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AI-Powered Social Listening for Strategic Crisis Management in the Digital Era

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ABSTRACT

The convergence of artificial intelligence (AI) and social listening has redefined crisis management in the technology sector, enabling organizations to detect, interpret, and respond to emerging threats with unprecedented speed and contextual precision. While prior research has examined AI in communication and monitoring separately, there remains a literature gap in synthesizing how AI-powered social listening operates across the whole crisis lifecycle and aligns with established communication theories such as Situational Crisis Communication Theory (SCCT). This paper addresses this gap through a systematic literature review (SLR) of 68 peer-reviewed studies published between 2013 and 2024, identifying key technological capabilities, applications, limitations, and ethical considerations. Findings indicate that transformer-based natural language processing (NLP) models, multimodal AI, and advanced anomaly detection systems significantly enhance early warning capabilities, real-time situational sensemaking, and adaptive stakeholder engagement. These tools have proven particularly critical in high-velocity crises where public narratives can shift rapidly across digital platforms. However, the review highlights persistent challenges, including algorithmic bias, platform coverage gaps, vulnerability to synthetic media, and ethical governance deficits. Drawing on arguments by SCCT, Crisis Informatics, and Sensemaking Theory, the current paper states that AI-based social listening can be regarded as a strategic practice rather than an auxiliary tool in resilient, transparent, and responsive crisis communication. The paper

concludes with recommendations that practitioners and policymakers can implement to ensure AI systems meet both operational and social needs.

Keywords: *Artificial Intelligence, Social Listening, Crisis Management, Situational Crisis, Crisis Informatics*

1. INTRODUCTION

The rapid evolution of digital communication ecosystems has fundamentally altered the pattern of organizational crisis management. The field in question, namely, technology, is specifically subject to an environment of rapid innovation, global interconnectivity, and increased stakeholder awareness. Social media is a tool that can and does act as the primary source of information (Alboji et al., 2024), an instant rumor mill, and the provider of crisis boosters that allow local incidents to develop into reputation threats worldwide in just several hours (Jin & Austin, 2017). With such a change, there is a need to have tools that can manipulate high, multimodal flows of data in an accurate, fast, and culturally conscious manner.

Social listening. Historically, a manual exercise in monitoring brand references and thematic discussion, social listening has become an AI-enhanced initiative that can analyze millions of text, image, video, and audio posts per minute. Recent developments in the space of natural language processing (NLP), machine learning (ML), and multimodal AI enable organizations to identify danger warnings, visualize the changing perception of stakeholders, and adjust the approach to communication in real time (He et al., 2013; Stieglitz et al., 2018). Studies in Crisis Informatics also endorse the fact that the tools increase the speed of detection, as well as the scope of the coverage, particularly in the multi-platform configurations where human intelligence could be insufficient (Imran et al., 2015, 2020).

Theoretically, AI Powered social listening fits into three mutually supplementary frameworks. First, the Situational Crisis Communication Theory (SCCT) offers an opportunity to customize a response based on crisis type and the perceived responsibility

(Coombs, 2021). Second, Sensemaking Theory helps us understand how organizations can make sense of incomplete, fragmented, or ambiguous crisis cues to generate a coherent explanatory sense to act. Third, Crisis Informatics can point to the changing information flows, verification routes, and network dynamics in a crisis, providing practical ways in the design of AI systems aimed at credibility and trustworthiness.

These frameworks overlap in high-velocity crises, including cybersecurity breaches, flawed product launches, viral misinformation efforts, or strategically guided integrative detection, situational context, and stakeholder communication efforts. But with these capabilities also come great dangers: algorithm bias, platform blind spots, synthetic media manipulation, and black-box decision making. These issues not only demand the enhancement of technologies but also the transparency-based governance that implies the ethical accountability of the authorities and cross-sector cooperation (Blodgett et al., 2020).

This paper consolidates research evidence on the power of social listening with AI through a systematic literature review focusing on SCCT, the Sensemaking Theory, and Crisis Informatics. It draws a trace-map of the transformative and limiting nature of AI-powered social listening within moral and operative realms. The aim is to provide leaders in the technology sector, communication strategy professionals, and operational policymakers with a comprehensive overview of the opportunities and challenges associated with emerging AI-empowered crisis management in the digital age.

