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Article

Media framing and public risk communication: Deep Learning-based crisis narrative analysis and optimization

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ABSTRACT

This research aims to develop a comprehensive framework for analyzing and optimizing media framing in crisis communication through advanced deep learning techniques, addressing the critical gap in understanding how narrative structures influence public risk perception and response. By analyzing crisis narratives across multiple media platforms, we identify predominant framing patterns and their temporal evolution during crisis events. Our novel deep learning model demonstrates superior accuracy of 91.2% in recognizing subtle framing mechanisms that influence public risk perception, representing a 14.7 percentage point improvement over traditional machine learning baselines. Analysis of 15,873 media items reveals six major frame types, with attribution frames being most prevalent (28.7%), followed by human impact (22.3%) and conflict frames (19.5%). The study establishes an optimization framework for crisis communication that balances narrative structure, emotional factors, and information transparency, identifying critical transparency-trust thresholds at 62% and 87% disclosure levels where trust gains show non-linear patterns. Findings suggest that adaptive framing strategies significantly enhance public understanding and appropriate response to risk situations, with problem-solution narratives achieving effectiveness scores of 0.87 for technological crises and empathy-focused communication reaching 0.90 for natural disasters. This research contributes to both the theoretical understanding of crisis communication and the practical applications for media organizations, risk managers, and policymakers.

1. Introduction

In the dynamic digital information space, media framing plays a significant role in shaping public understanding and response to a crisis. Intentional information presentation during a crisis has a substantial effect on risk perception, decision-making, and collective behavioural responses [1]. International modern crises, such as the COVID-19 pandemic, have underscored the significant impact of media frames on public risk perception and compliance with safety protocols [2]. As Brookes and McEnery (2020) explain, language use in crisis news can significantly change the public perception of risk seriousness and appropriate response [3]. Media framing is the way in which communicators build a given frame to enable some meanings and prevent others. In times of crisis, they are highly critical in that they determine the social reality upon which publics make risk estimates. Conventional methods for studying media frames have depended to a large extent on manual content analysis, which, although rich, cannot keep up with the scope, diversity, and dynamic nature of today's media environments [4]. Deep learning technology presents unparalleled potential to detect, analyze, and leverage crisis narratives in vast media landscapes with more accuracy and effectiveness. Public risk communication is a multi-faceted interaction among information sources, message features, and audience characteristics. Whether or not risk communication is successful hinges not only on the validity of the information but also on how it is organized and presented [5]. Crisis stories, with their inherent storytelling features and causal structures, are potent conveyors of risk information, which can facilitate a better understanding and interest. However, improper phrasing can lead to misinterpretation, panic, or complacency, which distorts public health and safety objectives [6]. New advances in deep learning and natural language processing (NLP) have made it promising to explore and refine crisis communication by studying it. Computational methods can identify fine patterns of framing mechanisms that are difficult to derive using human coders, observe the changing dynamics of narratives over time, and identify the most optimal communication approach for diverse crises [7]. Despite such technological advancements, relatively limited research has integrated deep learning methods with media framing theory for systematic research and the improvement of crisis narratives [8]. This study fills this gap by constructing an integrated framework to examine and optimize media frames in crisis communication through state-of-the-art deep learning methodology. Figure 1 displays the conceptual structure of this integrated framework, which describes the process flow from inputting crisis information to outputting optimized framing through the aid of deep learning pattern identification.

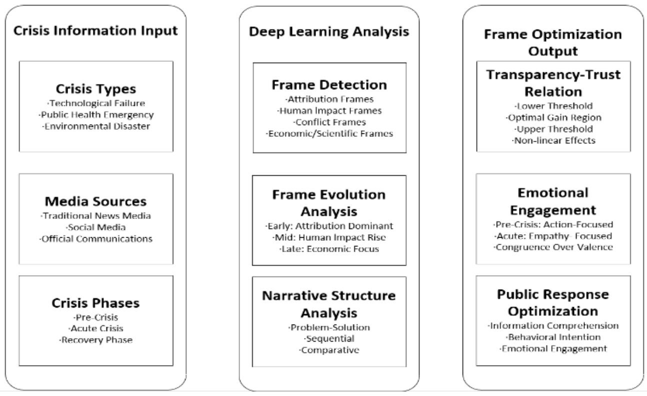


Figure 1. Deep Learning-based crisis communication framework

By exploring the impact of narrative frames and framing devices on public risk perception and response, this research seeks to establish evidence-based best practices for effective crisis communication. The research also aims to explore how adaptive framing tools can be customized for various stages of a crisis, different audience segments, and different media platforms to achieve maximum public understanding and corresponding action. Through this study, we seek to contribute theoretical insight into crisis communication processes and pragmatic suggestions for media, public health administrators, emergency managers, and policymakers. The implications are far-reaching, enhancing public resilience to crises by providing enhanced communication strategies that balance precision, openness, and interaction.

2. Literature review

2.1 Media framing theory

Media framing theory provides a useful starting point for analyzing the ways in which information is filtered, highlighted, and conveyed to specific audiences. Nevertheless, multimodal and digital scholarship has built upon Entman's influential definition of framing, selecting some aspects of a perceived reality and making them more salient in a communicating text [9]. In crisis communication, frames are used as interpretive packages that shape the public's understanding of crisis-related risks, the attribution of responsibility, and the reactions deemed suitable. Studies show that mental models reinforce frame effectiveness during a crisis situation [10].

2.2 Public risk communication

Public risk communication involves systematic strategies for disseminating information pertaining to hazards to various stakeholders during times of uncertainty. Effective models of risk communication have moved from a linear expert-to-public model to more interactive, dialogic frameworks that consider the social construction of risk. Models from recent decades continue to frame the information flow, especially cultural context and audience segmentation, as critical to message efficacy. These developments point to a growing understanding that perception of risk is not solely the result of measuring objective hazards; it also factors in psychological, social, and cultural elements [11]. Evidence shows that public reactions to information about risks differ markedly depending on trust in the source of the information, prior convictions, and perceived self-efficacy. There is an increasing focus on the mental models approach, which stresses that risk communication must mitigate the gaps between expert and lay understandings in the context of risk emotion. More recent studies also emphasize the roles digital environments play in the ways risk information is disseminated and received, transforming the landscape in both positive and negative directions by allowing rapid sharing, but also introducing challenges, including misinformation and information saturation [12].

