ASSESSMENT OF THE RECOVERY PROCESS USING SENTIMENT AND TOPIC ANALYSIS: THE CASE STUDY OF THE 2015 GORKHA EARTHQUAKE

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Abstract: *Recovery is a complex multidimensional long-term process of restoration of living conditions after a disaster. Memorial days of disasters represent an opportunity to evaluate the progress of these recovery processes. We evaluated Nepal's recovery progress based on text data posted on Twitter and Instagram from March 5th to May 2nd, 2020. This period includes dates before and after the 5th anniversary of the Gorkha earthquake (2015, 7.8Mw): April 25th, 2020. Hashtags in tweets related to the anniversary were: #eartHquake, #Nepal, #earthquake, #Nepalearthquake, #NepalQuake, #5yearson, and #Nepali. Text data collected from social media is unstructured data. In this paper, we used sentiment and topic analysis to extract meaningful information from the data. Through sentiment analysis (SA), we classified tweets according to their polarity: positive, negative or neutral, while with topic analyses, we classified tweets into topics. Both actions were performed to structure the data and extract meaningful information. We focused on analysing tweets three hours before and after the earthquake's exact anniversary, considering two hours: 11:56:25 Nepal standard time and 11:56:25 UTC resulting in an analysing period of twelve hours. Eventually, 2005 tweets were manually classified according to their polarity at the tweet level as 1011 (50%) tweets unrelated, 525 (26%) positive, 366 (18%) negative and 103 (5%) neutral The most frequent topics identified in tweets, without counting unrelated: 329 (16%) COVID-19, 286 (14%) restoration, 91 (5%) commemoration actions, 85 (4%) emergency response, 51 (3%) governance, 51 (3%) reported reconstruction, 22 solidarity (1%) and 18 (1%) distress. According to these sentiment and topic analyses at the tweet and sentence level and those SA analyses of tweets addressing restoration exclusively, Nepal's assessment of the recovery and process is positively, going beyond reconstruction actions, despite the inconveniences caused by COVID-19 in the fifth year.*

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Introduction

Recovery is a complex multidimensional long-term process of restoration of living conditions after a disaster (Contreras, Wilkinson, Balan, & James, 2021). Most authors divide post-disaster recovery into three (UNDP, 2022) or four phases (Chang, 2009; Contreras, 2016) emergency response or relief, early recovery, recovery, and development. Following an earthquake, there is substantial demand for information. While most data collection occurs during early recovery after the emergency phase (Murray, Pedersen, & Ziesche, 2018), few studies have collected data during the recovery or development phase (Ogie et al., 2022) to monitor the recovery process's progress. This shortage of information has resulted in limited knowledge of the impact of earthquakes on the medium and long term. Furthermore, governments and/or scientists rarely focus on monitoring long-term recovery (Shibuya & Tanaka, 2019), leaving recovery poorly understood (Rossetto et al., 2014; Smith & Wenger, 2007; Yan, Chen, & Wang, 2020). Memorial days of disasters represent an opportunity to evaluate the progress of these recovery processes (Rossetto et al., 2014).

In the past, data were collected almost exclusively during on-site missions. Nowadays, the availability of state-of-the-art instrumentation, mobile data collection technologies, social media (SM) and crowdsourcing platforms have increased the ability of field investigation teams to capture data (Contreras, Wilkinson, & James, 2021). There has been an ongoing argument for employing alternative sources of data and methods such as SM (Wilkinson et al., 2018). In recent years, SM has become a valuable tool for quickly collecting significant amounts of disaster data (Simon, Goldberg, & Adini, 2015; Yan et al., 2020). Image and text data from Twitter and Instagram platforms can support emergency response operations (Bossu et al., 2018; Eligüzel, Çetinkaya, & Dereli, 2020; Radianti, Hiltz, & Labaka, 2016; Ragini, Anand, & Bhaskar, 2018; Wong-Villacres, Velasquez, & Kumar, 2017; Wu & Cui, 2018), earthquake reconnaissance missions (Aktas et al., 2022; Contreras, Wilkinson, Fallou, et al., 2021; Contreras, Wilkinson, & James, 2021) and the long-term assessment of recovery processes after earthquakes in L'Aquila (Italy) (Contreras, Wilkinson, Balan, & James, 2022), Haiti, Chile and New Zealand (Contreras, Wilkinson, Balan, Phengsuwan, & James, 2020).