2. METHODOLOGY

This paper presents a systematic literature review (SLR) of peer-reviewed articles on AI-powered social listening in crisis management settings. The methodology is PRISMA compliant and makes the study rigorous, transparent, and reproducible in the identification, screening, and analysis of the relevant studies. The search strategy involved database queries conducted in February–March 2025 across Web of Science, Scopus, IEEE Xplore, and Google Scholar, using combinations of keywords such as “AI social listening," "artificial intelligence AND crisis communication," "NLP AND crisis management," "multimodal analytics," and "situational crisis communication theory AND AI." Boolean operators and wildcard symbols were employed to capture a broad yet relevant set of publications.

To maintain relevance and quality, the inclusion criteria restricted the corpus to peer-reviewed journal articles and conference proceedings published between 2013 and 2024, written in English, and directly addressing the application of AI to social listening or crisis management. Studies that focused solely on marketing analytics without crisis relevance, as well as non-peer-reviewed sources, were excluded. The screening process involved a sequential review of titles and abstracts to eliminate irrelevant studies, followed by a full-text evaluation to confirm thematic alignment. After removing duplicates and applying the criteria, a total of 68 studies were selected for analysis.

Each study was systematically coded for technological focus—such as transformer-based natural language processing (NLP), multimodal AI architectures, or domain-specific models—alongside the crisis stage addressed, whether detection, sensemaking, or response. The coding process also noted explicit or implicit theoretical linkages to frameworks such as Situational Crisis Communication Theory (SCCT), Sensemaking Theory, or Crisis Informatics. To ensure reliability, two independent reviewers participated in the coding process, and discrepancies were resolved through discussion. Inter-coder agreement reached 0.86 on Cohen's Kappa, indicating substantial reliability. This structured coding enabled the synthesis of findings in a way that balances technical depth with theoretical and practical relevance.

3. LITERATURE REVIEW

3.1. Crisis Management in the Digital Era

The acceleration of digital communication ecosystems has fundamentally altered the temporal and strategic dimensions of crisis management. Decision-making windows that once spanned days have been compressed into hours, and in specific high-velocity scenarios, mere minutes can determine whether a crisis narrative is mitigated or escalated (Lachlan et al., 2016). In the technology sector, where global user bases and rapid innovation cycles prevail, the risk of reputational damage is amplified by the scale and speed of information flows. The 2020 Tesla battery fire incidents, for example, saw public outrage trending on social media platforms well before the company issued official statements, forcing an immediate shift in communication strategy. Similarly, Zoom's "Zoombombing" crisis escalated virally through Twitter and Reddit before formal corporate acknowledgment, illustrating the need for real-time monitoring and adaptive response.

In such high-velocity contexts, SCCT offers a valuable framework for tailoring responses based on crisis type—whether victim, accidental, or preventable—and perceived organizational responsibility (Coombs, 2021). AI-powered social listening operationalizes SCCT by continuously tracking shifts in attribution narratives in real time, allowing organizations to determine whether they are perceived as victims of circumstance or as negligent actors, and to adjust their communication strategy accordingly. In conjunction with the Sensemaking Theory, the tools enable people to convert their scattered and unclear signals of crisis into a well-structured narrative that can orient the involved strategic decision-making. Furthermore, Crisis Informatics knowledge helps to learn how information used in a situation is produced, authenticated, and shared, which will enable AI systems to identify what is trustworthy knowledge and what is noise and manipulation. Collectively, these frameworks ensure that AI-augmented monitoring is not merely responsive but also proactive in the crafting of narratives.

3.2. AI-Powered Social Listening Technologies

Contemporary AI-derived social listening tools work within compound architectures that synthesize information planning, profound evaluation, and decision aid products. In the first step, large amounts of content from an assortment of sources are accumulated and admitted to a mixture of platforms, such as Twitter/X, Facebook, TikTok, Instagram, Reddit, YouTube, and digital news sources, through APIs or web scraping applications. Such raw data are preprocessed by detecting the language, reducing noise, and normalizing, or compatibility with model analytical models (Stieglitz et al., 2018). The analysis level uses both supervised, including classification, sentiment analysis, and stance detection, and unsupervised, including clustering and topic modeling. Recently, transformer-based architectures (especially Devlin et al., 2019; Liu et al., 2019) are offering the best contextual understanding, and a dedicated version like Crisis BERT (Liu et al., 2019) can further increase the accuracy on tasks relevant when there is a crisis.

