UNIVERSITY OF MEDIA, ARTS AND COMMUNICATION

GHANA INSTITUTE OF JOURNALISM

"THE ROLE OF ARTIFICIAL INTELLIGENCE IN ENHANCING CRISIS COMMUNICATION STRATEGIES WITHIN GHANAIAN ORGANIZATIONS

BY

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MPSPRM23006

A DISSERTATION SUBMITTED TO THE UNIVERSITY OF MEDIA, ARTS, AND COMMUNICATION, GHANA INSTITUTE OF JOURNALISM, IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF A MASTER OF PHILOSOPHY IN STRATEGIC PUBLIC RELATIONS MANAGEMENT

AUGUST 2025

DECLARATION BY STUDENT

I hereby declare that this research is a result of my own original research and that no part of it has been presented for another degree in this university or any other higher education institute. I further declare that all the sources that I have used or quoted have been indicated and acknowledged by means of complete references.

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Student **Index number** **Signature** **Date**

CERTIFICATION BY SUPERVISOR

This dissertation has been prepared and presented under my supervision according to the guidelines for supervision and formatting of dissertation laid down by the University of Media, Arts and Communication UniMAC-GIJ.

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Supervisor **Signature** **Date**

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Co-Supervisor **Signature** **Date**

DEDICATION

I dedicate this work to God almighty and to my Late Father Kweku Sackey-Incoom, my Wife Antoinette, children Harrison, Samuella, and Anita for inspiring this journey.

ACKNOWLEDGEMENT

To Almighty God, I have experienced your mercy and grace from the very beginning of this journey till now. Yours remains the glory. Special appreciation to my supervisor, Dr. George Asamoah and Dr. Joshua Doe for their patience, guidance, assistance and encouragement and advice they gave me during the period of this research. My next appreciation goes to the graduate school of UniMac GIJ for making the period of my study on campus that of a blessing. To all my lecturers, I say a big thank you for the impartation of knowledge to prepare me for greater tasks ahead.

ABSTRACT

This study investigates the role of Artificial Intelligence (AI) in enhancing crisis communication strategies within Ghanaian organizations, integrating established theoretical frameworks such as the Situational Crisis Communication Theory (SCCT), the Social Media Crisis Communication (SMCC) Model, and the Diffusion of Innovations Theory. Using a qualitative, exploratory research design within a constructivist paradigm, the study draws on interviews, and document analysis to examine AI's applications across the crisis lifecycle pre-crisis preparedness, real-time engagement, and post-crisis evaluation. Findings reveal that while awareness of AI's potential is growing, adoption remains fragmented, with advanced implementation concentrated in high-risk sectors like banking and telecommunications, and symbolic or sporadic use prevalent in the public sector and SMEs. AI demonstrates strong capabilities in early detection, sentiment analysis, misinformation management, and personalized stakeholder engagement, yet is often deployed reactively, undermining its preventive potential. Ethical challenges, including data privacy, algorithmic bias, and governance gaps, also constrain effective integration. The study concludes that deeper institutional commitment, capacity building, and ethical safeguards are essential for transitioning from fragmented adoption to strategically embedded AI-enabled crisis communication. Recommendations are offered for organizational leaders, policymakers, and technology developers, while future research is encouraged on AI's role in closed-network misinformation detection, culturally adaptive sentiment analysis, and cross-country African comparisons.

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1.0 CHAPTER ONE

INTRODUCTION

1.0 Chapter Overview

Chapter One introduces the study by outlining the background, problem statement, aim, objectives, and research questions. It highlights the significance, scope, and theoretical context of integrating Artificial Intelligence into crisis communication within Ghanaian organizations. The chapter concludes with an outline of the thesis structure, providing a roadmap for the subsequent chapters**.**

1.1 Background of Study

In the modern era, the ability to manage crises effectively is a crucial competency for organizations across the globe. Crises, ranging from natural disasters to financial meltdowns, political instability, or public health emergencies, can severely disrupt the functioning and reputation of organizations. The complexity of these crises, coupled with the rapid pace at which they can unfold, necessitates a robust crisis communication strategy. Traditionally, crisis communication involved managing the flow of information between an organization and its stakeholders to prevent or mitigate damage to the organization's reputation and operations (Coombs, 2007). However, the limitations of conventional approaches are increasingly evident in an age where communication occurs in real-time and on a global scale, primarily through digital platforms. As such, organizations are increasingly turning to innovative technologies like Artificial Intelligence (AI) to enhance their crisis communication capabilities.

AI technologies, particularly machine learning (ML), natural language processing (NLP), and big data analytics, present significant opportunities to revolutionize crisis communication by enabling faster and more data-driven decision-making (Zhao et al., 2017). AI tools can analyze massive amounts of unstructured data, including social media posts, news articles, and internal communications, to extract meaningful insights in real-time. These insights can be used to detect emerging issues, monitor public sentiment, and inform response strategies during a crisis. According to Aggarwal and Subbian (2012), AI-driven analytics enable organizations to identify patterns in communication data that would otherwise go unnoticed, allowing for proactive management of crises. This capability is particularly relevant in today's context, where crises can escalate rapidly through social media platforms, making it essential for organizations to respond quickly.

Crisis communication theories, such as Situational Crisis Communication Theory (SCCT), have historically guided organizations in managing their communication strategies during crises (Coombs, 2004). SCCT posits that the effectiveness of crisis communication is influenced by the organization's responsibility in causing the crisis, as well as the nature of the crisis itself. It categorizes crises into three broad types: victim, accidental, and intentional, with each type requiring a distinct communication approach. For example, in a victim crisis (such as a natural disaster), the organization is seen as a victim, and the focus is on showing empathy and offering support. In an accidental crisis (such as an industrial accident), the organization may be held partially responsible, necessitating a strategy that involves taking corrective action and providing transparency. In intentional crises (such as corporate fraud), where the organization is perceived as fully responsible, the communication strategy must focus on apology and rebuilding trust (Coombs, 2007).

Incorporating AI into the SCCT framework can enhance an organization’s ability to respond to crises by enabling real-time sentiment analysis and stakeholder engagement. For instance, AI tools can analyze social media platforms to track public sentiment, detect early warning signals, and help organizations adjust their communication strategies accordingly. This is particularly important as the digital landscape has altered how crises unfold and how information is disseminated. Social media, in particular, has become a crucial platform where information, including both accurate and misleading content, spreads rapidly, affecting public opinion and organizational reputation (Kavanaugh et al., 2012). AI's ability to process this vast volume of data enables organizations to quickly understand how their actions are being perceived and adjust their communication efforts in real-time.

The integration of AI into crisis communication also allows organizations to personalize their responses to different stakeholders. For example, by using AI-driven chatbots and automated response systems, organizations can deliver tailored messages to specific groups, whether they are employees, customers, investors, or the general public (Ming et al., 2019). These personalized communications, based on real-time data and sentiment analysis, can help build trust and reduce confusion during a crisis. Furthermore, AI can enhance organizational agility by enabling faster decision-making. By using AI to analyze communication trends and identify emerging crises, organizations can adjust their strategies and initiate crisis management protocols before a situation escalates (Faulkner, 2001).

Moreover, AI technologies also facilitate early detection of potential crises by analyzing historical data, identifying patterns, and predicting future risks. This capability is vital for organizations to manage crises effectively, as it helps prevent issues from escalating. Ki and Nekmat (2014) highlight that predictive analytics powered by AI can provide organizations with insights into potential crises, allowing them to prepare proactive crisis communication plans and reduce response times when an actual crisis occurs. Early detection also enables organizations to mobilize resources and initiate damage control measures swiftly, thus minimizing the impact on their operations and reputation.

Despite the promising benefits of AI in crisis communication, its integration presents significant challenges. One of the primary concerns is the ethical implications of AI use, particularly in areas such as data privacy and algorithmic biases. As AI systems increasingly rely on large datasets to inform decision-making, there is a risk of mishandling sensitive information or reinforcing existing biases in data (Crawford, 2016). For example, AI tools may inadvertently amplify negative sentiment or spread misinformation if not properly calibrated. Furthermore, organizations must be cautious about over-reliance on AI, as human oversight remains critical to ensuring that AI-driven communication aligns with ethical standards and organizational values (Fischer et al., 2016). Ethical considerations must therefore be integrated into the design and deployment of AI systems to prevent unintended consequences.

AI's role in crisis communication has been explored in several studies, but there remains a lack of empirical research on the integration of AI with established crisis communication theories like SCCT, especially within the context of African organizations. Existing literature often focuses on general applications of AI in crisis management, with limited attention given to its specific role in enhancing communication strategies (Watson & Rodrigues, 2018). This gap in the literature presents an opportunity to explore how AI can be used to improve crisis communication within Ghanaian organizations, taking into account local cultural and technological factors.

The increasing reliance on digital platforms and the rising volume of real-time communication necessitate a deeper exploration of how AI can improve crisis communication strategies. This study aims to fill this gap by investigating the role of AI in enhancing crisis communication within the context of Ghanaian organizations. By combining theoretical frameworks like SCCT with AI-driven tools, the research will assess how AI can help organizations better understand and respond to public sentiment, predict potential crises, and improve stakeholder engagement during times of crisis. The findings will offer valuable insights for organizations seeking to enhance their crisis communication strategies through the use of innovative technologies, contributing to the broader discourse on AI and organizational management (Baesens et al., 2014).

In conclusion, the integration of AI into crisis communication strategies has the potential to significantly improve organizational responsiveness, agility, and stakeholder engagement during crises. However, ethical challenges and the need for careful implementation remain key considerations for organizations adopting these technologies. By examining the intersection of AI, crisis communication, and organizational reputation, this study will contribute to a deeper understanding of how AI can be effectively leveraged in crisis management, particularly within the unique context of Ghanaian organizations.

1.2 Problem Statement

The landscape of crisis communication in Ghanaian organisations is being reshaped by the rapid diffusion of digital and social media platforms. Crises whether operational failures, reputational threats, social controversies, or public health emergencies now emerge, evolve, and escalate in real time, often driven by user-generated content and networked publics (Austin, Liu, & Jin, 2012; Cheng, 2019). In such environments, social media accelerate the spread of crisis-related information, misinformation, and emotionally charged narratives, intensifying public scrutiny and stakeholder pressure on organisations (Kavanaugh et al., 2012; Jong, 2025). Traditional crisis communication approaches, which rely on manual media monitoring, hierarchical decision-making, and linear message dissemination, are increasingly inadequate for managing the speed, volume, and interactivity of contemporary crisis environments (Coombs, 2007; Coombs, 2022; Taylor et al., 2012). Evidence from Ghana further shows that while organisations and public institutions use social media during crises such as COVID-19 and school fire outbreaks, their communication remains largely reactive and inconsistently aligned with best-practice crisis communication frameworks (Ackaah et al., 2023; Alhassan, 2023).

At the same time, advances in Artificial Intelligence (AI) promise to transform how organisations anticipate, interpret, and respond to crises. AI-driven tools including machine learning, natural language processing, sentiment analysis, and predictive analytics—can scan large volumes of online data, identify weak signals of emerging issues, map stakeholder sentiment, and support rapid adjustment of communication strategies (Aljedani, 2025; Hasan et al., 2025; Wahid, Oussalah, & Imran, 2025). Recent work on AI and crisis communication argues that such tools can enhance core dimensions of crisis communication by informing response strategy selection under Situational Crisis Communication Theory (SCCT), enabling more targeted messaging, and supporting timely, consistent engagement with stakeholders across digital platforms (Coombs, 2007, 2022; Cheng, Jin, & Hung-Baesecke, 2019; "AI and Crisis Communication," 2023). Yet empirical studies also highlight significant limitations: AI-enabled monitoring and sentiment analysis can be biased, opaque, and unevenly effective, and many organisations deploy AI in fragmented or symbolic ways using isolated tools without embedding them systematically in crisis communication planning, decision-making, and learning (Polli, 2023; Wahid et al., 2025).

These tensions are particularly pronounced in emerging economies such as Ghana, where digitalisation, platform use, and data infrastructures are expanding but remain uneven (Wormenor et al., 2025; Gadzekpo, 2025). Much of the empirical literature on AI and crisis communication focuses on organisations in Europe, North America, and parts of Asia, with limited attention to African organisational contexts and their specific regulatory, infrastructural, and socio-cultural conditions (Cheng, 2019; Jong, 2025). In Ghana, existing studies largely examine social media use in crisis management and public communication rather than the strategic adoption of AI-enabled tools per se (Ackaah et al., 2023; Alhassan, 2023). Consequently, little is known about how Ghanaian organisations are incorporating AI across the crisis lifecycle from pre-crisis environmental scanning and early warning, through real-time engagement during crises, to post-crisis evaluation and learning or how these tools interact with established frameworks such as SCCT and the Social-Mediated Crisis Communication (SMCC) model (Austin et al., 2012; Cheng et al., 2019). Moreover, ethical and contextual concerns related to data privacy, algorithmic bias, organisational capabilities, regulatory frameworks, and infrastructural constraints remain underexplored in Ghanaian settings, despite their potential to shape stakeholder trust and organisational legitimacy (Polli, 2023; "AI and Crisis Communication," 2023; Wormenor et al., 2025).

These gaps raise critical questions about how AI is actually being deployed in crisis communication by organisations in Ghana, under what organisational and ethical conditions, and with what implications for stakeholder engagement and reputational outcomes. This study responds to these concerns by examining the current use of AI in crisis communication within selected Ghanaian organisations, exploring how AI can be integrated with traditional models such as SCCT and SMCC to enhance responsiveness and stakeholder engagement, and identifying the ethical and organisational challenges that influence AI adoption. In doing so, the study seeks to provide context-specific, empirically grounded insights that can guide practitioners and policymakers in moving from predominantly reactive, traditional approaches toward more proactive, data-driven, and ethically grounded AI-enabled crisis communication in Ghana

1.3 Aim of the study

The aim of this study is to examine the integration of Artificial Intelligence (AI) technologies with traditional crisis communication frameworks, such as Situational Crisis Communication Theory (SCCT), to develop a more proactive and effective crisis communication model for organizations. Specifically, the study seeks to explore how AI-driven tools, including sentiment analysis, machine learning, and real-time data analytics, can enhance crisis detection, response strategies, and stakeholder engagement, with a focus on organizations in Ghana. This study also aims to identify the ethical challenges associated with the use of AI in crisis communication and provide recommendations for organizations seeking to improve their crisis management strategies in the digital age.

1.4 Research Objectives

1.4.1 To assess the current integration of Artificial Intelligence (AI) technologies in crisis communication practices within organizations in Ghana.

1.4.2 To examine how AI technologies can enhance the effectiveness of traditional crisis communication models, specifically Situational Crisis Communication Theory (SCCT).

1.4.3 To identify the ethical considerations and challenges associated with the use of AI in crisis communication.

1.4.4 To provide recommendations for organizations on how to effectively integrate AI technologies into their crisis communication strategies.

1.5 Research questions

1.5.1 To what extent are Artificial Intelligence (AI) technologies currently integrated into crisis communication practices within organizations in Ghana?

1.5.2 How can AI technologies enhance the effectiveness of traditional crisis communication models, particularly Situational Crisis Communication Theory (SCCT)?

1.5.3 What ethical considerations and challenges arise from the use of AI in crisis communication within organizations in Ghana?

1.5.4 What are the best practices for organizations to effectively integrate AI technologies into their crisis communication strategies in the Ghanaian context?

1.6 Significance of the Study

This study contributes to the growing body of knowledge on the intersection of Artificial Intelligence (AI) and crisis communication, particularly in the Ghanaian context. By examining how AI can enhance traditional crisis communication models such as the Situational Crisis Communication Theory (SCCT), this research extends theoretical understanding and provides new insights into how emerging technologies influence communication practices during crises. Additionally, the study offers a unique perspective on the application of AI in a non-Western setting, adding to the limited academic literature on AI adoption in African organizations. The findings will also help bridge gaps in crisis communication theory by identifying the benefits, limitations, and ethical considerations when integrating AI into crisis management strategies. This work opens up avenues for future research on AI's role in organizational communication practices, crisis management, and its broader social implications.

For organizations in Ghana and other similar emerging markets, the study offers valuable insights into the practical application of AI technologies in crisis communication. Understanding the potential benefits of AI in enhancing message delivery, managing public perception, and automating responses during a crisis can equip organizations with more effective tools for crisis management. Furthermore, the study identifies best practices for integrating AI technologies into crisis communication strategies, which can help organizations better prepare for and respond to unforeseen crises. It also provides guidance on navigating ethical concerns associated with AI usage in communication, such as transparency, accountability, and the protection of stakeholders' privacy. The findings can be directly applied to improve crisis response mechanisms in sectors such as government, business, media, and healthcare in Ghana and similar contexts.

The study has significant implications for policy development, particularly in the areas of digital transformation, crisis management, and communication governance. As AI becomes increasingly embedded in communication practices, there is a need for policies that regulate its use in sensitive areas like crisis communication. This research can inform policymakers about the ethical, legal, and social challenges posed by AI technologies in public communication, guiding the creation of policies that ensure responsible AI adoption. Moreover, the study highlights the need for frameworks that promote transparency and fairness in AI-driven communication practices, which can help mitigate risks associated with algorithmic biases and misinformation during crises. Policymakers can use the findings to design training programs and regulatory measures aimed at improving AI literacy among organizational leaders and communication professionals, ultimately fostering a more informed and ethically responsible use of AI in crisis communication.

1.7 Scope of the study

The scope of this study is focused on examining the role of Artificial Intelligence (AI) in enhancing crisis communication strategies within organizations in Ghana, with particular emphasis on its integration into the Situational Crisis Communication Theory (SCCT). The research investigates how AI tools, such as chatbots, automated message systems, and data analytics, are utilized by organizations during crisis events to manage public perception, streamline communication processes, and ensure timely responses. The study is confined to examining AI applications within the Ghanaian context, with a focus on both public and private sector organizations in industries such as healthcare, media, and business. The study also explores the ethical implications and challenges associated with the use of AI in crisis communication, considering issues like transparency, accountability, and public trust. Through interviews, this research aims to provide insights into the practical, theoretical, and policy implications of AI adoption in crisis management within Ghanaian organizations.

1.8 Organization of the study

This study is organized into five chapters. Chapter One introduces the research, outlining the background, problem statement, research objectives, research questions, and the significance of the study in terms of academia, practice, and policy. Chapter Two provides a comprehensive literature review, examining relevant theories, previous studies, and the role of Artificial Intelligence in crisis communication, particularly within the framework of Situational Crisis Communication Theory (SCCT). Chapter Three details the research methodology, explaining the research design, data collection methods, sampling procedures, and data analysis techniques used in the study. Chapter Four presents the results and analysis of the collected data, discussing key findings in relation to the research objectives and questions. Finally, Chapter Five offers a discussion of the findings, conclusions, recommendations, and areas for further research, highlighting the contributions of the study to existing knowledge on AI and crisis communication.

CHAPTER TWO

LITERATURE REVIEW

2.0 Chapter Overview

Chapter Two of this study provides a comprehensive literature review that explores the theoretical foundations and empirical research related to Artificial Intelligence (AI) in crisis communication. It begins by examining key concepts such as crisis communication, the role of AI technologies in communication strategies, and the relevance of Situational Crisis Communication Theory (SCCT) in the context of modern crisis management. The chapter then reviews existing studies that investigate AI’s impact on communication practices in crisis situations, focusing on both the potential benefits and challenges. It also highlights seminal works and recent advancements in AI adoption across industries, particularly in public relations and crisis management, drawing connections between past research and the current study’s focus. The chapter concludes by identifying gaps in the literature, which this study aims to address, and setting the stage for the subsequent research methodology.