Social media users post online, providing text data, including emoticons expressing their opinions, thoughts or sentiments during the anniversary of earthquakes. However, the text data is unstructured, making it necessary to use NLP techniques (Radianti et al., 2016). Natural language processing is a branch of artificial intelligence (AI) that enables machines to understand human language by analysing sentences and words, applying different approaches to extract information, and delivering outputs (Roldós, 2020). One specific NLP technique is SA, or 'opinion mining'. This NLP application classifies people's opinions, attitudes and emotions towards entities and their attributes, as expressed through written text, into a specific polarity (positive, negative or neutral) (Antypas, Preece, & Camacho Collados, 2022; Eligüzel et al., 2020; Kenny, 2009; Medhat, Hassan, & Korashy, 2014; Pirnau, 2018). These entities can be products, services (Kauffmann et al., 2020), events, organisations, individuals (Liu, 2015) or objects of social research (Antypas et al., 2022). Topic analysis (TA) is another NLP technique. This technique is based on topic classification (Roldós, 2020) or topic extraction (MonkeyLearn, 2022) that uses the data structure to identify the latent themes discussed in a body of text and the words that comprise each topic or theme (Berger & Packard, 2022).

On April 25th at 11:56 (06:11 UTC), an earthquake with a moment magnitude scale of M_w 7.8 struck Nepal. Numerous landslides followed it in the hills and mountains in the affected region (Wilkinson et al., 2019). Around 9,000 people were killed, and 100,000 people were injured. Around 500,000 houses were destroyed and another 269,000 damaged, which included historical and cultural monuments recognised as UNESCO World Heritage (WH) sites (Preventionweb, 2015). In the project Learning from Earthquakes (LfE) UK, we collected data about the progress of the recovery process for the tenth anniversary of the earthquakes, where the Earthquake Engineering Field Investigation Team (EEFIT) has deployed reconnaissance missions. Those missions were: the 2009 L'Aquila (Rossetto et al., 2009), 2010 Haiti (Booth, Saito, & Madabhushi, 2010), 2010 Maule, Chile (Lubkowski et al., 2010), 2011 Christchurch, New Zealand (Wilkinson et al., 2011), 2011 Tohoku, Japan (Pomonis et al., 2011), and 2015 Gorkha, Nepal (Wilkinson et al., 2019). In the framework of the project LfE, UK, we have collected Twitter data for the tenth anniversary of the L'Aquila, Haiti, Maule, Tohoku and Christchurch and the fifth anniversary of Nepal. Two EEFIT return missions have been organised: the 2022 Nepal and Indonesia return missions. For the case of Nepal, we decided to analyse the fifth anniversary (2020). This analysis allowed for a medium-term evaluation and also considered that the Nepali government gave the National Reconstruction Authority (NRA) a five-year term to rebuild the structures damaged by the earthquake (Panthi, 2020). Then it is an suitable time to evaluate the recovery process.

Methodology

We evaluated Nepal's recovery progress based on text data posted on Twitter and Instagram from March 5th to May 2nd, 2020. This period was selected based on SM monitoring and included dates before and after the fifth anniversary of the Gorkha earthquake: April 25th, 2020, 11:56:25 Nepali standard time (NST) (06:11: UTC) (Wilkinson et al., 2019). The methodology comprises six steps, as described in Figure 1.

