	24,276	90,210
2014	15,547	36,331	18,547	4284	4605	6104	19,718	94,164	274,151
2015	51,877	116,861	48,764	14,836	10,294	20,501	56,221	272,172	784,768
2016	106,295	215,924	115,856	28,024	31,532	36,080	123,976	511,512	1,606,316
2017	84,400	173,593	84,490	32,140	24,317	21,769	94,110	360,725	1,191,748
2018	67,656	151,116	59,680	24,429	16,396	14,586	61,706	267,569	723,154
2019	52,060	104,319	41,892	15,268	12,324	10,480	43,868	186,981	436,044
2020	46,336	86,927	34,160	13,047	11,848	8,882	41,872	164,766	417,833
Total	437,837	917,040	417,627	140,068	114,660	124,021	457,607	1,904,981	5,643,586
Percentage	4.31%	9.03%	4.11%	1.38%	1.13%	1.22%	4.51%	18.75%	55.56%

Figure 15. Emotion frequency based on the most intense emotion of each virtual reality tweet for each year over the years 2010–2020.

4.4. Educational Use of Virtual Reality

The 40 most commonly used words are displayed in Table 13. Reality, virtual, vr, education, and learn were the 5 words used the most. Table 14 presents the top-40 most frequently used tweets of which the top-5 were #VR, #VirtualReality, #education, #AR, and #edtech. In Figure 16, the annual and monthly frequency of tweets are presented with 2018 being the year with the most relevant tweets (22.1%). The top-20 most commonly used bigrams and trigrams are displayed in Tables 15 and 16. The polarity analysis using TextBlob revealed the majority of tweets were neutral (61.39%), followed by positive (31.11%) and negative (7.50%) while the results of VADER also showcased that most of the tweets were neutral (57.27%), followed by positive (35.49%) and negative (7.24%). The results of the polarity analysis are shown in Figures 17–19. Figure 20 presents the yearly emotion analysis. Anticipation (22.33%), trust (18.95%), and joy (6.97%) were the emotions mostly expressed from the tweets while 40.67% of the tweets were neutral as they did not express any specific emotion.

Table 13. Frequency of the top-40 most common words within the tweets of the educational virtual reality dataset.

Word	Freq.	Word	Freq.	Word	Freq.	Word	Freq.
reality	234,955	train	26,086	future	15,145	classroom	8484
virtual	226,367	technology	23,860	teach	13,936	history	8266
vr	172,733	new	23,748	way	13,668	video	8177
education	109,421	augmented	20,629	help	13,508	art	8157
learn	95,539	via	19,994	training	12,940	stem	8117
ar	35,500	university	18,081	ai	11,060	more	8093
edtech	33,823	class	17,041	college	10,660	elearning	8019
student	33,097	experience	16,748	game	10,618	teacher	7934
use	30,878	3d	16,021	world	10,279	like	7864
school	29,584	tech	15,747	immersive	8630	first	7699

Table 14. Frequency of the top-40 most common hashtags within the tweets of the educational virtual reality dataset.

Hashtag	Freq.	Hashtag	Freq.	Hashtag	Freq.	Hashtag	Freq.
#VR	121,439	#3D	7905	#edtechchat	4543	#EdTech	3396
#VirtualReality	44,094	#AugmentedReality	7642	#dyslexia	4400	#MR	3385
#education	35,220	#elearning	6828	#k12	4374	#schools	3281
#AR	30,131	#tech	6706	#tourism	4359	#ece	3048
#edtech	28,922	#history	6511	#stem	4146	#earlyed	3031
#virtualreality	21,475	#edchat	6188	#highered	4028	#collegechat	3029
#vr	17,884	#learning	6150	#WebVR	3669	#innovation	3006
#Education	11,961	#technology	5874	#ar	3636	#STEM	2971
#AI	8716	#art	5367	#IoT	3566	#XR	2845
#ARVRinEDU	8490	#museum	4899	#teacher	3516	#musetech	2841

Table 15. Frequency of the top-20 most common bigrams within the tweets of the educational virtual reality dataset.

