Al-Haouz Earthquake Misinformation Crisis in Morocco: A Content Analysis of Tweets on X

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Abstract

Information during natural disasters is as vital as shelter, food, and medical supplies. Social media has indeed facilitated the circulation of information over the past decades. Timely information about emergencies helps in risk assessment, decision-making, and public relief and awareness. However, where there is information on social media, misinformation is inevitable. The Al-Haouz earthquake has ignited a variety of speculations and misinformation on social media, specifically, causing distress and confusion among people. The current study aims to analyze the Al-Haouz earthquake content on X and identify its main misinformation themes. The dataset from X was extracted by a third party using the X API. The dataset was subsequently classified and coded manually. Approximately 9,000 tweets were retrieved from September 8, 2023, to December 31, 2023, using earthquake-related hashtags to identify prevalent misinformation themes and patterns. To this end, five misinformation themes have emerged from the collected dataset: misleading visual representation, sensationalist reporting, conspiracy theory, pseudoscientific explanation, and false prediction. Findings indicate a significant proportion of not-misinformation over misinformation tweets and the prominence of sensationalist reporting with a percentage of 60% over other misinformation themes, misleading visual representation, conspiracy theory, pseudoscientific explanation, and false prediction. This paper highlights the critical role of media literacy in mitigating the surge of misinformation during critical times. Understanding the dynamics of misinformation spread and locating prominent themes during critical periods allows policymakers, educators, and experts in the field to tailor effective and powerful crisis management tools and strategies to promote media literacy skills among the public.

Keywords: Crisis Management, Misinformation, Media Literacy, Earthquake, Morocco

Introduction

On September 8, 2023, Morocco experienced a magnitude 6.8 earthquake, resulting in more than 2,946 fatalities and approximately 5,700 injuries (Bureau for Humanitarian Assistance, 2024). The most severe damages and casualties were reported in Al-Haouz Province, located in the Marrakech-Safi Region, and in Taroudant Province, part of the Souss-Massa Region (Bureau for Humanitarian Assistance, 2024). Unlike other natural disasters, the inherent unpredictability of earthquakes often precipitates the spread of misinformation. According to a prior study (Kim et al., 2018), most critical and urgent situations are initially broadcast on social media rather than mass media channels. Indeed, technologies have brought many advantages to humanity; however, that does not eliminate their challenges. Information is now relative and multi-faceted with the democratization of media, allowing users to express their ideas, assumptions, and beliefs without significant restrictions. This many-to-many communication paves the way for information pollution and distrust, especially in critical moments.

During that period, Moroccan citizens received earthquake-related information via social media platforms, including WhatsApp, Facebook, X, and Instagram. The circulation of rumors, erroneous predictions, and conspiracy theories was inevitable at that critical juncture due to the lack of moderation and fact-checking instruments on social media. Certainly, misinformation is not unprecedented on social media platforms. In emergencies, misinformation rapidly exacerbates anxiety and confusion. Unlike other social media platforms, X has been specifically employed in times of crisis due to its timely and interactive features. X is primarily utilized for emergency detection, disaster risk assessment, emergency planning, response, and general information (Martínez-Rojas et al., 2018). A study on misinformation on Twitter indicated that information dissemination varies based on the nature of the crisis and its severity (Olteanu et al., 2015). In earthquakes, misinformation is omnipresent because access to reliable earthquake sources is restricted; immediate access to credible information is limited.

Social networking sites have long served as hotspots for the proliferation of misinformation, requiring a thorough and comprehensive analysis of the types and frequency of misinformation across various platforms, X, in this context, for effectively managing its dissemination. Understanding the online spread of misinformation becomes even more critical during times of crisis. This study aims to establish a robust foundation for future misinformation policy regulation and identify emerging patterns to mitigate the impact of erroneous information, particularly in dire circumstances.

This study aims to explore the Al-Haouz earthquake discourse on X by extracting and analyzing 9,000 posts pertinent to the earthquake. The dataset was subsequently cleaned and analyzed to ascertain the frequency of misinformation and non-misinformation in tweets associated with the Al-Haouz earthquake and to identify the principal themes of misinformation circulated on X during that period. Despite the considerable body of literature addressing the COVID-19 infodemic in Morocco (Maakoul et al., 2020; Ackah et al., 2022), misinformation during natural disasters in the Moroccan context remains insufficiently addressed in the literature.

This article is structured into four primary sections. The first section provides a comprehensive review of the relevant literature on the study's background and theoretical framework. The subsequent section details the methodology employed in the paper, including data collection and analysis procedures. The final two sections are devoted to presenting and interpreting the study's findings.

Literature review

In times of crisis, the internet proves helpful since it serves as an information hub, a communicative and mobilization platform. However, the opposite is also true. Social media can become a communication barrier and a misinformation amplification tool, destroying the process of an adequate communication flow. Researchers have studied users' attitudes and behaviors online in different social contexts for many years. It is even more dangerous if the situation is risky and unpredictable. The unpredictability of earthquakes is still an intricate and complex topic for seismologists, making it challenging to provide accurate forecasts due to the nonlinearity and chaotic nature of the geological processes (Koronovskii et al., 2021). The unpredictability of earthquake situations invites many misrepresented interpretations and explanations, leaving users susceptible to misinformation.