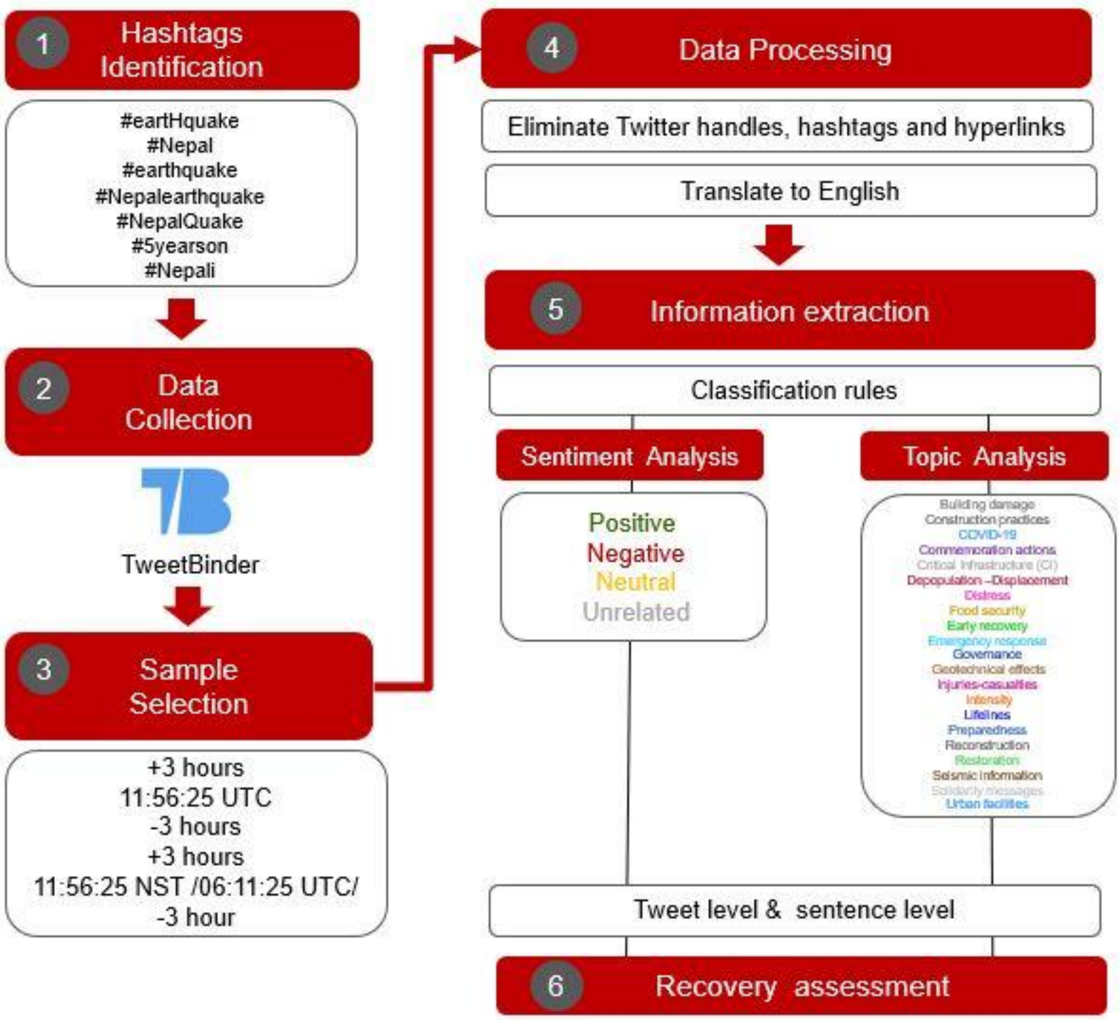

Figure 1. Methodology.

We started identifying the hashtags related to the memorial of the fifth anniversary of the 2015 Gorkha earthquake. We purchased Twitter data posted during the observation period using the hashtags identified before as a filter to collect data about the anniversary. For the sample selection, we used tweets posted three hours before and three hours after the earthquake's anniversary, considering two exactly different times: 11:56:25 NST /06:11:25 UTC and 11:56:25 UTC, resulting in an observation period of 12 hours. Tweets and posts containing spelling mistakes were then corrected, and those with special characters or written in languages other than English were translated. Uniform Resource Locator (URLs), retweet characters (RT), hashtags (#), symbols (e.g. @), links, and repeated characters in words (Ruz, Henríquez, & Mascareño, 2020) were removed. Emoticons were replaced by words, expressions, emotions, and actions they represent to ensure standardised data for analysis.

