

## Communicating the Crisis or Misinforming the Public? Analyzing the AI-Generated Visual Rhetoric of the 2025 California Wildfires

MENNA ELHOSARY<sup>1</sup>

City St George's, University of London, UK

BARIKISU ISSAKA

Michigan State University, USA

INUSAH MOHAMMED

Purdue University, USA

BALKISA SISSY

University of Cincinnati, USA

SABENA ABDUL RAHEEM

University of Iowa, USA

In January 2025, catastrophic wildfires devastated Southern California, prompting a surge in AI-generated visuals across social media. While these visuals might have aimed to raise awareness, they have also distorted perceptions of the crisis's scale, intensifying public fear and complicating emergency responses. This study depends on Foss's visual rhetoric model to systematically examine the visual rhetoric of AI-generated visuals that spread during the wildfires. Through qualitative and quantitative analyses of visuals shared on X, we analyze the rhetorical strategies and purposes behind these visuals and assess public sentiment toward them. Our findings reveal how visual generative AI

---

Menna Elhosary: [menna.elhosary@city.ac.uk](mailto:menna.elhosary@city.ac.uk)

Barikisu Issaka: [issakaba@msu.edu](mailto:issakaba@msu.edu)

Inusah Mohammed: [Moham129@purdue.edu](mailto:Moham129@purdue.edu)

Balkisa Sissy: [sissybm@mail.uc.edu](mailto:sissybm@mail.uc.edu)

Sabena Abdul Raheem: [sabdulraheem@uiowa.edu](mailto:sabdulraheem@uiowa.edu)

Date submitted: 2025-08-02

<sup>1</sup> *Funding:* The authors received no specific funding for this work.

*Conflicts of interest:* The authors declare no conflicts of interest.

*Ethics approval:* This study is based on analysis of publicly available content and does not involve human participants or identifiable personal data. Therefore, Institutional Review Board / Ethics Committee approval and informed consent were not required.

Copyright © 2026 (Menna Elhosary, Barikisu Issaka, Inusah Mohammed, Balkisa Sissy, and Sabena Abdul Raheem). Licensed under the Creative Commons Attribution Non-commercial No Derivatives (by-nc-nd). Available at <https://ijoc.org>.

amplifies both the communicative power and the risks of misinformation in crisis visuals. The study contributes to the growing body of scholarship on visual misinformation and crisis communication. It offers empirical insights into how AI-generated visuals shape public perception during crises. The study concludes with theoretical and practical implications.

*Keywords: crisis communication, visual generative AI, visual misinformation, natural disasters, California wildfires*

In January 2025, catastrophic wildfires hit Southern California, destroying more than 18,000 buildings and forcing the evacuation of over 200,000 residents. The wildfires were fueled by extreme weather conditions and led to an estimated economic loss of \$275 billion, which makes this the costliest natural disaster in U.S. history (Karlman et al., 2025). Amid the crisis, environmental activists and concerned citizens turned to AI-generated imagery and deepfakes to visualize the devastation (Chappell, 2025). Some news stories noted the circulation of such visuals and raised concerns that some AI-generated depictions exaggerated the scale of the disaster and contributed to public confusion and anxiety (e.g., Chappell, 2025; Karlman et al., 2025). While these stories are anecdotal rather than systematic examinations, they highlight growing concerns about the potential threat of AI-generated visuals during crises.

Using visuals in online crisis communication has long been shown to elicit emotional responses and mobilize support (Olesen, 2018). Drawing on visual rhetoric scholarship, images may be understood as symbolic and persuasive forms of communication that influence how audiences interpret situations and form beliefs (Foss, 2005). Visual content can effectively break through cluttered feeds by capturing users' attention and evoking emotional reactions (Chung & Lee, 2019). Research on crisis communication has established the power of visuals in facilitating persuasion and enhancing memorability (e.g., Elhosary, 2025a; Pang & Law, 2017; Peracchio & Myers-Levy, 2005).

More recently, the rise of visual generative AI, particularly text-to-image and text-to-video models, has revolutionized the visual communication and crisis communication landscapes. These tools have facilitated the creation of high-quality, photorealistic visuals in a fraction of a second and at a minimal cost, which simplified visualizations where traditional imagery is impractical, such as during natural disasters (Cools & Diakopoulos, 2024; Elhosary, 2025b; Hausken, 2024). Recent data showed that over 15 billion images were generated from text-to-image models in 2023. This figure exceeds Shutterstock's entire image library and constitutes almost one-third of all images ever uploaded to Instagram (Valyaeva, 2023).

Despite its capabilities, visual generative AI has raised concerns over its potential to exacerbate visual misinformation (Thomson et al., 2024). This was particularly noticeable during the 2025 California wildfires. Drawing on multiple quotes from experts and professionals, Chappell (2025) noted that massive amounts of AI-generated imagery and deepfakes, falsely portraying exaggerated scenes of destruction, exacerbated public fear and complicated the emergency efforts to manage the crisis. One notable example

is the fabricated image of the Hollywood sign in flames, which misled the public and intensified confusion about the true scale of the catastrophe (Sommerlad, 2025).

This dichotomy between crisis communication and misinformation demands a systematic exploration of the role of AI-generated visuals in constructing visual rhetoric during environmental crises and their potential to fuel visual misinformation and undermine crisis communication. Our work, guided by Foss's (2005) visual rhetoric model, addresses this research agenda by analyzing the AI-generated visual rhetoric that surrounded the wildfires. We engaged in systematic quantitative and qualitative content and sentiment analyses of AI-generated imagery and deepfakes that spread on X during the wildfires.

This approach allowed us to delve deeper into the whole cycle of AI-generated visuals, from the purpose behind their construction to their nature, function, and impact on the public. This research also provides empirical insights into the potential of text-to-image and text-to-video models to reshape the crisis communication landscape and exacerbate online misinformation. The work concludes with various theoretical and practical implications pertaining to visual generative AI and online crisis communication, providing insights to academics and practitioners alike.

### **Visual Storytelling and Crisis Communication on X**

Natural disasters pose significant threats to entire communities, as they can escalate into crises with devastating economic, political, and environmental consequences, which underscores the importance of effective crisis communication in ensuring public safety (Dogra, 2007). Social media has revolutionized crisis communication by enabling real-time information sharing (Seo & Vu, 2020). Among various platforms, X has emerged as a vital tool for crisis response because of its immediacy and accessibility. Panagiotopoulos et al. (2016) emphasize that effective crisis communication depends on the accurate and timely dissemination of information, a function that X can play a crucial role in facilitating during crises.