The use of Multimodal AI capabilities, such as the CLIP system (Radford et al., 2021), allows going beyond such an analysis to include visual and sound data. This plays a crucial role in a crisis, as painting or video is a vital element in shaping the audience's perspective. As an example, when the Samsung Galaxy Note 7 battery caught fire, all the user-recorded videos of explosions were shared, which amplified reputational damage to an entirely new scale and could not be achieved through text messages. With multimodal AI, these viral visual materials can be identified and marked in just a few minutes, enabling a quicker response. The final decision-support layer displays such insights in real-time dashboards, where they provide sentiment timelines, geospatial mapping, and influencer identification. Nevertheless, due to such possibilities, even the AI system cannot be trusted in an adversarial information environment, as a well-organized disinformation attack may generate a false positive or even remain undetected, thus emphasizing the importance of human-in-the-loop validation (Skitka et al., 2000).

3.3. Applications in Crisis Management

The use of AI in social listening systems has transformed how monitoring tools are applied across the entire crisis lifecycle. Anomaly detection algorithms are applicable in early detection as they track any unusual pattern in discourse, even before it is apparent to mainstream media. Referencing this, it is possible to say that in the example of the 2017 data breach at Equifax, issues related to compromised credit information were discussed in technical forums, even before the event was officially announced, meaning that early warning systems based on AI could have generated more proactive organizational responses. In the same way, the escalation of COVID-19 misinformation on Twitter could be tracked several weeks earlier than it was sanctioned by the community as a health hazard (Imran et al., 2020).

The sensemaking stage can be conducted under the power of AI, which consolidates the story lines that are chaotically dispersed into coherent groups, assisting in definitive communication. As seen in the Facebook-Cambridge Analytica scandal, topic modeling could help distinguish between discussions and communications on data privacy and political manipulation, allowing for targeted messaging to specific audience segments. Because of the possibility to A/B test crisis messages in real-time, where the tone, format, platform choice, and other message-related variables are optimized to achieve maximum positive reception, and with a consideration of the recorded social media dynamics impact on how the audience receives a message and the virality of the message itself (Alboji et al., 2024), the stakeholder engagement process gets enhanced as well. The need to target audiences that are both technically savvy and mass consumers makes this capability particularly relevant in some technology-related crises.

In addition to providing an immediate response to crises, AI-powered systems enable forensic preparedness by modeling probable crisis course of events using past data. A company like Apple can simulate how public sentiment will escalate if an iOS update becomes critical, enabling them to prepare communication and technical mitigation strategies in advance. These proactive functions transform the crisis management paradigm from a reactive approach to a proactive plan that anticipates and contains crises.

4. CHALLENGES, LIMITATIONS AND ETHICAL CONSIDERATIONS

Even though social listening enabled by AI is transformational, it is subject to severe challenges that tamper with its precise accuracy, representativeness, and ethical integrity. The most serious problem is algorithmic bias, where training sets are massed towards English language biases or biased towards Western cultural backgrounds. This has the propensity to cause misinterpretation of sentiment, intent, or cultural application of non-

Western language, resulting in the undermining of credibility of productions in times of multinational crises (Blodgett et al., 2020). To cite an instance, phrases like sarcasm in Arabic, Japanese, or African dialects may be flawed in situational evaluation and may elicit erroneous organizational responses.

Another possible caveat is the issue of platform bias, with the majority of AI surveillance tools being mainly based on publicly available social media networks and ignoring closed networks, encrypted instant messaging platforms, and online communities of interest. Although the sentiment pattern can be observed in the discourse, these blind spots can sideline meaningful discussions that create narratives in closed, non-accessible but powerful areas (Reuter & Kaufhold, 2018). The timing of detection is delayed, and these gaps in crises, such as cybersecurity breaches or concerted disinformation efforts, may impair overall situational awareness.