Text data collected from social media is unstructured, making it necessary to use NLP techniques (Radianti et al., 2016) to extract information. In this research, we used SA and TA. We performed a supervised (manual) classification based on rules defined by two of the co-authors for the assessment of the emergency response and early recovery of Albania (Contreras, Wilkinson, Alterman, & Hervás, 2022) and the recovery process of L'Aquila after the 2009 earthquake (Contreras, Wilkinson, Balan, et al., 2022). These classification rules were adapted for the case of Nepal. The polarity classification rules for SA are listed in Table 1. The classification rules for TA are listed in alphabetic order in Table 2.

Polarity	Rules
Positive	▪ Acknowledgement to donors ▪ Capacity building and preparedness for emergency response ▪ Efficient COVID-19 management ▪ Learning the lessons from the event ▪ Promotion of touristic attractions – Cultural expressions – local products ▪ Reconstruction actions: training, acknowledgements, new construction materials ▪ Solidarity messages to families who lost loved ones and to those who survived ▪ Stories of overcoming disabilities caused by the earthquake ▪ Supporting actions: emergency response, relocation, climate change adaptation
Negative	▪ Casualties and injured population ▪ COVID-19: lockdown, high rate of infections, flights cancelled ▪ Declining in remittances ▪ Difficulties for recovery ▪ Discrimination ▪ Poverty, illiteracy, inequalities, injustice, food insecurity, and poor water, sanitation and hygiene (WASH) ▪ Unfulfilled reconstruction goals
Neutral	▪ Seismic information ▪ Commemoration ceremonies

Table 1. Polarity classification rule set for SA.

Topic	Rules
Building damage	Report of damages in buildings
Critical Infrastructure (CI)	Facilities to respond to the emergency, e.g.Health care posts
Commemoration actions	Interviews with survivors, ceremonies, etc.
Construction practices	Housing quality after the earthquake
COVID-19	Effects and pandemic management
Depopulation-Displacement	Reduction in inhabitants after the earthquake
Distress	Signs or expressions of post-traumatic stress disorder (PSTD)
Early recovery	Actions to return to normality e.g. cleaning debris
Emergency response	Actions to save lives, e.g. search and rescue (SAR) activities
Food security	Problems with the food supply
Geotechnical effects	E.g. landslides and rockfalls.
Governance	Actions taken by the government during the post-disaster phase
Injuries & casualties	Casualties or injured population due to the earthquake
Intensity	Severity of ground shaking without mentioning a magnitude
Lifelines	E.g. Water, electricity, communication supply or roads
Preparedness	Eg. first-aid training, drills, contingency planning etc.
Reconstruction	Rebuilding of houses, infrastructure and/or monuments
Restoration	Restoring sustainable living conditions
Seismic information	Date, magnitude, epicentre and depth of the earthquake
Solidarity messages	Encouraging messages to survivals
Urban Facilities	Facilities different to CI, eg. Schools, temples, post offices, etc.
Unrelated	Topics not related to the anniversary of the earthquake

Table 2. Polarity classification rule set for sentiment analysis

Sentiment and topic analysis can be performed at three primary classification levels: document, sentence, and sub-sentence (MonkeyLearn, 2020). We performed the analyses at the tweet and sentence levels for this work. The recovery assessment can be done exclusively focused on SA. However, without the TA, it would not be possible to determine what is positive or negative in the recovery process. Then another option will be to check the sentiment analysis results per topic. The recovery process can be assessed based solely on the polarity of text data addressing this topic. This refined analysis can be done by combining the SA and TA at the tweet level or the TA at the tweet level, being 'restoration' as the main topic in the tweet with the SA at the sentence level. Another option is combining SA and TA at the sentence level.

Results

Hashtags identified in tweets related to the anniversary were: #Nepal, #earthquake, #Nepalearthquake, #NepalQuake, #5yearson, and #Nepali. The third-party vendor provided 183,361 tweets, 174,641 original (95%), and 8,720 (4.7%) retweets. The number of tweets containing hashtags mentioned before and the activity on Twitter during the observation period with those hashtags are plotted in Figure 2.