Bigram	Freq.	Bigram	Freq.
(virtual, reality)	147,007	(future, education)	3943
(vr, ar)	26,161	(learn, vr)	3938
(vr, virtualreality)	18,003	(history, museum)	3931
(vr, education)	12,832	(virtualreality, education)	3863
(reality, education)	10,107	(learning, edchat)	3796
(using, virtual)	7436	(changing, education)	3721
(augmented, reality)	6013	(reality, train)	3619
(education, edtech)	4905	(art, history)	3617
(education, art)	4217	(using, vr)	3517
(students, learn)	4123	(learn, virtual)	3363

Table 16. Frequency of the top-20 most common trigrams within the tweets of the educational virtual reality dataset.

Trigram	Freq.	Trigram	Freq.
(use, virtual, reality)	12,558	(augmented, virtual, reality)	2906
(virtual, reality, education)	9222	(virtual, reality, vr)	2885
(virtual, reality, train)	3581	(virtual, reality, apps)	2768
(education, art, history)	3477	(virtualreality, 3d, edtech)	2722
(art, history, museum)	3470	(virtual, reality, teach)	2629
(vr, virtualreality, 3d)	3147	(virtual, reality, could)	2454
(learn, virtual, reality)	3106	(virtual, reality, changing)	2391
(learning, edchat, edtechchat)	3044	(virtual, reality, headset)	2289
(edchat, edtechchat, elearning)	3021	(virtual, reality, field)	2166
(virtual, reality, technology)	2930	(way, students, learn)	2128

Monthly and annual tweets of the educational virtual reality dataset over the years 2010-2020

	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
January	118	95	94	162	302	1783	3652	5024	6188	4357	4011
February	66	76	77	116	158	899	3159	5393	6620	4309	4310
March	45	73	126	188	658	1320	3203	6232	6465	4804	3455
April	58	67	142	169	363	1229	3959	4707	5496	4492	2664
May	58	64	313	108	327	1493	4203	4911	5679	4157	2702
June	48	172	145	109	504	2063	3922	4791	5735	3773	2663
July	124	188	136	235	586	1864	4609	4539	5208	3937	2903
August	91	67	186	183	550	2898	3945	5337	4971	4041	2753
September	102	125	155	162	738	4347	4150	4765	5461	4457	2753
October	46	130	107	181	808	2657	4583	5417	5606	4867	2868
November	84	108	213	189	456	2421	4799	5833	4987	4131	2728
December	54	76	90	258	488	2052	3674	5017	3821	3315	2463

Over 6000
Over 5000
Over 4000
Over 3000
Over 2000
Over 1000
Over 0

Total	894	1241	1784	2060	5938	25,026	47,858	61,966	66,237	50,640	36,273
Percentage	0.3%	0.4%	0.6%	0.7%	2.0%	8.3%	16.0%	20.7%	22.1%	16.9%	12.1%

Figure 16. Monthly and annual tweets of the educational virtual reality dataset over the years 2010–2020.

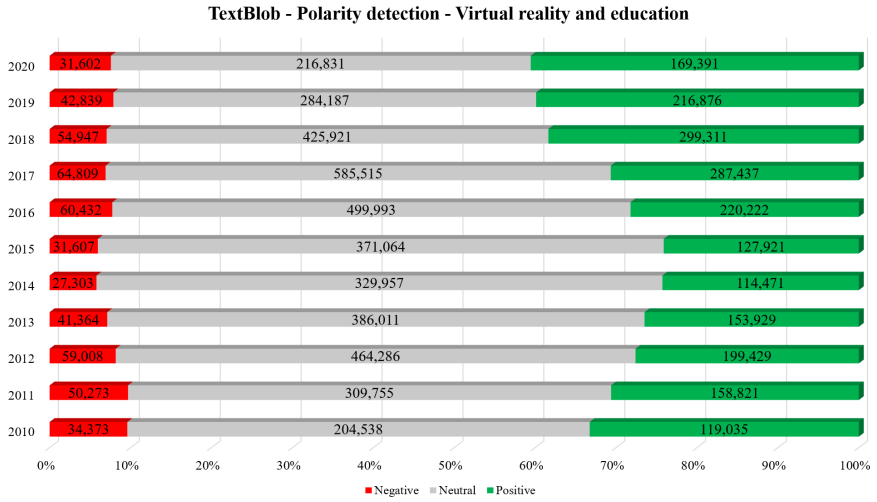

Figure 17. TextBlob polarity detection: Educational virtual reality dataset.