The platform offers valuable affordances that enable affected communities to engage in a dynamic exchange of information (Leonardi & Vaast, 2017). Media personalities and emergency responders leverage hashtags, tweets, retweets, and multimodal content to disseminate critical crisis information (Bruns & Burgess, 2015). The tweet format promotes concise communication, enhancing the accessibility and shareability of crisis updates (Okazaki et al., 2020). When combined with visuals, these updates become even more impactful, transcending language barriers and conveying a heightened sense of urgency (Lee et al., 2022).

Regardless, X has several limitations concerning crisis communication. First, the platform is overloaded with information, sometimes making it difficult for users to identify relevant updates (Chung & Lee, 2019). Second, when users try to narrow down the content through the use of keywords or hashtags, they may encounter irrelevant posts (Pond, 2016). Third, like many online platforms, X has become a hotspot for misinformation and disinformation, raising uncertainty about the credibility of the content shared (Gupta et al., 2013). Additionally, Pond (2016) highlights that the real-time nature of X can complicate efforts during crisis situations, as users find it challenging to keep up with the influx of updates.

Research on crisis communication has established the power of visuals in facilitating persuasion and enhancing memorability (e.g., Pang & Law, 2017; Peracchio & Myers-Levy, 2005). Visual storytelling<sup>2</sup> has, therefore, been a key strategy for crisis communication on X (Lee et al., 2022). Visuals are particularly effective in cutting through the clutter of textual updates, capturing attention, and providing direct depictions of disaster impacts (Chung & Lee, 2019). Real-time visuals enhance situational awareness by offering immediate, compelling representations of crisis events (Pond, 2016). They evoke richer cognitive responses, as they are perceived as inherently more realistic and credible than text (Graber, 1990; Sundar, 2008). This “realism heuristic” means that even manipulated visuals can be perceived as authentic, which results in lasting misperceptions that are difficult to correct once formed (Kasra et al., 2018; Peirce, 1986).

The rise of visual generative AI has further facilitated visual storytelling, particularly in situations where traditional photography is impractical, such as during natural disasters (Hausken, 2024), which could facilitate crisis communication. Several affordances make visual generative AI a powerful rhetorical tool, including accessibility, affordability, plausibility, and interactivity (Bontcheva et al., 2024; Cools & Diakopoulos, 2024). AI-generated visuals are becoming increasingly indistinguishable from authentic ones, making them highly convincing and difficult to debunk (Pocol et al., 2024). Additionally, social media algorithms’ nature of prioritizing emotionally engaging and visually striking content accelerates the spread of AI-generated visuals, particularly those designed to provoke strong reactions (Cao et al., 2020). In this context, Groh (2023) indicated that deepfakes spread more rapidly than text-based misinformation because of their emotional impact.

However, these tools have also led to an unprecedented surge in visual misinformation, with AI-generated visuals becoming increasingly difficult to distinguish from authentic ones (Sun et al., 2024). Visual misinformation is a significant concern during crises because of the powerful impact of imagery content on human perceptions. Deceptive visuals can trigger fear, anger, or anxiety, shaping public perception and behavior (Powell et al., 2015). Online platforms further exacerbate this issue, as social media algorithms prioritize engagement over accuracy, which enables striking, misleading images to spread widely regardless of their authenticity (Cao et al., 2020). The rise of generative AI has intensified these challenges, introducing sophisticated misinformation that remains underexplored. Generative AI now enables the rapid creation of hyperrealistic images and deepfakes almost instantly and at minimal cost, accelerating the spread of visual misinformation (Bontcheva et al., 2024). Thus, this dichotomy between crisis communication and misinformation demands a systematic exploration of the role of AI-generated visuals in constructing visual rhetoric during environmental crises.

### **Research Model: Visual Generative AI as a Visual Rhetoric Tool**

---

<sup>2</sup> Visual storytelling refers to the strategic use of visuals on social platforms to create a cohesive, graphical narrative and build a story (Walter & Gioglio, 2014). This is different from visual rhetoric, which refers to the use of visual elements to communicate meaning and persuade audiences to influence how they interpret situations and form beliefs (Foss, 2005), and representation, which refers to how visuals stand for ideas, people, and social relationships to help create and share meaning within a culture (Hall, 2020).

Visual generative AI is a specialized form of artificial intelligence capable of producing new visuals by analyzing and synthesizing large visual data sets (Paik et al., 2023). It generates visuals based on brief prompts, making it accessible to everyone, including those with basic technological skills (Cools & Diakopoulos, 2024). These tools are also relatively affordable, with free versions and premium subscriptions costing as little as \$10–50 per month (Bontcheva et al., 2024). They are adept at generating a wide range of visual styles—including realistic images—within seconds, facilitating visual storytelling more than ever (Rombach et al., 2022).

Visual rhetorical studies is an analytical approach to analyzing how visuals function as symbolic and persuasive forms of communication rather than treating them as neutral representations (Foss, 2005). Foss's (2005) visual rhetoric model postulated that the rhetoric of a visual can be deconstructed based on analyzing three main components: nature, function, and evaluation. The visual's nature incorporates its literal elements, either existing or implicit (Hill & Helmers, 2012). In the context of AI-generated images, this could be the degree of realism, the context of the visual, its emotional tone, and its persuasive appeal. The function of a visual is the action the image/video communicates to the viewers.

Unlike purposes, which pertain to the creator's intent, visual functions are tied more to the meaning of the image, which is not always the same as the creator's original intention (Foss, 1994). Interestingly, the function can vary significantly depending on the context (Abdullatif & Elgarrai, 2021; Elhosary & Elkashif, 2025). For example, although an activist might initially craft an AI-generated image to raise awareness about the disaster, their visual might lose its original context and misinform the public. This is common during disasters, as crisis images often lose their original context and transform into "floating signifiers" that symbolize disasters (Weikmann & Lecheler, 2023). This decontextualization makes it easier for various actors to repurpose misleading visuals.