Conceptual and theoretical Framework

Discourse destruction on social media is a broad spectrum ranging from mis-information, dis-information, to mal-information (Wardle & Derakhshan, 2017). Distinguishing between these types is key to understanding and framing the issue of information pollution online. According to Wardle and Derakhshan (2017):
Disinformation refers to the intentional spread of false information to cause harm.
Misinformation- refers to the non-deliberate information produced with no intention to cause harm.
Misinformation- refers to real information that is used to create harm.
Dallo et al. (2022, p.2) define the concept of misinformation as "information that is false or misleading according to the best available evidence at the time and that is communicated regardless of an intention to deceive." False connections, misleading content, inaccurate visuals, and manipulated texts, to name a few, are all forms of misinformation (Maci et al., 2024). Distinguishing between misinformation and disinformation is based on the intention of the agent. Nevertheless, interpreting the user's intentions behind information distortion is challenging in practice. For this purpose, misinformation is used in this study to refer to both terms, considering their inherent complexity.
Social Amplification of Risk (SAR) theory provides an insightful framework to understand the logic behind online information and misinformation spread in risky contexts. (Kasperson, et al., 1987). SAR serves as a comprehensive framework for the amplification and attenuation of public risk perception and the influence of cultural, social, and psychological factors in the harvesting of information. (Kasperson, et al., 1987). It draws from various disciplines of communication and psychology, making it a well-equipped tool to comprehend information flow in risk events. SAR posits that the analysis of risk information processing occurs in two primary stages. Stage 1, termed signal creation, is dedicated to the transmission of risk information (the signal) through social and cultural stations that shape the communicative event. Stage 2 addresses the societal responses and consequences arising from the risk event, which subsequently affect the dissemination of risk information, determining whether it is amplified or attenuated.
Kasperson et al. (1988) explain that risk communication is amplified when there is a heightened perception of risk, leading to significant public reactions to the identified hazard (Kasperson et al., 1988). Risk attenuation occurs with a decrease in risk perception, which may undermine the perceived severity of the

risk itself. These dynamics illustrate the intricate interplay between societal perceptions and the communication of risk information, particularly in contexts where information is scarce. Some of the societal and psychological stations related to the amplification or attenuation of risk communication are individual information processor (shaped by prior beliefs, cognitive bias, or emotional states), social networks (interpersonal sharing with friends and family), media channels (media narratives during periods of high risk), and cultural influence (pre-existing assumptions) (Kasperson et al., 2022). Therefore, risk communication in media goes through several stages that may lead to its amplification or attenuation, determining the risk standpoint (Kasperson et al., 1988). Initially, the framework was in traditional mass media contexts, and it has grown in complexity to adapt to the digital environment ("Risk sharing on Twitter"). Several studies have applied the framework in social media contexts (Chung, 2011; Chung & Choy, 2018; Fellenor et al., 2018; Zhang & Cozma, 2022). Applying the framework as a guiding theoretical lens is valuable for studying how misinformation spreads and providing a comprehensive synthesis as to why certain misinformation themes gain higher reach than others. By considering these insights, this study sets a comprehensible basis for misinformation propagation in natural disasters.

Social Media Ecosystems

Social media dynamics have impacted the transmission of information in the last decade. Its participatory feature has indeed facilitated the reach of information, especially in dire times. Nevertheless, this facilitation is accompanied by the acceleration of misinformation, disinformation, malinformation, and the propagation of hate speech. As a transformative and participatory mode of communication, social media platforms have facilitated the rise of influencers and creators, ameliorated visual communication, and promoted the rapid dissemination of information, alongside personalization and algorithmic curation. This phenomenon has resulted in an overwhelming abundance of information complications, especially in emergency contexts, where the affective filter is heightened by fear and anxiety (Sadiq & Saji, 2022). One common reaction to the psychological and cognitive functions of unforeseen circumstances is users generating and sharing information from various sources, reliable or unreliable, as a coping mechanism for the failed reception of trusted information (Oh et al, 2013), resulting in the dissemination of misinformation. In a study about the 2014 Carlton Complex Wildfire, the susceptibility to misinformation consumption can be attributed to the users' inability to distinguish factual from fictional information in a pool of user-generated content during disasters (Chauhan & Hughes, 2017). Another study about online false news on Twitter deduced that the spread of misinformation is faster and higher than non-misinformation, stating that approximately 70% of online users could not differentiate between false and correct information (Vosoughi et al, 2018). Besides fake news and misinformation, hate speech has also gained popularity with the emergence of social media platforms, also termed as cyberhate (Blaya, 2019). Cyberhate is the use of online rhetoric in "the forms of threats, discrimination, intimidation, marginalizing, otherings, and dehumanizing narratives" (Blaya, 2019). Moments of crisis evoke emotions of uncertainty and fear, leading to a surge of online activity seeking explanations, opinions, and information. This increased online activity often creates gaps for hate speech opportunities, or what is known on social media as cyberhate and cyberbullying. A study about hate speech discourse between citizens and elected representatives in the United Kingdom suggested a correlation between increased online activity and hate speech (Agarwal et al., 2021). The amplification of online

attention results in a heightened amount of cyberhate, which is also known as the pile-on effect, where online users profit from the high volume of attention to attract more views and generate hateful content (Agarwal et al., 2021). Social media interactions in vulnerable times may lead certain users to engage in the pile-on effect, thereby generating hateful content.

The algorithmic nature of social media also contributes to the formation of misleading content online. Similar to confirmation bias in psychology, the echo chamber effect is a phenomenon that occurs when a platform's algorithmic content generation reinforces users' pre-existing beliefs while marginalizing opposing viewpoints(Oh et al, 2013). For example, TikTok or X's curated feeds are tailored to users' preferences, leading to a deceptive echo chamber. With these technologies, fake news detection is getting even harder to detect and easier to generate (Kumar & Shah, 2018). Furthermore, several studies have shown that humans are psychologically inclined to support and confirm information that aligns with their pre-existing beliefs, while rejecting information that contradicts their viewpoints. (Metzger et al. 2020 ; Edgerly et al. 2020 ; Aïmeur et al., 2023).