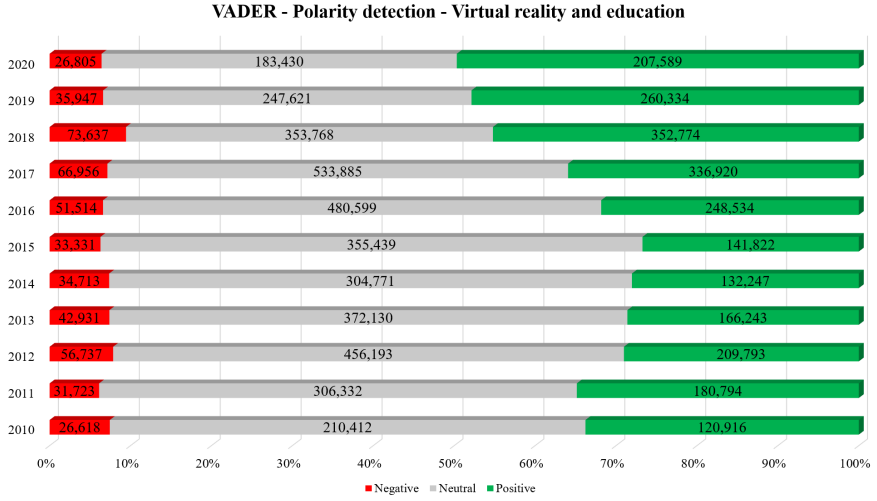

Figure 18. VADER polarity detection: Educational virtual reality dataset.

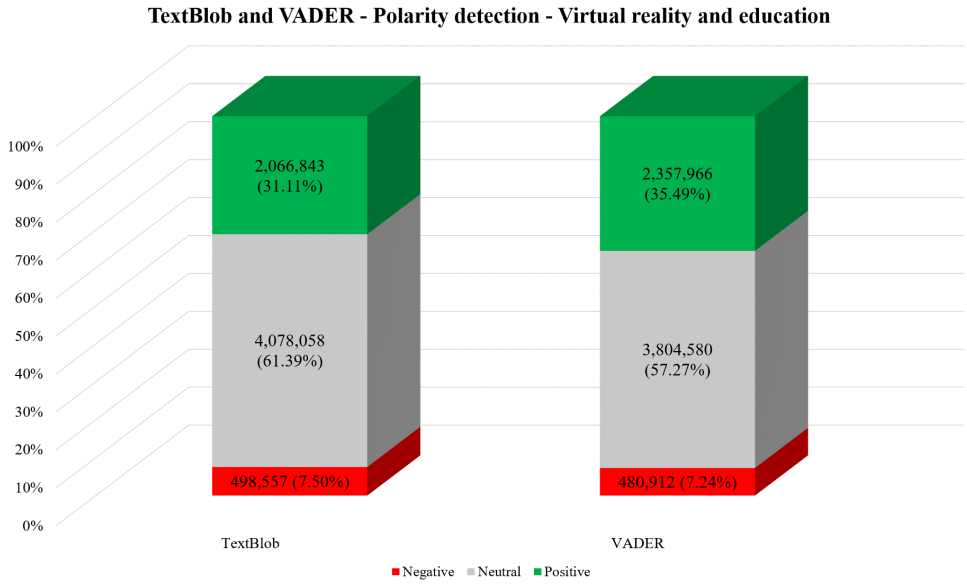

Figure 19. TextBlob and VADER polarity detection: Educational virtual reality dataset.