The evaluation of a visual is an assessment of how effectively the image served its intended function. In other words, the evaluation process goes beyond assessing aesthetic qualities to include an analysis of the image's broader societal implications. In this context, Abdullatif and Elgarrai (2021) noted, "If the nature of an image is red, shadowy, and tense, the function of the image is to instill fear and horror in the audience, and the evaluation would determine whether the audience is scared" (p. 152). Guided by Foss's (2005) visual rhetoric model, we aim to analyze this AI-generated visual rhetoric about the wildfires. By examining visuals' nature, function, and evaluation, we can better understand how AI-generated visuals communicate meaning, influence audiences, and serve persuasive purposes during a crisis. Accordingly, we propose the following research questions:

- RQ1: How were AI-generated visuals used to construct visual rhetoric about the 2025 California wildfires on X?*
- RQ2: What are the visual rhetorical functions that guided the construction of the AI-generated visuals about the 2025 California wildfires on X?*
- RQ3: How did the AI-generated visuals about the 2025 California wildfires affect X users' engagement, sentiment, and perceptions?*

## **Method**

### ***Data Collection***

This study employed a mixed-method approach, combining quantitative and qualitative content and sentiment analysis to analyze the visual rhetoric of the AI-generated visuals that spread on X during the 2025 California wildfires. The sample consisted of 83 X tweets featuring visuals flagged as AI-generated by 10 reputable fact-checking organizations. The data were collected in January 2025. The sample period began on January 7, 2025, when the wildfires erupted, and ended on January 31, 2025, when the wildfires were fully contained (Karlman et al., 2025). The following steps were undertaken to ensure a robust data collection process:

- 1) A list of fact-checking organizations affiliated with the International Fact-Checking Network was compiled. As of January 2025, the network included 148 organizations, from which we selected only English-language ones. This process resulted in 36 fact-checking organizations.
- 2) Articles published by these organizations were systematically reviewed to identify those that flagged visuals as AI-generated. The review was facilitated using the following keywords: "Los Angeles wildfires," "California wildfires," "LA wildfires," "deepfakes," and "AI-generated images." This led to the identification of 83 AI-generated visuals flagged by 10 organizations. The rest of the organizations did not flag any visuals about the wildfires.
- 3) After identifying the flagged visuals, a Google reverse image search was conducted to trace the original tweets on X, where these visuals were shared. This allowed us to understand the specific context in which these visuals were used on X.
- 4) We then extracted the top 100 comments on each visual tweet for qualitative and sentiment analyses.

### ***Coding Scheme***

The unit of analysis was every original visual tweet containing an AI-generated visual ( $n = 83$ ). The analysis was guided by Foss's (2005) visual rhetoric model, through which the visuals were analyzed based on their nature, function, and evaluation.

The visual's nature was operationally defined as the main elements of the visual, which we investigated through the following variables.

### *Type of AI Generation*

This variable aimed to capture the dominant type of AI-generated visuals that spread during the wildfires. We coded (1) an AI-generated image and (2) a deepfake video.

### *Realism*

This variable aimed to capture the degree of realism of the AI-generated visuals that spread during the wildfires. We coded for (1) photo/video realistic: images or videos that closely mimic real-world visuals; (2) hyperrealistic: extremely detailed realism, often with exaggerated or fantastical elements; (3) hybrid: visuals that blend real and artificial elements; (4) impersonation: videos that depict public figures making statements they never actually made, using techniques like face swapping, lip syncing, or voice cloning.

### *Visual Context*

This variable aimed to understand the key themes the AI-generated visuals focused on. We coded dichotomously for the following contexts: (1) wildfire magnification: AI-generated visuals exaggerating the scale or magnitude of the wildfires; (2) iconic sites/landmarks: AI-generated visuals featuring well-known landmarks affected by the wildfires; (3) government actions: AI-generated visuals depicting authorities taking actions or making statements they never did; (4) community panic/chaos: AI-generated visuals showing public crowds, panic, or chaotic human activity during the wildfires; (5) evacuation: AI-generated visuals depicting or reporting evacuation-related instances; (6) wildlife: AI-generated visuals focusing on animal suffering or deaths; (7) rescue operations: AI-generated visuals focusing on rescue operations for either human beings or animals.

### *Emotional Tones<sup>3</sup>*

This variable aimed to capture the emotional tone inherent in the AI-generated visuals based on observable features such as depicted actions, expressions, colors, and composition. We coded (1) high intensity for visuals conveying strong or intense emotions such as fear or anger, (2) low arousal for visuals conveying subdued emotions such as sadness or frustration, and (3) mixed for those conveying a combination of high- and low-arousal emotions.

### *Communicator*

This variable captured the following entities primarily responsible for spreading AI-generated visuals: (1) social media influencers, (2) media organizations, (3) fake accounts, (4) ordinary users, (5) activists, (6) aid organizations, public figures, and artists, or (7) others.

---

<sup>3</sup> Coding was based solely on the visual content and the coders' interpretation of the emotional tone depicted, not on audience responses. This ensures the variable reflects the nature of the visual rather than its function or evaluation.

### *Rhetorical Strategy*

This variable aimed to capture the main rhetorical strategy in the AI-generated visuals. Following the approach of Elhosary et al. (2024), we coded (1) ethos for AI-generated visuals that mostly focus on the presence of authority figures or testimonials to persuade viewers (e.g., deepfake videos), (2) pathos for AI-generated visuals that elicit viewers' emotions to sympathize with those affected by the disaster, and (3) logos for AI-generated visuals that primarily present evidence or data to persuade viewers.

The visual's function was operationally defined as the meaning the AI-generated visuals communicated to the viewers, which we captured through both the intended purpose of the visuals and their actual function.

### *Intended Purpose*

This variable aimed to investigate the intended purpose behind generating crisis-related visuals, which we investigated by analyzing the visual's accompanying captions and coding the following purposes, adapted from Lee et al. (2022): (1) delivering disaster news for visual tweets that raise awareness about the catastrophe; (2) call to action for visual tweets that encourage urgent responses such as evacuation, donations, or safety measures; (3) disaster resilience for visual tweets that showcase public or firefighters' resilience and the recovery/rescue operations of the catastrophe; (4) communicative actions for visual tweets that seek online engagement from the users.

We also added the following purposes to meet the unique nature of our work on visual generative AI: (5) misinformation for visual tweets that purposefully spread false or fabricated information about the disaster (e.g., deepfakes or manipulated visuals); (6) disaster imagination for visual tweets that imagined the disaster artistically, using generative AI to exemplify what has happened, clearly stating that the work is AI-generated.

### *The Function of Visuals*

This variable captured the interpretations the AI-generated visuals communicated about the crisis, as reflected in users' comments. We coded (1) crisis communication for comments that interpreted the visuals as effectively conveying important, accurate, or helpful information about the crisis; and (2) misinformation for comments that suggested the visuals were misleading, inaccurate, or harmful in their representation of the crisis.

The visual evaluation was operationally defined as audience perceptions of the AI-generated visuals, which we captured through the engagement metrics and an analysis of users' comments on the visuals.

### *Engagement and Virality*

We captured the frequency of the likes, comments, and retweets each visual tweet received.