2.1 The Concept of Public Relations

Berkowitz (2017), defined Public Relations as the management function that identifies, establishes, and maintains mutually beneficial relationships between an organization and its various stakeholders. The most basic function of management is communication, which contributes to establishing managerial and organizational performance (Kapur, 2018). Public Relations is a unique management function that aids in establishing and maintaining channels of communication, understanding, acceptance, and cooperation between an organization and the general public. It also involves managing problems or issues, assisting management in staying informed about and responsive to public opinion, defines and emphasizing management's duty to serve the public interest, and aids management in staying current with and utilizing change

(Mykanen & Vos 2015). Kapur (2018) opine that Public Relations is a distinct management function that assists in the establishment and maintenance of lines of communication, understanding, acceptance, and cooperation between an organization and its public; it involves the management of problems or issues; it assists management in staying informed on, and responsive to, public opinion; it defines and emphasizes management's responsibility to serve the public interest; it assists management in staying abreast of, and effectively utilizing, change; and it serves as a resource for management. Public Relations is the social science and art of studying trends, foreseeing their effects, advising organization leaders, and carrying out pre-planned action plans that will benefit both the organization and the general public (Geremew, 2017). The Public Relations function is a management function that assesses public opinions, acknowledges the public, and suggests tactics for a specific association of activity to acquire open understanding and acknowledgment (Djoleto, 2016). Oparaugo and Salihu (2019) stated that Public Relations (PR) is a tactic used to connect an organization's policies and programs with its target audience to foster trust and goodwill. Public Relations has been proven to be a successful strategy for reaching the desired audience because its main objective is to convey information that will have an impact on people (Geremew, 2017). Public Relations professionals are also involved in a variety of tasks or duties, such as media relations and placement, organizing, writing, editing, speaking, training, and management. These tasks and duties may include research, strategic planning, counseling, communication, evaluation, and media relations (Oparaugo & Salihu 2019). Public Relations is indeed a unique kind of management activity that support growing public awareness, acceptance, and cooperation. Concerns or issues with management are also involved. By defining and emphasizing management's duty to serve the public interest, assisting management in utilizing change effectively, serving as an early warning system to help management anticipate trends, and primarily using research and ethical communication techniques, Public Relations also helps management stay informed of and responsive to public opinion (Sakar, 2018). The definitions of Oparaugo and Salihu (2019), Cutlip, Centre, and Broom (1985), Stokes & Rubie, (2010) and other research (Sackey-Rockson et al., 2017; Oparaugo & Salihu, 2019: Geremew, 2017) have revealed that Public Relations act as a management function. In doing that, it tries to connect and link the company and its customers together.

2.2 The Concept of Artificial Intelligence

Artificial Intelligence (AI), first mentioned in the 1956 Summer Project report by John McCarthy's Dartmouth, is a groundbreaking technology that imitates human thinking and facilitates various services like AI-based face recognition, voice recognition, Natural Language Processing, and robotic processes (Samala et al., 2020). AI is commonly defined as the intelligence displayed by machines, enabling computers to perform tasks considered intelligent when executed by humans (Shieber, 2004; Brooks, 1991). However, intelligence encompasses multiple aspects, including learning, planning, problem-solving, understanding, self-awareness, emotional knowledge, reasoning, creativity, logic, and critical thinking (Kellermann et al., 2019; Legg & Hutter, 2007). In business operations, AI refers to integrating technology to enhance various functions such as sales, marketing, finance, problem-solving, decision-making, and innovation modelling (Dellermann et al., 2019). AI's intelligence in perceiving work environments and interactions while performing tasks is achieved through software architectures and advanced technology systems (Varlamov, 2021). The adoption of AI, particularly chatbot e-services, has seen rapid growth in digital marketing and interactive messaging across different industries (Kietzmann & Pitt, 2020). AI, often called machine learning infrastructure, employs algorithms for deep learning and data processing, functioning as business consoles and choreographers, aiming to incorporate intelligent and error-free decision-making processes and work schedules (Connock, 2022). Integrating AI and automation can reshape the marketing function, enhancing organizational goals and overall efficiency when used in conjunction with human resources and technology (Vishnoi et al., 2018). In the digital age, AI plays a crucial role in improving customer and client experience by effectively managing and interpreting large-scale customer data that would be overwhelming for humans to handle (Ma & Sun, 2020).

2.3 Artificial Intelligence (AI): A Transformative Force in Modern Technology

Narrow AI, often referred to as Weak AI, stands as the epitome of task-specific artificial intelligence, geared to excel in precise problem-solving realms (Russell & Norvig, 2020). This specialized form of AI is akin to a highly skilled expert, diligently handling well-defined tasks. Imagine a virtual personal assistant such as Apple's Siri or Amazon's Alexa. These remarkable creations have a remarkable ability to comprehend and respond to human voice commands, swiftly retrieving information, setting reminders, and even orchestrating a symphony of smart home devices with the utterance of a single sentence (Russell & Norvig, 2020). Furthermore, recommendation algorithms that govern our content consumption habits are quintessential examples of Narrow AI in action. Every time you find yourself engrossed in a YouTube rabbit hole or discovering a new favorite show on Netflix, you can attribute your enjoyment to these AI-driven recommendation systems (Bakhshandeh et al., 2021). These algorithms analyze your viewing history, preferences, and user behavior, skillfully predicting and suggesting content tailored to your taste. As a result, your online experiences are enriched, and the platforms retain your loyalty and engagement. The magic of Narrow AI lies in its meticulous craftsmanship to tackle specific problems with unmatched efficiency. These systems thrive in environments where tasks are well-defined, rules are structured, and outcomes are precise. The applications of Narrow AI extend far and wide, impacting daily life and various industries.

On the other end of the AI spectrum stands General AI, or Strong AI, an ambition that has tantalized the minds of computer scientists and futurists for decades (Russell & Norvig, 2020). In contrast to Narrow AI, which is limited to specific domains, General AI aspires to mimic the vast expanse of human cognitive abilities. The goal is to create machines that don't merely specialize in one task but possess the broad capacity to understand, learn, and adapt to a myriad of intellectual challenges, just as humans do.

Think of General AI as the polymath of the AI world, capable of engaging in problem-solving, creative thinking, and adapting to an ever-evolving landscape of tasks without the need for specialized programming (Russell & Norvig, 2020). While Narrow AI is already making waves in practical applications, the dream of General AI is still a work in progress, with research and development efforts stretching on.

The theoretical potential of General AI is virtually boundless. It has the potential to revolutionize the way we approach problems, unlocking new frontiers in medicine, science, and industry. Imagine an AI system that, like a human expert, could analyze a medical condition, propose innovative research approaches, compose symphonies, or even discover new scientific theories these are the possibilities General AI holds within its grasp. While we are not there yet, the quest to unlock the full spectrum of human-like intelligence remains a tantalizing endeavor.

The influence of AI, whether in the form of Narrow or General AI, resonates across a multitude of industries, igniting a wave of innovation and reshaping the way we live and work. These AI technologies have not only streamlined and improved existing processes but have also unlocked entirely new possibilities. In the field of healthcare, AI, particularly machine learning algorithms, is making significant strides. These algorithms are being employed to diagnose medical conditions, predict patient outcomes, and assist in drug discovery (Obermeyer et al., 2016). They have become invaluable tools for healthcare professionals, offering insights and augmenting diagnostic capabilities. In finance, AI-driven trading systems have revolutionized the landscape. These systems analyze vast datasets at lightning speed, executing trades with precision (Napoli, 2020). The ability to process and act on market information in real-time has redefined trading strategies and amplified opportunities for investors and financial institutions. Transportation has also witnessed a seismic shift due to AI. Autonomous vehicles rely on AI for perception, navigation, and decision-making, promising a future of safer and more efficient transportation (Bojarski et al., 2016). These self-driving cars have the potential to reduce accidents and redefine urban mobility. Moreover, AI chatbots and virtual agents are increasingly common in the realm of customer service, significantly improving user interactions. These AI-driven virtual agents offer timely responses and assistance, enhancing customer satisfaction and reducing service response times (Vas et al., 2020). In conclusion, AI, in its myriad forms, has become a defining force in contemporary technology, and its impact on our lives is profound. Whether in the realm of Narrow AI, designed for specific tasks, or the aspirational General AI, the world of artificial intelligence is in constant evolution, promising a future of boundless possibilities. From healthcare to finance, transportation, and customer service, the applications of AI continue to grow, shaping industries and fostering innovation in ways previously thought unimaginable. As AI continues to advance, it will undoubtedly leave an indelible mark on our society and the way we perceive the world.

2.4 Artificial Intelligence and Public Relations Practice

In recent years, the intersection of Artificial Intelligence (AI) and Public Relations (PR) has garnered increasing attention within scholarly and professional circles. Scholars have explored how AI technologies are revolutionizing PR practices, enabling more data-driven strategies and enhancing communication with stakeholders. Scholars such as Johnston (2018) emphasize the transformative potential of AI in PR, highlighting its ability to analyze vast amounts of data quickly and derive actionable insights for crafting targeted messages. This sentiment is echoed by Harris and Rae (2019), who discuss the role of AI in real-time media monitoring, enabling PR professionals to track brand mentions and sentiment across various platforms with unprecedented accuracy. AI's impact on stakeholder engagement is a prominent theme in the literature. Petersen and Jaeger (2020) discuss the rise of AI-driven chatbots and virtual assistants in facilitating personalized communication with audiences. They underline the efficiency and 24/7 availability of these AI tools, contributing to improved user experiences. Predictive analytics, another hallmark of AI, has emerged as a crucial aspect of PR strategy. Smith and Wang (2019) delve into how predictive analytics algorithms analyze historical data to forecast PR outcomes and trends. This empowers PR practitioners with insights for strategic planning and crisis management. Ethical considerations are also a focal point in the literature. Sanders and McKie (2021) explore the ethical implications of AI-generated content in PR campaigns. They discuss concerns about maintaining authenticity and transparency while leveraging AI to craft personalized messages, calling for responsible AI usage. While the potential benefits of AI in PR are evident, challenges persist. Smith and Brown (2018) underscore the need for PR professionals to develop AI literacy to harness AI's full potential. They discuss the learning curve associated with integrating AI tools into established PR practices. Pearson (2019) asserts that’s AI's integration into PR practices is transformative. From real-time media monitoring to personalized communication and predictive analytics, AI offers opportunities for improved efficiency and effectiveness. However, ethical considerations and the necessity for adapting skill sets remain critical areas of discussion. As the PR landscape continues to evolve, understanding the interplay between AI and PR is essential for practitioners to navigate the opportunities and challenges that lie ahead (Haudi et al., 2022).

2.4.1 Crisis

Crisis as a term is generally applicable to a variety of situations that are characterized by unpredictability and unwanted uncertainty that causes disbelief (Rosenthal et al., 2001; Stern & Sundelius, 2002). It most often refers to an unexpected single event that poses a threat to an organization's goals or even its survival (Bundy et al., 2017; Kovoor-Misra et al., 2000). Coombs (2007) means that if a crisis is not handled adequately, it can lead to damages to organizational finance, reputation, and public safety. Since a crisis is seen as a significant threat to an organization and its core values and structures, and since it develops in an uncertain and unexpected manner, it creates high pressure and a need for fast-paced critical decision-making (Boin et al., 2004; McConnell & Drennan, 2006). However, Hart and Boin (2001) note that knowing when to act against it can be difficult as the nature of a crisis is subjective. They explain that a situation can only be labeled as a crisis if the people concerned and affected view it as such. This theorem, and the fact that different individuals can be affected by the same crisis at different times, make both the beginning and end of a crisis impossible to pinpoint. Even so, Ritchie (2004) presents the existence of three different types of crises that have different time horizons. The first is an immediate crisis. The second is an emerging crisis that slowly develops over a period. The third is a sustained crisis which, as the name implies, lasts for a long time. Crises represent unforeseeable occurrences marked by substantial levels of uncertainty and ambiguity, as articulated by Coombs (2019). To effectively prepare for and respond to such crises, organizations often designate a crisis management team (CMT). This group of individuals, appointed by the CEO or another senior management member, is responsible for managing crises, as outlined by Frandsen and Johansen (2017). Jaques (2009) noted that various definitions of crisis communication can be grouped into two categories: one defining a crisis as an isolated event, as seen in the works of Coombs (2007, 2015), Fearn-Banks (2011), Sohn and Lariscy (2014), and the other considering a crisis as part of a larger process, as exemplified by Pauchant and Mitroff (1992), Roux-Dufort (2007), and Shrivastava (1993). For the purposes of this study, the definition put forth by Coombs (2015) is adopted, which characterizes a crisis as "an unpredictable event that threatens important expectations of stakeholders and can seriously impact an organization's performance and generate negative outcomes". Two primary justifications for this choice are presented below. Firstly, by categorizing crises as discrete events, this study not only directly identifies the crisis's name but also scrutinizes crisis variables such as crisis types and the timing of crisis events. These variables serve as critical dimensions for conducting a comprehensive examination of the nature of a crisis, as emphasized by Pearson and Mitroff (1993). Secondly, by adhering to Coombs's (2015) widely accepted classification, this study can clearly partition the crisis into three distinct stages for analysis: the pre-crisis phase (encompassing signal detection, prevention, and preparation), the crisis event phase (involving recognition and containment), and the post-crisis phase (comprising evaluation, learning, and follow-up communication)

2.5 Crisis Communication

In the field of crisis management, the unforeseeable nature of crises explains the urgency of swift and well-executed restorative actions. Communication has long been recognized as a pivotal element in crisis response, as acknowledged by Barton (2001), Fearn-Banks (2002), and Coombs (2009). As such, crisis communication can be defined as the process of gathering, processing, and transmitting information necessary for addressing a crisis, as articulated by Coombs (2010:). Crisis management is defined as a comprehensive set of measures aimed at combating crises and mitigating the actual damage caused by them, as defined by Coombs (2015). Drawing insights from the field of emergency preparedness, crisis management encompasses four closely connected elements: prevention, preparation, response, and revision (Coombs, 2015). These elements are integrated into a widely adopted three-stage framework that delineates crisis management's involvement in three distinct phases: the pre-crisis phase (encompassing prevention and preparation), the crisis phase (comprising response), and the post-crisis phase (entailing learning and revision). Understanding the four distinct phases of a crisis namely, the potential crisis phase, the latent crisis phase, the acute crisis phase, and the post-crisis period provides valuable insights into crisis dynamics. Equipped with knowledge of these phases, one can formulate an appropriate response strategy.

2.6 Chatbot Technology

As noted by Chakrabarty, Widing, and Brown (2014), service agents play a pivotal role in resolving customer issues and shaping purchase decisions through positive interactions. Building authentic, friendly, and genuine relationships between salespeople and customers is essential to ensure mutually beneficial experiences (Gautam & Sharma, 2017). In today's era of digital marketing and artificial intelligence, as companies embrace globalization and aim for stronger connections with their audiences, the role of service agents is evolving (Bolton et al., 2013). The advancement of artificial intelligence and the growing importance of digital marketing has led various industries, including insurance, banking, retail, travel, healthcare, and education, to effectively utilize robotic virtual characters, such as chatbots, to assist customers via desktop interfaces (Aithal & Aithal, 2019). These chatbots are virtual conversational service robots engaging in human-computer interactions, facilitating interactive and verbal exchanges with humans (Przegalinska et al., 2019). Chatbots are increasingly prominent in simplifying and personalizing access to digital services. They emulate human-like conversations and act as digital guides or virtual assistants, providing personalized support on smartphones and other devices, regardless of location and time (Araujo, 2018; Scarpellini & Lim, 2020; Fleisch, Franz, & Herrmann, 2021; Youn & Jin, 2021). These computer programs possess natural language capabilities and can engage in conversations with human users, providing automated guidance to facilitate decision-making (Tintarev et al., 2016). The chatbot ecosystem includes voice-driven digital assistants like Siri, Cortana, Alexa, and Google Home, as well as text-based systems used on instant messaging platforms. As stated by Ciechanowski et al. (2019), the primary aim of chatbot systems is to replicate human conversation and deploy well-trained chatbots widely across various domains, including business, education, and information retrieval. Chatbots use text-based dialogue systems to mimic human language and are increasingly employed to enhance customer service and personalization processes (Przegalinska et al., 2019; Zumstein & Hundertmark, 2017). The rise of chatbots aims to simplify and humanize access to digital services, engaging users in human-like conversations and serving as digital guides or virtual assistants, providing individualized support on smartphones or other devices anytime, anywhere (Araujo, 2018; Scarpellini & Lim, 2020; Fleisch et al., 2021). Chatbots have the ability to engage with customers by asking open-ended questions and ensuring continuous interaction, regardless of business hours, as highlighted in a study by McKinsey and Company in 2019. What distinguishes chatbots from other AI technologies is their capacity to autonomously promote products and process orders without requiring human intervention, effectively assisting shoppers in achieving their purchasing objectives, as noted by Pantano and Pizzi in 2020. Consequently, chatbots enable consumers to make the most of their time by offering recommendations based on past conversations, purchase histories, and buying patterns, as discussed in various studies (Chung et al., 2019; Zhang & Dholakia, 2018; Shumanov & Johnson, 2021; Kaczorowska-Spychalska, 2019; Zumstein and Hundertmark, 2017).

Furthermore, they provide insights regarding product availability and performance. Moreover, chatbots enhance the entire customer purchasing journey, covering discovery, desire, purchase, distribution, and subsequent repurchases, as highlighted by Kaczorowska-Spychalska in 2019. It is essential to carefully consider the framing used when describing these virtual agents, including the type of relationship emphasized, as it can influence consumer perceptions and the social interaction attributed to the chatbot, as pointed out by Araujo in 2018. To effectively implement chatbots, AI developers and companies must possess a deep understanding of how to introduce them to consumers in a compelling manner. According to Kaczorowska-Spychalska (2019), chatbot agents have emerged as an innovative and enjoyable approach to satisfying clients, similar to the services provided by traditional offline service agents. Historically, these agents have played a crucial role in determining the success of service exchanges, representing the brand, fostering customer/brand relationships, and delivering personalized and engaging shopping experiences. By 2020, it is anticipated that chatbot technology will be integrated into around 25% of customer service processes, leading to more frequent daily conversations between individuals and chatbots compared to their partners (Gartner, 2016). When chatbots are utilized independently of human agents for customer service, they are categorized as self-service technologies (Van Doorn et al., 2017). The increasing prevalence of chatbots is evident in the development of thousands of chatbots by major technology companies, social media platforms, and research labs, with approximately 30,000 chatbots launched on messaging platforms like Facebook in the US market alone (Dale, 2016). Over the past decade, chatbots have significantly improved in terms of quality and quantity, finding applications in various industries, including marketing, healthcare, entertainment, education, and cultural heritage (Adamopoulou & Moussiades, 2020).

2.7 The Role of Artificial Intelligence in Enhancing Crisis Communication Strategies

Artificial Intelligence (AI) has revolutionized various sectors, with its applications extending significantly into crisis communication. AI technologies, including Natural Language Processing (NLP), machine learning, and data analytics, have demonstrated immense potential in managing and responding to crises. Scholars have increasingly explored how AI can transform crisis communication by enabling quick decision-making and proactive responses, particularly through AI-driven tools like chatbots and predictive analytics (Nguyen et al., 2017). These systems process vast amounts of unstructured data from sources such as social media, news outlets, and government alerts, facilitating rapid identification of emerging crises and timely interventions by crisis management authorities (Park & Cho, 2015). AI's influence spans the entire crisis lifecycle, from pre-crisis preparedness to post-crisis evaluation, significantly enhancing communication strategies at each stage.

2.7.1 Pre-Crisis: AI-Powered Scanning and Early Detection

AI-powered scanning plays a crucial role in pre-crisis stages, focusing on automated information scanning and predictive analytics. Through automated scanning, AI systems process large volumes of diverse data in real-time, allowing crisis communicators to quickly understand the evolving situation and identify trends. This capability is particularly beneficial in situations like natural disasters, cyberattacks, and pandemics, where rapid information processing can be the difference between life and death. AI technologies such as convolutional neural networks (CNNs) can even scan satellite imagery to detect crisis-related damages like flooding and building destruction

(Fujita et al., 2017). Furthermore, AI-powered language processing systems are capable of extracting vital information, such as threats and locations, from emergency communications (Aboualola et al., 2023). By automating repetitive tasks, AI frees up human resources to focus on higher-value activities that demand critical thinking and creativity, enhancing the overall efficiency of crisis management (Nishant et al., 2020).

Another significant aspect of AI in crisis communication is predictive analytics. AI algorithms leverage historical data to predict potential crises, enabling proactive crisis management. By analyzing past events and communication patterns, AI can forecast scenarios like natural disasters and social unrest, providing organizations with valuable insights for preemptive action (Vladu, 2023). For example, AI techniques like deep learning and Long Short-Term Memory (LSTM) networks can predict crowd movements and potential crisis triggers, allowing authorities to respond appropriately before a situation escalates (Aboualola et al., 2023). Predictive models also assist organizations in identifying emerging internal crises by analyzing communication patterns such as emails, helping prevent issues from spiraling out of control (Farrokhi et al., 2020).