Emotion frequency based on the most intense emotion of each tweet of the educational virtual reality dataset for each year over the years 2010-2020

	Joy	Trust	Fear	Surprise	Sadness	Disgust	Anger	Anticipation	Neutral
2010	75	166	37	31	28	14	37	214	292
2011	50	270	28	7	17	24	53	267	525
2012	79	296	231	15	32	40	154	399	538
2013	128	315	64	113	19	13	77	514	817
2014	486	792	395	57	29	21	156	1662	2340
2015	1168	5512	1539	603	39	93	843	4286	10,943
2016	2576	7167	2067	741	191	396	1671	10,104	22,945
2017	4518	8756	3051	832	311	356	1267	12,081	30,794
2018	4720	14,017	3153	1114	594	567	1852	15,905	24,315
2019	4324	11,252	2070	1584	464	448	1546	12,399	16,553
2020	2768	8294	1598	676	433	308	1148	9,136	11,912
Total	20,892	56,837	14,233	5773	2157	2280	8804	66,967	121,974
Percentage	6.97%	18.95%	4.75%	1.92%	0.72%	0.76%	2.94%	22.33%	40.67%

Figure 20. Polarity frequency of the tweets of the educational virtual reality dataset.

4.5. Topic Modeling Analysis

To identify the prominent topics discussed, topic modeling was applied to all data. Based on the analysis, 11 topics related to augmented and virtual reality emerged. The topics are related to education, new technologies, digital and social media use, marketing and advertising, the industrial domain, the health domain, gaming, fitness and exercising, devices, the travel and tourism domain, and software development kits (SDK). The related to each topic words are displayed in Table 17.

Table 17. Topics identified.

Topics	Related Words
Education	classroom, class, edtech, education, learning, elearning, mobile learning, educational, training, books, students, teaching, webinar, seminar, university, college, school, teacher, and study.
New technologies	artificial intelligence, machine learning, robotics, blockchain, innovative technologies, and emerging technologies.
Digital and social media use	youtube, twitter, facebook, instagram, snapchat, content, sharing, social media, video, music, movies, trailer, and ebooks.
Marketing and advertising	marketing, campaign, brand, advertisement, design, startup, information, business, trends, events, restaurants, entrepreneur, newsletter, sales, survey, market, and ecommerce.
Industrial domain	industrial transformation, workforce, maintenance, systems, innovation, manufacturing, industry, and fintech.
Health domain	medical, medicine, doctor, patients, health, healthcare, surgery, therapy, and anatomy.
Gaming	gaming, games, gamification, multiplayer, player, playing, cardboard games, digital games, virtual games, and indie games.
Fitness and exercising	physical activity, exercise, fit, fitness, train, training, trainer, sport, and active.
Devices	mobiles, glasses, oculus, hololense, gadgets, wearables, drones, headset, camera, phones, smartphones, desktop, and gopro.
Travel and tourism domain	Travel, tourist, etourism, tourism, location, and sights.
Software development kits	unity, arcore, and arkit.

5. Discussion

Augmented reality and virtual reality are gradually gaining in popularity as they are being applied in several domains including education. Due to their immersive and interactive nature, they can create safe and secure environments which enrich and improve the educational process, facilitate educators' job, and lead to increased student academic performance [8]. Despite this fact, to successfully adapt and integrate these technologies in educational contexts, it is essential to understand the public's viewpoints. As a result, this study analyzed four datasets of over 17 million tweets from January 2010 to December 2020 using text mining, sentiment analysis, and topic modeling methods to comprehend public perspectives, sentiments, attitudes, and discourses.

According to the analysis, the international acceptance and positive assessment of these technologies can be noticed. This is in line with the positive perspectives and acceptance that the educational community displays regarding these technologies [18–21]. More specifically, due to their immersive nature, augmented reality and virtual reality share common elements which can be crucial for their effective application in educational contexts [14,86]. As it can be seen from the most commonly used words and hashtags, similar words and hashtags are being used within the general use datasets for both augmented reality and virtual reality and the same applies to the educational datasets. The period of 2016 to 2018 was the time that most people discussed these technologies with 2018 being the year that had the most tweets related to the use of both augmented reality and virtual reality in education. This can be justified by the fact that several consumer devices (e.g., Oculus Rift, HTC Vice, PlayStation VR, etc.) were released during that time period, which, in turn, increased people's interest in these technologies. Popular areas, such as gaming, also demonstrated a drastic increase in the use of augmented reality and virtual reality applications which further boosted the public's acceptance and engagement with them.