### *Users' Sentiment*

In total, the visual tweets in our sample received 209,070 comments, making a comprehensive analysis unfeasible. Therefore, we filtered the comments for relevance and extracted the first hundred that appeared for each visual tweet, resulting in a data set of 8,300 comments. We categorized these into negative, positive, and neutral, with positive comments conveying optimism or trust, negative comments expressing fear or skepticism, and neutral comments reflecting uncertainty.

### *Users' Perceptions*

To further understand how users interpreted and discussed AI-generated visuals about the wildfires, we conducted a qualitative content analysis of the extracted comments. The analysis aimed to identify how users made sense of the visuals. All comments were imported into NVivo to facilitate the analysis. We followed a conventional inductive qualitative analysis approach (Hsieh & Shannon, 2005), which allowed categories to emerge from the data rather than depending on predefined categories. First, we read all comments multiple times to achieve data familiarity. During this stage, preliminary notes were made about recurring patterns and ideas. Then we conducted an initial coding of the comments to capture key perceptions, concerns, or interpretations expressed by users. All codes were derived directly from the data. Following our initial coding, we reviewed the codes and merged overlapping or similar ones and grouped them into broader categories. Finally, we organized the codes into higher-order categories, which structured the presentation of our findings.

### ***Intercoder Reliability***

For the visual tweets, the first author coded the whole sample ( $N = 83$ ). To ensure reliability, an outsider coder was trained on ( $n = 10$ ) tweets and then coded 10% of the sample ( $n = 8$ ). Scott's pi values were acceptable for all variables and ranged from .87 to 1.00. Specifically, agreement was 1.00 for the type of AI generation, visual context, communicator, and function of visuals, and it was .87 for realism, communicated emotions, rhetorical strategy, and intended purpose. For users' sentiment, the first author coded the whole sample ( $N = 8,300$ ). To ensure reliability, an outsider coder was trained on ( $n = 80$ ) comments and then coded 10% of the sample ( $n = 830$ ). Scott's pi value for this variable was .82.

### ***Data Analysis***

Quantitative data were analyzed using IBM-SPSS, through which descriptive statistics were calculated for each coded variable. Qualitative data were analyzed using NVivo 14.

### **Results**

The data set included 83 visual tweets featuring AI-generated visuals, categorized into AI-generated images ( $n = 44$ ; 53%) and deepfake videos ( $n = 39$ ; 47%). On average, visual tweets received 8,8611 likes ( $SD = 50,660$ ), ranging from 1,256 to 2,690,096. The average number of comments was 2,272 ( $SD = 11,952$ ), with a range of 110–81,326. Retweets averaged 1,674 ( $SD = 4,188$ ), ranging from 10 to

22,000. These figures indicate a high degree of overdispersion across all engagement metrics. However, this overdispersion does not affect our data or findings, as our analysis does not involve statistical inference on the effects of specific variables on user engagement.

RQ1 sought to understand how AI-generated visuals constructed visual rhetoric about the 2025 California wildfires. This was captured through the visuals' nature, as defined by Foss's (2005) visual rhetoric model. Our analysis showed that the most frequent type of visual tweets was photo-/videorealistic scenes ( $n = 32$ ; 38%), depicting highly realistic images. The second most common type was hybrid visuals ( $n = 23$ ; 27.7%), which featured authentic scenes altered with elements such as fires and flames. Hyperrealistic visuals ranked third ( $n = 20$ ; 24%), characterized by exaggerated realism. The least common type was impersonation ( $n = 8$ ; 9.6%), which depicted public figures or authorities making statements they never actually made.

The most frequently depicted context was community panic and social unrest ( $n = 17$ ; 20%), closely followed by images of landmarks allegedly affected by disasters ( $n = 15$ ; 18%). Other common themes included destruction scenes ( $n = 13$ ; 15.6%), fire exaggeration ( $n = 12$ ; 14.6%), and rescue efforts ( $n = 11$ ; 13.2%). On the other hand, wildlife received comparatively less focus ( $n = 10$ ; 12%), while government and authorities' responses were the least common ( $n = 5$ ; 6%). The visual tweets were mainly created by social media influencers ( $n = 39$ ; 52%), artists ( $n = 28$ ; 37.3%), and activists ( $n = 8$ ; 10.6%).

More than half of the visual tweets conveyed low-arousal emotions ( $n = 44$ ; 58.6%) such as sympathy and hope. High-arousal emotions followed ( $n = 31$ ; 41.4%), communicating fear, panic, and anger, while neutral emotions were missing from the data. The majority of the visual tweets utilized pathos, the emotional appeal, as their primary rhetorical strategy ( $n = 67$ ; 89%), aiming to elicit intense emotions in viewers; a few visuals utilized ethos, the authority appeal ( $n = 8$ ; 9.6%), impersonating public figures to make the communicated message seem more powerful, while logos, the logical appeal, was missing.

RQ2 sought to explore the visual rhetorical purposes that guided the construction of AI-generated visuals about the 2025 California wildfires. This was analyzed through the visuals' function, which includes both the intended purpose and actual function. Our analysis revealed that nearly a third of the visuals were aimed at illustrating and exemplifying the crisis ( $n = 35$ ; 42.1%), followed by those designed to misinform the public by depicting community panic or fires in unaffected areas ( $n = 30$ ; 36.1%). A smaller portion of the visuals conveyed community resilience in response to the disaster ( $n = 11$ ; 18%), and the fewest visuals focused on raising awareness through news about the catastrophe ( $n = 7$ ; 8.4%).

To understand the actual function of these visuals, we analyzed user comments. Our analysis revealed that over three-fourths of users perceived the visuals as misinformation ( $n = 6,729$ ; 81%). Their comments expressed skepticism about the visuals and their origins or served as warnings to others, highlighting that the visuals were misleading and AI-generated. In contrast, only a small portion of users ( $n = 1,571$ ; 18.9%) interpreted the visuals as a means of communicating the crisis. Their comments focused on the emotional impact of the visuals or the disaster itself, without mentioning skepticism about the visuals' authenticity.

RQ3 aimed to understand the impact of the AI-generated visuals about the 2025 California wildfires on X users' engagement, sentiment, and perceptions. In terms of engagement, our analysis revealed that AI-generated visuals were highly engaging, garnering a total of 8,152,700 likes, with an average of 88,611 likes per tweet. They also received 209,700 comments, averaging 2,272 comments per visual tweet, and 154,009 retweets, with an average of 1,674 per visual tweet. In terms of sentiment and perceptions, negative comments were the most prevalent ( $n = 3,212$ ; 38.6%), expressing skepticism, frustration, and distrust toward the visuals, particularly because of concerns about misinformation. Positive comments followed closely ( $n = 2,905$ ; 35%), with users appreciating the emotional impact of the content, particularly in raising awareness about the wildfires. Neutral comments were the least common ( $n = 2,183$ ; 26.3%), with users confused or uncertain about the factuality of the visuals.