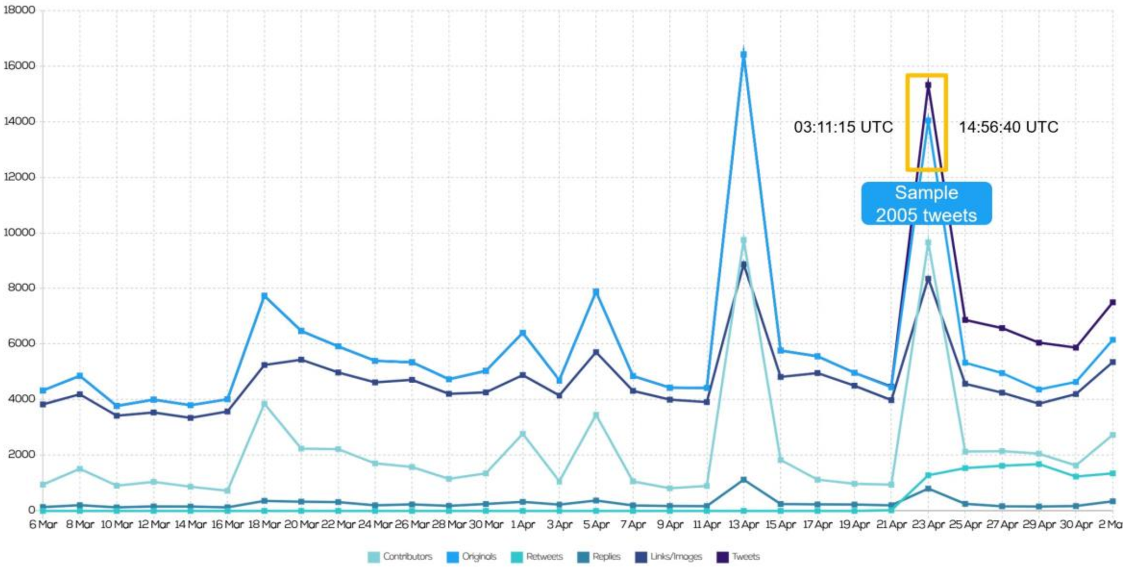

Figure 2. Twitter activity from March 6th to May 2nd, 2020. Adapted from: TweetBinder

Tweets posted around the exact time of the 5th anniversary of the 2015 Gorkha earthquake in Nepal are presented in Figure 3 a) and b), respectively.

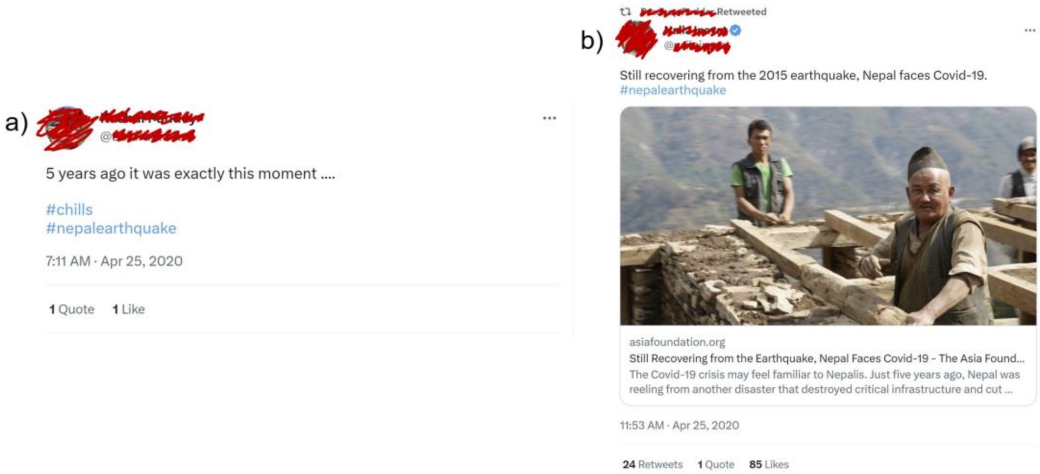

Figure 3. Tweets posted around the exact time of the anniversary of the Gorkha earthquake: a) 11:56:25 NST /06:11:25 UTC/07:11:25 CET and b) 11:56:25 UTC