Crisis Communication on Social Media

It is evident that social media play a pivotal role in facilitating information in times of crisis. The speedy nature of social media also makes it a fertile ground for the exacerbation of misinformation. Existing literature reveals a growing focus on studying crisis communication through the lens of social media (Muralidharan et al., 2011; Flores-Saviaga & Savage, 2020). Studies about crisis communication vary from false rumors and misinformation to providing solutions to combat the barriers of crisis communication. A study examining the impact of misinformation on social media on risk perception in various disaster scenarios used different case studies to examine the communication chain and the role of authorities and organizations in combating misleading content (Dallo et al., 2023). The growing interest in crisis communication over the past decades can be attributed primarily to globalization and specifically to technological advancements.

Online information dissemination differs from one platform to another. In fact, several researchers have investigated the discrepancies between social media platforms in terms of audience demographics, characteristics, and functionalities (DePaula et al., 2022; Paniagua & Korzynski, 2017). The selection of platforms during natural disasters, such as earthquakes, is influenced by a variety of factors, mainly receiving and sharing news-related content, exchanging it with friends, raising funds, and sharing necessities (Flores-Saviaga & Savage, 2020). While Facebook, Instagram, and WhatsApp, for instance, are perceived to be more visual and conversational, X, on the other hand, is more oriented towards political and timely news matters (DePaula et al., 2022; Bestvater et al., 2022), making it popular during crisis situations. Additionally, the hashtag and trending topics features on X amplify information visibility and access, allowing users to interact accordingly. For these reasons, X has been used extensively during critical situations, such as COVID-19 (Skafle et al., 2022; Zaidi & Munir, 2023; Tran et al., 2021), and rainstorms. (Zhai & Thill, 2017), hurricanes (Murthy & Gross, 2017), storms (Kim et al., 2018), floods (Said et al., 2020), and earthquakes (Flores-Saviaga & Savage, 2020; Vozab et al., 2023; Dryhurst, et al., 2022). The participatory nature of social media enables the public to exchange information related to earthquakes on social platforms. Furthermore, it employs crowdsourcing techniques to disseminate information and enhance its spread during emergencies such as earthquakes, floods, rainstorms, and tsunamis (Martínez-Rojas et al., 2018).

Because the Circum-Pacific Belt (Ring of Fire) is considered the most active seismic zone (USGS, 2023), several earthquake studies are situated in regions encircling the Pacific Ocean, including North, South, and Central America, Japan, Indonesia, the Philippines, New Zealand, etc. In Japan, for instance, an experimental study about a crowd-sourced system to combat misinformation and false rumors was conducted to examine participants' reactions to rumor-tweets and criticism-tweets related to the Great East Japan earthquake in 2011 (Tanaka et al., 2013). Tanaka et al (2012) carried out another study about the psychological factors contributing to rumor and criticism spread on Twitter during the Great East Japan. In the same vein, a Chinese intervention experiment was conducted to examine the impact of two intervention tools (rule-based and knowledge-based) on the trust and sharing of seismic rumors (Sun et al.,2024). Another study in New Zealand identified the emotional content of tweets after the Christchurch earthquakes in 2010 and 2011 (Anthony et al., 2024). Through the use of machine learning tools, a large dataset of tweets was extracted and classified into six main emotional categories (fear, anger, sympathy, worry, gratitude, and humour). Rivera-Loaiza et al. (2018) carried out a comparative study analyzing social media responses to two earthquakes in Mexico in 2017; the study gathered data from Twitter to identify trending themes and hashtags used (Rivera-Loaiza et al., 2018). Similarly to the spread of COVID-19 hoaxes, earthquake misinformation is as damaging to people, considering their mental vulnerability. Notably, disseminating misinformation does not always lead to logical and scientific arguments. In fact, online users are inclined to believe in and spread distorted information as a human reaction to understand something bigger than them (Dallo et al., 2022). This is due to the scientificity of seismology research, as the lack of science literacy and earthquake information among people leads to misinformation beliefs (Dallo et al, 2022). In another study about the Wenchuan earthquake, the fear of missing out (FOMO) is a factor that drives the spread of earthquake misinformation, which can be explained by impulsive and anxious sharing, along with the desire for social validation (Gong & Ren, 2023). Vozab et al. (2023) asserted the role of anxiety during critical periods, claiming that foggy communication may lead to stress and, therefore, entice the spread of distorted content online. Even among experts, there is questionable consensus about earthquake information, stressing the importance of detailed and unambiguous earthquake communication (Dryhurst et al., 2022). In seismology, information follows a systematic and timely logic of pre-earthquake, earthquake, and post-earthquake (Dallo et al., 2022). These seismic phases are crucial to detecting common earthquake information. According to Dallo et al. (2022), pre-earthquake available information is called seismic hazard, forecasting an earthquake and its magnitude approximately. In the earthquake and post-earthquake phases, available information evolves around aftershock forecasting, rapid information, and impact assessment (Dallo et al., 2022). Alongside accurate and available information about the earthquake cycle (before, during, and after), misinformation is abundant within the online earthquake discourse. It thrives between what is perceived as the truth and deception, making it hard to decipher. Some predominant examples of seismic misinformation are related to earthquake prediction, conspiracy theories, and human-induced earthquakes. While misinformation can be disseminated before, during, or after the incident, its effects are long-lasting, especially in the online sphere, if not addressed in a timely and efficient manner.