Our qualitative analysis revealed that most users were touched by the visuals. However, many of them felt deceived when discovering that the visuals were AI-generated, either from the community notes or from replies to their comments, and they also demanded clearer labeling of AI-generated content. The visuals evoked strong emotional responses, particularly sadness and empathy for those affected by the wildfires. Furthermore, many users expressed concerns about media integrity, highlighting the growing difficulty in distinguishing between real and fabricated visuals and the potential erosion of trust in crisis communications. Discussions also touched on policy and ethics, with calls for stricter guidelines on the use of AI-generated visuals and greater consideration of their ethical implications. Additionally, some users raised environmental concerns, linking AI's energy consumption to climate change. Detailed qualitative results with examples from user comments are provided in the discussion section to contextualize user perspectives alongside interpretation and broader implications.

## Discussion

### *Potential Threats of AI-Generated Visuals*

Our analysis revealed that AI-generated visuals frequently exploit the realism heuristic, a cognitive shortcut where lifelike imagery is perceived as truthful, even when it is actually manipulated (Kasra et al., 2018). Many visuals employed hybrid techniques, merging authentic photographs with generative elements such as artificial flames. This blending of real and fabricated content made it difficult for viewers to distinguish between genuine and manipulated scenes. For example, one visual showed the iconic Hollywood sign in flames, with an extra mistakenly added L, yet many viewers overlooked this mistake. Several users expressed strong emotional reactions, describing the content as deeply distressing, while others conveyed sympathy for those affected in California. Some users also sought clarification about whether the fires were ongoing. These responses, among many similar ones, highlight the persuasiveness and perceived realism of AI-generated visuals.

These findings align with Kahneman's (2011) discussion of intuitive judgment and mental shortcuts. According to Kahneman (2011), intuitive thinking operates quickly using mental shortcuts (heuristics) to judge plausibility and coherence. It relies on familiarity and emotional cues, often bypassing careful analysis. In the case of AI-generated visuals, this means intuitive processing made manipulated or exaggerated

images appear credible and emotionally compelling, increasing the likelihood that viewers perceived them as authentic during disasters.

Furthermore, the visuals predominantly emphasized emotionally charged scenes such as widespread panic, dramatic destruction of iconic landmarks, and exaggerated fires. By highlighting fear and chaos, the AI-generated visuals likely leveraged emotional salience and affective responses that shape judgments under uncertainty, consistent with research showing that emotional reactions play a substantive role in how people appraise evidence and risks (e.g., Bandes & Salerno, 2014; Slovic et al., 2005).

The emphasis on emotional and negative appeals may be a deliberate strategy to highlight the devastation of the disaster and convey its urgency, particularly given that negative imagery and depictions of vulnerability are known to garner higher online engagement during crises (Elhosary, 2025a). For instance, Miller and LaPoe (2016) found that visuals triggering negative emotions are generally more recalled than neutral or less emotional visuals. In addition, Chung and Lee's (2019) work demonstrated that negative visuals evoke higher public responses toward corporate social responsibility campaigns than positive visuals. This means content creators and influencers might have intentionally generated negative and emotionally charged visuals to garner engagement.

This highlights a potential threat where creators might prioritize emotional and negative appeals to boost engagement and ignore relief efforts because they are not as engaging. During the wildfires, for instance, this approach largely sidelined stories of organized responses and recovery, including those by federal and state efforts (Austin, 2025), the Department of Defense (Lambert, 2025), and California's firefighting agencies (Nelson, 2025). These management efforts were largely absent from AI-generated visual rhetorics, reflecting deliberate negligence of stories that could have communicated stability, agency, and hope in the face of crisis. This reflects a rhetorical bias, emphasizing devastation while marginalizing narratives of competence, resilience, and agency.

In addition to concerns about public perceptions, ethical and credibility-related issues emerged as key risks. Many viewers expressed skepticism toward AI-generated content, highlighting concerns about its potential to mislead audiences as well as its broader environmental impact. Some users explicitly linked generative AI to climate-related harm, while others criticized the use of fabricated visuals for engagement purposes. These responses reflect growing public concern about both the credibility and societal implications of generative visuals. This suggests that while AI can elicit emotional responses, its misuse or lack of transparency can undermine public trust and reduce the effectiveness of crisis communication, particularly in climate-related disasters.

### ***The Good News: The Public Is Not Uniformly Vulnerable to AI Deception***

Our qualitative analysis showed that the public is not uniformly susceptible to visual generative AI. Many users actively questioned the authenticity of the visuals, engaged in debates over the ethical implications of using generative AI tools, and expressed frustration over the lack of transparency. User discussions often reflected a paradox between emotional impact and ethical considerations. While some users described the visuals as heartbreaking and powerful, others criticized the creators and platforms for

not labeling them as AI-generated. Emotional reactions were often overshadowed by frustration, especially when users realized the visuals were not authentic, such as when replies to their comments mentioned that the content was AI-generated. Accusations of deception and exploitation dominated the discussions, with many users criticizing the lack of clear labeling of AI-generated content and condemning the use of fabricated visuals for engagement purposes, highlighting a divide between the emotional impact of AI visuals and the ethical concerns about their transparency.

The audience also debated the appropriateness and utility of AI in crisis communication. Some users defended the use of AI-generated visuals, suggesting they can help convey urgency or raise awareness when authentic footage is unavailable. In contrast, others rejected such content, arguing it undermines authenticity and is unnecessary given the availability of real images. Both comment types were made on an AI-generated video showing firefighters rescuing animals during the fires. This means the rhetorical intent behind the visuals, even if it was showcasing the severity of the wildfires or depicting emotional responses, was overshadowed by skepticism about their authenticity. Misleading visuals, such as those depicting fires in unaffected areas or exaggerating community panic, likely contributed to the public's overall distrust. This highlights the challenge of effectively using AI-generated visuals in crisis communication, especially when the audience is increasingly cautious about the possibility of manipulation.