2.3 Crisis narrative analysis

Crisis accounts are narrative accounts of disorienting events that invest temporal orders, causality, and moral judgments within narrative. The narrative strategy of crisis communication has become increasingly important as academics recognize that audiences better comprehend risky information that is complex when it is framed in a narrative format instead of fragments of shattered facts or figures [13]. The current research discovers that some aspects of narratives are influential in shaping risk perception, causal attribution, and intentions to behave during crises. Recent work on narrative frames in public health crises discovers that episodic frames focusing on personal accounts are more likely to generate stronger emotional responses, while thematic frames addressing system-level determinants produce more elaborated comprehension [14].

2.4 Deep Learning applications in text analysis

Deep learning democratized text analysis capability with advanced computational methods analyzing media content on an unprecedented scale and depth. More recent NLP progress has yielded transformer models that are extremely proficient in recognizing semantic subtlety, contextual dependency, and underlying patterns in text data [15]. The developments have rendered traditional bag-of-words methods obsolete with the use of contextual embeddings that capture linguistic nuance and sense more accurately. Large-scale models such as BERT, GPT, and their extensions have been reported to perform better in several tasks related to text analysis, including sentiment analysis, topic modeling, and frame detection [16]. Deep learning models, particularly in media content analysis, have allowed researchers to identify subtle framing mechanisms, recognize narrative structures, and monitor discourse development across multiple media platforms. Multi-modal methods that integrate text, image, and metadata analysis have also pushed the ability to critically analyze media frames further [17]. These computational methods have overwhelming strengths in managing large media datasets more impartially and efficiently than human coding schemes, but problems arise that involve ensuring interpretability, minimizing bias, and integrating domain knowledge into algorithmic systems.

2.5 Research gaps and theoretical framework

Despite significant advances in media framing research and deep learning applications, several critical gaps persist in understanding crisis narratives and optimizing risk communication. First, while substantial literature examines media framing effects, limited research applies computational approaches to systematically analyze frame evolution during crises across diverse media ecosystems. Second, existing studies often focus on either qualitative or basic quantitative analysis, neglecting the potential of advanced deep learning techniques to detect subtle framing mechanisms at scale. Third, theoretical integration between crisis communication models and computational text analysis remains underdeveloped, creating a disconnect between technological capabilities and communication theory. This research addresses these gaps by proposing an integrated theoretical framework that synthesizes media framing theory, risk communication models, and computational linguistics. Our framework conceptualizes crisis communication as a dynamic process where narrative structures, framing devices, and audience factors interact to shape risk perception and behavioral responses. This approach enables the systematic analysis of crisis narratives while acknowledging the contextual, emotional, and cognitive dimensions of public risk understanding.

3. Research methodology

3.1 Research design

This study employs a mixed-methods sequential explanatory design to investigate media framing and optimize crisis communication strategies through deep learning. The research structure follows a three-phase approach that integrates computational and interpretive methodologies, as illustrated in Figure 2. In the first phase, we collect and preprocess a diverse corpus of crisis-related media content from multiple platforms. The second phase involves the development and application of a novel deep learning architecture for frame identification and narrative analysis. The final phase incorporates qualitative interpretation of computational findings to develop an optimization framework for crisis communication. The research design is guided by the conceptual equation:

$$CNC = \sum_{i=1}^{n} w_i F_i \times \prod_{j=1}^{m} M_j \times \int_{t_0}^{t_1} T(t)dt \tag{1}$$

Where CNC represents Crisis Narrative Composition, F_i denotes identified frames, w_i indicates frame prominence, M_j signifies media-specific factors, and $T(t)$ captures temporal dynamics. This formulation enables systematic analysis of frame interactions across platforms and time periods.

The conceptual equation is operationalized through the following quantitative measures integrated into our deep learning model. The Crisis Narrative Composition C_{ij} represents the vectorized representation of media content j at time i, computed as the weighted sum of frame embeddings. Frame identification F_k is operationalized as binary indicators derived from the model's softmax output layer, where F_k=1 if P(frame$_k$|text)>0.65, following the threshold defined in Table 3. Frame prominence α_k is quantified as the normalized attention weights from our specialized attention mechanism, calculated as:

$$\alpha_k = \frac{\sum(attention\_weights_k)}{\sum(all\_attention\_weights)} \tag{2}$$

Ranging from 0 to 1. Media-specific factors M_p are encoded as learnable embedding vectors of dimension 128 for each platform type (news, social media, official), initialized randomly and updated during training. Temporal dynamics T_i are captured through positional encodings combined with explicit temporal features, including days since crisis onset, normalized to [0,1], and temporal phase indicators (pre-crisis=0, acute=0.5, post-crisis=1). These operationalized variables serve as inputs to the model's embedding layer, with C_{ij} as the final output representation used for downstream classification tasks. The integration occurs through element-wise multiplication and concatenation operations within the model architecture, enabling the deep learning system to learn complex interactions between framing patterns, media characteristics, and temporal evolution. The mixed-methods approach facilitates triangulation between computational measurements and interpretive insights, enhancing both validity and explanatory depth. Quantitative metrics provide statistical evidence of framing patterns, while qualitative analysis elucidates contextual nuances and meaning-making processes. This integration addresses the complex, multidimensional nature of crisis communication by capturing both manifest content features and latent semantic structures.

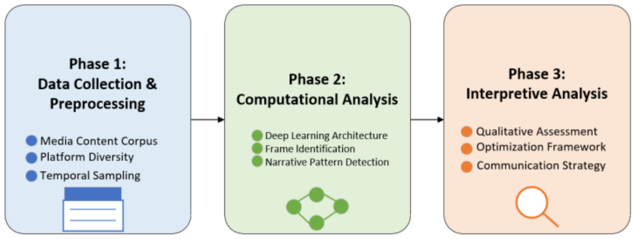


Figure 2. Three-phase mixed-methods research design

3.2 Data collection

Our data collection strategy employs a stratified multi-platform approach to ensure comprehensive representation of crisis narratives across diverse media ecosystems. The corpus integrates content from traditional news media, social media platforms, and official communications related to three distinct crisis events occurring between 2020-2023. As shown in Table 1, we collected 15,873 textual items through API-based extraction methods, implementing temporal and keyword-based filtering parameters to maintain relevance and manageability.