Fact-checking and Media Literacy

During disasters like the Al-Haouz earthquake, fact-checking and media literacy skills are instrumental in mitigating misinformation on social media. In fact, X has indeed attempted to combat misleading information by implementing a crowdsourcing tool to ensure the public's access to reliable and timely information during critical times. (About Community Notes on X, s.d.). As of November 2022, X has launched its crowdsourced fact-checking pilot program, Community Notes, formerly known as Birdwatch, to minimize misinformation on the platform (Coleman, 2021). Although the program seizes the spread of misleading content by providing a side fact-checking note to users, it is still in its infancy with plenty of limitations (Mahadevan et al., 2021). Community Notes, although useful sometimes, have been proven not to reduce the misinformation engagement significantly (Allen et al., 2021). This may be attributed to the system's structure, as contributors are allowed to propose new notes only after accumulating a track record of accurately rating notes to raise the metric rating impact of the note (*Center for Countering Digital Hate, n.d.)*. The process of building a track record prior to the sharing of the note takes some time to label the notes accurately. For this reason, X's Community Notes feature was addressed in several studies, highlighting its scarce impact on misinformation spread. A study revealed that the diffusion of fact-checked notes is predominantly active in "large accounts with high social influence" and view counts (Chuai et al., 2024). However, the high visibility and interactivity of Tweets do not necessarily imply high effectiveness, especially if the notes were not provided in the Tweet's first viral phase. In a report by the Center for Countering Digital Hate about X's Community Notes, the feature is noted to be particularly lacking, especially "when it comes to divisive topics where it is rare for contributors from a range of political leanings to reach consensus on whether a note is 'Helpful'." (*Center for Countering Digital Hate, n.d.)*. While fact-checking programs and websites are needed in urgent scenarios, the issue is not solely rectifying misinformation claims, but their timely availability, considering their rapid and destructive spread.

Apart from community-based, third-party, and automatic fact-checking programs, debunking misinformation can also take the form of social corrections whereby users provide corrective comments or posts on the misleading content to prevent it from circulation (Said et al., 2020). However, flagging content online can lead to the spread of misinformation in itself. Mis-corrections are common on social media, causing confusion among users; thus, perceiving real content as less credible (Stoeckel, et al., 2024). In contrast to previous decades, social media guidelines and policies integrate timely fact-checking algorithms to uphold users' rights to accurate online information, for example, the implementation of Community Notes on X, although it is not yet available in most countries (Mahadevan et al., 2021), and the community-driven approach to content moderation on Meta. In 2025, Meta officially ended the third-party and independent fact-checking program as part of its new content moderation strategy to community-driven content moderation (Rosenberger, 2025). Advocating for free speech and removing content censorship with their new Hateful Conduct policy (Car, 2025). Meta's decision to adopt X's Community Notes approach has created controversy among users, fearing that this shift may lead to increased misinformation dissemination and political bias (Rosenberger, 2025). Despite Meta's counter-misinformation and cyberhate strategy, it still needs rigorous refinement and development to ensure its effectiveness in combatting all forms of misinformation. In the context of addressing misinformation, media literacy represents a crucial competency in combating the ongoing information crisis. Media literacy is defined as the ability to access, analyze, evaluate, create, and act upon mediated messages (Aufderheide & Firestone, 1993; Livingstone, 2004; NAMLE, 2020). Its universal aim is to equip individuals with the essential skills required to navigate the evolving media

landscape in a well-informed manner. According to prior research about natural disasters online, education about media use during natural disasters is crucial alongside the implementation of technical tools on social media platforms to process online content in times when accurate information is scarce (Rudyawan et al., 2023; Zoonen et al., 2024).

Methodology

The primary focus of this study is to explore the characteristics and frequency of misinformation about Al-Haouz earthquake on X. Therefore, the research questions posed in this study are as follows: (i) What are the frequencies of earthquake misinformation and not-misinformation tweets on X? (ii) What are the main misinformation themes circulated during that period on X? To answer these research questions, a systematic methodology was implemented in this respect.

Data Collection

Drawing upon existing academic research methodologies on online crisis communication spread (Dallo et al., 2023; Shahi, 2021), this study adopts a hybrid extraction method to process relevant data. The dataset for this study was collected from X by a third-party using X API and manual data scraping to ensure a relevant and randomized dataset. The data was extracted using the hashtags #earthquakemorocco, #زلزال_الحوز, # Elhaouz, #زلزال_مراكش, # MarrakeshEarthquake, #moroccoearthquake, #زلزال_في_المغرب, #, #زلزال_المغرب, # Morocco, and #earthquake within the timeframe from 8 September to 31 December, 2023. The extraction process resulted in 9,057 tweets in Arabic, French, English, and Spanish for analysis, which were anonymized prior to scrutiny to ensure ethical integrity and user privacy. Upon the cleaning and screening of tweets, the dataset was reduced to 5,594 tweets. Figure 1 indicates the study's data collection and analysis workflow in detail.

Content Analysis

Since the study is exploratory in nature, a content analysis was conducted to highlight the main misinformation themes emerging in the dataset. The rationale for selecting content analysis as the primary methodological approach is rooted in its ability to offer a systematic and replicable method for analyzing large textual and audio-visual data. Content analysis has been employed in analyzing numerous scholarly studies related to crisis communication (Muralidharan et al., 2011; Flores-Saviaga & Savage, 2020). Prior to the coding procedure, a comprehensive review of the literature on earthquake misinformation was performed to generate an initial coding framework (Muralidharan et al, 2011; Dryhurst et al., 2022; Flores-Saviaga & Savage, 2020). A detailed codebook was designed to provide a clear and consistent coding system to detect and categorize misinformation themes in the dataset. Five main misinformation themes have emerged from the dataset, which were defined as follows:

1- *Misleading Visual Representation* – includes tweets containing images, videos, GIFs, or other visual content presenting misleading, incorrect, or deceptive information about the earthquake.

2- *Sensationalist Reporting* – includes tweets charged with strong emotions to provoke irrational and emotional reactions through exaggerated magnitudes, alarming language, cherry-picked details, hate speeches, and political campaigns.
3- *False Prediction* – includes tweets claiming to predict and foresee future events related to the earthquake without rigorous scientific and accurate backup.
4- *Conspiracy Theory* – includes tweets attributing the cause of the earthquake to secret organizations or hidden agendas without providing credible evidence.
5- *Pseudoscientific Explanation* – includes tweets explaining seismic activities using non-scientific standards.