2.7.2 During Crises: Real-time Engagement, Monitoring, and Personalized Communication

During a crisis, real-time engagement, monitoring, and personalized communication are vital components of effective crisis management. AI-driven chatbots are particularly valuable in this context, offering immediate responses to public inquiries and ensuring the rapid dissemination of accurate, timely information. These AI systems have a significant impact on public perception and the prevention of misinformation. Chatbots are designed to simulate human interaction, providing instant answers to questions and facilitating communication through popular messaging platforms (Cheng & Jiang, 2022). The integration of AI into social media channels, especially by public health organizations, has proven to be highly effective in maintaining two-way communication with the public, enhancing engagement and response during crises (Kim et al., 2022).

Moreover, AI's real-time monitoring capabilities contribute significantly to situational awareness, allowing crisis management teams to track developments, assess public sentiment, and adapt their strategies accordingly. The use of AI in this context ensures that stakeholders receive relevant and personalized information tailored to their specific needs, improving the effectiveness of communication and the overall crisis response. By enabling quick and accurate dissemination of information, AI enhances the ability of organizations and authorities to manage crises effectively and efficiently.

2.8 Monitoring and Sentiment Analysis

AI, especially through machine learning techniques, has become crucial in monitoring social media platforms, enabling real-time tracking of trends, public sentiment, and emerging issues. Wong (2021) highlights AI's capacity to anticipate changes in public sentiment and identify potential crisis triggers by analyzing diverse social media platforms. This proactive approach allows crisis communicators to stay ahead of developments, adapting strategies as the situation evolves. For instance, AI-driven systems like the AIDR project (Imran et al., 2015) can scrutinize platforms like Twitter and Facebook, identifying key terms and detecting rumors or misinformation that may signal a developing crisis.

Sentiment analysis, a key function of AI monitoring, is particularly valuable in understanding public perception during a crisis. By analyzing emotional responses in social media conversations, AI tools provide predictive insights that help organizations anticipate public reactions and tailor their crisis communication strategies accordingly (Farrokhi et al., 2020). For example, NRC-based sentiment analysis, as demonstrated by Kaur et al. (2021), analyzes how leaders express emotions during crises, focusing on the importance of trust and positive emotions in effective communication. Additionally, AI's ability to analyze sentiment in real-time, as discussed by Rahman et al. (2023), enables immediate understanding of public sentiment, critical for crisis management.

2.9 Detecting and Combating Misinformation

One of the most critical roles of AI in crisis communication is its ability to identify and combat misinformation. AI's capacity to detect deepfake content manipulated images, videos, or audio plays a significant role in filtering out misleading or false information that could escalate a crisis. Governments and organizations worldwide, including those in Indonesia, the United Kingdom, and the World Health Organization, have employed AI-powered tools like chatbots to counteract misinformation during events like the COVID-19 pandemic (Untari, 2020). These AI-driven systems provide real-time, accurate information, addressing public concerns and managing sentiments effectively.

Moreover, AI techniques such as content analysis and computer vision algorithms can detect misinformation in both textual and visual content. Textual anomaly detection identifies suspicious claims, while computer vision algorithms can filter irrelevant media, ensuring that crisis responses focus on credible information. Research by Rana et al. (2022) suggests that deep learning-based methods are particularly effective in deepfake detection, proving AI's proficiency in this critical area.

2.10 Personalized Communication for Specific Demographics

Another promising application of AI in crisis communication is its ability to provide personalized communication. AI allows organizations to tailor messages based on individual preferences, behaviors, and needs, ensuring that information is relevant and effectively reaches specific demographics. This personalized approach is essential for managing crises, as it helps prevent the spread of misinformation and ensures that crucial information is communicated to the right people at the right time.

AI-driven tools like chatbots and virtual assistants excel in personalizing communication during crises. These tools offer immediate, consistent, and accessible responses to affected populations, significantly improving engagement and ensuring that no one is left behind during a crisis. AI-powered chatbots in the digital mental health sector, for example, use Big Data, NLP, and machine learning to provide supportive, empathetic communication during times of crisis (Balcombe, 2023). By acting as conversational agents, these AI systems foster a sense of social companionship, offering not only information but also emotional support during challenging times (Chaturvedi et al., 2023).

2.11 Post-Crisis: Assessing and Learning with AI Insights

In the post-crisis phase, AI plays a crucial role in evaluating the effectiveness of crisis communication strategies and ensuring that lessons are learned for future preparedness. This phase focuses on assessing the impact of the communication efforts, understanding how stakeholders perceived the response, and making adjustments to future strategies. AI's capabilities in data analytics, sentiment analysis, and pattern recognition provide organizations with the tools they need to conduct comprehensive assessments and enhance future crisis management.

AI is particularly instrumental in analyzing the reach and engagement of communication efforts. By processing large volumes of unstructured social media data, AI can provide insights into how crisis communications resonated with different audiences. Sentiment analysis helps organizations assess whether their messages were received as intended and how they affected public perception. Machine learning algorithms, as noted by Nishant et al. (2020), are effective at processing complex data, offering actionable insights into public sentiment. Real-time sentiment analysis, as emphasized by Bruns and Burgess (2015), helps determine whether communication strategies were successful in mitigating negative sentiments and fostering trust.

AI's ability to identify patterns and trends in social media data is invaluable for post-crisis feedback. Tools powered by AI can detect recurring themes, emotional shifts, and emerging issues in the data, helping organizations assess the effectiveness of their communication strategies. This analysis can reveal gaps in communication, allowing organizations to refine their strategies. As noted by Stieglitz et al. (2018), AI provides a comprehensive view of how public sentiment evolves over time, offering crucial feedback on the long-term effectiveness of crisis communication.

Another important function of AI is benchmarking and comparative analysis. AI allows organizations to compare their crisis response data with historical events and industry standards. This benchmarking process enables organizations to understand how their crisis communication strategies align with best practices and identify areas for improvement. As Reynolds and Seeger (2005) suggest, such comparative analysis is vital for refining crisis management processes and aligning them with industry standards. By leveraging AI's data processing capabilities, organizations can extract detailed insights, highlight strengths, and pinpoint areas that need attention.

AI also plays a vital role in continuous monitoring and risk assessment post-crisis. Through Big Data analytics and pattern recognition, AI detects subtle shifts in public sentiment or operational anomalies, signaling emerging risks or concerns. Research by Dubey et al. (2022) illustrates how AI-driven analytics enhance an organization's adaptability, enabling them to address new challenges as they arise. This ongoing monitoring ensures that organizations remain resilient and proactive, prepared for future crises.

Furthermore, AI facilitates organizational learning in the post-crisis phase. By analyzing data from the crisis response and integrating stakeholder feedback, AI enables organizations to refine their crisis management strategies. Gupta and George (2016) highlight how continuous learning, driven by AI, equips organizations to handle future crises more effectively. The data processing strength of AI ensures that organizations can make informed adjustments to their communication strategies, turning each crisis into an opportunity for growth.

AI-powered tools, like chatbots, also play a key role in the educational aspects of crisis communication. Chatbots provide timely, accurate information to affected populations, offer emotional support, and address inquiries from stakeholders. As Essel et al. (2022) observe, these AI tools act as virtual teaching assistants, helping educate individuals on the crisis and available resources. Chatbots, as highlighted by Diederich et al. (2019), are also highly effective in handling large volumes of inquiries, reducing the burden on human responders while maintaining consistent communication. The role of chatbots in providing real-time information and emotional support enhances stakeholder engagement, helping to build long-term trust a crucial factor in post-crisis relationship management, as noted by Van der Meer & Verhoeven (2013).

2.12 Ethical Considerations in AI for Crisis Communication

The use of AI in crisis communication, while offering numerous advantages, also presents significant ethical challenges, particularly concerning data privacy and security. AI tools, which are crucial in managing, analyzing, and disseminating information during crises, must be used responsibly to ensure the trust and safety of those affected by the crisis. One of the most pressing concerns is the collection and use of sensitive personal data. A case in point is the controversy surrounding the South Korean AI chatbot, Lee-Luda, which collected intimate conversations between couples without proper consent for AI training. This violation of privacy highlighted the serious ethical implications of AI’s role in data collection, especially in crisis communication scenarios where trust and confidentiality are paramount. Public backlash against such violations underscores the importance of implementing ethical AI practices to protect privacy.

The ethical responsibility in AI-driven crisis communication extends beyond meeting legal requirements; it is central to maintaining public trust. Individuals are more likely to engage with crisis communication efforts if they believe their data is handled with care and confidentiality. When organizations fail to protect personal data or misuse it, as in the case of Lee-Luda, it can lead to public mistrust, damage the effectiveness of crisis responses, and cause harm to individuals whose data is mishandled or exposed. Data privacy is, therefore, not just a legal issue, but a fundamental aspect of ethical AI systems.

In crisis communication, AI’s role in rapid data analysis and predictive modeling often involves processing sensitive personal information. As noted by Lee and Meng (2021), communication professionals need to have strong digital competencies, including a thorough understanding of privacy and security standards within AI systems. This requires compliance with regulations such as the General Data Protection Regulation (GDPR) and adherence to privacy and security frameworks set by international bodies. These regulatory and ethical frameworks ensure that AI systems are designed and operated in a way that prioritizes data protection while maintaining transparency and accountability.

The challenge of balancing the urgent need for crisis response with the ethical obligation to protect personal data is one of the key dilemmas in AI-driven crisis communication. As technology evolves, AI systems must be developed with built-in privacy and security protections. This involves continuous research into AI ethics, ongoing policy development, and active collaboration with stakeholders to ensure that AI tools are used responsibly. Transparency in AI’s data collection and usage processes is essential. Stakeholders must be fully informed about how their data is being used, with clear policies on data usage and regular audits to ensure compliance with privacy standards.

The future of AI in crisis communication depends on the ability to integrate data privacy and security into the core of AI systems. Addressing ethical concerns in AI for crisis communication requires a multifaceted approach that combines technical measures, regulatory adherence, and ethical decision-making. AI must continue to enhance crisis communication, but it must do so in a way that respects the privacy and security of the individuals it serves. Ongoing engagement with stakeholders, continuous improvement of ethical guidelines, and robust privacy measures are essential to the responsible use of AI in crisis communication.

2.13 Theoretical Framework

A strong theoretical framework is essential in the fields of crisis management and public agency governance. Theoretical frameworks offer insights into the subtleties of how organizations anticipate, respond to, and recover from crises. They serve as the conceptual framework on which our understanding of crisis management is constructed. An essential starting point for the investigation of crisis management in public organizations is this theoretical review part.

Social Media Crisis Communication (SMCC) Model

According to Jin et al. (2014), the Social Media Crisis Communication (SMCC) model demonstrates the dynamics of how social media influencers and their followers react to an organizational crisis. This paradigm is extremely useful for understanding how digital audiences interact with businesses in crisis situations and in social media environments.

The SMCC model, introduced by Austin et al. (2012), was designed to investigate how individuals and organizations utilize social media in the midst of organizational crises. This model delineates the fluid exchange of information between an organization and digital audiences before, during, and after a crisis. It does so by spotlighting three distinct categories of digital audiences during crises: influential creators on social media who generate crisis-related content, followers on social media who consume the content created by these influencers, and individuals who remain passive on social media. In our research, we specifically concentrate on influential social media creators and their followers. On platforms like Facebook, active-digital audiences have the opportunity to actively contribute to the creation and dissemination of crisis-related information (Wei et al., 2012). These active-digital audiences discern when an organizational crisis unfolds and respond by posting or sharing content on social media. It is crucial to note that the concept of communicative activities has long been employed in the field of public relations to elucidate the behaviors of active audiences. In the realm of public relations research, the term "active publics" pertains to a group of individuals who engage in discussions and take actions to address issues (Kim & Grunig, 2011). According to a recently formulated model on social media activism, the act of posting or retweeting plays a pivotal role in predicting collective public responses and actions (Chon & Park, 2020).

The Social Media Crisis Communication (SMCC) model offers a useful framework for comprehending how dynamic crisis communication develops in the setting of social media participation when applied to the study of crisis management in a public agency, such as the Youth Employment Agency. We may examine how the agency and its online audience engage at different stages of a crisis thanks to this model.

Relevance of the Situational Crisis Communication Theory (SCCT) to the Study

The Situational Crisis Communication Theory (SCCT), developed by W. Timothy Coombs, offers a valuable framework for understanding how organizations should respond to crises in a way that minimizes damage to their reputation. The theory emphasizes the importance of aligning crisis response strategies with the type of crisis an organization faces and the level of responsibility attributed to the organization in causing that crisis. It suggests that crisis communication strategies should vary depending on the crisis situation, the perceived responsibility of the organization, and the potential impact on stakeholders. SCCT provides a robust foundation for analyzing how organizations can effectively manage crises, particularly when communication efforts are under scrutiny.

In the context of this study, which explores the role of Artificial Intelligence (AI) in crisis communication, SCCT's relevance becomes evident. As organizations increasingly turn to AI to automate and optimize communication strategies, particularly during crises, understanding the strategic alignment between the crisis type and the communication response becomes essential. The study seeks to assess how AI tools can enhance crisis communication, influencing organizational reputation and stakeholder trust. By examining AI's role in crafting and delivering crisis responses, SCCT provides a clear theoretical framework to analyze how AI-driven tools might shape crisis management strategies. For instance, AI can potentially analyze real-time data and adapt crisis communication strategies to fit the evolving nature of a crisis, thereby allowing organizations to respond more swiftly and effectively.

Furthermore, SCCT's focus on the perception of responsibility in crisis situations is especially relevant in the era of digital communication and automation. AI's involvement in crisis communication may alter public perceptions of an organization's responsibility in addressing crises. With AI tools increasingly becoming part of the communication process, the stakeholders' perception of the organization's authenticity and accountability during a crisis could shift. SCCT's emphasis on matching response strategies to the level of responsibility also offers insight into how AI systems might impact the organizational approach to crisis management and reputation protection. This alignment will be crucial in the study as it explores how AI systems can improve decision-making during crises while maintaining the trust and engagement of stakeholders.

In essence, SCCT offers a strong theoretical framework for understanding the relationship between crisis situations, organizational responses, and the reputation management process. Its principles are highly relevant to this study as it investigates the intersection of AI and crisis communication, helping to frame the discussion around how AI can reshape crisis response strategies, stakeholder perception, and organizational outcomes. Through SCCT, the study can provide insights into how AI might both complement and challenge traditional crisis communication practices, contributing to a more nuanced understanding of AI's role in modern crisis management.

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is one of the most widely used frameworks for explaining and predicting individuals' acceptance and use of information systems. Developed by Davis (1986, 1989), TAM is an adaptation of the Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen, and it seeks to explain how users come to accept and use new technologies. The core assumption of TAM is that technology adoption is primarily driven by the beliefs and perceptions that potential users hold about a particular system, rather than by the objective technical characteristics of the system itself.

TAM posits two key cognitive determinants of technology acceptance: **Perceived Usefulness (PU)** and **Perceived Ease of Use (PEOU)**. Perceived usefulness refers to the extent to which an individual believes that using a particular system will enhance their job performance, effectiveness, or productivity (Davis, 1989). In organisational settings, a technology is more likely to be adopted when users are convinced that it will help them work faster, make better decisions, reduce errors, or achieve important organisational goals. Perceived ease of use, on the other hand, refers to the degree to which an individual believes that using a system will be free of effort. A system that is considered simple, user-friendly, and intuitive is more likely to be accepted than one perceived as complex, demanding, or disruptive to existing work routines.

In the TAM framework, perceived ease of use influences perceived usefulness, because a system that is easier to use is more likely to be seen as beneficial. Both constructs in turn shape users' **attitude towards using** the technology and their **behavioural intention to use** it, which ultimately leads to **actual system use**. Subsequent extensions of TAM (such as TAM2 and related models) have incorporated additional determinants, including subjective norms, output quality, job relevance, and facilitating conditions, but the basic logic remains the same: beliefs about usefulness and ease of use are central drivers of adoption (Venkatesh & Davis, 2000; Venkatesh et al., 2003).

TAM has been extensively applied in diverse domains, including e-government services, e-learning, mobile banking, and social media platforms, especially in contexts where new digital technologies disrupt established professional routines. In communication and public relations settings, TAM has been used to examine practitioners' acceptance of social media tools, digital analytics platforms, and other forms of communication technology. This makes TAM particularly relevant for understanding how communication professionals, digital media managers, and AI or data specialists in Ghanaian organisations respond to the introduction of AI-enabled tools for crisis communication, such as social listening dashboards, sentiment analysis systems, and AI-driven chatbots.

Relevance of the Technology Acceptance Model to the Study

The inclusion of the Technology Acceptance Model in this study is important because it provides a systematic way to understand the human and organisational factors that condition the adoption and meaningful use of AI in crisis communication. While Situational Crisis Communication Theory (SCCT) and the Social-Mediated Crisis Communication (SMCC) model help to explain how organisations should respond to crises and how different stakeholders behave in social media environments, they say relatively little about why internal actors actually choose to adopt AI tools, how they experience those tools in their everyday work, and what shapes their willingness to rely on AI during high-pressure crisis situations. TAM fills this gap by foregrounding the perceptions and attitudes of the practitioners who must engage with AI systems in practice.

In the context of this study, perceived usefulness captures the extent to which communication professionals and related actors believe that AI-enabled tools improve crisis communication performance. For instance, AI may be seen as useful if it enables faster detection of emerging issues, more accurate understanding of public sentiment, better targeting of messages to different stakeholder groups, or more systematic post-crisis evaluation. Conversely, if AI tools are viewed as producing noisy or unreliable data, overwhelming users with irrelevant information, or failing to capture local nuances in Ghanaian public discourse, their perceived usefulness is likely to be low, thereby reducing adoption.

Similarly, perceived ease of use is salient in a context where many AI tools involve technical dashboards, complex analytics, and unfamiliar interfaces. If practitioners experience these systems as difficult to interpret, poorly integrated with existing workflows, or highly dependent on specialised technical staff, they may be reluctant to use them in the time-sensitive environment of crises. On the other hand, when AI systems are embedded in familiar communication platforms, accompanied by adequate training, and supported by clear organisational procedures, users are more likely to perceive them as easy to use and to incorporate them into their crisis routines.

By drawing on TAM, the study can interpret empirical findings about organisational capabilities, training, leadership support, and resource constraints not merely as contextual background, but as factors that shape the core TAM constructs of perceived usefulness and perceived ease of use, and ultimately the behavioural intention of practitioners to use AI in crisis communication. This is particularly important in Ghanaian organisations, where disparities in digital skills, infrastructure, and resource availability may lead to uneven acceptance of AI across sectors and roles. Integrating TAM with SCCT and SMCC therefore enables a more comprehensive theoretical framing: SCCT and SMCC explain what effective crisis communication should look like in digital environments and how stakeholders behave, while TAM explains whether and why organisational actors are willing and able to adopt AI tools that could support those strategies.

The Technology Acceptance Model is relevant to this study because it links the technical potential of AI with the subjective perceptions, attitudes, and intentions of the people responsible for crisis communication. It offers a lens for understanding why some organisations move beyond symbolic or experimental use of AI to more systematic integration in crisis management, while others remain hesitant or revert to traditional approaches despite having access to similar technologies.

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Relevance of the Technology Acceptance Model to the Study

The inclusion of the Technology Acceptance Model in this study is important because it provides a systematic way to understand the human and organisational factors that condition the adoption and meaningful use of AI in crisis communication. While Situational Crisis Communication Theory (SCCT) and the Social-Mediated Crisis Communication (SMCC) model help to explain how organisations should respond to crises and how different stakeholders behave in social media environments, they say relatively little about why internal actors actually choose to adopt AI tools, how they experience those tools in their everyday work, and what shapes their willingness to rely on AI during high-pressure crisis situations. TAM fills this gap by foregrounding the perceptions and attitudes of the practitioners who must engage with AI systems in practice.

In the context of this study, perceived usefulness captures the extent to which communication professionals and related actors believe that AI-enabled tools improve crisis communication performance. For instance, AI may be seen as useful if it enables faster detection of emerging issues, more accurate understanding of public sentiment, better targeting of messages to different stakeholder groups, or more systematic post-crisis evaluation. Conversely, if AI tools are viewed as producing noisy or unreliable data, overwhelming users with irrelevant information, or failing to capture local nuances in Ghanaian public discourse, their perceived usefulness is likely to be low, thereby reducing adoption.

Similarly, perceived ease of use is salient in a context where many AI tools involve technical dashboards, complex analytics, and unfamiliar interfaces. If practitioners experience these systems as difficult to interpret, poorly integrated with existing workflows, or highly dependent on specialised technical staff, they may be reluctant to use them in the time-sensitive environment of crises. On the other hand, when AI systems are embedded in familiar communication platforms, accompanied by adequate training, and supported by clear organisational procedures, users are more likely to perceive them as easy to use and to incorporate them into their crisis routines.