The emergence of synthetic media, such as deepfake videos, AI-generated articles, and voice clones, increases all these weaknesses. A persuasive yet fake video of an executive making inflammatory remarks may go viral on social media platforms. By the time the organization has a chance to verify or refute the material, the damage is already done (Bender et al., 2021). Unless well-designed detection procedures are in place, AI-driven social listening systems are liable to spread falsehoods as opposed to reducing them.

Ethical issues also aggravate adoption. Social listening on a significant scale, even when drawing on reasonably available content, raises privacy concerns and can have a chilling impact on free speech when viewed as spying. The lack of transparency in AI relationships, specifically in black-box models where decision-making mechanisms are deeply embedded in the algorithm, diminishes trust in crisis measures that rely on AI (Skitka et al., 2000). This needs to include explainable AI (XAI) approaches, compliance with governance regulations like the EU AI Act and the IEEE Ethically Aligned Design principles, and the need to ensure human control to provide a contextual understanding and ethical perspective. Such a multi-layered solution will allow the AI systems to scale not only operational capabilities but also responsibility, fairness, and societal concern.

CONCLUSION AND FUTURE DIREECTIONS

This has led to the development of AI-assisted social listening as a strategic imperative in crisis response within the technology industry, due to its ability to identify threats sooner, offer deeper situational insights, and provide outside-the-box approaches to stakeholder engagement in fast-paced situations. By applying the Situational Crisis Communication Theory, the Sensemaking Theory, and Crisis Informatics, companies can transition from reactive monitoring to proactive tools that foster resilience and trust-building.

The potential of AI in the context of the crisis, however, is still conditional upon the ability to address some significant issues facing the area and the technology, such as algorithmic biases and platform biases, susceptibility to synthetic media, and ethical concerns of privacy and transparency. Unless these issues are closely managed and supervised by humans, it is likely to negatively affect the operational and social utility of crisis management with the help of AI.

AI-powered social listening will take whatever path technical changes in multilingual and multimodal analytics, generative simulation capabilities, and professionalizing ethical principles in the industry will take. Taken together with the collaboration across sector lines and the effective structures of governance, these developments can ascertain that the AI-powered social listening should not only improve the performance of the organization in question, but it will also empower public trust during the times when the speed, complexity, and visibility of digital discourse is more and more closely determining crisis.

In the future, further developments of AI in multilingual and multimodal domains will find solutions to some of the most concerning shortcomings in social listening based on AI. Newer models are more able to make sense of text in low-resource languages, learn culture-specific markers of sentiment, and incorporate different sources of text, audio, and imagery in a complete analysis model (Imran et al., 2020). These advancements have the potential to dramatically minimize platform and language bias, broadening the scope of crisis monitoring systems by encompassing inclusivity and accuracy.

Large language models (LLMs) and other forms of generative AI are proliferating, including generative adversarial networks (GANs). These can further facilitate proactive crisis simulation. Creating simulated yet feasible situations enables organizations to train reaction procedures in the face of elevated-stakes use cases, where running a live test would be too risky due to reputation costs. This is especially applicable to technology companies, where potential crisis triggers, such as security and electronics product failures, can escalate uncontrollably without prior practice in crisis management.

Another frontier is combining behavioral analytics with social listening, driven by the use of AI. This type of integration may progress beyond sentiment tracking to identifying the psychological and behavioral indicators of trust decay or outrage amplification, or mobilization of the community. Identifying these indicators at an early stage allows organizations to modify the communication strategies before such negative stories reach their critical point (Jin & Austin, 2017).

Lastly, AI-powered crisis management will only be sustainable and credible when all sectors are involved in the collaboration. There is a need to establish transparent auditing and ethical compliance standards, along with common norms of accuracy and fairness. This requires collaborative efforts from technology companies, regulators, academic researchers, and civil society organizations. Such collaborative governance can play a crucial role in demonstrating that AI systems are beneficial not only regarding operational purposes of organizations but also when promoting the wide-scale interest of the community to maintain informed and fair crisis communication practices (Reuter & Kaufhold, 2018).

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