The coding procedure went through two main stages. The first stage was dedicated to categorizing tweets as misinformation and non-misinformation following the veracity analysis. The tweets were then coded accordingly to their respective themes in the second stage. Two media and communication PhD researchers coded 200 tweets from the extracted dataset, which were selected randomly. Cohen's Kappa was used to measure the inter-rater reliability of the coding patterns of both raters, resulting in k=0.49 for misinformation and not-misinformation, K=0.51 for sensationalist reporting theme, K=0.68 for conspiracy theory theme, K=0.94 for false prediction theme, K=0.47 for misleading visual representation theme, and K=0.41 for pseudoscientific explanation theme. The Cohen's Kappa values range from moderate to almost perfect agreement, showcasing the relative consistency of the coding process.

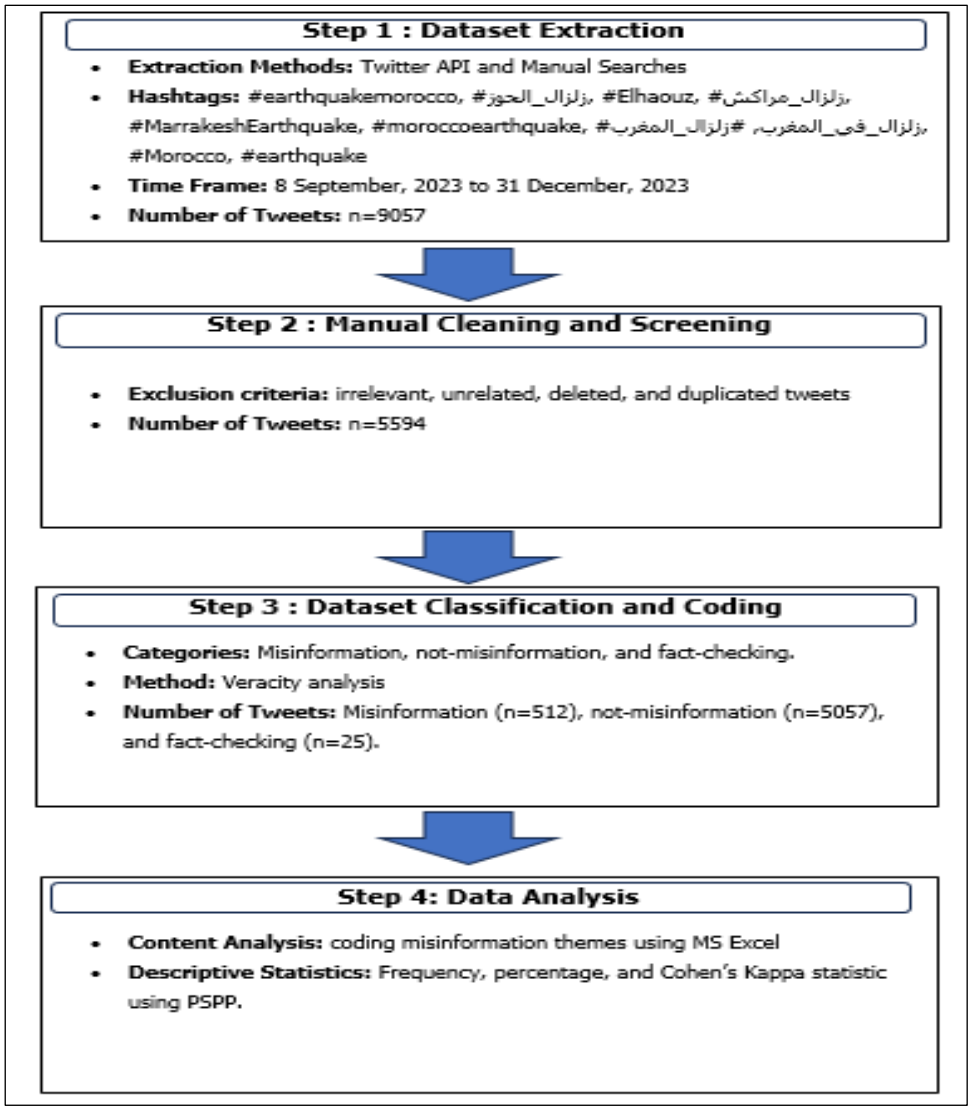
Veracity Analysis

To verify the truthfulness of the collected tweets, a manual veracity analysis was also conducted to support the content analysis. (Lozano, et al., 2020). This process enhances the evaluation of content reliability through the following steps:

Step 1: Reviewing the tweet content.
Step 2: fact-checking the tweet by looking up and tracing claims using fact-checking platforms and reverse image searches.
Step 3: Cross-checking claims with available and verified data, along with official reports.
Step 4: Labelling the claims as misinformation or not-misinformation on MS Excel.

Fact-checking websites, like *AFP Fact Check* (Agence France-Presse, 2017), *Misbar* (Misbar, 2022), *Fatabayano* (Fatabyyano, 2016), *Reuters Fact Check* (Reuters Fact Check, s.d.), and *Snopes* (Snopes, 1995) were utilized to detect misinformation posts. In case of information unavailability on the fact-checking websites, Google Image was employed to trace information source. X's Community Notes feature was also helpful in detecting misinformation claims since debunking is done by providing credible sources.