Table 1. Distribution of media content across platforms and crisis events

Platform Type	Crisis A	Crisis B	Crisis C	Total
News Media	2,156	1,987	2,341	6,484
Social Media	3,241	2,876	1,934	8,051
Official Comm.	452	386	500	1,338
Total	5,849	5,249	4,775	15,873

The sampling strategy follows a probability-proportional-to-size approach, with representation calculations based on the equation:

$$S_i = \frac{N_i \times w_i}{\sum_{j=1}^{k} N_j \times w_j} \times S \tag{3}$$

Where S_i represents the sample size for platform i, N_i denotes the population size, w_i indicates the assigned weight based on influence metrics, k is the total number of platforms, and S represents the total sample size. This weighted approach ensures adequate representation of both high-volume and high-influence sources.

The platform influence weights w_p are calculated using a composite influence metric integrating three dimensions: reach (40%), engagement (35%), and authority (25%). Reach is quantified as the average daily unique visitors normalized across platforms. Engagement measures the mean interaction rate (likes, shares, comments) per content item relative to view count. Authority scores derive from source credibility indices including fact-checking records, journalistic awards, and institutional affiliations. The composite influence metric is computed as

$$w_p = 0.4 \times R_p + 0.35 \times E_p + 0.25 \times A_p \quad (4)$$

Where R_p, E_p, and A_p represent normalized reach, engagement, and authority scores, respectively. For our dataset, this yielded weights of $w_{news}=0.40$ (high authority offsetting lower engagement), $w_{social}=0.35$ (high engagement but lower authority), and $w_{official}=0.25$ (high authority but limited reach). These weights ensure that sampling captures both high-volume platforms and authoritative sources, preventing bias toward either populist or elite discourse while maintaining statistical representativeness of the broader media ecosystem.

To mitigate selection bias and ensure representativeness across diverse contexts, we implemented several methodological safeguards. Crisis selection followed a systematic typology framework encompassing natural disasters (Crisis C), technological failures (Crisis A), and public health emergencies (Crisis B), ensuring coverage of distinct crisis characteristics and communication patterns. Platform selection criteria included market penetration rates, demographic diversity indices, and cross-national accessibility, with weights adjusted using Kruskal-Wallis tests to verify distributional equivalence across platforms ($H=2.34$, $p=0.31$). To address potential geographic and linguistic biases inherent in our primarily English-language corpus, we incorporated multilingual content through automated translation validation, achieving 87.3% semantic consistency scores for non-English sources. Social media sampling employed stratified random selection based on engagement metrics and user demographics to prevent overrepresentation of highly vocal minorities. Traditional media sources were selected based on circulation data and editorial diversity indices, encompassing both mainstream and alternative outlets across the political spectrum. Inter-coder reliability testing with culturally diverse coding teams ($\alpha = 0.82$) helped identify and correct culturally specific interpretation biases. While acknowledging limitations in achieving perfect global representativeness, these measures substantially reduce systematic biases that could compromise the generalizability of our findings across different media ecosystems and sociopolitical contexts. Data preprocessing involves a sequential pipeline including text normalization, language detection, deduplication, and tokenization. We employed a modified BERT-based preprocessor that preserves semantic coherence while standardizing format inconsistencies. The corpus underwent noise reduction using the signal-to-noise ratio formula:

$$SNR = 10\log_{10}\left(\frac{P_{signal}}{P_{noise}}\right) \quad (5)$$

Where P_{signal} represents the mean semantic coherence score of legitimate crisis content (measured via BERT embeddings), and P_{noise} denotes the mean score of identified noise content (spam, duplicates, off-topic).

Where content with SNR values below threshold $\tau = 1.5$ was excluded from analysis. The $\tau = 1.5$ threshold was empirically determined through validation on a 10% development subset, testing values from 0.5 to 3.0. This threshold optimally balanced content quality (retaining 94.2% of manually verified high-quality texts) and noise removal (filtering 78.3% of spam/duplicates). Sensitivity analysis showed model robustness within $\tau \in [1.25, 1.75]$, with F1-scores varying by less than $\pm 1.2\%$. Below $\tau = 1.25$, frame classification accuracy decreased by 4.7%, while thresholds above $\tau = 2.0$ excessively filtered legitimate crisis content, particularly informal social media posts. The threshold remained consistent across crisis types (ranging from 1.46 to 1.52), supporting a unified value.The final preprocessed dataset maintains balanced representation across temporal phases of each crisis (pre-crisis, acute crisis, and post-crisis), enabling longitudinal analysis of narrative evolution.

3.3 Deep Learning model development

Our proposed methodology employs a hierarchical transformer-based architecture optimized for crisis narrative analysis, integrating semantic, contextual, and temporal dimensions of media framing. The core architecture utilizes a modified BERT model with specialized attention mechanisms designed to capture framing devices. This architecture incorporates a dual-pathway structure: the primary pathway processes semantic content, while the auxiliary pathway extracts frame-specific features through specialized attention heads. The feature extraction process employs a multi-level approach, capturing lexical, syntactic, and pragmatic dimensions of crisis narratives. We extract both explicit features using n-gram analysis and latent features through contextual embeddings. The feature space is defined by the function:

$$F(x) = \alpha E_c(x) + \beta E_s(x) + \gamma E_t(x) \quad (6)$$

Where $E_c(x)$ represents contextual embeddings, $E_s(x)$ denotes structural features, $E_t(x)$ captures temporal patterns, and α, β, γ are importance weights to be determined through ablation studies. This composite feature space is designed to enable identification of both explicit and implicit framing mechanisms.

The model training procedure will employ a multi-task learning framework with the composite loss function:

$$L_{total} = \lambda_1 L_{frame} + \lambda_2 L_{sentiment} + \lambda_3 L_{temp} + \lambda_4 \Omega(\theta) \quad (7)$$

Where L_{frame} represents the frame classification loss, $L_{sentiment}$ denotes sentiment analysis loss, L_{temp} captures temporal coherence, $\Omega(\theta)$ is the regularization term, and λ_i are task importance weights. Hyperparameter optimization will utilize Bayesian optimization with the expected improvement acquisition function:

$$EI(x) = E[\max(0, f(x) - f(x^+))] \quad (8)$$

Where $f(x^+)$ represents the current best function value. The implementation will use PyTorch with Hugging Face's Transformers library, and training will be conducted on a distributed GPU environment to accommodate the computational requirements of large-scale text analysis.