Applying the parameters defined in the methodology, we analysed a sample of 2005 tweets (Contreras et al., 2023). The SA at the tweet level indicates that 1011 (50%) tweets were unrelated, 525 (26%) had positive polarity, 366 (18%) negative and 103 (5%) neutral. The same analysis at the sentence level indicates that 1,017 (51%) sentences were unrelated, 457 (23 %) sentences had positive polarity, 369 sentences (18 %) had negative, and 161 (8%) had neutral polarity. The results of the SA are plotted in Figure 4

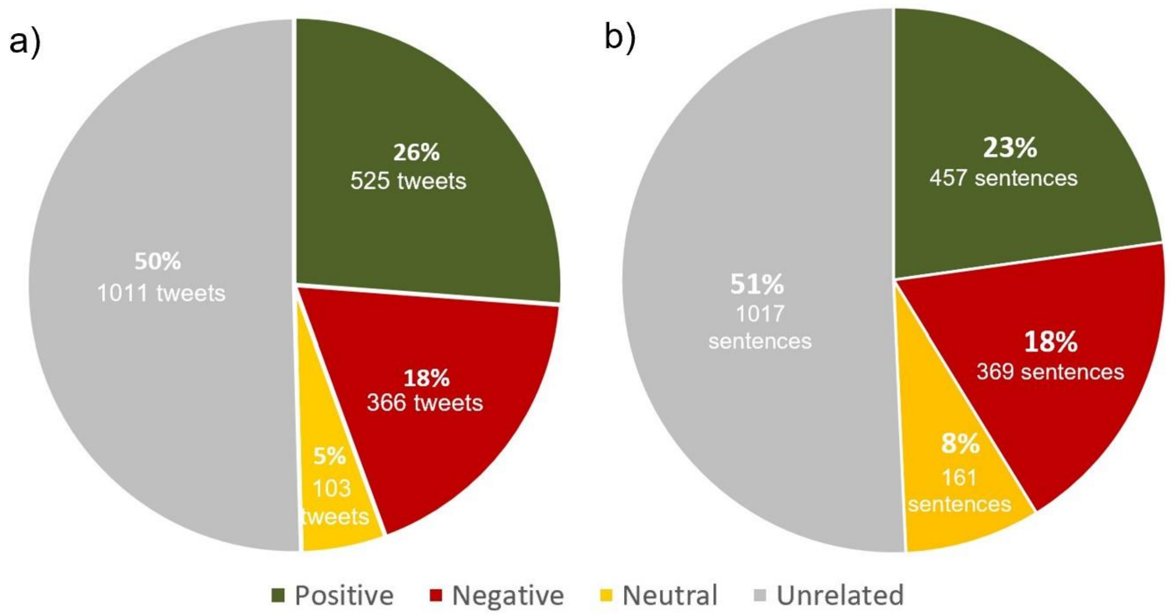

Figure 4. Sentiment analysis results a) tweet level and b) sentence level.

The TA at the tweet level indicates that 1011 tweets were unrelated (50%). Apart from those tweets, 329 (16%) reported about COVID-19, 286 (14%) discussed restoration progress, 91 (5%) mentioned commemoration actions, 85 (4%) emergency response activities, 51 (3%) discussed topics related to governance, only 51 (3%) reported about reconstruction, 22 tweets contains solidarity messages (1%) and 18 (1%) emotional distress signals. Other topics discussed in the tweets included in the sample are listed in Table 3 and plotted in Figure 5a). The topic analysis at the sentence level indicates that 1080 sentences were unrelated (29%), 489 discussed restoration progress (14%), 481 (13%) reported about COVID-19, and 267 (7%) sentences included seismic information. Emergency response actions were mentioned in 242 (7%) sentences, Injured population and casualties were remembered in 151(4%) sentences, and commemoration actions were mentioned in 129 sentences (4%). Governance capabilities are discussed in 125 (3%) sentences, and solidarity messages are included in 111 (3%) sentences. Availability of urban facilities is discussed in 94 (3%) sentences, and progress in the reconstruction in 81 (2%) sentences. The topic of intensity is reported in 69 (2%) sentences, as well as preparedness in 39 (1%) of the sentences. Other topics commented on sentences included in the sample are listed in Table 3 and plotted in Figure 5b).