Figure 1: Workflow of the Data Collection and Analysis



Source: own elaboration

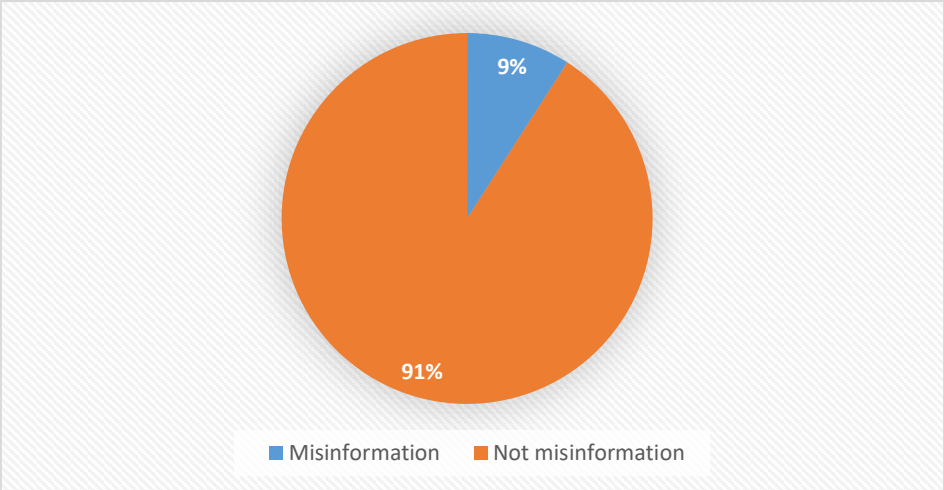
Results

This section organizes the study's results in alignment with the research questions addressed. The first sub-section presents the findings pertinent to the first research question (RQ1), and the second sub-section concentrates on the outcomes related to the second research question (RQ2).

Frequency of Misinformation and Not-misinformation Tweets

After the filtering process of the dataset (n=9057), only 5594 tweets were considered for analysis, given the majority of non-representative tweets were removed, e.g. irrelevant, deleted, or duplicated tweets. The tweets were then categorized into misinformation (n=512) and not-misinformation (n=5082).

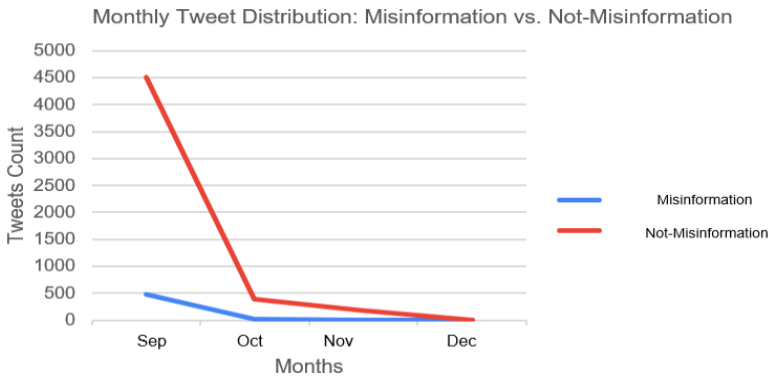
Figure 1: P*ercentages of Misinformation and Not-misinformation Tweets*



Source: own elaboration

As illustrated in Figure 2, the highest percentage of not-misinformation (91%) in relation to misinformation (9%) is substantial, indicating the accuracy of tweets about the Al-Haouz earthquake discourse on X. This prominence of not-misinformation tweets on X aligns with a study conducted on the dynamics and characteristics of earthquake misinformation (Dallo et al., 2023). Interestingly, amongst the not-misinformation category, some instances of fact-checking were identified (n=25), aiming to flag misleading content by either providing factual information or debunking misinformation claims. Figure 3 presents the monthly distribution of misinformation and not-misinformation tweets. The figure reveals a notable decrease in the volume of both misinformation and not-misinformation tweets between September and October, with not-misinformation tweets fluctuating from approximately 4,500 to below 500 tweets. In contrast, misinformation tweets count decreased from approximately 500 tweets in September to fewer than 100 in October. The convergence continued through November and December, reaching a significantly low tweets activity in both categories. Furthermore, the data revealed the disproportionate decrease of the not-misinformation category compared to the misinformation category after experiencing an initial online activity peak in September.

Figure 1: P*ercentages of Misinformation and Not-misinformation Tweets*



Misinformation Themes

The content analysis performed on the dataset resulted in the emergence of 5 main misinformation themes (see *Table 1*). Notably, sensationalist reporting appears to be amongst the prominent themes on X, with a percentage of 60%, followed by the misleading visual representation theme with a percentage of 31%. However, the themes of conspiracy theory (5%), pseudoscientific explanation (3%), and false prediction (1%) have the lowest percentages (see *Table 1*). During the coding process, two tweets (n=2) were categorized into two distinct themes. This accounts for the additional two tweets in the overall total of coded misinformation themes per tweet (n=514). Figure 4 highlights a chronological fluctuation of different misinformation themes in the allocated time period. The largest proportion is constituted by the prominence of the misleading visual representation (n=156) and sensationalist reporting (n=295) themes in September while other misinformation themes demonstrated a negligible tweet count, conspiracy theory (n=22), pseudoscientific explanation (n=7), and false prediction (n=4). October indicated a gradual shift of misinformation themes with sensationalist reporting (n=12) and a significant decrease in misleading visual representation (n=2). October has also demonstrated a substantial increase in conspiracy theory in the pseudoscientific explanation theme (n=9) and a slight drop in false prediction (n=2) and conspiracy theory (n=2). In November, conspiracy theory dominated other themes with 2% of Tweets, followed by false prediction (1%) and sensationalist reporting (1%). Figure 4 demonstrates a temporal dynamicity of different misinformation themes over the three-month period. The analysis further reveals a corresponding shift in the dominant modalities of the thematic dissemination. Text-based posts (n=247) represent the predominant misinformation tweet type within the dataset, with 220 categorized under sensationalist reporting. Video-based posts (n=159) constitute the second most frequent modality, comprising 119 misleading visual representation posts and 14 conspiracy-related posts. The least frequent modality is picture-based posts (n=106), including 60 sensationalist reporting posts and 34 misleading visual representation posts.