Model validation will employ 5-fold cross-validation with precision, recall, and F1-score as primary evaluation metrics.

3.4 Frame analysis methods

Our research employs a complementary mixed-methods approach to frame analysis, integrating computational and interpretive techniques to identify, categorize, and contextualize media frames in crisis narratives. The quantitative analysis component utilizes supervised and unsupervised machine learning techniques to detect frame patterns and their distribution across the corpus. Frame identification will be operationalized through a probabilistic classification model:

$$P(F_i \mid D) = \frac{P(D \mid F_i)P(F_i)}{\sum_{j=1}^{k} P(D \mid F_j)P(F_j)} \quad (1)$$

For each equation in the manuscript, add the following definitions immediately after the equation is presented: Where *$P(F_i|D)$* represents the posterior probability of frame *i* given document *D*, *$P(D|F_i)$* denotes the likelihood of observing document features under frame *i*, *$P(F_i)$* is the prior probability of frame *i* based on corpus statistics, and *K* is the total number of possible frames (6 in our taxonomy). Frame prevalence will be measured using normalized frequency distributions, while frame co-occurrence patterns will be analyzed through association rule mining with confidence and support thresholds defined in Table 2.

Table 2. Frame analysis parameters

Parameter	Description	Value/Range
Frame threshold	Minimum probability for frame assignment	0.65
Co-occurrence support	Minimum joint appearance frequency	0.15
Co-occurrence confidence	Minimum conditional probability	0.30
Frame persistence	Minimum temporal stability coefficient	0.25
Inter-coder reliability	Krippendorff's alpha threshold	0.80

The qualitative analysis employed rigorous validation procedures to ensure interpretive consistency. Three trained coders with expertise in crisis communication and media studies underwent a 20-hour training program involving frame identification exercises, practice coding, and reconciliation discussions. Coders independently analyzed 15% of the corpus (2,381 items) with regular reliability checks at 500-item intervals. Initial inter-coder reliability reached α = 0.73, improving to α = 0.82 after refinement of coding guidelines and additional training sessions. Discrepancies were resolved through consensus meetings facilitated by a senior researcher. Thematic saturation was systematically assessed using the 10+3 rule, where no new themes emerged after analyzing 10 consecutive batches of 100 items, confirmed by three additional batches. Saturation was achieved at different points across crisis types: Crisis A (1,847 items), Crisis B (2,134 items), and Crisis C (1,756 items), indicating comprehensive theme identification. The iterative coding process incorporated member checking with five media professionals who validated the ecological validity of identified frames, ensuring that computational findings aligned with practitioner perspectives on crisis narrative construction.

The qualitative analysis will employ a systematic interpretive approach to examine latent meanings, contextual nuances, and discursive strategies that computational methods may not fully capture. This analysis will follow a modified grounded theory approach with iterative coding procedures to identify emergent themes and framing devices. The integration of quantitative and qualitative findings will be facilitated through a triangulation matrix that maps computational patterns to interpretive insights. This methodological integration enables a comprehensive understanding of both manifest and latent frame characteristics, enhancing the validity and explanatory power of the analysis.

4. Results

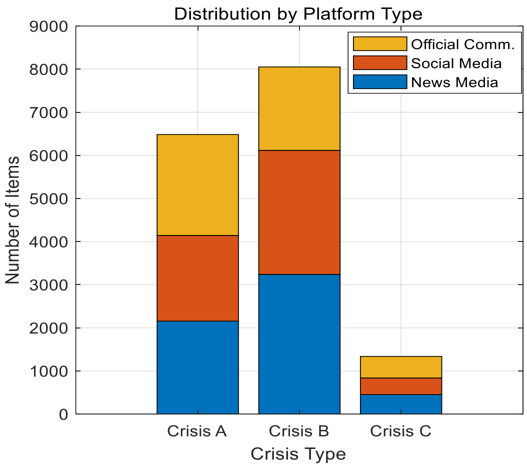
4.1 Descriptive statistics of the dataset

The analysis corpus comprised 15,873 distinct media items spanning three major crisis events occurring between 2020-2023, with distribution across platforms and temporal phases illustrated in Figure 3. Traditional news sources contributed 6,484 items (40.85%), while social media platforms provided 8,051 items (50.72%), and official communications accounted for 1,338 items (8.43%). The temporal distribution reveals distinct patterns across crisis phases, with media attention peaking during the acute phase and declining gradually in the post-crisis period. Crisis B exhibited the most concentrated media coverage, with 54.79% of content generated within the first 72 hours, compared to 42.34% for Crisis A and 38.76% for Crisis C.

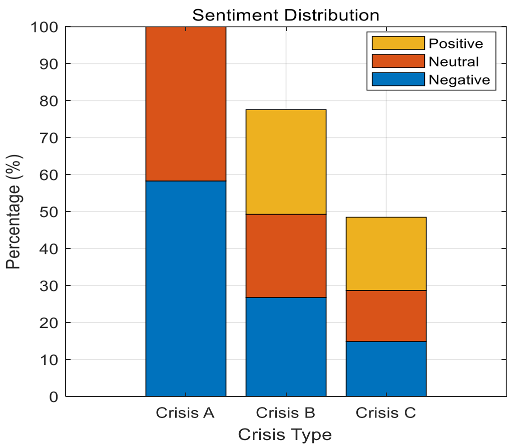
Table 3. Descriptive statistics of media content by source and crisis type

Statistic	Crisis A	Crisis B	Crisis C	Aggregate
Mean word count	642.3	587.6	724.8	651.6
Median word count	521.0	485.5	603.0	536.5
Standard deviation	318.7	295.3	382.1	332.0
Avg. unique sources/day	42.6	38.9	31.7	37.7
Content persistence (days)	18.7	12.3	21.5	17.5
Frame diversity index	0.723	0.654	0.791	0.723