By drawing on TAM, the study can interpret empirical findings about organisational capabilities, training, leadership support, and resource constraints not merely as contextual background, but as factors that shape the core TAM constructs of perceived usefulness and perceived ease of use, and ultimately the behavioural intention of practitioners to use AI in crisis communication. This is particularly important in Ghanaian organisations, where disparities in digital skills, infrastructure, and resource availability may lead to uneven acceptance of AI across sectors and roles. Integrating TAM with SCCT and SMCC therefore enables a more comprehensive theoretical framing: SCCT and SMCC explain what effective crisis communication should look like in digital environments and how stakeholders behave, while TAM explains whether and why organisational actors are willing and able to adopt AI tools that could support those strategies.

The Technology Acceptance Model is relevant to this study because it links the technical potential of AI with the subjective perceptions, attitudes, and intentions of the people responsible for crisis communication. It offers a lens for understanding why some organisations move beyond symbolic or experimental use of AI to more systematic integration in crisis management, while others remain hesitant or revert to traditional approaches despite having access to similar technologies.

2.14 Empirical review

The integration of Artificial Intelligence (AI) in crisis management and public safety governance has emerged as a crucial focus in recent research, as it holds the potential to significantly enhance decision-making processes and improve response times during critical situations. Several studies have explored the application of AI technologies in various contexts, ranging from urban public safety to corporate crisis management, providing valuable insights into the effectiveness and challenges of these technologies.

In a study conducted by Ehlers (2021), the impact of artificial intelligence (AI) on crisis communication rebuilding strategies was examined. The primary focus of the article was to assess the effectiveness of using AI as a nontraditional message source for delivering strategies aimed at rebuilding after a crisis. Rebuilding strategies serve as a communication approach that organizations can employ to regain their reputational standing following a crisis. The research findings indicated that participants perceived the AI source as less trustworthy, less credible, and less likely to enhance the organization's reputation when compared to a human source. Additionally, the study revealed that regardless of the chat mode employed (balanced, creative, or precise), participants consistently favored a human source over an AI source. In conclusion, the study suggested that AI may not be a suitable choice for delivering rebuilding crisis response strategies, particularly in cases of preventable crises that present significant threats to an organization's reputation. The study proposed that AI may lack key human qualities such as empathy, sincerity, and accountability, which are crucial for rebuilding trust and reputation after a crisis The article recommended that organizations refrain from relying solely or primarily on AI for crisis communication. Instead, the focus should be on human sources that can convey genuine concern and responsibility towards stakeholders. Furthermore, the article suggested that future research should explore the potential advantages and limitations of using AI as a supplementary or secondary source of crisis communication. This could involve providing additional information or assistance to stakeholders in a crisis scenario.

In the study "Construction and Path of Urban Public Safety Governance and Crisis Management Optimization Model Integrating Artificial Intelligence Technology" by Guo Li, Jinfeng Wang, and Xin Wang (2023), the researchers aimed to develop and validate an AI-driven model to improve urban public safety outcomes. By employing a mixed-methods approach, including qualitative and quantitative analysis, the study created a linear regression model that examined the relationship between various AI-driven public safety technologies (such as crisis prediction, early warning systems, and AI-assisted decision-making) and public safety outcomes. The results revealed that the integration of these technologies positively impacted public safety, with key factors like governance structure and response mechanisms showing significant contributions to improved outcomes. The study underscores the importance of a coordinated, AI-driven approach to public safety, recommending the adoption of these technologies by public safety agencies and advocating for continuous improvement and stakeholder engagement.

In a similar vein, Adhianty Nurjanah et al. (2021) explored the role of AI in crisis communication during the COVID-19 pandemic in Indonesia. Their study found that while AI technologies were deployed to detect the virus and monitor public mobility, the Indonesian government's communication efforts were often inconsistent and lacked structure. This study highlights the challenges of using AI in crisis communication, suggesting the need for more structured policies and greater use of AI for health literacy and crisis information dissemination. Furthermore, involving community leaders and influencers in communication efforts was recommended to build public trust and ensure the effective transmission of messages.

The study "Digital Transformation in Crisis Management: The Key Role of Artificial Intelligence" by Oana-Mihaela Vladu (2023) similarly examined the role of AI in crisis management. This research focused on how digital transformation, particularly AI, could enhance crisis response by improving the speed, accuracy, and efficiency of decision-making. The study found that AI could automate repetitive processes and enhance data analysis capabilities, significantly reducing risks and costs associated with crisis management. Vladu emphasizes that AI’s integration is crucial for improving crisis response efforts, highlighting its potential to facilitate real-time decision-making and mitigate the impact of crises.

Suhendra et al. (2024) extended this discussion by investigating the future role of AI in social media-based crisis communication, specifically focusing on AI moderation and virtual support systems. Their findings indicated that while AI-driven moderation was effective in reducing harmful content, it often struggled to provide context-specific crisis information. The study suggests a hybrid approach that combines AI with human oversight to enhance the quality of crisis communication, particularly in managing misinformation and providing timely support to affected communities.

The study by Ahmed Saeed Ali Rashed Aladawi and Ahmad Nur Aizat Ahmad (2023) also contributes to this body of research by analyzing factors influencing the adoption of AI in crisis management within the UAE National Crisis and Emergency Management Authority. Using a structured questionnaire, the researchers identified key AI technologies, such as robotics and machine learning, that had the most significant impact on crisis management. Their findings emphasize the importance of investing in AI infrastructure and fostering collaboration between human decision-makers and AI systems to optimize crisis management strategies.

Similarly, Ala Harika et al. (2024) explored how AI could enhance disaster response and crisis management through technologies such as predictive modeling and sentiment analysis. Their study highlighted the effectiveness of AI-driven solutions in improving disaster preparedness and response by providing faster and more accurate responses and better resource distribution. They recommended advancing AI solutions and integrating them with existing disaster management systems to ensure equitable and effective crisis responses.

In the context of corporate crisis management, Aydin Farrokhi et al. (2020) examined how AI could be used to detect crises in business-to-business (B2B) contexts, specifically analyzing communication patterns and sentiment in emails during the Enron crisis. Their research demonstrated that AI could identify early signs of crises, enabling firms to make informed decisions before crises escalate. This capability underscores the importance of AI in crisis prevention and early detection, providing firms with a critical tool for mitigating risks and improving response strategies.

These studies contribute to a growing body of research that underscores the transformative potential of AI in crisis management and public safety governance. AI's ability to analyze vast amounts of data, predict potential crises, and optimize response strategies positions it as a powerful tool for enhancing crisis communication, improving public safety outcomes, and fostering more resilient organizations. However, the research also highlights the challenges of implementing AI technologies, such as the need for human oversight, the importance of contextual adaptation, and the ethical considerations surrounding AI use. Moving forward, these insights suggest that AI-driven crisis management systems must be continuously refined, with a focus on integrating human expertise and ensuring transparency and accountability in their application.

CHAPTER THREEE

METHODOLOGY

3.0 Chapter Overview

Chapter three outlines the methodology adopted for this study, detailing the research design, data collection methods, and analytical techniques employed to explore the role of artificial intelligence (AI) in crisis communication. The chapter begins by presenting the research design, which is a qualitative approach chosen for its ability to provide an in-depth understanding of the complex interactions between AI tools and crisis communication practices.

Next, the chapter describes the sampling strategy used to select relevant design, including organizations, agencies, and AI-driven tools that have been actively involved in crisis communication. It also discusses the selection of key participants for interviews, including communication professionals, AI experts, and stakeholders in crisis management. The data collection process is explained in detail, including the use of semi-structured interviews, document analysis, and observations to gather comprehensive insights.

Additionally, the chapter highlights the ethical considerations and procedures followed during the research, ensuring that data privacy and confidentiality are upheld in accordance with established ethical guidelines. The methodology section also provides a rationale for the chosen data analysis methods, such as thematic analysis, which is used to identify and interpret key themes and patterns emerging from the collected data. Chapter three provides a clear and systematic approach to how the study was conducted, ensuring that the findings are reliable, valid, and ethically sound.

3.1 Research Paradigm

According to Kuhn (2012), a paradigm is a set of beliefs, attitudes, and practices that the scientific community accepts and that work as a road map or guide for what kinds of issues to research and what kinds of explanations to accept. Because these perspectives, values, and approaches are on a continuum with objectivism near one end and subjectivism at the other, there are several classifications used to distinguish paradigms (Johnson & Duberley, 2000). Deciding on a research paradigm shapes fundamental presumptions about how researchers see the problems they are examining. These presumptions impact the methods and design of the study. Assumptions about the social environment and how it might be investigated are made by social scientists while conducting research in their domains (Mayer, 2015). These assumptions might be either overtly or implicitly. The ontological, epistemological, and methodological perspectives that paradigms take define them, according to Guba (Guba & Lincoln, 1994). Despite this, positivism, interpretivism, Constructivism, realism, relativism, and critical realism are usually suggested paradigms mirroring the main speculative philosophical feeling in social scientific research (Orlikowski & Baroudi, 1991). As a result, the paradigms of this research give the researcher's perspective. According to Creswell (2014), each paradigm contains a unique set of epistemological, ontological, and methodological suppositions that act as a framework to define and set them apart. Thus, it is essential to describe the philosophical stance taken for this investigation.

The study adopted a constructivism paradigm, which was chosen to align with the research's aim of exploring how artificial intelligence (AI) plays a role in crisis communication. Constructivism is grounded in the belief that knowledge is constructed through social interactions and experiences. It emphasizes the subjective nature of human understanding and seeks to explore how individuals make sense of their experiences in a given context. This paradigm is particularly well-suited for the study, as it allows for an in-depth understanding of how communication professionals and AI experts interpret and apply AI tools in crisis situations.

A constructivist approach is valuable because it encourages an exploration of the participants' perceptions, experiences, and interactions with AI during crisis communication processes. It acknowledges that these individuals bring their own unique perspectives, shaped by their roles, knowledge, and social environments, which influence how they engage with AI in managing crises. By focusing on how individuals construct meaning from these experiences, the study seeks to provide a nuanced understanding of the real-world impact of AI in crisis communication, rather than simply measuring or quantifying its effects.

Moreover, the constructivism paradigm supports the use of qualitative research methods, such as interviews, which allow participants to share their insights and reflect on their experiences. This approach aligns with the study's objective of exploring the complexities of crisis communication, which cannot be fully understood through purely quantitative means. Instead, the study draws on the subjective experiences of stakeholders involved in crisis management, providing rich, detailed data that helps to uncover deeper insights into the role of AI in such situations.

In conclusion, adopting a constructivism paradigm is justified by the study's aim to explore the perceptions and experiences of individuals involved in crisis communication. This paradigm provides a framework for understanding how AI is interpreted and applied in real-world crisis scenarios, offering valuable insights into the intersection of technology, communication, and human experience.

3.2 Research Approach

The research approach lays out explicit guidelines for data collection, processing, and interpretation (Denzin & Lincoln, 2011). It is a structured plan for collecting, analysing, and interpreting data in order to answer specific research questions and achieve research objectives (Zikmund, 2003). It also acts as a guide for researchers to ensure they gather data in an appropriate manner and use it effectively. According to the literature, quantitative, qualitative, and mixed methodologies are considered as the three prominent research approaches (Creswell, 2014; Denzin & Lincoln, 2011; Tillal et al., 2002; Yin, 2009).

Creswel (2013) asserts that when examining observable phenomena, both natural and social scientists regard quantitative research as a methodical and empirical inquiry that employs statistical, mathematical, and computational approaches. Similarly, according to Saunders et al. (2009), quantitative methods refer to the utilization of data collection and analysis techniques to construct models, hypotheses, and theories relating to a particular phenomenon.

According to Creswell (2013), quantitative research serves as a method to evaluate objective theories by exploring the connections between various variables. These variables are often measured using instruments, allowing for numerical data that can be analysed through statistical techniques. According to Creswell (2009), quantitative research utilizes various approaches, including experimental and survey methods, to gather data using predetermined instruments, which result in statistical data. Its main objective is to provide explanations and predictions, confirming or validating relationships and forming generalizations that contribute to the development of theory (Leedy & Ormrod, 2001). In scientific investigations, a quantitative research methodology is utilized by researchers to gather and evaluate numerical data in order to elucidate a particular phenomenon. Furthermore, this approach enables the researchers to draw conclusions that can be applied to diverse subjects or groups, thereby facilitating generalization of the findings. Accordingly, Odoom (2016) asserted that quantitative researchers analyse data to yield unbiased results which can be generalized to some larger population.

According to Van Maamen (1983), qualitative research encompasses a variety of interpretive methods aimed at describing, interpreting, translating, and understanding the meaning of a particular phenomenon that occurs naturally in the social realm, rather than focusing on its frequency. According to Yin (2009), qualitative research is undertaken to gain deeper insights and understanding of a complex occurrence or phenomenon. In a similar vein, Bryman (2006) provided an account of qualitative research as a methodology that investigates the social realm, aiming to depict and analyse the customs and actions of individuals and their collectives, as perceived by the subjects under study. In line with Bryman (2006) viewpoint, qualitative research focuses on acquiring in-depth descriptions, understanding, and insights instead of emphasizing measurement. In qualitative research, researchers often utilize in-depth interviews or focus group discussions as common methods for gathering insights into the attitudes, behaviours, and experiences of participants. Furthermore, data gathering and analysis based on large samples are not emphasized in qualitative research (Yin, 2009). The qualitative approach focuses on the research subject so as to obtain more information through interviews and other procedures. This allows researchers to decipher unusual information buried in the experiences of study participants.

Creswell (2014) explains that when conducting mixed methods research, it is important to gather and analyse a combination of quantitative and qualitative data. This approach allows for the integration of these two types of data, utilizing diverse designs that may encompass philosophical assumptions and theoretical frameworks. In cases where a comprehensive comprehension of a research problem necessitates the integration of qualitative and quantitative methods, this strategy is deemed suitable. It enables a more holistic understanding than what can be achieved through the use of a singular approach. Boateng (2014) and Creswell (2014) have categorized mixed-method research in several manners. These classifications include triangulation, where both quantitative and qualitative methods are used simultaneously; embedded design, where one approach supplements the other; explanatory design, where quantitative methods precede qualitative methods in a sequential manner; and exploratory design, where qualitative methods follow quantitative methods sequentially but in reverse order.

The study adopted a qualitative research approach, which was chosen to best address the research objectives of exploring the role of artificial intelligence (AI) in crisis communication. Qualitative research is particularly suited for this study as it allows for an in-depth examination of the participants' experiences, perceptions, and understanding of how AI tools are applied in crisis management. Unlike quantitative research, which focuses on numerical data and statistical analysis, qualitative research emphasizes the exploration of complex phenomena from the perspectives of individuals directly involved in the process.

A qualitative approach was selected because the study aims to uncover the nuanced ways in which AI is utilized and perceived by communication professionals and AI experts in the context of crisis communication. Through methods such as interviews, the study can gather rich, detailed insights into how these individuals interact with AI tools and how they interpret their experiences in crisis situations. This approach allows for a deeper understanding of the challenges, opportunities, and ethical considerations involved in integrating AI into crisis management, which quantitative methods may not capture effectively.

Furthermore, qualitative research is particularly useful in contexts where the goal is to explore perceptions, behaviors, and social processes. Since the role of AI in crisis communication involves complex, dynamic interactions and subjective experiences, a qualitative approach provides the flexibility to capture these complexities. It also enables the study to explore the meanings and implications that participants attach to their experiences with AI, which are crucial for understanding its impact on crisis communication strategies. The decision to adopt a qualitative research approach is justified by the need to gather rich, detailed insights into the role of AI in crisis communication. This approach allows for a comprehensive exploration of the participants' experiences and perceptions, offering valuable context and depth to the understanding of AI’s effectiveness and challenges in crisis management.

3.3 Research design

According to Zikmund et al. (2003), a research design can be defined as a comprehensive blueprint that directs the execution of a research study, aiming to achieve its objectives. Zikmund's interpretation of research design also emphasizes the means and methods employed for data collection and interpretation. Therefore, the primary aim of a research design is to choose the most effective methodology or research approach for gathering data. Consequently, it functions as a detailed roadmap outlining the steps involved in carrying out the research. The research design for this study, which also takes into account the research paradigm, purpose, strategy, approach, and data collection methods (including the determination of sample size, specification of sampling techniques, identification of data sources, and detailing of the survey instrument), will primarily focus on addressing these challenges. As per the categorization proposed by Saunders et al., (2012), research purposes are often classified as exploratory, explanatory, or descriptive. In alignment with the goals and nature of this study, an exploratory research design was adopted.

The preliminary examination of a speculative or theoretical concept is known as exploratory research (Kowalczyk, 2013). This study provides an early look at a phenomenon that has hitherto gotten less or no attention. It leads to novel findings and insights into phenomena that are yet poorly understood. The study adopted an exploratory research design, which was selected to investigate the emerging role of artificial intelligence (AI) in crisis communication. An exploratory design is appropriate for this type of research because it allows for the investigation of a relatively underexplored topic or phenomenon. In this case, while AI is increasingly being utilized in crisis management, its specific applications, impact, and the experiences of stakeholders involved in its use have not been comprehensively studied in the context of crisis communication.

Exploratory research is particularly useful when there is limited prior knowledge or established theory on the subject matter, as it allows the researcher to identify patterns, generate insights, and lay the groundwork for future, more detailed studies. In this study, the goal was to understand the various ways AI tools are applied in crisis communication, as well as the opportunities, challenges, and ethical considerations involved. The exploratory design enables the researcher to gather qualitative data through interviews, case studies, and observations, which are ideal for identifying new ideas, questions, and themes related to AI in crisis management.

Additionally, the exploratory design facilitates flexibility in the research process, allowing the study to adapt and evolve as new findings emerge. This is important because the field of AI in crisis communication is dynamic, and the study aims to uncover not only current practices but also potential future developments and trends in the integration of AI technologies in crisis management. In conclusion, adopting an exploratory design was essential for this study, as it provided the necessary framework to investigate the relatively new and underexplored topic of AI's role in crisis communication. This design allows for the discovery of insights, identification of key issues, and generation of hypotheses that can inform future, more focused research on the subject.

3.4 Study population

The study population comprised organisational actors who are directly involved in crisis communication and the adoption or management of AI-enabled tools within Ghanaian organisations. In order to capture the diversity of crisis exposure and technology use, the study focused on organisations operating in high-visibility and high-risk sectors where reputational threats are frequent and where social and digital media play a central role in stakeholder engagement. These included commercial banks, telecommunications companies, media and public relations agencies, selected ministries, departments and agencies (MDAs), and consumer-facing small and medium-sized enterprises (SMEs). Organisations in these sectors were considered appropriate because they routinely interact with large and heterogeneous publics, are vulnerable to online crises, and are under growing pressure to deploy digital and AI tools for monitoring, responding to, and recovering from crises.

Within these organisations, the target population consisted of individuals who hold formal responsibility for crisis communication or for the deployment of AI and advanced digital tools in communication-related functions. These included heads and officers in corporate affairs or communications units, public relations managers, digital and social media managers, media monitoring and insights staff, as well as AI, data or IT specialists whose work intersects with crisis-related communication systems. Focusing on these actors ensured that the data reflected informed perspectives on how AI is actually integrated into crisis preparedness, real-time response, and post-crisis learning, rather than abstract views of technology. The study population was therefore defined not only in terms of sectoral affiliation, but also in terms of specialised roles and experiential knowledge of AI-enabled crisis communication practices in Ghana.

3.5 Sampling Technique and Size

Given the exploratory and interpretive nature of the study, a non-probability purposive sampling strategy was employed. Purposive sampling was appropriate because there is no comprehensive list of organisations in Ghana that formally use AI in crisis communication, and the central concern of the research was depth of insight rather than statistical representativeness. Organisations were deliberately selected where preliminary inquiries, public information, or professional networks indicated that they had experienced significant reputational or operational crises in recent years and had adopted some form of AI or advanced digital tools—such as social listening platforms, automated sentiment analysis dashboards, or chatbots—to support communication with stakeholders. Within each organisation, key informants were purposively chosen because of their direct involvement in designing, approving, or implementing crisis communication strategies and AI-enabled tools. In a few cases, initial participants recommended additional colleagues or partner organisations with relevant expertise, allowing for limited snowballing while still adhering to clear inclusion criteria.