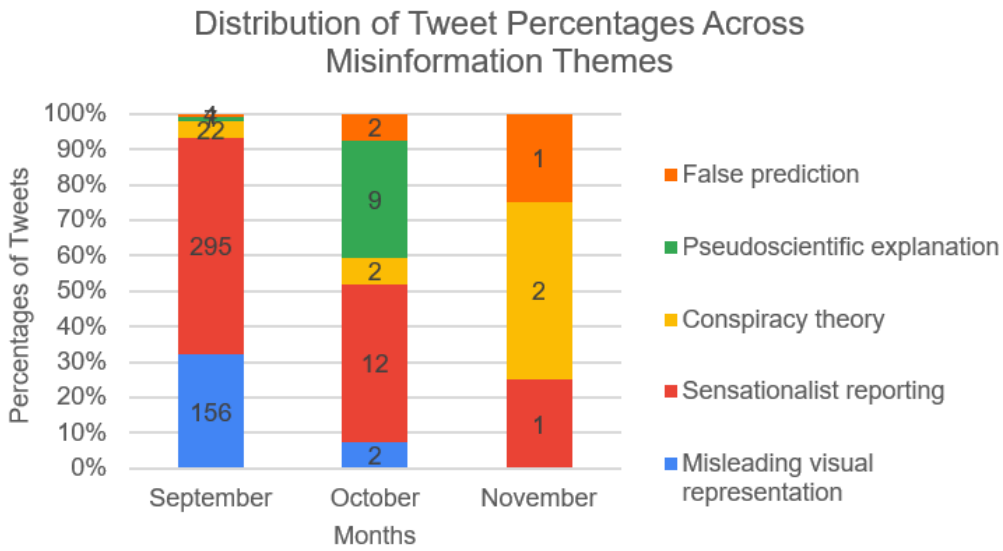
Table 1: *Misinformation Themes on X*

Misinformation Themes	**Numbers of Coded Tweets**	**Percentages of Coded Tweets**

Theme 1: Sensationalist Reporting	308	60%
Theme 2: Misleading Visual Representation	157	31%
Theme 3: Conspiracy Theory	28	5%
Theme 4: Pseudoscientific Explanation	14	3%
Theme 5: False Prediction	7	1%
Total	514	100%

Source: own elaboration

Figure 4: Monthly Distribution of Misinformation Themes on Twitter



Source: own elaboration

Discussion

The study indicates a prominence in sensationalist reporting (60%) and misleading visual representation (31%) on X, emphasizing the platform's visual nature. The dominance of these themes can also be attributed to the nature of natural disasters, as earthquakes bring about risky and severe distractions, making the targeted audience inclined to be hooked by visual and sensationalist instances. Although the sum of misinformation was minimal compared to not-misinformation, distinguishable misinformation themes emerged, highlighting the content nature and usage of X during critical situations.

Contrary to expectations, this study did not yield significant findings regarding the impact of online misinformation within the discourse surrounding the AL-Haouz earthquake. However, it provides valuable insights about online misinformation during critical times. It also adds to the body of knowledge about the different earthquake misinformation themes in a context where earthquakes are scarce. It is evident that

many Moroccan users have moved to X due to its reputation as a platform where seismologists and earthquake forecasters share their predictions and insights on the subject. This has led to the proliferation of misleading and distorted content. Although seismologists are experts in the field, they may not provide accurate and detailed predictions of the disaster (Dallo et al., 2023). Therefore, earthquake specialists can only provide approximate earthquake forecasts. Similar to past studies about crisis misinformation (Zaidi & Munir, 2023; Ong'ong'a & Demuyakor, 2020), propaganda, emotional, and political misinformation, which fall within the sensationalist reporting theme, appear to have the highest percentages during critical times. This phenomenon may be linked to the information gap, alongside individuals' susceptibility and psychological amplification. Indeed, the Social Amplification of Risk (SAR) theory states that the reception of risk-related information through various channels is influenced by individuals' prior psychological, personal, and cultural experiences (Kasperson et al., 1987). In response to risky events, individuals exhibit behavioral responses (Kasperson et al., 1987), which intensify their vulnerability. As illustrated in Table 2, instances of fabricated visuals and emotionally charged content are more frequent and engaging. The sensationalist reporting theme targets tweets about exaggerated magnitude levels, faulty assumptions about public figures or official humanitarian donations, and politicized content aiming to spread terror. The misleading visual representation theme revolves around edited and unrelated visual representations. For example, several tweets have included unrelated footage of a collapsed house in Casablanca due to construction problems dating back to 2022 (see Table 2).

There were also instances of wreckage from unrelated earthquakes in Turkey, Japan, and China. It is also worth mentioning that the popularity of sensationalist and visual misinformation about the Al-Haouz earthquake reflects the social amplification of risk through sensationalism and, therefore, higher interactivity. Although the amplification was not that significant in the dataset, the initial phase of the earthquake was characterized by factors that inherently contribute to the SAR theory (Kasperson et al., 1987). The abrupt and sudden nature of earthquakes triggers high levels of anxiety and uncertainty (Kasperson et al., 1988). This is indeed mirrored in the initial phase of the AL-Haouz earthquake, with a dominance of sensationalist reporting and misleading visual representations reflecting the social amplification of risk through sensationalism. The limited availability of official information regarding the disaster amplified users' emotional reactions, particularly during the initial period of the earthquake, in September. Emotional vulnerability for information may lead to reliance on unverified sources and emotionally charged tweets. Even though the amplification of risk was not significantly higher in the extracted dataset, there is a possible tendency for such content to be prevalent in the information landscape following earthquakes. Misinformation tweets gathered in October and November knew an attenuation of risk. This may be attributed to the surge of official updates, humanitarian appeals, and expressions of solidarity. As the immediate crisis response evolved into a longer-term recovery phase in subsequent months, there was a discernible decline in the overall volume of tweets pertaining to the event. Moreover, the data uncovered a temporal dynamic of crisis-related information across the examined themes of misinformation from September to November. Although sensationalist reporting dominated the extracted tweets, the theme of conspiracy theories gained relative prominence in November. In addition to this, it can be deduced that text-based tweets were the most prominent form, with 247 misinformation tweets, followed by videos and then images. This prominence suggests that written narratives had a crucial role in the spread of misinformation.