Tweet level			**Sentence level**		
Topic	**Nr**	**%**	**Topic**	**Nr**	**%**
Unrelated	1011	50	Unrelated	1080	30
COVID-19	329	16	Restoration	489	14
Restoration	286	14	COVID-19	481	13
Commemoration actions	91	5	Seismic information	267	7
Emergency response	85	4	Emergency response	242	7
Governance	51	3	Injuries & casualties	151	4
Reconstruction	51	3	Commemoration actions	129	4
Solidarity	22	1	Governance	125	3
Distress	18	1	Solidarity	111	3
Injuries & casualties	10	0	Urban facilities	94	3
Seismic information	10	0	Reconstruction	81	2
Food insecurity	8	0	Building damages	73	2
Urban facilities	8	0	Intensity	69	2

Tweet level			Sentence level		
Topic	**Nr**	**%**	**Topic**	**Nr**	**%**
Critical infrastructure	5	0	Preparedness	39	1
Geotechnical effects	4	0	Depopulation & displacement	38	1
Lifelines	4	0	Distress	37	1
Preparedness	4	0	Lifelines	23	1
Construction practices	3	0	Food insecurity	20	1
Early recovery	3	0	Geotechnical effects	20	1
Building damages	1	0	Critical infrastructure	19	1
Depopulation & displacement	1	0	Construction practices	19	1
Intensity	0	0	Early recovery	10	0
Total	2005	100	Total	3617	100

Table 3. TA results at the tweet and a sentence level

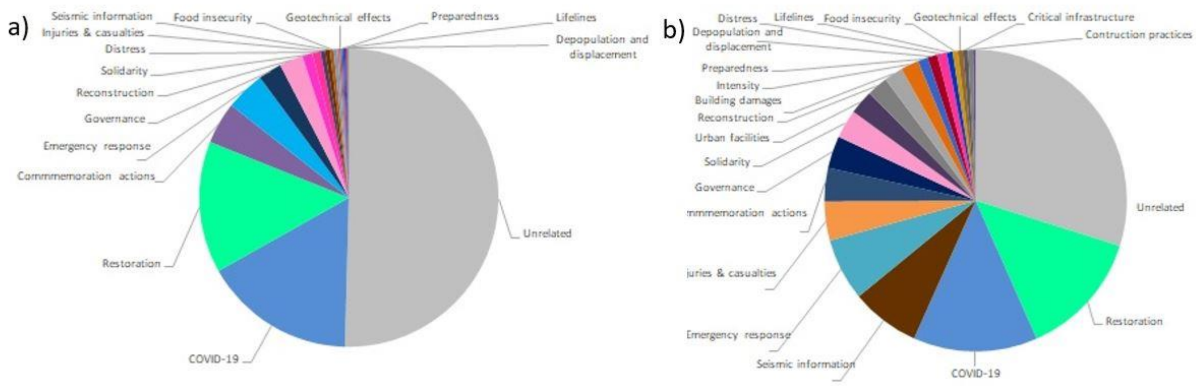

Figure 5. TA results: a) tweet level and b) sentence level.

The SA results at the tweet level for the text data commenting only on recovery have the majority of positive polarity, as it is depicted in Figure 6a. The result at the sentence level, having recovery as the main topic, reports also majority of positive polarity in Figure 6b.