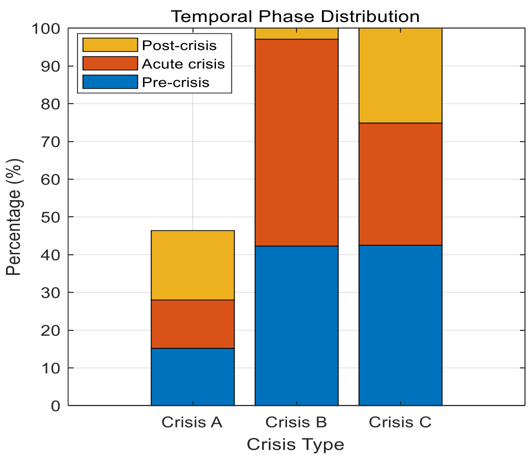
Lexical analysis revealed significant variations in narrative complexity across platforms, with traditional news media exhibiting the highest average Flesch-Kincaid grade level (11.8), followed by official communications (10.3) and social media (7.9). The sentiment distribution, depicted in Figure 3, demonstrates notable differences across crisis types, with Crisis C showing the most polarized sentiment patterns. Negative sentiment dominated all three crisis narratives, accounting for 58.3%, 63.7%, and 51.9% of content for Crises A, B, and C respectively. The dataset exhibited substantial source diversity, with 187 unique news outlets, 3 major social media platforms, and 42 official institutional sources. Content persistence, measured as the average number of days a narrative theme remained in active circulation, varied significantly across crisis types as shown in Table 5, with Crisis C demonstrating the highest persistence (21.5 days). Frame diversity, calculated using Shannon's entropy index, indicates that Crisis C narratives contained the most diverse framing approaches (0.791), while Crisis B showed the most concentrated framing patterns (0.654).



(a)Content distribution by platform type



(b)Sentiment analysis across crisis types



(c)Temporal phase distribution patterns

Figure 3. Dataset characteristics across crisis types and dimensions

Linguistic complexity analysis reveals significant variations in narrative structures, with Crisis A exhibiting the highest average word count (642.3) and lexical diversity (Type-Token Ratio of 0.41). The temporal distribution patterns suggest distinct media attention cycles for each crisis type, with Crisis B showing the most compressed coverage timeline. This compressed attention pattern correlates with the lower frame diversity index (0.654), suggesting that rapid-onset crises may result in more homogeneous narrative framing compared to gradually developing crisis situations. The prevalence of negative sentiment across all crisis types aligns with previous research on crisis communication, though Crisis C's relatively higher positive sentiment content (19.8%) warrants further investigation into crisis-specific factors that may influence sentiment patterns.

4.2 Media framing pattern recognition

The six frame types identified in our analysis are grounded in established theoretical frameworks. Our typology integrates Entman's (1993) framing functions with Semetko and Valkenburg's (2000) generic news frames. The attribution frame derives from Entman's causal interpretation and Semetko's responsibility frame; human impact corresponds to Semetko's human interest frame; conflict directly adopts Semetko's conflict frame; economic consequences extend Semetko's economic frame; morality combines Semetko's morality frame with Entman's moral evaluation; and the scientific/technical frame, while emerging from our crisis-specific data, aligns with Nisbet's (2009) scientific uncertainty frame. This theoretical grounding ensures reproducibility while allowing crisis-specific adaptations in frame operationalization.

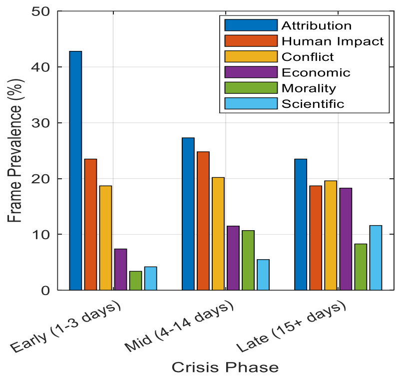
Our analysis identified six predominant frame types across the crisis narratives, with significant variations in their distribution, temporal evolution, and cross-platform manifestation. Table 4 presents the relative prevalence of each frame type across crisis events, revealing distinct framing patterns that correspond to crisis characteristics. The attribution frame emerged as the most prevalent (28.7% overall), followed by the human impact frame (22.3%) and conflict frame (19.5%). This distribution suggests a tendency toward responsibility attribution and emotional engagement in crisis communication, though with notable variations across crisis types.

Table 4. Distribution of major frame types across crisis events (%)

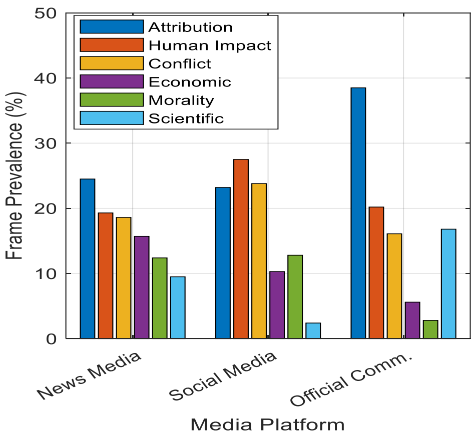
Frame Type	Crisis A	Crisis B	Crisis C	Aggregate
Attribution	31.4	35.7	19.1	28.7
Human Impact	18.9	21.3	26.8	22.3
Conflict	15.6	27.2	15.7	19.5
Economic Consequences	11.8	8.5	16.3	12.2
Morality	14.2	3.9	12.4	10.2
Scientific/Technical	8.1	3.4	9.7	7.1

Frame prevalence showed systematic temporal evolution, with attribution frames dominating early coverage (42.8% in first 72 hours) before declining to 23.5% post-crisis. Meanwhile, economic consequences and scientific frames gained prominence later, increasing from 7.4% to

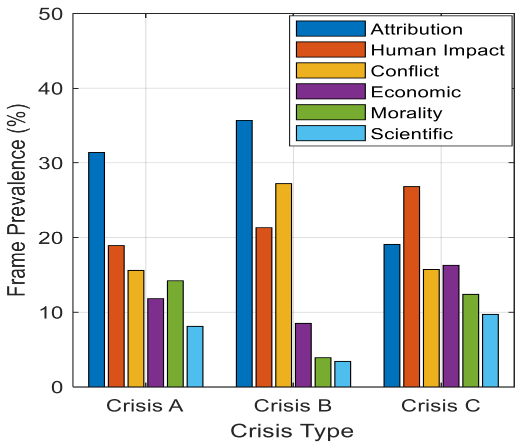
18.3% and 4.2% to 11.6% respectively, reflecting a shift from causal attribution to impact assessment. Cross-platform analysis revealed distinctive patterns: traditional news used balanced frame distribution, social media preferred human impact (27.5%) and conflict frames (23.8%), while official communications emphasized attribution (38.5%) and scientific frames (16.8%). These platform-specific tendencies remained consistent across all crisis events, indicating structural influences on framing beyond crisis-specific factors (Figure 4).