The text-based tweets were mainly about misleading the earthquake magnitudes or promoting cyber hate and hate speech.

Table 2: *Sample Tweets of Misinformation Themes on X*

Misinformation Themes	**Sample Tweets**
Sensationalist Reporting	*(1) Cristiano Ronaldo is providing shelter for those affected by the earthquake in Morocco.* *He has made his Pestana CR7 Hotel in Marrakesh, Morocco available. https://t.co/DMkHSXyLrS #marakesh #ouarzazate* *(2) بردّاً و سلاماً لأهلنا في #المغرب إثر الزلزال الذي ضرب مدن الدار البيضاء و الرباط بقوة 7 على سلم ريختر و الحمدلله لا بلاغات عن ضحايا لحد الان.* *Our great solidarity to our people in #Morocco after major 7 magnitude quake that hit Dar Al Bayda & Rabat, no reports of casualties yet https://t.co/5ViBZUNDS4 #moroccoearthquake #marrakeshearthquake* *(3) 🌏The increasing seismic activity is a consequence of the destabilization of our planet's core. #EgonCholakian, a renowned scientist, urges all scientists and #politicians to take urgent #actionnow for the #survival of all humanity! #Morocco_earthquake #ClimateActionNow #Climate https://t.co/xa3oXyPioa #marrakeshearthquake #prayformaroc* *(4) In the aftermath of the devastating magnitude 7 earthquake that struck Morocco last week, several countries, including France, have extended offers of assistance to aid the stricken regions.* *https://t.co/TXonN0dFCH #seismemaroc #morocco*
Misleading Visual Representation	*(1) Horrific moment of collapse of a house caught on security camera #earthquake at #Morocco in the region of #Marrakech* *Pray for Morocco 🇲🇦 😭✊ (Video: Building collapsed in Casablanca) #moroccoearthquake https://t.co/jgmHyo1wqi #essaouira #Elhaouz* **Visual Representation:** A video of a collapsing building in Casablanca that dates back to 2022. *(2) The mosque was martyred due to the earthquake in Morocco, but the 5-time adhan is still going on.* *#verifiedpakistan https://t.co/tBNWE5QGvq #moroccans #Elhaouz* **Visual Representation:** A video purporting to be from Syria and Iraq, which has been available on the internet since 2017. *(3) Update: Morocco Quake Death Toll Exceeds 2,900, 300,000 homeless, and one-third are children. 💔*

	Source:https://t.co/2y1F9jceaa *Stay safe👍* *Video capturing blue light before the earthquake.* *- What I know is that the light comes from a festival.* *#StaySafe #earthquake #Marocco https://t.co/AEWHbNmQkh #solidarit #earthquakemorocco* **Visual Representation:** A video from the earthquake in Turkey. (4) *Prayers for the Morocco earthquake 6.6 hit Morocco, Resulting in 280 deaths* *May Allah bless Morocco #Morocco #HaniaAamir #DollarRate India and Pakistan #ArifAlvi #PakvsInd #PakistanCricket Turkey G_20 Dubai #ReleaseImranKhan Shameful Pakistanis #AudioLeaks #زلزال* *Welcome to India https://t.co/plj7rorfSr #morocoearthquake #marakesh* **Visual Representation:** The clip was taken in Oita, Japan, in January 2022.

Source: own elaboration

This study's findings raise intriguing questions about potential actions to mitigate the proliferation of misinformation online. Media literacy education is one way to equip users with the necessary skills to navigate the media landscape (Zoonen et al., 2024; Rudyawan et al., 2023). Implementing strict fact-checking regulations in social media platforms is another way to promote accurate and credible information, especially during dire times. The findings in the present study are consistent with the findings of Olteanu et al. (2015), asserting that X is the most used medium to communicate crisis-related information. In another similar study, it was concluded that because of X's brevity and rapidity, it is widely utilized in disaster events compared to other social media platforms (Muralidharan et al., 2011).

As in every scientific study, this study faced some methodological limitations. The manual content and veracity analysis limited larger dataset analysis. Therefore, it affects the generalizability of the study. Another limitation is data authenticity, as deciphering authentic data from fake accounts can be complex, especially with the rise of social media bots. Technological limitations can be considered the main hurdle encountered in this study. Though this research is not generalizable, it is informative and exploratory, aiming to provide valuable insights into the online earthquake discourse.

Conclusion

This study examines misinformation discourse following the 6.8 magnitude earthquake that struck Morocco on September 8, 2023. The findings reveal the prevalence of different forms of misinformation on X, specifically sensationalist reporting and misleading visual representations. While X's Community Notes proved useful, the social media platform still requires algorithmic regulations to minimize the spread of misinformation during emergencies across all regions. Consequently, comprehensive analyses of large-scale datasets in the field of crisis communication are essential for acquiring a more nuanced comprehension of information dissemination in dire times. This paper adopts an exploratory approach to study the

misinformation about the Al-Haouz earthquake. Furthermore, this study advocates for the imperative integration of media literacy skills on both global and national scales, positing it as a fundamental prerequisite for fostering an informed and resilient society in the digital era.

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