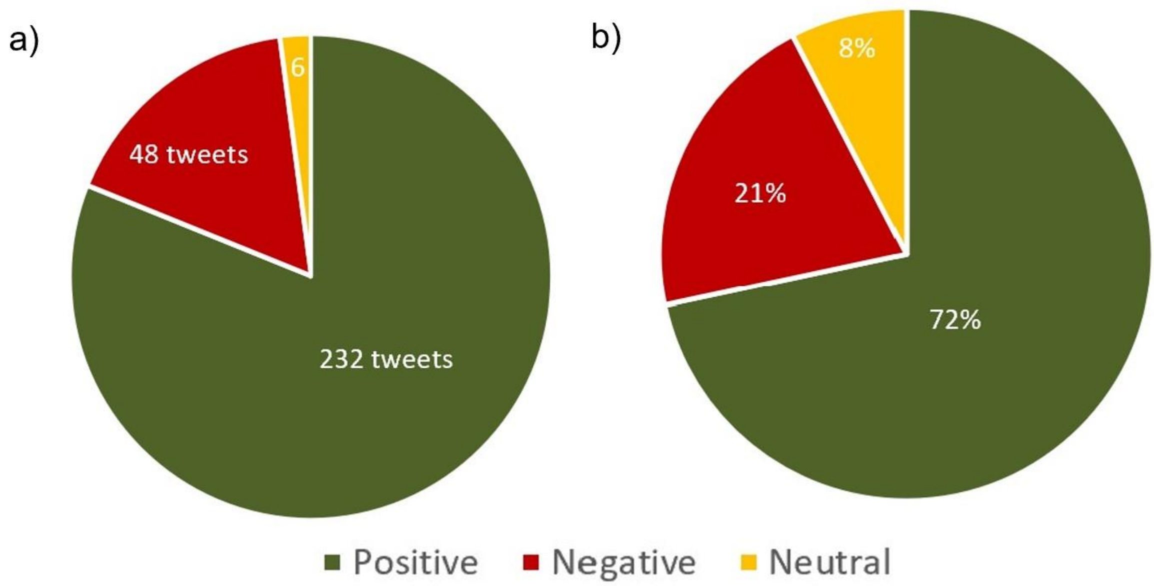

Figure 6. SA of the topic of recovery a) tweet level and b) tweet and sentence level.

Discussion

The hashtag #earthquake must not be used as a filter to collect Twitter data regarding the anniversary of earthquakes. This hashtag will add a large amount of useless noisy data about worldwide earthquakes around the anniversary, requiring considerable time to be removed.

The differences between the results of the SA at the tweet and sentence levels are insignificant. The results are very similar. Apart from unrelated tweets, most tweets have a positive polarity, followed by negative and neutral. The granularity in the analysis did not change its result. Instead, the results of topic analysis at the tweet and sentence level showed differences in the number and proportion of topics discussed. Topics such as 'intensity' are not reported at the tweet level but appear at the sentence level. Besides the unrelated tweets, the topic of recovery is one of the most frequent topics, which allows us to confirm that the period around the anniversary of the earthquakes is an ideal time to collect text data about this topic for its assessment.

The fact that the 5th anniversary of the 2015 Gorkha earthquake in Nepal coincided with the start of the COVID-19 pandemic explains being one of the most frequent topics at the tweet and sentence level. Emergency response is another of the most frequent topics commented on in tweets and sentences because users compare the response to COVID-19 with the response to the earthquake. Reconstruction is not among the most frequent topics discussed in the tweets or the sentences. According to our classification rules, this can be seen as a sign that recovery in Nepal has focused more on restoring sustainable living conditions than merely rebuilding houses, infrastructure and monuments.

Conclusion

According to these sentiment and topic analyses at the tweet and sentence level and those SA analyses of tweets addressing recovery exclusively, Nepal's assessment of the recovery and process is positively, going beyond reconstruction actions, despite the inconveniences caused by COVID-19 in the fifth year. The recovery started with the quick emergency response and the support of international NGOs working in the country, which also have developed capacities among the population during these five years. Tweets with negative polarity mainly discuss inconveniences generated by the COVID-19 pandemic, including delays in the reconstruction goals.

Acknowledgement

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