A subset of users raised broader societal concerns, including desensitization to visual deception, erosion of trust, and normalization of misinformation, emphasizing the need for ethical standards. For example, one user expressed concern that the increasing realism of AI-generated content may soon make it difficult to distinguish between authentic and fabricated visuals. This comment was made in response to an AI-generated video depicting a large-scale nighttime wildfire in California, with flames advancing toward an urban area as traffic and emergency lights gathered below. Calls for stricter regulation and transparent labeling were also prominent, reflecting growing public demand for accountability in the use of generative AI, particularly in sensitive contexts.

Comments expressing frustration over the lack of transparency were common, with many users criticizing the absence of clear labeling of AI-generated content and rejecting its increasing presence. Others also questioned the appropriateness of using generative AI for sensitive topics, arguing that such content was ill-timed and unsuitable in serious contexts. This reflected concerns about exploiting real tragedies for the sake of engagement. These conversations underscore a growing public demand for transparency and accountability in the use of generative AI, especially when addressing crises.

Environmental issues were also raised, with some users criticizing the use of generative AI to depict climate disasters. Statements highlighting the environmental impact of AI reflected skepticism about the alignment between the content and the issue it aimed to address, with some users suggesting that generative AI itself contributes to climate-related harm. This further reinforced the call for ethical guidelines about the use of generative AI. Some users dismissed such content entirely on these grounds, expressing strong opposition to the use of AI when addressing climate-related issues.

These reactions demonstrate a critical engagement with AI-generated visuals: Users are capable of evaluating the credibility, ethical implications, and societal consequences of these images, rather than

accepting them uncritically. This suggests that while AI visuals can evoke strong emotions and increase engagement, their effectiveness in crisis communication is contingent on transparency, ethical use, and alignment with accurate reporting.

### Conclusion

Guided by Foss's (2005) visual rhetoric model, this study analyzed the AI-generated visual rhetoric that surrounded the 2025 California wildfires, focusing on their nature, function, and impact. By exploring how visual rhetorical strategies were employed to either inform or mislead, this research offers critical insights into the dual role of visual generative AI, with its ability to powerfully communicate the urgency of a crisis and its simultaneous potential to distort public perception and erode trust in crisis communication. The findings highlight that while AI-generated visuals have the potential to foster empathy, they also intensify mistrust and confusion, particularly during critical moments of crises. The study emphasizes that visual generative AI tools are reshaping how crises are communicated and perceived in the digital age. While AI-generated visuals have proven to be a powerful tool for eliciting emotional responses, their use in crisis situations requires transparency and adherence to ethical standards to prevent misinformation.

However, this study is not without limitations. First, the analysis focused exclusively on content circulated on X, which limits the generalizability of the findings to other social media platforms that may have different affordances, moderation practices, and audience dynamics. Second, the data set relied on AI-generated visuals that were flagged and verified by fact-checking organizations. Because of the limitations of current AI detection tools, this meant the analysis was largely constrained to content that went viral or received sufficient public attention to warrant fact-checking. As a result, less visible or rapidly circulated AI-generated visuals may not be represented. Finally, audience perceptions were inferred from user comments rather than examined through experimental or survey-based methods. While comments provide valuable insight into spontaneous audience reactions, they cannot fully capture cognitive and emotional responses in a controlled or systematic way.

The findings point to the need for further research on how AI influences the public's cognitive and emotional processing of crisis information, especially when representing real-world tragedies. Future research should investigate how audiences interpret and emotionally respond to AI-generated visuals compared with authentic crisis imagery and whether disclosure labels alter perceptions of credibility, urgency, or willingness to share such content. It is also important to examine how repeated exposure to AI-generated crisis imagery may contribute to long-term skepticism toward visual evidence more broadly. These questions are particularly urgent across different crisis contexts, including natural disasters, public health emergencies, and armed conflicts, where visual information plays a critical role in shaping public understanding and response. Future research would also benefit from expanding analyses beyond a single platform and incorporating experiments or surveys to more directly examine how visual generative AI influences public cognitive and emotional processing during crises.

Theoretically, this study contributes to the understanding of crisis communication visual rhetoric, particularly in the context of AI-generated visuals. The analysis highlights the complex role of AI-generated visuals in shaping public perceptions, contributing to the emerging body of research on visual generative

AI, visual misinformation, and crisis communication. The results indicate the emotional power of AI-generated visuals, which can be beneficial and problematic to crisis communication. While emotionally charged visuals can foster empathy and urgency, they can also lead to misinformation and erode public trust, especially when the audience becomes increasingly skeptical of the authenticity of such visuals. This suggests that while AI-generated visual rhetoric is impactful, it may unintentionally undermine the narrative of hope and agency, which is crucial for effective crisis communication.

Practically, the work illustrates the critical need for greater transparency in the creation and dissemination of AI-generated visuals. It recommends that online platforms implement clear labeling to help users distinguish between generative and authentic content. The findings emphasize that such labeling is essential for maintaining credibility and ensuring the effectiveness of crisis communication. Despite statements from social media companies about the implementation of clear labeling (e.g., Clegg, 2024; Dunton, 2023) and existing regulations, such as a proposed bipartisan U.S. bill requiring clear labeling of AI-generated video and audio (Klepper, 2024) and the AI Labeling Act of 2023, which proposes mandatory disclosures across media formats (Schatz, 2023), the analysis revealed that only a few instances were appropriately labeled. This issue could be exacerbated by Meta's recent decision to discontinue third-party fact-checking collaborations in favor of a community notes system, where users assess the accuracy of posts on the platform (McMahon et al., 2025).

The study further provides valuable insights for crisis communication professionals who wish to integrate AI-generated visuals into their efforts. It outlines both the opportunities and limitations of these visuals, underscoring the importance of clear labeling. Furthermore, the research raises significant concerns for regulatory bodies and policy makers, urging them to establish clear guidelines for the ethical use of visual generative AI, particularly when addressing sensitive topics such as natural disasters. The growing public demand for accountability in the use of generative AI, as indicated by the analysis, points to the need for regulatory frameworks to mitigate the potential harms of visual manipulation, especially when it could undermine trust in critical information sources.

## References

- Abdullatif, R., & Elgarrai, S. (2021). The power of political cartoons: A case study of Zunar's "Twit cincin." *Jurnal Komunikasi: Malaysian Journal of Communication*, 37(1), 146–180.  
<https://doi.org/10.17576/JKMJC-2021-3701-09>
- Austin, S. (2025, January 24). *California will spend \$2.5 billion to help the Los Angeles area recover from wildfires*. AP News. <https://apnews.com/article/california-fire-relief-newsom-la-special-session-ab1e62d70198b5a7086e77932da93be9>
- Bandes, S. A., & Salerno, J. M. (2014). Emotion, proof and prejudice: The cognitive science of gruesome photos and victim impact statements. *Arizona State Law Journal*, 46(4), 1003–1056.