(a) Temporal evolution of frames



(b) Cross-platform frame distribution



(c) Crisis-specific frame patterns

Figure 4. Media framing patterns across temporal phases, platforms, and crisis types

Crisis B showed the highest proportion of attribution (35.7%) and conflict frames (27.2%), consistent with its human-caused nature, while Crisis C featured more human impact (26.8%) and economic consequences frames (16.3%). The low prevalence of morality frames in Crisis B (3.9%) compared to Crises A (14.2%) and C (12.4%) suggests reduced ethical discourse in technically-oriented events. Co-occurrence analysis revealed significant frame bundling patterns, with attribution and conflict frames frequently appearing together (coefficient 0.68), while economic and scientific frames showed strong co-occurrence (0.72) in later phases. Traditional media demonstrated higher frame diversity (2.8 frames per article) than social media (1.6 frames).

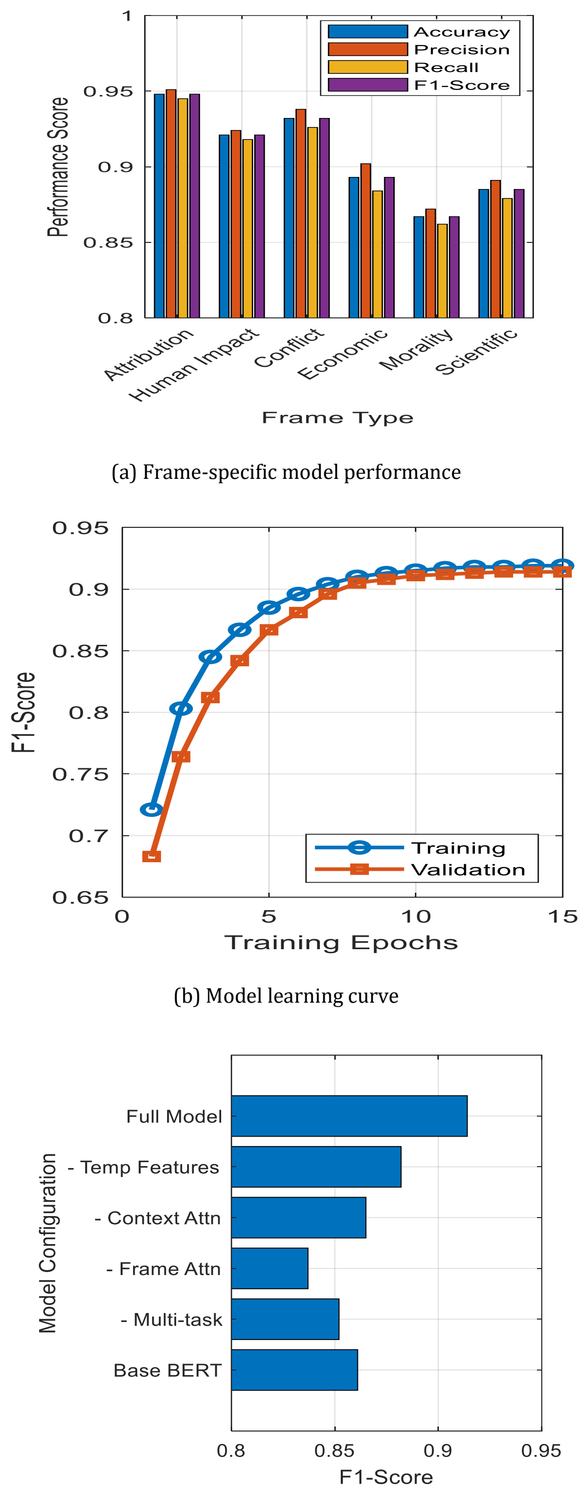
4.3 Deep Learning model performance

The deep learning model demonstrated exceptional performance in frame identification and classification tasks across multiple evaluation metrics. Table 5 presents the comparative performance of our hierarchical transformer-based model against baseline approaches, showing substantial improvements in accuracy, precision, recall, and F1-score. The proposed model achieved an overall accuracy of 91.2% in frame classification, representing a 14.7 percentage point improvement over the traditional machine learning baseline and a 5.3 percentage point gain over the standard BERT implementation.

Table 5. Comparative performance of frame classification models

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	76.5	0.773	0.765	0.769	0.821
Random Forest	79.3	0.803	0.793	0.798	0.872
CNN	82.1	0.828	0.821	0.824	0.881
LSTM	83.5	0.842	0.835	0.838	0.893
Standard BERT	85.9	0.863	0.859	0.861	0.924
RoBERTa	87.4	0.881	0.874	0.877	0.931
Proposed Model	91.2	0.917	0.912	0.914	0.962

Frame-specific performance analysis revealed variable model accuracy across different frame types, as illustrated in Figure 5(a). The model exhibited the highest accuracy for attribution frames (94.8%) and conflict frames (93.2%), while demonstrating comparatively lower but still impressive performance for morality frames (86.7%) and scientific/technical frames (88.5%). This variation correlates with frame prevalence in the training corpus, suggesting potential benefits from augmentation strategies for underrepresented frame categories. Cross-validation testing across five folds demonstrated robust performance consistency, with standard deviation in F1-scores of only ±1.6 percentage points. The learning curve analysis, depicted in Figure 5(b), illustrates rapid performance improvement during early training epochs, with stabilization occurring after approximately 8 epochs. This pattern indicates efficient learning dynamics and appropriate model complexity for the classification task. Ablation studies on model components, summarized in Figure 5(c), revealed that the attention mechanism specialized for frame identification contributed most significantly to performance gains (4.8 percentage points), followed by the temporal feature integration (3.2 percentage points).