As far as the sentiment analysis is concerned, it is worth noting that only a small percentage of tweets were negative in all four cases. Most tweets were either positive or

neutral. Particularly for the case of education, a significant number of tweets were positive for both augmented reality and virtual reality. The results can be further justified as both tools used have different sentiment scores and yet, resulted in the majority of the sentiments following the exact same order in each case. The ability of both augmented reality and virtual reality to offer entertaining, personalized, and engaging activities as well as the novelty of these technologies could be a reason for their being mostly positively assessed.

Positive emotions, such as anticipation, trust, and joy, were mostly expressed within the tweets when referring to both the general and educational use of these technologies. As a high number of tweets were neutral, it can be said that the benefits that these technologies can yield are not yet widely known to the public. Due to the fact that occupation is a private field, it could not be retrieved. As a result, specific comments based on occupation, enterprise, or marketing activities cannot be made. The role of educators is vital in cultivating the minds of students and preparing them for their future. Despite educators being positive toward including new technologies in their teaching activities and toward receiving suitable training [87–89], the lack of appropriate equipment, technical skills, or training to develop augmented reality and virtual reality applications could be a contributory factor to the neutrality of tweets.

Furthermore, augmented reality and virtual reality are characterized by being increasingly flexible, diverse, and applicable [90,91]. This fact was also evident from the topic analysis. The results of the topic analysis also revealed the ability of these technologies to be used in combination with other novel technologies (e.g., artificial intelligence, robotics, machine learning, etc.) and to be integrated into several domains, such as education [92,93], industry [94,95], travel and tourism [96,97], health [98,99], etc., yielding several benefits. The use of these technologies for marketing and advertising purposes and their ability to be incorporated into social media was also highlighted as a topic. Studies have showcased the benefits of including augmented reality and virtual reality in advertising, marketing, and promotion [100,101]. Additionally, their use as a means to help people exercise to stay fit and healthy was evident. Recent studies have demonstrated the benefits of augmented reality and virtual reality in this domain [102,103]. Due to their immersive and engaging nature, these technologies are increasingly being used for gaming and entertainment purposes. There are specific SDKs that can be used to develop augmented reality and virtual reality applications which can run on particular devices (e.g., mobiles, head-mounted devices, tablets, etc.) afterwards [104,105]. As many software and hardware advances took place during the specific time period to overcome some of the initial technical challenges and limitations, it was not surprising that topics related to SDKs and devices also emerged.

6. Conclusions

As extended reality technologies become more mature, they are being applied to several domains, including education. Although they can yield several educational benefits, it is essential to take the public's viewpoints into account too in order for their implementation to be more effective.

This study aimed at analyzing social media data to better comprehend the public's perspectives, sentiments, attitudes, and discourses concerning the adoption and integration of augmented reality and virtual reality in education. For that reason, over 17 million tweets were retrieved, processed, and analyzed using text mining, sentiment analysis, and topic modeling methods. The results showcased that the majority of the public were positively disposed toward the general and educational use of both augmented reality and virtual reality. Moreover, they mostly expressed positive emotions (e.g., anticipation, trust, and joy) when referring to them. The flexibility and applicability of these technologies were also evident as they can be successfully applied into several domains. Based on the topic analysis, 11 topics emerged that were related to education, new technologies, digital and social media use, marketing and advertising, the industrial domain, the health domain, gaming, fitness and exercising, devices, the travel and tourism domain, and SDKs. The close relationship between augmented reality and virtual reality and their common

application fields were also highlighted. Overall, their ability to positively affect teaching and learning processes and their role as effective educational means were evident. Future research can look into different social media platforms and use the results of this study to make comparisons with those of specific educational samples.

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