- Bontcheva, K., Papadopoulous, S., Tsalakanidou, F., Gallotti, R., Dutkiewicz, L., Krack, N., Teyssou, D., Nucci, F. S., Spangenberg, J., Srba, I., Aichroth, P., Cuccovillo, L., & Verdoliva, L. (2024). *Generative AI and disinformation: Recent advances, challenges, and opportunities*. European Digital Media Observatory (EDMO) / vera.ai / AI4Trust / AI4Media / TITAN White Paper. <https://publica.fraunhofer.de/entities/publication/c3c82b4f-d189-482e-a98c-fc29f5a264d5>
- Bruns, A., & Burgess, J. (2015). Twitter hashtags from ad hoc to calculated publics. In N. Rambukkana (Ed.), *Hashtag publics: The power and politics of discursive networks* (pp. 13–27). New York, NY: Peter Lang Publishing.
- Cao, Q., Shen, H., Gao, J., Wei, B., & Cheng, X. (2020, January). Popularity prediction on social platforms with coupled graph neural networks. In *Proceedings of the 13th International Conference on Web Search and Data Mining* (pp. 70–78). Houston, TX: Association for Computing Machinery.
- Chappell, B. (2025, January 16). *LA's wildfires prompted a rash of fake images. Here's why*. NPR. <https://www.npr.org/2025/01/16/nx-s1-5259629/la-wildfires-fake-images>
- Chung, S., & Lee, S. Y. (2019). Visual CSR messages and the effects of emotional valence and arousal on perceived CSR motives, attitude, and behavioral intentions. *Communication Research*, 46(7), 926–947. <https://doi.org/10.1177/0093650216689161>
- Clegg, N. (2024, February 6). *Labeling AI-generated images on Facebook, Instagram and Threads*. Meta Newsroom. <https://about.fb.com/news/2024/02/labeling-ai-generated-images-on-facebook-instagram-and-threads/>
- Cools, H., & Diakopoulos, N. (2024). Uses of generative AI in the newsroom: Mapping journalists' perceptions of perils and possibilities. *Journalism Practice*, 20(3), 878–896. <https://doi.org/10.1080/17512786.2024.2394558>
- Dogra, N. (2007). "Reading NGOs visually"—Implications of visual images for NGO management. *Journal of International Development: The Journal of the Development Studies Association*, 19(2), 161–171. <https://doi.org/10.1002/jid.1307>
- Dunton, C. (2023). *Get helpful context with About this image*. Google. <https://blog.google/products/search/about-this-image-google-search/>
- Elhosary, M. (2025a). Vulnerability or resilience tweets? A comparative analysis of media outlets versus non-governmental organizations visual representations of the 2023 Morocco earthquake survivors. *International Communication Gazette*, 87(3), 238–265. <https://doi.org/10.1177/17480485241267710>

- Elhosary, M. (2025b). Pixels of prejudice: Decoding embedded biases in AI-generated news imagery and their implications for visual journalism—Toward an algorithmic-mediated visual framing. *Journalism & Mass Communication Quarterly*. Advance online publication. <https://doi.org/10.1177/10776990251360690>
- Elhosary, M., Abbas, L., & Fahmy, S. S. (2024). "Woman, life, freedom": A visual rhetoric analysis of #MahsaAmini on X. *International Journal of Communication*, 18, 5559–5584.
- Elhosary, M., & Elkashif, M. (2025). Cartooning, framing, and virality: Unraveling the power of political cartoons during the 2023–2024 Gaza War—A comparative approach. *International Communication Gazette*. Advance online publication. <https://doi.org/10.1177/17480485251357870>
- Foss, S. K. (1994). A rhetorical schema for the evaluation of visual imagery. *Communication Studies*, 45(3–4), 213–224. <https://doi.org/10.1080/10510979409368425>
- Foss, S. K. (2005). Theory of visual rhetoric. In K. Ken Smith, S. Sandra Moriarty, G. Gretchen Barbatsis, & K. Kenney (Eds.), *Handbook of visual communication: Theory, methods, and media* (pp. 141–152). Mahwah, NJ: Lawrence Erlbaum Associates.
- Graber, D. A. (1990). Seeing is remembering: How visuals contribute to learning from television news. *Journal of Communication*, 40(3), 134–156. <https://doi.org/10.1111/j.1460-2466.1990.tb02275.x>
- Groh, M. (2023). The science and art of human and artificial intelligence collaboration [Doctoral dissertation, Massachusetts Institute of Technology]. <https://dspace.mit.edu/handle/1721.1/152001>
- Gupta, A., Lamba, H., Kumaraguru, P., & Joshi, A. (2013, May). Faking Sandy: Characterizing and identifying fake images on Twitter during Hurricane Sandy. In *Proceedings of the 22nd International Conference on World Wide Web* (pp. 729–736). Rio de Janeiro, Brazil: Association for Computing Machinery. <https://doi.org/10.1145/2487788.2488033>
- Hall, S. (2020). The work of representation. In T. Prentki & N. Abraham (Eds.), *The applied theatre reader* (pp. 74–76). Abingdon, UK: Routledge.
- Hsieh, H. F., & Shannon, S. E. (2005). Three approaches to qualitative content analysis. *Qualitative Health Research*, 15(9), 1277–1288.
- Hausken, L. (2024). Navigating the complex terrain of photography and temporality. *Philosophies*, 9(3), 60. <https://doi.org/10.3390/philosophies9030060>
- Hill, C. A., & Helmers, M. (Eds.). (2012). *Defining visual rhetorics*. Abingdon, UK: Routledge.