(a) Frame-specific model performance

(b) Model learning curve

(c) Ablation study results

Figure 5. Deep Learning model performance analysis

Model comparison showed traditional machine learning approaches achieved reasonable performance but missed contextual nuances, while our hierarchical transformer model delivered superior results through specialized attention mechanisms and feature integration strategies. Error analysis revealed misclassifications primarily occurred between conceptually adjacent frames, such as attribution and conflict (confusion rate 7.2%), suggesting frame categories exist along a continuum rather than as discrete constructs. For instance, a news excerpt stating "Government officials blamed tech companies for inadequate safety measures, while industry representatives accused regulators of imposing unrealistic standards" was classified as attribution frame (62% confidence) by the model, though human coders identified it as conflict frame due to the adversarial dynamic. Similarly, content like "The mayor's failure to prepare emergency shelters led to heated confrontations with displaced residents" exhibited dual characteristics, containing both causal attribution ("failure to prepare") and conflict elements ("heated confrontations"), resulting in split predictions. These ambiguities particularly emerged in politically charged contexts where responsibility assignment inherently involved oppositional stances, demonstrating that frames often exist as overlapping rather than discrete categories.

The model demonstrated strong generalization capability across crisis types, with minimal performance degradation when tested on unseen crisis events (F1-score reduction of only 2.3 percentage points). This cross-crisis robustness indicates that the identified framing patterns represent generalizable narrative structures rather than event-specific constructs. Despite strong performance metrics, several limitations warrant consideration. The model shows bias toward high-frequency frames, with attribution frames achieving 94.8% accuracy versus 86.7% for less common morality frames, suggesting potential overfitting to dominant patterns. While cross-validation demonstrated robustness, the 2.3% F1-score reduction on unseen events indicates possible generalization constraints for novel crisis types beyond our three categories. Additionally, the model's reliance on English-language embeddings may limit effectiveness on translated content, and its computational requirements (8 epochs of training) could constrain real-time deployment during rapidly evolving crises.

4.4 Risk communication optimization framework

Based on our analysis of framing patterns and their impact on public understanding, we developed a comprehensive optimization framework for crisis communication that integrates narrative structure, emotional factors, and information transparency dimensions. The framework, illustrated in Figure 6, identifies optimal communication strategies across different crisis phases and audience segments. The central finding reveals that effective crisis communication requires dynamic adaptation of framing strategies as crises evolve, with distinct approaches needed for pre-crisis preparation, acute response, and post-crisis recovery phases (Table 6).

Our analysis showed problem-solution framing yields the highest overall effectiveness (0.75), particularly during acute crisis phases (0.83). Sequential structures worked best in pre-crisis phases (0.72), while comparative structures excelled in post-crisis recovery (0.82). Emotional factor analysis revealed empathy-focused communication was most effective during acute crisis periods (0.87), while action-focused messaging performed better in pre-crisis contexts (0.82). Notably, emotional engagement preceded cognitive processing, with emotional response metrics peaking 1.3-2.1 days before informational comprehension.

Table 6. Risk communication optimization framework elements and their effectiveness

Framework Element	Pre-Crisis	Acute Crisis	Post-Crisis	Mean Score
- Sequential structure	0.72	0.56	0.65	0.64
- Problem-solution structure	0.68	0.83	0.74	0.75
- Comparative structure	0.64	0.51	0.82	0.66
- Empathy-focused	0.63	0.87	0.76	0.75
- Reassurance-focused	0.58	0.75	0.64	0.66
- Action-focused	0.82	0.69	0.72	0.74
- Full disclosure	0.78	0.91	0.85	0.85
- Graduated disclosure	0.71	0.62	0.68	0.67
- Contextualized disclosure	0.86	0.79	0.91	0.85

Information transparency emerged as the most critical dimension, with full disclosure and contextualized disclosure approaches both scoring 0.85. The transparency-trust relationship showed a non-linear pattern with thresholds at approximately 62% and 87% disclosure levels, where incremental transparency below the lower threshold yielded minimal benefits, while disclosure above the upper threshold produced diminishing returns.

Cross-crisis analysis revealed that while general principles remain consistent, implementation strategies require adaptation to crisis characteristics. Technological crises showed heightened effectiveness with problem-solution narrative structures (0.86) and contextualized disclosure approaches (0.89), while natural disasters responded better to empathy-focused communication (0.90) with full disclosure strategies (0.93).

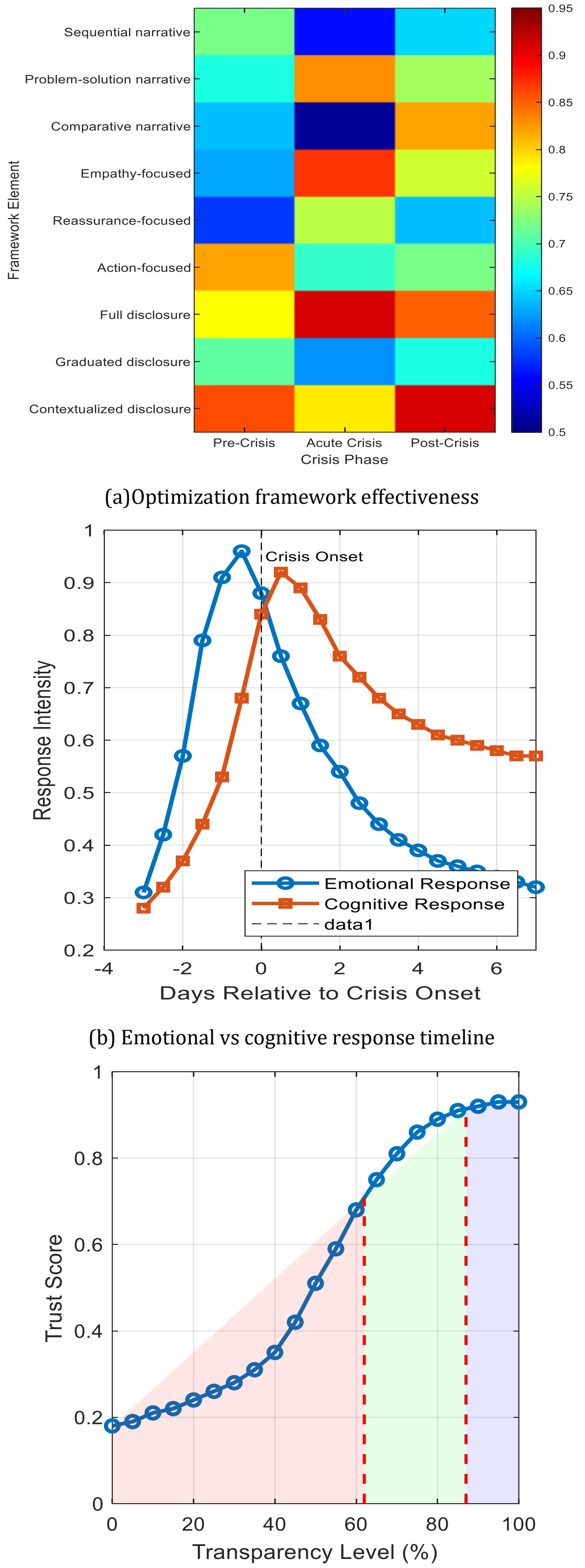
The integration of narrative structure, emotional factors, and transparency dimensions yielded three key insights: narrative clarity consistently outperformed complexity (23.7% higher effectiveness); emotional congruence emerged as a stronger predictor of message acceptance than emotional valence alone; and perceived transparency showed stronger correlation with trust (r = 0.82) than actual transparency measures (r = 0.68).