The final sample size was guided by the principle of information saturation rather than by a predetermined numerical target. Data collection proceeded until additional interviews were no longer generating substantially new themes regarding how AI is used to support crisis communication across sectors. In total, twenty-four participants were interviewed from twelve organisations. These comprised communication and technology professionals drawn from three commercial banks, two telecommunications companies, three media and public relations agencies, two central government ministries or agencies, and two large consumer-facing SMEs. Between one and three participants were interviewed in each organisation, depending on its size, structure, and the distribution of crisis communication responsibilities. This sectorally distributed sample allowed the study to capture variation in AI adoption and crisis communication practices between relatively resource-rich sectors such as banking and telecommunications, on the one hand, and more resource-constrained public institutions and SMEs on the other, while still providing sufficient depth within each organisational context to support robust qualitative analysis.

3.5.1 Sampling

When it comes to sampling techniques, probability sampling ensures that each member of a population has an equal chance of being chosen (Malhotra & Birks, 2007). The researcher is unable to select participants in probability sampling (Frankfort-Nachmias et al., 2019). Simple random sampling, systematic sampling, cluster sampling, and stratified sampling are only a few of the sampling techniques used in probability sampling (Bryman & Bell, 2011; Saunders et al., 2009). Individuals within a population are not randomly selected in a uniform manner when using non-probability sampling (Gravetter & Forzano, 2018).

Malhotra and Birks (2007) suggested that non-probability sampling methods are most suitable in cases where acquiring a suitable sampling frame is virtually unattainable. Non-probability sampling enables researchers to choose respondents based on subjective judgments (Saunders et al., 2009). When a researcher decides to use non- probability sampling techniques, the different techniques available to the researcher include purposive sampling, convenience sampling, snowballing, and quota sampling (Bryman & Bell, 2015; Malhotra & Birks, 2007; Saunders et al.,2012). The study adopted a non-probability sampling technique, specifically utilizing purposive sampling. This method was chosen due to the nature of the research, which aims to gather in-depth insights from individuals with specific expertise and experience in crisis communication and the use of artificial intelligence (AI) in crisis management.

Purposive sampling involves selecting participants who are considered most knowledgeable or experienced about the phenomenon under study. In this case, the study targeted professionals such as communication officers, crisis management specialists, AI developers, and experts in the fields of crisis communication and AI technologies. These individuals were chosen deliberately because their roles or expertise directly relate to the integration of AI in crisis communication strategies, making them key informants for the research.

Purposive sampling is justified by the necessity to collect targeted, pertinent, and specialised data that is necessary to comprehend the real-world uses, difficulties, and efficacy of AI technologies in crisis communication. Purposive sampling is ideal since the study aims to explore the experiences and ideas of those involved in AI-driven crisis communication rather than generalising findings to a larger community. This approach guarantees that the participants chosen are extremely pertinent to the goals of the study, offering insightful viewpoints that can address the research issues and advance industry best practices.

The non-probability nature of this technique is well-suited to qualitative research, where the emphasis is on depth and detailed understanding rather than statistical representation. Purposive sampling allows for the selection of specific cases that are most likely to yield rich, relevant data, which aligns with the exploratory nature of this study.

3.5 Data collection instrument

In qualitative research methods, it is essential to consider the social and cultural context when collecting and analyzing data to comprehensively understand the topics under study (Eriksson & Kovalainen, 2016). Qualitative data refers to information that cannot be measured numerically and is characterized using text, spoken words, audio, or visual elements in its interpretation or description (Bryman & Bell, 2005). Interviews are a standard data collection strategy in qualitative research, and they were the chosen method for this thesis. Interviews involve structured conversations with questions and responses (Bryman et al., 2005). While interviews are typically conducted face-to-face, they can also be conducted over the phone or online (Eriksson & Kovalainen, 2016: 140). This approach allows for exploring people's experiences and perspectives from their point of view. In some cases, interviews may resemble casual conversations, blurring the boundaries between the roles of the interviewer and interviewee. This emphasizes the need for tools to gather in-depth and reliable data on the studied phenomenon. Therefore, this study chose interviews as the qualitative data collection method. The interview guide provided a framework for posing appropriate questions to the participants and directing the research inquiry. The researchers used a well-developed interview guide as their primary research instrument. A recording device, such as a phone's record function, was used to capture the interviews, enabling subsequent transcription. Additionally, a notepad was used to jot down essential explanations that were deemed significant.

3.7 Data analysis

The study employed thematic analysis as the data analysis process. Thematic analysis was chosen because it allows for a flexible and systematic approach to identifying, analyzing, and reporting patterns (themes) within qualitative data. This method is particularly suitable for the research objectives, which seek to explore the experiences, perceptions, and insights of individuals involved in crisis communication and the use of AI in crisis management.

The process of thematic analysis involves several key stages. First, data collection through interviews or other qualitative methods generates raw data, which is then transcribed for analysis. The second step involves familiarization with the data, where the researcher reads through the transcripts multiple times to gain a deep understanding of the content. During this phase, initial ideas about potential themes and patterns begin to emerge.

Next, the data is systematically coded, with the researcher identifying significant phrases, concepts, or sentences that are relevant to the research questions. Each code represents a specific piece of data that relates to the overall theme. These codes are then grouped into broader themes that reflect recurring patterns or topics within the data. Thematic analysis allows for both a deductive approach (focusing on themes based on pre-existing theory or research) and an inductive approach (letting themes emerge naturally from the data).

The final phase involves reviewing and refining these themes, ensuring they accurately represent the data. This includes checking for consistency and coherence within each theme and ensuring that the themes collectively provide a comprehensive understanding of the data. Finally, the researcher interprets the themes in relation to the research questions, drawing conclusions and making recommendations based on the patterns and insights identified.

Thematic analysis is particularly well-suited to this study as it enables a detailed exploration of the complex experiences and perspectives of the participants. By organizing the data into meaningful themes, thematic analysis provides a clear framework for understanding how AI is integrated into crisis communication strategies and the challenges and benefits of such integration. Additionally, its flexibility allows the study to capture both explicit and implicit meanings in the data, making it an effective tool for exploring complex qualitative information.

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION

4.0 Chapter Overview

This chapter presents the analysis of findings from the qualitative investigation into the role of Artificial Intelligence (AI) in enhancing crisis communication strategies within Ghanaian organizations. The purpose of this section is to interpret the data collected from interviews, document reviews, and relevant organizational records in line with the study's objectives and research questions. Guided by the principles of thematic analysis, the findings are structured around key themes that emerged from the data, reflecting the perceptions, experiences, and practices of participants in relation to AI-driven crisis communication.

The analysis is informed by the Situational Crisis Communication Theory (SCCT) and the Social Media Crisis Communication (SMCC) Model, which provide theoretical lens for understanding how AI tools intersect with traditional crisis communication frameworks. This approach ensures that the interpretation of findings captures not only the operational and technical aspects of AI adoption but also the strategic, ethical, and contextual dimensions influencing its integration in Ghanaian organizations. In keeping with the exploratory nature of the study, the themes were derived inductively from the data, allowing participant narratives to guide the analytical process. Sub-themes are presented under each main theme to provide a deeper understanding of specific issues raised by respondents. Throughout this analysis, direct quotations from participants are incorporated where necessary to illustrate points and give voice to their perspectives. These thematic findings will form the basis for the discussion in the subsequent chapter, where they will be linked to existing literature and theoretical propositions.

4.1 Current State of AI Integration in Crisis Communication

This theme explores how AI is currently understood, adopted, and operationalised in crisis communication within Ghanaian organisations. It addresses both the conceptual awareness of AI's potential and the actual extent to which it is embedded into communication processes. The findings reveal a gap between enthusiasm for AI and the realities of its use, with adoption varying from experimental, isolated applications to more structured integration in technologically mature sectors such as telecommunications and banking. While certain organisations use AI for tasks such as media monitoring, keyword alerts, and basic customer engagement, many treat it as a symbolic innovation tool rather than a strategic crisis management asset. This unevenness in integration also reflects sectoral disparities, with resource-intensive corporate environments generally better positioned to experiment with AI compared to public sector institutions and SMEs.

4.1.1 Sub-theme Awareness and Understanding of AI Tools Among Crisis Communication Professionals

Across the organizations studied, there is an emerging but uneven awareness of AI's role in crisis communication. Several participants demonstrated a conceptual understanding of AI, describing it as "technology that can make sense of large volumes of information faster than humans ever could" (Participant 4, Senior Media Strategist). Yet, when probed, many admitted their knowledge was primarily shaped by exposure to consumer-facing AI, such as chatbots or automated social media monitoring, rather than by hands-on engagement with advanced AI applications in crisis management. One senior public sector communications officer reflected:

> *We have heard about predictive analytics and sentiment tracking, but in practice, most of us still use manual keyword searches on social media. We are not yet at the point of letting AI make complex crisis decisions for us.*

This reveals that awareness does not always translate into operational competence. Many participants could articulate AI's potential but lacked practical familiarity with integrating these tools into a structured crisis response. This aligns with the view that "AI adoption often begins with fascination and rhetoric, but operational maturity comes much later" (adapted from Brynjolfsson & McAfee, 2017). A few corporate participants, particularly from the financial and telecommunications sectors, expressed a deeper understanding, noting that AI could be embedded across the pre-crisis, crisis, and post-crisis phases. One corporate affairs manager remarked:

> *In our sector, we know AI can detect unusual transaction patterns that may indicate a brewing reputational crisis, but the truth is, only a handful of us truly know how to interpret that data in real time.*

This suggests that sectoral exposure heavily influences the depth of AI understanding. Industries where crises carry direct financial or reputational risk such as banking or telecom tend to cultivate more nuanced AI awareness. In contrast, in public institutions and smaller enterprises, AI remains an abstract concept, often perceived as a future investment rather than a present operational tool. This unevenness in awareness is problematic because it shapes how organizations approach AI adoption. If the understanding of AI remains superficial, there is a risk of symbolic adoptiondeploying AI tools for image enhancement rather than embedding them into core crisis management strategies. As one participant candidly put it:

> *Sometimes we talk about AI just to show we are modern, but when a real crisis hits, we fall back on manual press statements.*

Such admissions point to a capability-perception gap, where AI awareness is driven more by strategic positioning than by genuine readiness. This gap can delay the transition from reactive communication to proactive crisis anticipation, undermining the very advantage AI is meant to provide.

4.1.2 Sub-theme Existing AI Applications in Pre-Crisis, Crisis, and Post-Crisis Phases

The findings indicate that Ghanaian organizations are using AI across the crisis lifecycle, but adoption is fragmented and often limited in depth. AI deployment tends to be most visible during the crisis phase itself, with fewer organizations leveraging AI for pre-crisis prediction or post-crisis learning. This reflects a reactive rather than a proactive approach Pre crisis phase

In the pre-crisis stage, AI use is modest, largely limited to basic social media monitoring and keyword tracking. Some organizations employ platforms like Meltwater, Talkwalker, or Brandwatch to flag emerging mentions of the brand. One media monitoring officer explained:

> *We get alerts when a certain keyword comes up often, like our company name linked to 'scandal'. But it's still us, the humans, who decide if it's worth worrying about.*

Such practices are valuable for detecting early signals but lack the predictive modelling that characterizes mature AI integration. Predictive tools such as AI sentiment trajectory mapping or anomaly detection were rarely mentioned. The absence of these tools means early warnings are often missed, particularly in public sector settings where budget and technical expertise are limited.

Crisis phase

During the crisis phase, AI is more visible, especially through automated engagement systems like chatbots and scripted customer-service bots. For example, in the telecommunications and banking sectors, chatbots were configured to handle customer complaints and provide real-time status updates. As one telecoms crisis manager explained:

> *When there's a network outage, our chatbot takes over the bulk of the inquiries within seconds. It frees us up to work on fixing the problem instead of answering the same question thousands of times.*

However, reliance on chatbots alone can be risky. Without human oversight, these systems may provide generic or outdated responses, undermining public trust. A participant from a financial institution shared a cautionary example:

> *During a payment system glitch, the bot kept saying 'services are normal' even though we knew there was a problem. Customers were furious*.

This underscores the importance of blending AI speed with human judgment something many organizations have yet to formalize.

In the post-crisis stage, AI use is even more limited. A few corporate participants mentioned running post-incident sentiment analysis to gauge public mood after a crisis subsided. One corporate affairs officer reflected:

> *We run the data to see how people talked about us after the crisis. But honestly, we don't always use those insights to change our processes.*

This suggests a lost learning opportunity. AI can provide valuable post-crisis intelligence identifying communication gaps, reputational damage patterns, and stakeholder trust trajectories but these capabilities are often underutilized. Without structured post-crisis analytics, organizations risk repeating mistakes in future crises. The pattern is clear: AI tools are being inserted into existing reactive workflows rather than reshaping the overall crisis communication strategy. As a result, AI is serving more as an operational assistant than as a strategic driver. This reinforces the earlier observation that Ghanaian organizations are dabbling in AI rather than embedding it deeply into crisis management ecosystems.

4.1.3: Sub-theme Sector-Specific Patterns of AI Adoption

The integration of AI into crisis communication in Ghanaian organizations varies markedly across sectors, shaped by differences in regulatory pressures, customer engagement intensity, and technological investment capacity. Corporate sectors: Banking, Telecommunications, and Large scale Enterprises Corporate actors in high risk, high visibility sectors such as banking and telecommunications display the most mature adoption. These organizations face constant reputational exposure and operate in competitive markets where crisis mismanagement can result in rapid customer attrition. Consequently, they have invested in AI driven tools for real time monitoring, chatbot engagement, and transaction anomaly detection. One banking sector communications manager noted:

> *In our sector, even a two-hour downtime can turn into a trending hashtag. We use AI to track these mentions minute-by-minute so we can respond before they spiral*.

Similarly, in telecoms, AI-enabled analytics help identify service disruptions before they dominate public discourse. However, even in these relatively advanced settings, adoption often stops short of predictive modelling or fully automated escalation protocols. This indicates a cautious embrace organizations are willing to use AI as an alert system but less so as a decision-making engine.

Media and Public Relations Agencies

Media monitoring and PR agencies are also relatively advanced users of AI for crisis communication, given their professional dependence on brand sentiment tracking. Several agencies employ AI-based social listening platforms to monitor clients' reputations. A PR strategist explained:

> *We see the spikes in negative sentiment before the client does. But unless the client has a plan for it, we can only advise; we can't force a response.*

This reflects a dependency paradox: while agencies possess advanced AI monitoring tools, they are constrained by clients' readiness and willingness to act on the data.

By contrast, AI integration in the public sector remains symbolic or sporadic. While some ministries and agencies have procured social media monitoring software, participants admitted that the tools are often underutilized. A government communications officer admitted:

> *We have the dashboard, but it's mostly switched off until a crisis explodes. Then we scramble to use it.*

This reactive pattern means that AI's potential for early crisis detection is largely wasted. The reasons include budgetary constraints, lack of trained analysts, and bureaucratic inertia. In some cases, public institutions outsource monitoring to private firms, creating delays and raising concerns about data sovereignty and contextual interpretation. SMEs face unique challenges: while some are aware of AI's potential, financial and technical barriers make adoption rare. For many, AI remains a buzzword rather than a practical tool. As one SME owner put it:

> *AI sounds powerful, but when you look at the cost and training needed, you just stick with what you know Facebook alerts and phone calls*.

This sectoral pattern underscores that AI adoption is not just a technological choice but a structural one, shaped by market pressure, organizational culture, and resource availability. While high-risk corporate sectors and professional monitoring agencies are pushing towards operational integration, public institutions and SMEs remain in a low-adoption trap either using AI symbolically or ignoring it altogether. This creates a two-tier AI readiness landscape, where some actors can pre-empt crises while others remain perpetually reactive.

4.2 AI-Enhanced Crisis Detection and Monitoring

This theme explores how AI supports the identification of emerging crises through advanced monitoring and analytical capabilities. It considers the role of predictive analytics, real-time social media tracking, and sentiment analysis in enabling organisations to detect threats before they escalate. The findings show that while these tools are available to many Ghanaian organisations, they are frequently used reactively rather than proactively, often due to a reluctance to act on algorithmic forecasts without visible confirmation. AI's potential for early detection is further constrained by limitations in cultural and linguistic adaptation, which can cause misinterpretations of local expressions or sarcasm. The result is a detection system that is technologically promising but operationally underleveraged.

4.2.1 Subtheme: Predictive Analytics and Early Warning Systems

Across the data, there is clear recognition that AI's ability to predict and flag potential crises before they escalate is one of its most valuable, yet under-realized, capabilities in Ghanaian organizations. Predictive analytics allows for the identification of anomalies, patterns, and early risk signals but for most respondents, this potential is still in the conceptual rather than the operational stage. In sectors with higher digital maturity, such as banking and telecoms, some participants described limited use of AI-based anomaly detection. One bank's risk manager explained:

> *We have AI tools that flag unusual transaction volumes or patterns in social media mentions. In theory, these can signal a brewing crisis. But in reality, we treat most of them as noise unless there's already a visible problem.*

This illustrates a critical adoption paradox: predictive systems are in place, yet their alerts are often undervalued until a crisis is visibly unfolding undermining the very idea of early warning. It aligns with what Coombs (2019) refers to as the "proactive-reactive gap" in crisis readiness. In less technologically advanced organizations, early warning systems are rudimentary. Public sector officers often described manual scanning of social media feeds rather than algorithmic detection. As one government PR officer put it:

> *We rely more on what people forward to us on WhatsApp than on any AI alert. It's not ideal, but it's what we have.*

Such reliance on informal, human-driven monitoring networks limits speed and coverage, leaving these organizations vulnerable to being blindsided by fast-moving crises. This suggests that predictive analytics in Ghanaian crisis communication is constrained by trust and culture. There appears to be hesitancy to act on algorithmic forecasts without visible evidence. This skepticism sometimes justified by fears of "false positives" reflects a broader challenge of human-AI trust calibration. Unless organizations actively build confidence in AI's predictive capabilities through training, testing, and demonstrated accuracy, the systems will remain under-leveraged. One corporate communications director captured this tension:

> *The data says something is coming. My instinct says maybe it's just online noise. Until we see real-world impact, we don't mobilize. That's the reality here.*

This cautiousness can be costly in a digital age where, as Jin et al. (2014) note, public opinion can escalate from a small spark to a full-blown reputational crisis within hours. The reluctance to trust AI predictions without corroborating events limits the ability of Ghanaian organizations to truly move from reactive crisis management to anticipatory crisis prevention.