- Kahneman, D. (2011). *Fast and slow thinking*. New York, NY: Allen Lane and Penguin Books.
- Karlamangla, S., Jiménez, J., Zhuang, Y., Selig, K., & Nostrant, R. (2025, January 8). What we know about the wildfires in Southern California. *The New York Times*.  
<https://www.nytimes.com/2025/01/08/us/wildfires-los-angeles-california.html>
- Kasra, M., Shen, C., & O'Brien, J. F. (2018, April). Seeing is believing: How people fail to identify fake images on the Web. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems* (pp. 1–6). Montreal, Canada: Association for Computing Machinery.  
<https://doi.org/10.1145/3170427.3188604>
- Klepper, D. (2024). *New bipartisan bill would require labeling of AI-generated videos and audio*. PBS NewsHour. <https://www.pbs.org/newshour/politics/new-bipartisan-bill-would-require-labeling-of-ai-generated-videos-and-audio>
- Lambert, D. (2025, January 14). *About 2,500 Guardsmen helping fight California wildfires*. National Guard Association of the United States. <https://www.ngaus.org/newsroom/about-2500-guardsmen-helping-fight-california-wildfires>
- Lee, S. S., Lim J. R., & Shi, D. (2022). Visually framing disasters: Humanitarian aid organizations' use of visuals on social media. *Journalism & Mass Communication Quarterly*, 101(3), 749–773.  
<https://doi.org/10.1177/10776990221081046>
- Leonardi, P. M., & Vaast, E. (2017). Social media and their affordances for organizing: A review and agenda for research. *Academy of Management Annals*, 11(1), 150–188.  
<https://doi.org/10.5465/annals.2015.0144>
- McMahon, L. Kleinman, Z., & Subramanian, C. (2025, January 7). *Meta to replace "biased" fact-checkers with moderation by users*. BBC News. <https://www.bbc.co.uk/news/articles/cly74mpy8klo>
- Miller, A., & LaPoe, V. (2016). Visual agenda-setting, emotion, and the BP oil disaster. *Visual Communication Quarterly*, 23(1), 53–63. <https://doi.org/10.1080/15551393.2015.1128335>
- Nelson, J. (2025, January 9). *California firefighters use AI to combat growing wildfire threats*. PreventionWeb. <https://www.preventionweb.net/news/california-firefighters-use-ai-combat-growing-wildfire-threats>
- Okazaki, S., Plangger, K., West, D., & Menéndez, H. D. (2020). Exploring digital corporate social responsibility communications on Twitter. *Journal of Business Research*, 117, 675–682.  
<https://doi.org/10.1016/j.jbusres.2019.09.006>
- Olesen, T. (2018). More than words? A test of the effect of emotionally charged photographs. *Nordicom Review*, 39(2), 35–48. <https://doi.org/10.2478/nor-2018-0010>

<https://doi.org/10.65476/v7dgqs35>

- Paik, S., Bonna, S., Novozhilova, E., Gao, G., Kim, J., Wijaya, D., & Betke, M. (2023, September). The affective nature of AI-generated news images: Impact on visual journalism. In *2023 11th International Conference on Affective Computing and Intelligent Interaction (ACII)* (pp. 1–8). Cambridge, MA: IEEE.
- Panagiotopoulos, P., Barnett, J., Bigdeli, A. Z., & Sams, S. (2016). Social media in emergency management: Twitter as a tool for communicating risks to the public. *Technological Forecasting and Social Change, 111*, 86–96. <https://doi.org/10.1016/j.techfore.2016.06.010>
- Pang, N., & Law, P. W. (2017). Retweeting #WorldEnvironmentDay: A study of content features and visual rhetoric in an environmental movement. *Computers in Human Behavior, 69*, 54–61. <https://doi.org/10.1016/j.chb.2016.12.003>
- Peirce, C. S. (1986). *The fixation of belief. Writings of Charles S. Peirce: A chronological edition* (Vol. 3, pp. 242–257). Bloomington: Indiana University Press.
- Peracchio, L. A., & Meyers-Levy, J. (2005). Using stylistic properties of ad pictures to communicate with consumers. *Journal of Consumer Research, 32*(1), 29–40. <https://doi.org/10.1086/429599>
- Pocol, A., Istead, L., Siu, S., Mokhtari, S., & Kodeiri, S. (2024). Seeing is no longer believing: A survey on the state of deepfakes, AI-generated humans, and other nonveridical media. In *Computer Graphics International Conference* (pp. 427–440). Cham, Switzerland: Springer.
- Pond, P. (2016). The space between us: Twitter and crisis communication. *International Journal of Disaster Resilience in the Built Environment, 7*(1), 40–48. <https://doi.org/10.1108/IJDRBE-08-2013-0030>
- Powell, T. E., Boomgaarden, H. G., De Swert, K., & De Vreese, C. H. (2015). A clearer picture: The contribution of visuals and text to framing effects. *Journal of Communication, 65*(6), 997–1017. <https://doi.org/10.1111/jcom.12184>
- Rombach, R., Blattmann, A., Lorenz, D., Esser, P., & Ommer, B. (2022). High-resolution image synthesis with latent diffusion models. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (pp. 10684–10695). New Orleans, LA: IEEE.
- Schatz, B. (2023). *AI Labeling Act of 2023*. <https://www.govinfo.gov/app/details/BILLS-118s2691is>
- Seo, H., & Vu, H. T. (2020). Transnational nonprofits' social media use: A survey of communications professional and an analysis of organizational characteristics. *Nonprofit and Voluntary Sector Quarterly, 49*(4), 849–870. <https://doi.org/10.1177/0899764020908340>
- Slovic, P., Peters, E., Finucane, M. L., & MacGregor, D. G. (2005). Affect, risk, and decision making. *Health Psychology, 24*(4S), S35–S40. <https://doi.org/10.1037/0278-6133.24.4.S35>

- Sommerlad, J. (2025, January 10). No, the Hollywood sign is not on fire. *The Independent*.  
<https://www.independent.co.uk/news/world/americas/did-the-hollywood-sign-burn-down-b2676991.html>
- Sun, Y., Jang, E., Ma, F., & Wang, T. (2024, May). Generative AI in the wild: Prospects, challenges, and strategies. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). Honolulu, HI: Association for Computing Machinery.  
<https://doi.org/10.1145/3613904.3642160>
- Sundar, S. S. (2008). The MAIN model: A heuristic approach to understanding technology effects on credibility. In E. Metzger & A. Flanagin (Eds.), *Digital media, youth, and credibility* (pp. 73–100). Cambridge, MA: MacArthur Foundation Digital Media and Learning Initiative.
- Thomson, T. J., Thomas, R. J., & Matich, P. (2024). Generative visual AI in news organizations: Challenges, opportunities, perceptions, and policies. *Digital Journalism*, 13(10), 1693–1714.  
<https://doi.org/10.1080/21670811.2024.2331769>
- Valyaeva, A. (2023, August 15). AI image statistics for 2024: How much content was created by AI. *Everypixel Journal*. <https://journal.everypixel.com/ai-image-statistics>
- Walter, E., & Gioglio, J. (2014). *The power of visual storytelling*. New York, NY: McGraw-Hill.
- Weikmann, T., & Lecheler, S. (2023). Visual disinformation in a digital age: A literature synthesis and research agenda. *New Media & Society*, 25(12), 3696–3713.  
<https://doi.org/10.1177/14614448221141648>