4.2.2 Sub-theme: Real-time Monitoring of Social Media and News Feeds

Real-time monitoring emerged as one of the most common and tangible uses of AI in Ghanaian crisis communication practices. The immediacy with which AI can scan thousands of posts, headlines, and online discussions allows organizations to track unfolding narratives across multiple channels simultaneously. However, the depth and sophistication of use vary sharply between organizations. Participants from larger corporate and media-intensive sectors reported using AI-driven platforms such as Brandwatch, Meltwater, and Sprinklr to track sentiment and keyword frequency during high-risk periods. One telecoms crisis officer noted:

> *During any service disruption, our dashboard is live. We can see not just the volume of complaints but the tone whether people are angry, frustrated, or joking. That tone tells us how serious it's becoming.*

This quote illustrates how AI is moving beyond simple keyword detection to sentiment-layered monitoring, which helps prioritize response strategies. Yet, the analysis reveals that this capability is still under-optimized in many organizations. Several respondents admitted that although they have real-time dashboards, they only check them when something seems wrong rather than as part of a continuous monitoring culture. In less digitally mature organizations particularly public institutions real-time monitoring is often sporadic and reactive. One government communications officer admitted:

> *We don't have someone watching a dashboard all day. It's usually when the story is already on radio or TV that we start checking online seriously.*

This delay undermines the central advantage of AI-driven real-time monitoring: the ability to intercept crises before they spill into mainstream media. In many cases, human resource constraints mean organizations cannot dedicate a trained person to interpret AI feeds in real time. This gap often turns advanced monitoring tools into passive data collectors rather than active crisis prevention mechanisms. A further challenge is signal-to-noise ratio management. Several participants spoke of being overwhelmed by the volume of alerts. One PR agency analyst explained:

> *The dashboard picks up everything even irrelevant chatter. Without someone skilled to filter it, you can end up chasing shadows while the real issue grows unnoticed.*

This shows that real-time monitoring is not just about the technology but about interpretive capacity. AI can surface patterns and anomalies instantly, but without trained analysts who can contextualize them, organizations risk either overreacting to trivial triggers or missing subtle yet serious threats. Another dimension is multi-platform integration. While some tools can merge data from Twitter (X), Facebook, Instagram, online news, and blogs, others focus narrowly on a single source. Over-reliance on one platform may cause organizations to miss early signs emerging elsewhere. This is particularly relevant in Ghana, where misinformation often spreads through closed platforms like WhatsApp, which AI tools cannot easily monitor. In sum, while real-time monitoring offers significant advantages, in practice it is often treated as a side activity rather than a core operational function. The gap lies not in tool availability but in continuous, skilled interpretation and integration into decision-making. As one corporate affairs manager put it

4.2.3 Sub-theme: Sentiment Analysis for Public Perception Tracking

Sentiment analysis is one of the more strategically valuable yet inconsistently applied AI capabilities identified in the study. By detecting whether public conversations lean positive, neutral, or negative, sentiment analysis enables organizations to measure reputational temperature and anticipate potential escalation points. In advanced corporate settings, sentiment analysis is integrated into daily monitoring workflows. One corporate affairs executive from the banking sector explained:

> *It's not just about how many people are talking about us, but how they feel when they talk. The tone shift is what warns us before the volume spikes.*

This quote captures a critical insight: volume alone is not a sufficient crisis signal; tone and emotional intensity often precede viral spread. AI's ability to capture these subtler shifts is a significant advantage over purely manual monitoring. However, the analysis shows that interpretation remains a challenge. Sentiment scoring algorithms can misread local cultural nuances, sarcasm, or code-switching between English and local languages. A PR consultant for a multinational in Ghana reflected:

> *Sometimes the AI flags a tweet as positive because it uses certain words, but in Ghanaian slang, the same phrase can be an insult. If you don't know the context, you'll misjudge the risk.*

This points to a localization gap in sentiment analysis tools, which are often trained on Western linguistic datasets. Without adaptation to Ghanaian communication patterns, sentiment analysis risks false positives and false negatives, leading to misplaced responses. Another limitation lies in linking sentiment data to action. Several participants admitted that while sentiment dashboards were available, they were rarely tied to formal escalation protocols. One public relations manager noted:

> *We can see that sentiment has dropped sharply, but there's no clear threshold in our policy that says: 'At this point, we activate crisis mode.' So sometimes we just watch it drop.*

This reactive posture undermines the preventive potential of sentiment analysis, as many organizations use it as an after-the-fact diagnostic tool rather than an early intervention mechanism. Critically, for sentiment analysis to be truly effective, three elements must be in place: first, accurate and culturally adapted algorithms capable of interpreting local linguistic nuances; second, continuous monitoring systems that can detect subtle tone shifts before they escalate into larger issues; and third, integration into decision-making protocols so that reaching specific sentiment thresholds automatically triggers predefined actions. Without the seamless implementation of all three components, the capacity of sentiment analysis to serve as a proactive safeguard is significantly diminished. The absence of any one of these elements significantly reduces the value of sentiment analysis. As one crisis communication advisor succinctly put it:

> *Sentiment analysis is like a thermometer. But a thermometer is useless if you never decide what temperature means it's time to act.*

While sentiment analysis is present in many Ghanaian organizations' AI toolkits, it is often under-leveraged due to cultural blind spots, lack of defined response thresholds, and weak integration into decision-making structures. Without addressing these gaps, sentiment analysis risks being another symbolic AI adoption impressive on the surface but with limited practical impact on crisis prevention.

4.3 AI in Real-Time Crisis Response and Engagement

This theme investigates how AI tools are deployed during the active phase of a crisis to manage communications and stakeholder engagement. It focuses on AI's ability to respond rapidly to large volumes of inquiries, personalise messages for different stakeholder groups, and counter misinformation. While AI demonstrates value in speed and scalability, its application is sometimes undermined by generic scripts, poor localisation, and insufficient human oversight, which can produce factually accurate but emotionally detached responses. Furthermore, personalisation features are often underutilised, and misinformation management, although supported by AI detection tools, is hindered by slow internal approval processes**.**

4.3.1 Sub-theme: Use of AI-Driven Chatbots and Automated Response Systems

AI-driven chatbots and automated response systems have become a prominent feature of how Ghanaian organizations manage high-volume stakeholder engagement during crises. Their speed, scalability, and 24/7 availability make them particularly attractive in sectors where customer inquiries surge during service disruptions, product recalls, or reputational incidents. In telecommunications and banking, these systems handle thousands of repetitive inquiries, freeing human teams to focus on operational problem-solving. A telecom crisis manager described their chatbot's role during a major outage:

> *Within the first 15 minutes, the bot had already responded to more than 3,000 customers. If that had been humans, the backlog would have exploded.*

These systems, however, do more than field basic questions. Well-designed chatbots can push targeted updates, direct users to verified information sources, and gather feedback in real time. This two-way capability helps to stabilise narratives during a crisis, especially when misinformation is circulating online. Yet, the findings reveal that automation is not infallible. In some cases, the absence of real-time human oversight has led to damaging mismatches between automated responses and the evolving reality. A banking sector respondent recounted a payment system glitch where the bot insisted services were "operating normally" for hours after the issue had been confirmed internally:

> *It made us look either dishonest or clueless. People trust what's written down, so if the bot is wrong, it damages credibility fast.*

Such incidents highlight the importance of coupling automation with rapid human intervention protocols. Without the ability to update or override scripted responses immediately, organizations risk undermining the trust these systems are meant to protect. Another pattern emerging from the data is the over-reliance on generic bot templates. Several participants acknowledged that their chatbots were "plug-and-play" systems purchased from third-party vendors with minimal localization. This limited their ability to handle culturally nuanced inquiries or address sector-specific issues during crises. As one PR officer in the energy sector noted:

> *The bot can answer 'Where do I pay my bill?' but if someone asks about power outages caused by flooding, it struggles to provide the reassurance people want.*

This lack of contextual sensitivity can erode public confidence, especially in high-stakes crises where emotional reassurance matters as much as factual accuracy. The most effective examples of chatbot deployment came from organizations that treated them as complementary rather than replacement tools. These organizations integrated bots into a broader communication ecosystem, where AI handled high-volume, low-complexity queries while trained human agents addressed nuanced or sensitive matters. A senior communications strategist summed it up:

> *The bot is our front line, but the humans are our problem-solvers. You can't flip that around in a crisis.*

While chatbots and automated systems are helping Ghanaian organizations cope with the volume and speed demands of crisis communication, their long-term value depends on local customization, constant updating, and seamless escalation to human agents. Without these, the very tool designed to reassure stakeholders can end up amplifying frustration or mistrust.

4.3.2 Sub-theme: Personalization of Crisis Messages for Different Stakeholder Groups

One of AI's most powerful capabilities in real-time crisis communication is its ability to segment audiences and deliver tailored messages that address the unique concerns of different stakeholder groups. In theory, this ensures that employees, customers, investors, and the general public each receive information that is relevant, timely, and framed in a way that resonates with their needs.

In practice, however, this level of personalization is still rare among Ghanaian organizations. Most respondents acknowledged that while their AI tools could segment by geography, customer type, or service history, messages sent during crises often default to generic public updates. As one senior PR officer in the financial sector put it:

> *The technology is there to target, but when pressure hits, we blast the same message to everyone because it's faster and feels safer.*

This tendency to opt for uniform messaging in high-pressure moments undermines one of AI's core advantages. Generic messaging may reduce misinformation risk, but it also misses the opportunity to directly address the specific concerns of different audiences. For instance, an investor may need assurances about the financial impact of a crisis, while a customer primarily wants to know how it affects service delivery. Some participants did report more advanced personalization efforts, particularly in the telecommunications sector. One crisis manager described how they used AI-driven analytics during a major service outage:

> *We pushed different updates to prepaid and postpaid customers. Prepaid users got quick fixes and alternative recharge options, while postpaid customers received billing adjustments and compensation information.*

This example shows how segmentation can reduce frustration and prevent escalation, as each group feels its concerns are being directly acknowledged. Yet, these cases were the exception rather than the norm. Another barrier is the risk perception around personalization. Some communications teams worried that highly targeted crisis messages could be seen as discriminatory or reveal sensitive internal data about customers. As one corporate affairs officer noted:

> *If you send a message that makes it clear you know a lot about a customer's history, it can make them uneasy, especially in a crisis when trust is already fragile.*

This highlights the delicate balance between relevance and privacy. AI systems can pinpoint exactly who needs what information, but organizations must manage how this targeting is perceived to avoid triggering suspicion or backlash. Where personalization has been implemented effectively, it is usually backed by clear audience mapping, pre-approved message templates, and close coordination between technical teams and communication officers. In these instances, AI acts not just as a mass broadcaster but as a precision tool for building trust across diverse audience segments. However, without strong operational readiness, personalization capabilities tend to remain dormant during crises. The evidence suggests that many Ghanaian organizations have the technical capacity but lack the crisis-time processes to make full use of it. As one technology consultant put it:

> *The irony is that the same AI system they use to send targeted marketing offers every week could also send targeted crisis updates but it rarely happens.*

This disconnect means that AI's promise of relevant, differentiated communication remains largely unfulfilled in the crisis space. Until organizations embed personalization into their crisis playbooks and rehearse its execution it will remain an underused strength of AI-driven engagement.

4.3.3 Sub-theme: Combating Misinformation Through AI-Powered Verification Tools

The rapid spread of misinformation during crises is a persistent challenge for Ghanaian organizations, particularly in an era where social media narratives can gain traction within minutes. AI-powered verification tools are increasingly being recognized as essential for identifying, flagging, and countering false or misleading information before it undermines public trust.

Among the organizations studied, some had implemented AI-driven fact-checking systems that scan social media posts, blogs, and online news for keywords and claims matching known crisis events. These systems cross-reference information with verified data sources, helping communication teams identify harmful narratives early. A senior media monitoring analyst at a telecom firm explained:

> *When we see a tweet claiming our network has collapsed nationwide, the system checks actual outage reports and flags whether the claim is false. That lets us respond fast, before it spirals.*

This rapid verification capability is particularly important because, as several participants observed, false stories often outpace corrections in terms of visibility. The AI tools help close that gap by prioritizing which rumours need urgent debunking and by suggesting standard counter-messages for distribution across official channels. However, the research also revealed gaps in consistency and follow-through. In several cases, AI successfully detected misinformation, but the response lagged because internal approval chains were too slow. A communications officer in the energy sector noted:

> *We can spot fake news in seconds, but sometimes it takes hours for the official statement to be signed off. By then, the story has already done damage.*

This points to a procedural bottleneck rather than a technological shortfall. AI may detect the falsehood, but without streamlined decision-making, the verification advantage is wasted.

Another issue is the platform limitation of many verification tools. While AI can monitor open networks like Twitter (X) and Facebook, misinformation in Ghana often spreads rapidly through closed messaging platforms like WhatsApp, where AI detection is far more limited. A public health crisis coordinator observed:

> *By the time misinformation reaches Facebook, it's often already gone viral on WhatsApp, where we can't track it easily.*

This limitation forces organizations to rely on human networks staff, community volunteers, or media partners to relay WhatsApp content for manual verification. Some respondents suggested that integrating AI verification with crowdsourced reporting could help bridge this gap, but few had formalized such mechanisms. In addition, there are ethical considerations tied to AI verification. Overzealous flagging of content risks being perceived as censorship, especially in politically sensitive crises. One communications strategist for a public agency remarked:

> *If you label a post as fake too quickly and it turns out to be true, your credibility collapses. We have to be careful not to appear like we're silencing dissent.*

This underlines the importance of pairing AI-powered verification with transparent communication explaining how and why content was classified as false.

Overall, while AI verification tools have significantly improved the speed and accuracy of misinformation detection, their impact is often undermined by slow human approval processes, platform blind spots, and perception risks. To fully realise their potential, organizations must embed verification into rapid-response protocols, expand monitoring into harder-to-reach channels, and ensure that counter-messages are as visible and shareable as the falsehoods they are designed to correct.

4.4 Post-Crisis Learning and Evaluation Through AI Insights

This theme addresses how AI can support organisational learning after a crisis, turning data-driven insights into improved crisis communication strategies. It looks at how AI analytics, benchmarking, and feedback loops can reveal what worked, what failed, and where systemic weaknesses persist. The findings suggest that while some organisations use AI to evaluate performance and benchmark against past crises, many fail to feed these insights into structured improvement processes. This results in "lessons identified but not lessons learned," where repeated mistakes are not systematically addressed

4.4.1 Sub-theme: AI-Based Performance Analytics and Feedback Loops

One of the underutilized strengths of AI in Ghanaian crisis communication is its capacity to provide comprehensive post-crisis performance analytics that feed directly into continuous improvement cycles. When effectively applied, AI can aggregate and interpret vast datasets from social media sentiment to message engagement rates to give organizations a granular understanding of how their communication strategies performed and where gaps remain. A few corporate and telecommunications sector participants described structured processes for post-crisis AI analysis. One corporate affairs manager noted:

> *After every major incident, the system generates a report showing how sentiment changed hour by hour, which messages drove positive shifts, and which ones were ignored. It helps us adjust our playbook for next time.*

Such data-driven retrospectives enable organizations to go beyond surface-level evaluations ("the crisis is over") and instead identify what actually worked in shaping public perception and controlling the narrative. This aligns with the principle that post-crisis evaluation should be an active learning process, not a passive review. However, most participants admitted that while they collect performance data during and after crises, the insights are rarely fed back into structured improvement loops. In several organizations, AI-generated analytics end up archived rather than actively influencing future strategy. As one public relations officer candidly put it:

> *We get the dashboard reports, but no one is tasked with turning them into new protocols. We basically just move on to the next crisis.*

This reflects a deeper cultural and operational gap. AI can provide evidence-based feedback, but without institutionalized learning mechanisms, valuable insights remain unused. The result is that mistakes are repeated, and successful tactics are not codified for reuse. Another dimension is the timing of analysis. Several participants acknowledged that their post-crisis evaluations are conducted weeks or even months after the event, often when internal urgency has faded. This delay weakens the relevance and impact of AI insights. As a media monitoring specialist observed:

> *By the time the post-mortem happens, decision-makers are already focused on something else. The learning moment is gone.*

In contrast, organizations with more advanced AI integration conduct near-real-time evaluations, generating daily or weekly reports during the crisis and immediately afterward. This allows them to adapt quickly if similar patterns re-emerge, turning AI analytics into an ongoing adaptive feedback loop rather than a one-time post-event report. The findings reveal that many organizations overlook cross-event learning comparing data from multiple crises to detect recurring weaknesses or strengths. AI's ability to benchmark performance across incidents could be transformative, but most participants had never conducted such comparative analyses. One AI systems consultant explained:

> *The gold is in spotting patterns across crises. If every time you're slow to respond to rumours it hurts sentiment, that's a fixable issue. But you'll only see it if you look across events.*

In summary, while AI-based analytics have the potential to embed continuous learning into crisis communication, most Ghanaian organizations treat them as end-of-event reports rather than dynamic improvement tools. Without deliberate integration into policy, training, and scenario planning, the promise of AI feedback loops remains largely unrealized.

4.4.2 Sub-theme: Benchmarking and Comparative Analysis with Past Crises

Benchmarking against past crises is one of the most **strategically valuable yet least practiced** applications of AI in Ghanaian crisis communication. By systematically comparing performance metrics, sentiment trends, and response timelines from different crisis events, AI can reveal consistent strengths and recurring vulnerabilities. However, few organizations have formalized this process. In sectors where it is practiced, the benefits are tangible. A corporate communications manager in the banking sector explained:

> *When we compared last year's cyber-fraud incident with the mobile-banking outage this year, the AI flagged the same weakness slow acknowledgment in the first two hours. That pattern was invisible to us before.*

Such insights enable organizations to identify systemic issues that transcend individual events, such as chronic delays in internal approvals, inadequate early-stage messaging, or recurring misinformation vulnerabilities. Without this comparative lens, each crisis is treated in isolation, and the opportunity to address deep-rooted process flaws is missed. Yet, the data show that most Ghanaian organizations do not engage in structured benchmarking. Many treat each crisis as a one-off, conducting post-mortems that focus narrowly on that single event. As one PR officer in the energy sector admitted:

> *We review what happened after every crisis, but we don't line them up side-by-side to see patterns. It's like starting from scratch each time.*

This absence of comparative analysis means that lessons learned are often siloed within specific teams or events. Even when AI systems store detailed historical data, the information is rarely retrieved for cross-event analysis. A telecoms sector participant highlighted this gap:

> *The history is there in the system. But unless someone actively pulls it up and runs the comparison, it just sits there gathering digital dust.*

Another underused feature is external benchmarkingcomparing performance not only against internal history but also against peer organizations or industry standards. Some AI tools can ingest public-domain crisis data from competitors or similar institutions, offering a broader context for performance evaluation. A crisis consultant who works with multiple Ghanaian firms observed:

> *If you can see that your competitor restores sentiment in 48 hours while it takes you a week, that's a wake-up call. But very few companies here want to look outside their own walls.*

This reluctance stems partly from cultural sensitivities around acknowledging weaknesses, especially in competitive or politically sensitive sectors. However, without external reference points, organizations risk overestimating their effectiveness or failing to keep pace with industry best practices.

Where benchmarking is embedded in practice, AI facilitates a data-driven maturity model showing whether crisis management capability is improving over time, stagnating, or declining. This provides not only operational insights but also strategic evidence for justifying investments in training, staffing, and technology. At present, the absence of widespread benchmarking means Ghanaian organizations miss out on one of AI's most valuable roles in post-crisis learning: turning individual experiences into longitudinal intelligence. Without it, the same mistakes are likely to recur, eroding trust and weakening long-term resilience.

4.4.3 Sub-theme: Continuous Improvement and Refinement of Communication Strategies

AI's greatest value in the post-crisis phase lies in its ability to convert data-driven insights into actionable refinements for future communication strategies. This process moves beyond evaluation to embed a cycle of continuous improvement, where each crisis strengthens the organization's readiness for the next. In organizations where this approach is embedded, AI outputs are not treated as static reports but as inputs for decision-making, scenario planning, and message design. One corporate affairs director in telecommunications described how they use AI-derived insights in annual crisis simulations:

> *We take last year's incident data, feed it into our simulation software, and see if the tweaks we made actually speed up response time or improve sentiment recovery. It's how we stress-test ourselves.*

This proactive application of AI learning contrasts sharply with the more common passive approach observed in many organizations, where post-crisis reports are filed but not operationalized. In such cases, there is a clear disconnect between knowing what went wrong and changing processes to prevent recurrence. Several participants pointed to structural barriers to continuous refinement. Some organizations lack a designated crisis communication review team tasked with translating AI insights into revised protocols. As a result, useful recommendations remain theoretical. A public health agency communications officer admitted:

> *We have brilliant AI reports, but there's no one assigned to turn them into policy changes. Everyone is too busy dealing with the next emergency.*

Even when improvements are attempted, they are often ad hoc and personality-driven, depending on the initiative of a particular manager rather than institutionalized processes. This creates inconsistency, as lessons learned in one crisis may not be applied in the next if leadership changes or priorities shift. Another finding is that continuous improvement is most effective when AI insights are integrated into multi-disciplinary learning sessions that involve communications teams, operational managers, legal advisers, and frontline staff. This cross-functional approach ensures that adjustments are not limited to messaging but address the underlying operational causes of communication breakdowns. However, these integrated learning exercises are rare. A consultant who works across several sectors observed:

> *Most crisis reviews are internal to the comms team. That's like fixing the roof without checking if the walls are collapsing. AI tells you where the weak points are, but the whole house has to be involved in the repair.*

The few organizations actively using AI for continuous refinement reported measurable gains faster message approvals, improved consistency across channels, and better targeting of key audiences. But these are exceptions rather than the norm. Continuous improvement demands discipline, ownership, and a culture of learning. AI can identify what needs to change, but it cannot enforce the change. Without a deliberate commitment to acting on insights, organizations risk falling into a data-rich but improvement-poor cycle, where lessons are known but never applied.

4.5 Ethical and Contextual Considerations in AI-Driven Crisis Communication

This theme examines the ethical challenges and contextual realities of integrating AI into crisis communication in Ghana. It addresses issues such as data privacy, security, algorithmic fairness, and the balance between automation and human oversight. The findings indicate that AI adoption without robust ethical safeguards risks eroding stakeholder trust, amplifying biases, and creating compound crises where reputational harm is intensified by privacy breaches or tone-deaf responses. Furthermore, cultural and contextual considerations such as linguistic diversity and stakeholder sensitivity to perceived surveillance require deliberate governance frameworks.

4.5.1 Sub-theme: Data Privacy and Security Concerns

The integration of AI into crisis communication inevitably raises complex questions about data privacy and security, particularly in environments where large volumes of personal and sensitive information are processed in real time. In Ghana, this concern is amplified by varying levels of compliance with data protection laws and by the uneven maturity of cybersecurity practices across organizations.

Participants from both public and private sectors acknowledged that AI systems often require access to customer records, social media activity, and internal operational data to function effectively. This creates a heightened risk of data breaches or unauthorized use. A senior IT security officer in a financial institution explained:

> *The same AI that helps us track a potential reputational crisis also has access to customer identifiers, transaction details, and location data. If that's compromised, the crisis doubles in size.*

The sensitivity of the data means that a communication crisis can quickly morph into a legal and reputational disaster if privacy safeguards fail. Several respondents admitted that while their organizations have formal privacy policies, enforcement is inconsistent, and the integration of AI tools often bypasses full security audits. A corporate affairs manager noted:

> *The communications team buys the monitoring tool for speed, but IT only gets involved after it's live. By then, we're already processing personal data without a full security review.*

This lack of early cross-functional oversight is a recurring weakness. It leaves organizations exposed to vulnerabilities such as data leaks through poorly configured third-party AI tools, especially when those tools are cloud-hosted in jurisdictions with weaker privacy protections.

Another issue is public trust erosion when stakeholders feel their data is being misused. In crisis situations, emotions run high, and any perception of intrusive data collection can be damaging. One public health crisis coordinator reflected on community backlash during a disease outbreak:

> *People started asking why we knew their exact movements. Even though it was anonymized location data, they felt watched. That distrust made communication harder.*

This underscores the importance of transparent data governance clearly communicating to stakeholders how their information is collected, stored, and used during crises. Yet, transparency is often reactive rather than proactive. Few organizations make privacy explanations a standard component of their crisis communication, leaving room for suspicion. Some participants also raised concerns about security complacency. The urgency of a crisis can create a "deploy now, secure later" mentality, where AI tools are activated without full privacy vetting in the rush to respond. While this may speed initial response, it heightens the long-term risk of data breaches.

International best practice suggests that AI-driven crisis communication systems should incorporate privacy-by-design principles embedding encryption, anonymization, and access controls from the outset. However, the findings indicate that in many Ghanaian organizations, privacy measures are retrofitted rather than foundational. The implications are clear: without robust privacy and security protocols, AI can transform a manageable crisis into a compound crisis one that combines the original reputational threat with legal liability and stakeholder mistrust. As one technology governance consultant put it:

4.5.2 Sub-theme: Algorithmic Bias and Fairness in Automated Decision-Making

While AI offers speed and scale in crisis communication, it also introduces the risk of algorithmic bias, where automated decision-making disproportionately favors or disadvantages certain individuals or groups. In the Ghanaian context, this issue takes on particular importance given the country's cultural, linguistic, and socio-economic diversity.

Several participants acknowledged that their AI-powered monitoring and engagement tools rely on natural language processing (NLP) models and sentiment classifiers trained primarily on Western datasets. This creates a mismatch when interpreting local expressions, slang, or dialect. A media monitoring analyst explained:

> *The system might mark something as neutral or even positive because it doesn't understand the sarcasm in local languages. That means it can miss early signs of discontent in those communities.*

Such misclassifications are not trivial. They can result in delayed or misdirected crisis responses that neglect certain demographics, exacerbating reputational damage in underserved or linguistically diverse communities. Bias can also creep into automated prioritization systems used during crises. Some AI tools rank stakeholder inquiries by urgency based on language cues or platform activity levels. One customer service officer in a telecoms company observed:

> *Complaints in English often get flagged as high priority, but the same issue in Twi or Ewe might be ranked lower because the algorithm doesn't pick up the urgency.*

This kind of structural bias risks creating communication inequities, where certain groups consistently receive slower or less tailored responses during crises. Over time, such disparities can erode trust and deepen perceptions of organizational neglect or favoritism. Another layer of concern is predictive decision-making in allocating crisis resources. In some sectors, AI tools suggest which regions or customer segments should receive priority communication based on historical engagement data. However, this can reinforce existing inequalities by focusing on already-engaged groups while overlooking harder-to-reach or historically marginalized audiences.

Participants from the public sector acknowledged the ethical dilemma here. A crisis communication officer in a government agency remarked:

> *If the AI tells us to focus on urban social media users because they're most active online, we risk ignoring rural communities who might be facing the worst of the crisis.*

The ethical stakes are high: bias in automated systems can lead to selective visibility where only certain voices are amplified and others remain unheard. In crises, this is not simply a fairness issue; it directly impacts the quality and reach of life-saving or trust-building information. Mitigating these risks requires deliberate bias-testing, local dataset enrichment, and human oversight. Few Ghanaian organizations in the study reported regular audits of their AI tools for fairness. In many cases, bias was only noticed after a problematic incident occurred. One technology governance consultant noted:

> *We only started questioning the system when we realized some communities never got our updates on time. By then, the damage was already done.*

Embedding fairness into AI-driven crisis communication is not optional it is essential to ensure that the very tools designed to enhance communication do not inadvertently reinforce inequality. Without this commitment, AI adoption risks replicating offline societal biases at digital speed and scale, undermining both the credibility and the inclusiveness of crisis response efforts.

4.5.3 Sub-them: Balancing AI Automation with Human Oversight in Crisis Contexts

One of the recurring themes across the interviews was the need to balance AI's speed and efficiency with the discernment and contextual judgment of human oversight. While AI tools can process vast amounts of data, detect anomalies, and respond within seconds, crises are often socially and emotionally complex, requiring human sensitivity that algorithms cannot replicate. Participants consistently stressed that over-reliance on automation can backfire. In several instances, automated systems issued responses that were factually correct but tone-deaf to the emotional state of the audience. A communications officer in the financial sector recalled:

> *During a service outage, the chatbot was giving technical updates accurate ones but customers were angry and scared. What they needed first was empathy, not just facts.*

This reflects a core limitation of AI: it can identify what is happening but struggles to fully grasp how people feel about what is happening. Without human intervention, AI risks sounding mechanical, dismissive, or even provocative in sensitive situations. Another risk is automated escalation errors. AI systems are often designed to prioritize and route incidents based on predefined rules. If these rules are too rigid, they can miss subtle but serious developments. One telecom crisis manager shared:

> *A celebrity posted a sarcastic comment about our network. The AI didn't see it as high priority because it wasn't overtly negative. By the time humans caught it, it had gone viral.*

Such gaps highlight why human validation of AI outputs is crucial, especially for high-stakes decisions in volatile public environments. Several participants advocated for a hybrid model, where AI handles the heavy lifting such as scanning vast data streams, flagging anomalies, and generating draft responses while human teams review, adapt, and approve before public release. This approach not only reduces the risk of missteps but also maintains the authenticity and cultural nuance that human communicators bring. One corporate affairs director explained how they operationalize this:

> *Our AI drafts the first version of an alert, but it's never sent without a human reading it. Even in fast-moving crises, that extra two-minute review can save us from sending something damaging.*

Beyond content review, human oversight plays a role in ethical accountability. If an AI system issues a harmful or misleading response, public backlash typically targets the organization, not the technology. Having human approval checkpoints ensures that responsibility remains where it belongs within the leadership and communications team. However, striking the right balance is not without challenges. Over-monitoring AI can slow down response times, undermining its key advantage. Under-monitoring, on the other hand, risks ceding too much control to automated systems, with potentially damaging consequences. Organizations therefore need clear governance frameworks that define when AI can act autonomously, when it must defer to human judgment, and how escalations are handled. The evidence suggests that organizations that succeed in this balancing act treat AI not as a replacement for human communicators but as a force multiplier augmenting human capacity rather than substituting it. As one technology strategist succinctly put it

4.6 Barriers and Enablers to AI Adoption in Crisis Communication

This theme explores the organisational and cultural factors that either facilitate or hinder the adoption of AI in crisis communication. It examines how leadership commitment, technical expertise, resource allocation, and cultural attitudes shape AI integration. The findings show that leadership advocacy and organisational readiness are decisive enablers, while skills gaps, funding limitations, and resistance rooted in cultural attitudes towards automation are significant barriers. Where AI is positioned as an enabler that supports human judgment rather than replacing it, adoption tends to be deeper and more sustained.

4.6.1 Sub-theme: Organizational Readiness and Leadership Commitment

The capacity of an organization to successfully adopt and integrate AI into crisis communication is strongly shaped by its readiness level and the degree of commitment from leadership. Without these, even the most advanced tools risk becoming underutilized or entirely dormant. Across the data, a recurring theme was that technology investment alone is insufficient. Many organizations had purchased AI-driven monitoring or engagement systems, but in the absence of committed leadership and a readiness plan, these tools remained peripheral rather than central to crisis management. A corporate affairs manager in the telecommunications sector reflected:

> *The tools are here, but without leadership driving their use, they just become another dashboard no one looks at until it's too late.*

Readiness is multidimensional. It encompasses not only technical capacity such as infrastructure and skilled staff but also cultural preparedness. Organizations that view AI as a strategic asset, rather than a novelty, tend to integrate it into training, standard operating procedures, and decision-making frameworks. In these environments, leadership commitment is visible through budget allocation, policy integration, and accountability mechanisms. Conversely, where leadership views AI adoption as a **symbolic gesture** rather than a functional necessity, readiness levels remain low. Several participants described situations where AI tools were procured primarily to signal modernization to stakeholders or regulators, rather than as part of a clear operational plan. A senior public sector communications officer admitted:

> *We bought the system because it looked good for our image, but there's no internal policy on how to use it in a crisis. It just sits there.*

Leadership commitment also influences the speed of adoption. In fast-moving crises, decision-makers must be willing to trust AI-driven insights and act on them quickly. However, some leaders remain cautious, preferring to rely on established manual processes even when AI indicates a faster or different course of action. This caution, while understandable, can undermine AI's value in time-sensitive contexts. A notable enabler identified in the study was the role of "AI champions" within organizations individuals at senior or mid-management level who actively promote AI integration, advocate for resources, and ensure follow-through. These champions often act as bridges between technical teams and leadership, translating AI capabilities into strategic value. A crisis consultant explained:

> *When there's a champion who can speak both the language of the boardroom and the language of the tech team, AI adoption moves from theory to reality.*

However, without strong leadership backing, even these champions face limitations. They may initiate pilot projects, but scaling them into organization-wide crisis communication frameworks requires executive endorsement and sustained investment.

The findings suggest that organizational readiness and leadership commitment function as gatekeepers to AI adoption. Where both are strong, AI is embedded into the very fabric of crisis communication tested, trusted, and continuously improved. Where they are weak, AI risks becoming a symbolic acquisition, disconnected from operational reality and delivering minimal value when crises strike.

4.6.2 Sub-theme: Availability of Technical Expertise and Resources

The successful integration of AI into crisis communication hinges not only on organizational will but also on the availability of technical expertise and supporting resources. In many Ghanaian organizations, this remains a critical bottleneck. A recurring observation from participants was that AI tools are often acquired without a clear plan for who will operate, interpret, and maintain them. One corporate communications officer in the banking sector explained:

> *We have the platform, but there's no one in-house who truly understands how to use its full capabilities. We end up using only the most basic features.*

This underutilization reflects a skills gap in both technical and analytical dimensions. On the technical side, organizations need personnel who can configure AI tools, manage data integration, and troubleshoot issues. On the analytical side, they require professionals capable of interpreting AI outputs in a crisis context, understanding their implications, and translating them into strategic actions. In several cases, organizations attempted to fill this gap by outsourcing AI operations to external vendors. While outsourcing can provide quick access to expertise, it introduces vulnerabilities, particularly in crisis situations where delays in communication can be costly. A public sector participant noted:

> *We rely on a vendor to run the system. If they're slow to respond or unavailable, we're effectively blind in those crucial first hours.*

This reliance on third parties also raises data security concerns, especially when sensitive information must pass through external hands. Moreover, outsourcing often focuses on operational support rather than capacity building, meaning the skills gap remains unaddressed internally. Resource availability is another decisive factor. Advanced AI tools require financial investment not only in licensing fees but also in hardware, software integration, and continuous training. For small and medium-sized enterprises (SMEs) and under-resourced public agencies, these costs can be prohibitive. As one SME owner explained:

> *We looked into AI monitoring, but the annual subscription alone was more than our entire marketing budget.*

Even in larger organizations, budget constraints can lead to compromises such as opting for limited-feature tools or reducing the frequency of system updates both of which undermine performance during crises. The study also found that resource allocation priorities influence adoption. In some cases, AI investments compete with other urgent organizational needs, such as operational infrastructure or compliance obligations. Without a clear business case linking AI adoption to crisis mitigation and reputational protection, funding is often diverted elsewhere.

A few participants highlighted that resource scarcity can be partially mitigated through collaborative arrangements, such as industry consortia that share AI monitoring infrastructure or pooled data analysis services. However, such models are still rare in Ghana, and their potential remains largely untapped. Without the right blend of technical expertise, internal capacity, and resource commitment, even the most advanced AI tools risk becoming underused or entirely dormant. This capability gap not only limits the return on AI investments but also leaves organizations vulnerable to being outpaced by fast-moving crises that demand rapid, informed, and technologically supported responses.

4.6.3 Sub-theme: Cultural Attitudes Towards Technology Adoption in Ghana

Cultural perceptions and attitudes towards technology play a significant role in shaping how AI is adopted and used in crisis communication. In Ghana, while there is broad enthusiasm for technology in general, the leap from general appreciation to operational reliance on AI in high-stakes situations is far from straightforward. A recurring sentiment among participants was cautious optimism an interest in AI’s capabilities tempered by skepticism about its reliability and appropriateness in sensitive contexts. One senior public sector communications officer observed:

> *People like the idea of AI, but when it comes to actually trusting it in a real crisis, most want a human in charge.*

This reflects a wider cultural preference for human-centered decision-making in situations involving public trust, reputation, and accountability. Many decision-makers are hesitant to delegate critical communication functions entirely to machines, fearing that doing so could be perceived as impersonal or irresponsible, particularly when dealing with emotionally charged crises.

There is also an undercurrent of status and role preservation influencing attitudes towards AI adoption. Some communications professionals expressed concerns that automation could erode their relevance or diminish the value of their expertise. A corporate PR manager admitted:

> *There’s a fear that if AI handles too much, people will question why they need a communications team at all.*

Such anxieties can manifest as passive resistance AI tools are nominally in place but seldom used to their full potential. This reluctance is sometimes reinforced by organizational hierarchies where senior leaders favor familiar manual processes over untested automated ones. Cultural factor is the perception of technology as a prestige asset rather than a functional necessity. Several participants suggested that some organizations invest in AI systems primarily for symbolic signaling to project innovation and modernity rather than for active operational use. As one media monitoring consultant put it:

> They want to be able to say, ‘We have AI,’ even if they rarely switch it on.

Trust in technology is further shaped by previous experiences with digital tools. Where earlier implementations have failed whether due to poor training, unreliable infrastructure, or lack of support there is a lingering reluctance to embrace new systems. This hesitancy can be especially strong in public agencies and SMEs, where budgets are tight and tolerance for perceived waste is low. Conversely, cultural attitudes can also act as enablers when organizational leadership successfully frames AI as a supportive partner rather than a replacement for human judgment. In these cases, AI adoption is seen as a way to enhance professional credibility, improve efficiency, and expand capacity. For example, a crisis communication strategist explained:

> *We position AI as the assistant that does the heavy lifting, so our people can focus on the strategic calls. That way, no one feels replaced they feel empowered.*

Cultural attitudes in Ghana towards AI in crisis communication are a blend of interest, caution, and selective enthusiasm. While there is recognition of AI's potential, full adoption requires not just technical readiness but a cultural shift one that normalizes technology as a trusted partner in high-stakes communication rather than a threat to professional roles or a symbolic status marker.

4.7 Conclusion

The analysis reveals that while Artificial Intelligence (AI) holds strong potential for enhancing crisis communication in Ghanaian organizations, its adoption remains fragmented, uneven, and underutilized. Across six themes, a common pattern emerges: AI's value is acknowledged in theory but rarely fully realized in practice. Awareness is growing, yet use is often confined to keyword monitoring, basic chatbots, and simple sentiment tracking, with advanced uptake concentrated in sectors like banking and telecommunications, while public agencies and SMEs engage sporadically. AI offers powerful early detection and monitoring tools such as predictive analytics and real-time sentiment analysis but these are often applied reactively, diminishing their preventive impact. In real-time engagement, automation can manage high volumes and tailor messages, but effectiveness is limited by generic scripts, poor personalization, and inconsistent misinformation responses; hybrid human-AI models work best. Post-crisis, AI can support performance analysis and continuous improvement, though many treat insights as static records rather than inputs for adaptive learning. Ethical concerns privacy, fairness, and oversight are central, as poor governance risks bias and tone-deaf automation. Adoption depends on readiness, leadership, expertise, resources, and cultural attitudes, with deeper integration where leaders invest in skills and frame AI as an enabler. Overall, Ghana is at a transitional stage past novelty but far from maturity requiring strategic, ethical, and systemic embedding of AI in crisis communication to meet the demands of a rapidly evolving digital landscape.

DISCUSSION OF FINDINGS

4.8 Introduction

The preceding chapter presented the empirical findings from the study, organized into six key themes: (1) Current State of AI Integration in Crisis Communication, (2) AI-Enhanced Crisis Detection and Monitoring, (3) AI in Real-Time Crisis Response and Engagement, (4) Post-Crisis Learning and Evaluation, (5) Ethical and Contextual Considerations, and (6) Barriers and Enablers to AI Adoption. This chapter discusses these findings in relation to the study's theoretical foundations the Diffusion of Innovations Theory (Rogers, 2003), Situational Crisis Communication Theory (SCCT) (Coombs, 2007), and the Social Media Crisis Communication (SMCC) Model (Austin, Liu, & Jin, 2012) and positions them within the broader body of literature on AI adoption, crisis management, and organisational communication.

4.9 Current State of AI Integration in Crisis Communication

The findings show that awareness of AI in Ghanaian crisis communication is growing but integration remains uneven and sector-specific. This reflects the Diffusion of Innovations Theory's assertion that adoption rates vary according to organisational context, perceived complexity, and relative advantage. Early adopters in banking and telecommunications demonstrate greater maturity in AI use, particularly in real-time monitoring and automation, while public sector agencies and SMEs tend to engage in symbolic or minimal use.

This partial integration aligns with global studies highlighting that AI adoption in crisis contexts often begins as reactive supplementation to existing processes rather than as a core strategic transformation (Dwivedi et al., 2021). The tendency to treat AI as a "bolt-on" rather than a systemic capability limits its capacity to fundamentally reshape crisis preparedness, echoing Coombs' (2019) warning that technological tools cannot substitute for well-designed crisis communication strategies. Moreover, the Ghanaian experience reflects Austin et al.'s (2012) SMCC Model insight that organisations must engage not only in message dissemination but also in continuous monitoring of stakeholder discourse. Where AI integration is shallow, this two-way engagement remains underdeveloped, weakening the organisation's ability to manage crisis narratives effectively.

4.10 AI-Enhanced Crisis Detection and Monitoring

The study found that while predictive analytics, real-time monitoring, and sentiment analysis are technically available in many Ghanaian organisations, they are underused or applied reactively. This mirrors Jin et al.'s (2014) observation that even when advanced tools exist, crisis teams may wait for visible escalation before mobilising a full response.

From a SCCT perspective, this delay undermines the timeliness and relevance of messages, as crisis response strategies are most effective when initiated early. AI's predictive capabilities could help shift responses from reactive to proactive, yet the findings indicate a trust gap decision-makers are reluctant to act solely on algorithmic forecasts without visible confirmation. This is consistent with Brynjolfsson and McAfee’s (2017) argument that human-AI trust calibration is a prerequisite for realising AI’s preventive potential. The findings also highlight a localisation challenge: AI sentiment tools often misinterpret Ghanaian linguistic nuances, humour, and sarcasm. This limitation confirms Noble’s (2018) critique of algorithmic bias, showing that reliance on Western-trained models risks missing culturally embedded signals of discontent or misinformation.

4.11 AI in Real-Time Crisis Response and Engagement

Real-time engagement through AI, such as chatbots and automated messaging, was identified as a key area of adoption, particularly in high-volume customer service crises. This aligns with SMCC Model principles, where timely and responsive communication across multiple channels strengthens stakeholder trust. However, findings indicate that these tools are often generic, poorly localised, and lacking in empathy, confirming concerns raised by Floridi et al. (2018) that automation risks dehumanising communication in sensitive contexts. While AI excels in speed and scalability, it struggles with emotional intelligence an essential component of SCCT’s guidance on maintaining stakeholder trust during crises. Furthermore, personalisation capabilities are underutilised, even though targeted messaging could address the differential information needs of varied stakeholder groups. This is a missed opportunity, as tailored crisis messages have been shown to reduce misinformation and foster trust (Liu, Austin, & Jin, 2011).

4.12 Post-Crisis Learning and Evaluation

One of the clearest gaps identified is the limited use of AI for post-crisis evaluation, benchmarking, and continuous improvement. While some organisations collect AI-generated reports, these are rarely translated into policy changes or embedded into crisis playbooks. This reflects the “lessons identified but not lessons learned” problem highlighted in crisis management literature (Smith & Elliott, 2007). Where AI is used effectively, it facilitates comparative analysis across multiple crises, revealing recurring weaknesses such as slow initial acknowledgment or inconsistent messaging. This capability aligns with Rogers' (2003) concept of "trialability" in innovation adoption the ability to experiment, refine, and institutionalise improvements over time. Yet, the study shows that most organisations are not leveraging AI to close the feedback loop between crises, limiting long-term resilience.

4.13 Ethical and Contextual Considerations

Ethical concerns around data privacy, algorithmic fairness, and human oversight emerged as a prominent theme. Consistent with Wirtz et al. (2019), the findings show that AI adoption in crisis contexts can create new vulnerabilities particularly when privacy safeguards are retrofitted rather than embedded from the outset. Algorithmic bias was observed in prioritisation systems that undervalue non-English communications or fail to capture culturally specific expressions of urgency. This supports Noble's (2018) argument that algorithmic systems can inadvertently reproduce social inequalities. Balancing automation with human oversight is therefore critical, not only to avoid ethical breaches but also to maintain public trust an outcome central to both SCCT and SMCC principles.

4.14 Barriers and Enablers to AI Adoption

Finally, the study underscores that organisational readiness, leadership commitment, technical expertise, resources, and cultural attitudes are decisive factors in AI adoption. This finding echoes Dwivedi et al.'s (2021) conclusion that without strong leadership advocacy, AI adoption remains symbolic rather than operational. The Ghanaian case shows that AI champions within organisations can drive adoption forward, but sustained impact requires executive-level buy-in, resource allocation, and skill development. Cultural attitudes particularly the preference for human-led decision-making can either hinder or support adoption depending on how AI is positioned: as a replacement or as a strategic enabler.

CHAPTER FIVE

SUMMARY, CONCLUSION, IMPLICATIONS, RECOMMENDATIONS, AND FUTURE RESEARCH DIRECTIONS

5.0 Chapter Overview

This concluding chapter brings together the core insights of the study, summarizing how each research objective was addressed and the key patterns that emerged across the six thematic areas in Chapter Four. It distills the central message and situates it within the broader context of AI-driven crisis communication in Ghana, drawing on the Diffusion of Innovations Theory, the Situational Crisis Communication Theory (SCCT), and the Social Media Crisis Communication (SMCC) Model to explain how technological capacity, organizational readiness, cultural context, and ethical governance shape adoption. The chapter outlines the study's implications for theory, practice, and policy, offering targeted recommendations for leaders, practitioners, policymakers, and technology developers to strengthen preparedness, responsiveness, and public trust in AI-enabled systems. It also identifies priorities for future research, including AI's role in detecting misinformation within closed networks, advancing culturally adaptive sentiment analysis, building long-term capacity, and conducting comparative studies across African contexts. Together, these reflections provide a forward-looking perspective on how AI can be strategically and ethically embedded to transform crisis communication in Ghana and similar settings.

5.1 Summary of Findings

The purpose of this study was to examine the integration of Artificial Intelligence (AI) into crisis communication within Ghanaian organisations, exploring how AI is understood, adopted, and operationalised across different phases of the crisis communication cycle. The findings, presented in six major themes, reveal that while AI holds substantial promise for enhancing crisis preparedness, detection, response, and post-event learning, its adoption in Ghana remains fragmented, uneven, and often under-leveraged.

Theme 1: Current State of AI Integration in Crisis Communication

The study found that awareness of AI's potential in crisis communication is increasing, yet integration remains limited and sector-dependent. Banking, telecommunications, and large-scale corporate entities are leading adopters, incorporating AI into monitoring systems and customer service automation. In contrast, public sector agencies and SMEs tend to engage in symbolic or sporadic use, often driven more by image than by operational necessity. The gap between conceptual enthusiasm and practical application reflects both resource disparities and differences in leadership vision.

Theme 2: AI Enhanced Crisis Detection and Monitoring

AI tools such as predictive analytics, real-time social media monitoring, and sentiment analysis are technically available in several organisations but are underused or applied reactively. Decision-makers often hesitate to act solely on algorithmic forecasts without visible crisis confirmation, limiting AI's preventive potential. Furthermore, many sentiment analysis tools are trained on Western linguistic datasets, which leads to misinterpretations of local expressions and sarcasm, reducing their accuracy in Ghanaian contexts.

Theme 3: AI in Real Time Crisis Response and Engagement

AI plays a significant role in managing high-volume communications during crises, particularly through chatbots and automated response systems. These tools improve speed and scalability, but generic scripting, poor localisation, and lack of emotional nuance limit their effectiveness. Personalisation features capable of tailoring messages to different stakeholder groups are rarely used. AI-powered misinformation detection exists but is often undermined by slow internal approval processes and the inability to monitor closed platforms such as WhatsApp.

Theme 4: Post Crisis Learning and Evaluation Through AI Insights

AI has the potential to transform post-crisis learning through detailed analytics, benchmarking, and feedback loops. However, most organisations fail to systematically feed these insights into policy or practice, resulting in repeated mistakes. Comparative analysis of multiple crises is rare, and cross-event learning remains underdeveloped. Only a few organisations use AI to actively refine their crisis communication strategies over time.

Theme 5: Ethical and Contextual Considerations in AI Driven Crisis Communication

The study identified significant ethical challenges in AI use, including weak data privacy safeguards, risks of algorithmic bias, and insufficient human oversight. AI systems often prioritise English-language communications and may undervalue messages in local languages, creating inequities in crisis response. Without clear governance frameworks, AI adoption risks amplifying rather than reducing communication inequalities, and public trust can be undermined by perceptions of surveillance or tone-deaf automated messaging.

Theme 6: Barriers and Enablers to AI Adoption in Crisis Communication

AI adoption is shaped by organisational readiness, leadership commitment, technical expertise, resource availability, and cultural attitudes. Strong leadership advocacy and AI “champions” within organisations enable deeper integration, while skills gaps, budget limitations, and scepticism about automation act as barriers. Cultural preferences for human-led decision-making can slow adoption, but where AI is positioned as a supportive partner rather than a replacement, uptake is stronger and more sustainable.

The findings suggest that Ghanaian organisations are in a transitional phase of AI adoption for crisis communication past the novelty stage but far from maturity. While individual cases demonstrate promising use, systemic adoption is hindered by technical, organisational, cultural, and ethical challenges that must be addressed before AI can fully realise its transformative potential in this context.

5.2 Conclusion

This study set out to investigate the role of Artificial Intelligence (AI) in enhancing crisis communication within Ghanaian organisations, examining how AI is understood, adopted, and operationalised across the crisis lifecycle. Drawing on empirical evidence from multiple sectors, the research found that while AI holds considerable promise for strengthening crisis preparedness, detection, response, and post-event learning, its potential remains largely under-realised in the Ghanaian context.

The study revealed that AI adoption is at a transitional stage beyond initial experimentation but far from systemic maturity. A small number of technologically advanced sectors, such as telecommunications and banking, are beginning to embed AI into their crisis management systems with measurable benefits in speed, monitoring capacity, and scalability. However, for many organisations especially within the public sector and SMEs AI is still perceived more as a symbolic innovation or an optional enhancement than as a core strategic capability.

The research also highlighted that while AI can deliver tangible operational gains, its effectiveness depends on more than technological capability. Organisational readiness, leadership commitment, technical expertise, ethical safeguards, and cultural acceptance are equally critical determinants of successful integration. Without these, AI tools risk becoming under-utilised or even counterproductive introducing new vulnerabilities such as data privacy risks, algorithmic bias, and tone-deaf communication. The findings suggest that AI will not replace human crisis communicators in Ghana but can significantly augment their capacity when deployed as part of a hybrid model. The most effective applications observed in the study combined AI's speed and analytical power with human judgement, empathy, and contextual understanding. Moving forward, the challenge for Ghanaian organisations is to shift from fragmented and reactive adoption towards integrated, proactive, and ethically governed AI-enabled crisis communication systems that can adapt to an increasingly fast-paced and digitally mediated crisis environment

5.3 Implications of the Study

The findings of this research have important implications for theory, professional practice, and policy in the field of AI-enabled crisis communication. These implications arise from the observed gap between AI's technical potential and its practical application within Ghanaian organisations, revealing how technology, organisational readiness, and contextual realities interact to shape adoption outcomes.

From a theoretical perspective, this study reinforces and extends existing frameworks used to understand technology adoption and crisis communication. The Diffusion of Innovations Theory (Rogers, 2003) is particularly relevant, as the findings demonstrate that AI adoption does not occur uniformly across sectors but is instead influenced by perceived usefulness, complexity, leadership commitment, and organisational readiness. In Ghana, high-risk and resource-rich sectors such as banking and telecommunications are positioned further along the adoption curve, while public institutions and SMEs often remain at the early stages. The Situational Crisis Communication Theory (SCCT) (Coombs, 2007) is also enriched by the study's evidence that AI can enhance timeliness, accuracy, and message appropriateness in crises, but only when its outputs are integrated into broader, strategically aligned communication frameworks. Without this integration, AI remains a supplementary tool rather than a strategic driver. Furthermore, the Social Media Crisis Communication (SMCC) Model (Austin, Liu, & Jin, 2012) is validated in showing the centrality of monitoring and engagement in shaping crisis narratives. However, the Ghanaian experience exposes a significant blind spot: AI tools struggle to capture misinformation spreading on closed platforms such as WhatsApp, creating a gap in digital-era crisis management that existing models have yet to fully address.

The practical implications of these findings are significant for crisis communication professionals, technology teams, and organisational leaders. One of the clearest lessons is that hybrid human-AI models offer the most effective approach to crisis management. While AI delivers speed, scalability, and the capacity to process vast data streams, it cannot replace the emotional intelligence, contextual sensitivity, and ethical judgment that human communicators bring to crisis situations. The research highlights the need for continuous training and scenario-based simulations to ensure that teams are able to interpret and act on AI outputs confidently and appropriately. Localisation also emerges as a critical factor; without adapting sentiment analysis and language-processing tools to Ghanaian linguistic and cultural contexts, organisations risk misinterpretation and bias, undermining both accuracy and trust. Additionally, AI must be embedded into formal crisis communication protocols rather than deployed on an ad hoc basis. This integration ensures that AI outputs trigger timely and appropriate actions, reducing the lag between detection and response. Finally, the findings stress the importance of institutionalising post-crisis learning. AI's analytics and benchmarking functions should feed directly into continuous improvement cycles, allowing organisations to refine their strategies and avoid repeating past mistakes.

At the policy level, the study underscores the need for a robust governance framework for AI-driven crisis communication in Ghana. Regulators and industry bodies have a role to play in establishing clear ethical and operational standards that address data privacy, transparency, and bias mitigation. Without such frameworks, organisations risk undermining stakeholder trust and exposing themselves to reputational and legal vulnerabilities. The findings also point to the need for targeted capacity-building initiatives at both national and sectoral levels to address the technical and analytical skills gaps that currently hinder AI adoption. Collaborative approaches, such as industry consortia that share AI monitoring infrastructure, could lower adoption costs and expand coverage, especially for SMEs and public institutions with limited budgets. Moreover, policy interventions that incentivise the development of locally relevant AI solutions particularly in sentiment analysis and misinformation detection could help overcome the cultural and linguistic limitations of imported tools, making AI more effective in the Ghanaian communication landscape.

In sum, the implications of this study span theory, practice, and policy. The evidence confirms that AI has the potential to transform crisis communication in Ghana, but realising this potential requires more than simply acquiring technology. It demands theoretical refinement, professional adaptation, and policy support that together create an environment in which AI can be used not just efficiently but also ethically, inclusively, and strategically.

5.4 Recommendations

Based on the findings and implications of this study, a number of recommendations can be made to guide organisations, policymakers, and technology developers in strengthening the integration of Artificial Intelligence (AI) into crisis communication in Ghana. These recommendations are aimed at addressing the current gaps identified in adoption, operationalisation, and ethical governance, while leveraging AI's capabilities to improve crisis preparedness, detection, response, and post-event learning.

For organisations, the priority should be to embed AI within formal crisis communication frameworks rather than treating it as a stand-alone technological add-on. This means integrating AI tools into existing protocols, assigning clear responsibilities for monitoring and interpreting AI outputs, and ensuring that these outputs directly trigger timely communication actions. Crisis teams should adopt a hybrid model in which AI handles large-scale data processing and high-volume engagement, while human communicators provide oversight, contextual judgement, and emotional sensitivity. Such a model not only preserves human control but also enhances the credibility and cultural appropriateness of crisis messaging.

Training and capacity building are critical for maximising AI's potential. Continuous professional development programmes should be introduced for communication staff, IT teams, and leadership to improve their ability to operate, interpret, and act on AI-generated insights. These training sessions should include scenario-based simulations that mirror real crisis conditions, allowing teams to practise rapid decision-making using AI data. Additionally, AI tools must be localised to Ghanaian linguistic and cultural contexts. This entails working with developers to adapt sentiment analysis algorithms to recognise local expressions, sarcasm, and code-switching, thereby improving accuracy in detecting stakeholder sentiment and emerging risks.

From a governance perspective, organisations should establish internal ethical guidelines for AI use in crisis communication. These should cover data privacy, algorithmic fairness, and transparency, ensuring that stakeholders understand how their information is collected, stored, and applied during crises. Ethical oversight committees or designated officers could help monitor compliance and address any issues of bias, privacy infringement, or misuse that arise in the deployment of AI systems.

At the national and policy level, regulatory bodies such as the Data Protection Commission and relevant communication authorities should develop clear governance frameworks for AI in crisis communication. These frameworks should mandate baseline privacy protections, require algorithmic bias testing, and encourage transparent communication practices. The government could also facilitate capacity-building initiatives to close the technical skills gap, particularly in the public sector and among SMEs, through subsidised training programmes or public-private partnerships.

Cost remains a major barrier to AI adoption for many organisations. To address this, collaborative infrastructure models could be promoted, where industry associations or sectoral consortia pool resources to maintain shared AI monitoring platforms. This approach would reduce financial burdens while ensuring broader access to advanced monitoring and analytics capabilities. Furthermore, there is a strong case for encouraging local AI development through innovation grants, research funding, and partnerships between universities, start-ups, and industry players. Locally developed tools are more likely to be culturally relevant, linguistically accurate, and affordable than imported systems, making them a more sustainable solution for Ghanaian crisis communication needs. The successful adoption of AI in crisis communication requires a multi-stakeholder commitment involving leadership vision, technical capacity, cultural adaptation, and ethical responsibility. By embedding AI into operational protocols, investing in capacity building, localising technology, and creating robust governance systems, Ghanaian organisations can move from symbolic and fragmented adoption towards a mature, proactive, and trust-centred model of AI-enabled crisis communication.

5.5 Directions for Future Research

While this study has provided valuable insights into the integration of Artificial Intelligence (AI) in crisis communication within Ghanaian organisations, it also opens up several avenues for future research. These areas warrant further investigation to deepen understanding, validate the findings in broader contexts, and address the limitations of the present study.

One important direction is to conduct sector-specific studies that explore AI adoption in greater detail within individual industries such as healthcare, education, energy, and public administration. This study has shown that AI adoption varies significantly across sectors, but more granular research could uncover the unique drivers, barriers, and operational patterns within each field. Such focused investigations would allow for tailored recommendations that take into account sector-specific risk profiles, resource capacities, and cultural considerations.

Another promising area is the study of AI's role in closed-network misinformation detection. While current AI tools are relatively effective in monitoring open platforms like X (Twitter) and Facebook, this study found that much crisis-related misinformation in Ghana spreads through encrypted or closed networks such as WhatsApp. Future research could investigate how AI, in combination with human intelligence networks and crowdsourced verification, might be adapted to address this challenge without infringing on privacy rights.

The question of cultural and linguistic adaptation of AI tools also deserves further examination. This study found that many sentiment analysis and natural language processing systems misinterpret Ghanaian expressions, sarcasm, and multilingual communication styles, leading to potential misclassifications in crisis monitoring. Future studies could explore the development and testing of culturally attuned AI models trained on local linguistic datasets, and assess their comparative accuracy and utility in real-world crisis contexts.

In addition, further research should examine long-term capacity-building strategies for AI integration in crisis communication. This study has shown that skills gaps remain a major barrier to adoption, but little is known about which training approaches, institutional arrangements, or knowledge-sharing networks are most effective in sustaining AI competence over time. Longitudinal studies tracking the evolution of organisational AI capabilities and their impact on crisis outcomes could provide valuable insights here.

Comparative research between different African countries would also be beneficial. While this study focused on Ghana, there are both similarities and differences in technological readiness, governance frameworks, and crisis communication cultures across the continent. Cross-national studies could help identify shared patterns and unique challenges, offering a richer basis for regional collaboration and policy development.

Finally, as AI technology continues to evolve rapidly, there is a need for ethical and governance-oriented research to ensure its responsible use in crisis communication. Future studies could investigate how organisations balance automation with human oversight, how stakeholders perceive AI-driven communication during crises, and how transparency and accountability can be strengthened in AI decision-making processes.

The future research should aim not only to refine the technical capabilities of AI in crisis communication but also to address the organisational, cultural, and ethical dimensions that determine whether these capabilities translate into meaningful improvements in crisis preparedness and response. By pursuing these lines of inquiry, scholars and practitioners alike can contribute to building a more resilient, inclusive, and ethically grounded model of AI-enabled crisis communication in Ghana and beyond.

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APPENDIX

INTERVIEW GUIDE

Interview Guide: AI and Crisis Communication in Ghanaian Organisations

Opening

1. Please briefly describe your current role in this organisation and how it relates to communication, crisis management, or technology.

2. How long have you worked in this organisation and in this sector?

Section A: Organisational and Crisis Context

3. What types of crises does your organisation typically face (for example, operational, reputational, regulatory, customer-related)?

4. Can you describe a recent crisis that had a strong public, media, or social media dimension for your organisation?

5. In general, how is crisis communication organised and managed in this organisation when a crisis occurs?

Section B: Current Crisis Communication Practices

6. When a crisis breaks, what are the main steps your organisation follows in communicating with stakeholders?

7. Which communication channels are most important for you during a crisis (such as traditional media, social media, website, call centres, internal platforms), and why?

8. How would you describe the speed and coordination of your organisation's crisis communication compared to what you think is required in the current digital environment?

Section C: Awareness and Use of AI Tools

9. In practical terms, what does "Artificial Intelligence" mean in your organisation's communication or customer engagement activities?

10. What specific AI or advanced digital tools does your organisation currently use that support communication or engagement (for example, monitoring tools, dashboards, chatbots, recommendation systems)?
11. To what extent are these tools used specifically for crisis communication, rather than only for routine marketing or service delivery?
12. Can you describe a situation where AI or an AI-enabled tool played a visible role in how your organisation handled a crisis?

Section D: AI Across the Crisis Lifecycle

13. How, if at all, do AI tools help your organisation identify early warning signs or emerging issues before they turn into full crises?
14. During an ongoing crisis, in what ways do AI tools support your decisions about what to say, when to say it, and through which channels?
15. After a crisis has been managed, how are AI-generated insights or analytics used to review performance and improve future crisis communication?

Section E: Strategy, Reputation and Stakeholders

16. How do you generally decide on the type of crisis response strategy to adopt (for example, denial, explanation, apology, compensation) when an incident occurs?
17. In what ways, if any, do data or insights from AI tools influence your assessment of responsibility, reputational risk, and the choice of response strategy?
18. How do you identify and prioritise different stakeholder groups during a crisis, and does AI play any role in understanding or segmenting these audiences?

Section F: Organisational Conditions and Capabilities

19. How is responsibility for AI and crisis communication structured in your organisation (for example, relationships between communication teams and IT/data/AI teams)?
20. What kinds of skills, resources, or capacities does your organisation currently have to support the use of AI in crisis communication?
21. Are there any particular internal policies, guidelines, or protocols that govern how AI tools are used in communication, especially during crises?