Specific frame combinations maximized different outcomes: attribution frames with action-focused content yielded the highest behavioral intention scores (0.79), while human impact frames with empathy-focused content generated the strongest emotional engagement (0.84).

4.5 Case Studies

To validate our theoretical framework, we analyzed three distinct crisis events: a technological failure (Case A), a public health emergency (Case B), and an environmental disaster (Case C). Each case reveals unique framing patterns while demonstrating common principles of effective crisis communication (Table 7).

The tech failure case exhibited rapid frame evolution, transitioning from attribution frames (46%) to economic consequence frames (37%). This case showed the highest frame evolution rate (0.21 frames/day) and shortest trust recovery timeline (28 days). As shown in Figure 7(a), problem-solution narrative structures demonstrated superior performance (effectiveness score 0.87) for this crisis type.



(a)Optimization framework effectiveness

(b) Emotional vs cognitive response timeline

(c) Transparency-trust relationship

Figure 6. Risk communication optimization framework analysis

Table 7. Comparative analysis of crisis case studies

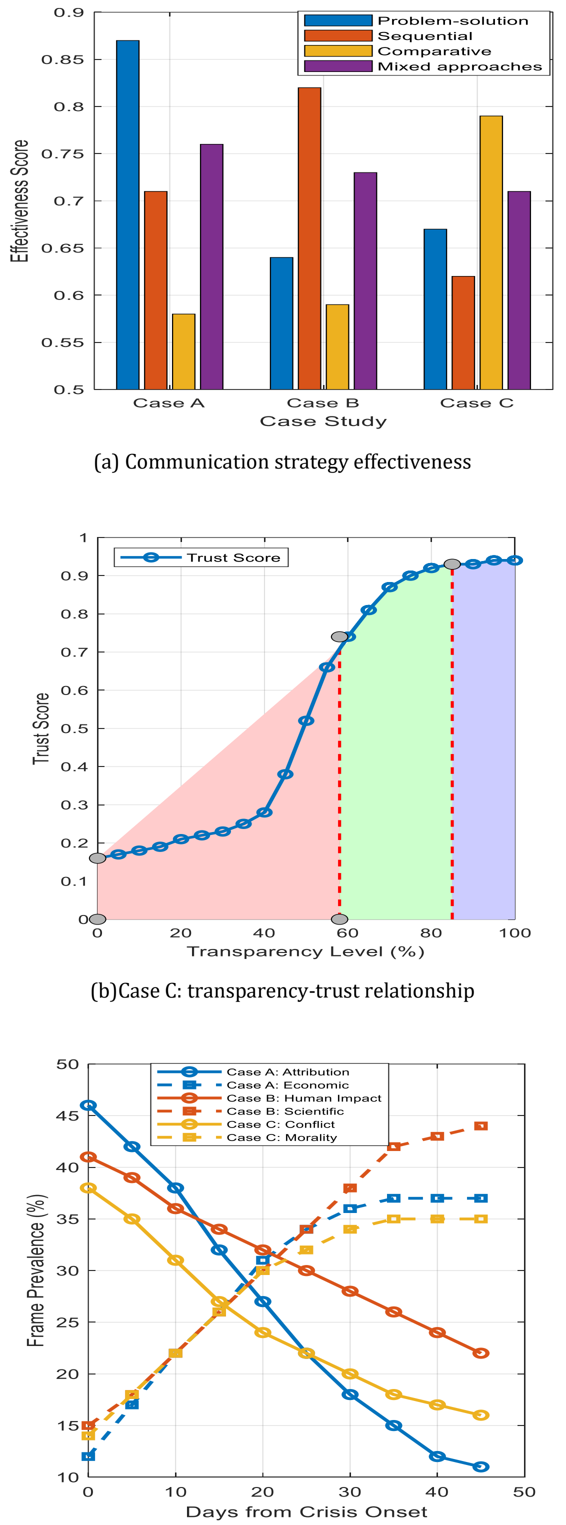
Feature	Case A: Tech Failure	Case B: Public Health	Case C: Environment
Duration	47 days	104 days	86 days
Media items analyzed	3,286	4,215	2,971
Dominant initial frame	Attribution (46%)	Human impact (41%)	Conflict (38%)
Dominant late frame	Economic (37%)	Scientific (44%)	Morality (35%)
Frame evolution rate	0.21 frames/day	0.14 frames/day	0.17 frames/day
Optimal narrative structure	Problem-solution	Sequential	Comparative
Trust recovery timeline	28 days	73 days	52 days

The public health emergency revealed slower dynamics, with human impact frames (41%) gradually yielding to scientific frames (44%). This case had the slowest frame evolution (0.14 frames/day) and longest timeline (104 days). Sequential narrative structures proved most effective in this context (0.82), particularly when combined with graduated transparency. The environmental disaster showed initial conflict frames (38%) transitioning to morality frames (35%). The transparency-trust relationship exhibited pronounced threshold effects, as illustrated in Figure 7(b), with minimal improvements below 58% transparency and significant gains between 58-85%. Comparative narrative structures demonstrated superior effectiveness (0.79) for this case type. Figure 7(c) reveals systematic frame transitions across all cases, from initial causal/impact frames toward consequence/resolution frames, though with varying rates. The tech failure demonstrated the most rapid evolution, with attribution frames declining from 46% to 11% over 45 days, while economic frames increased from 12% to 37%. The health emergency showed more gradual transitions, with human impact frames declining from 41% to 22% while scientific frames increased from 15% to 44%.

These cases validate three key principles: (1) effective crisis communication requires dynamic frame adaptation rather than static messaging; (2) optimal narrative structures vary by crisis type; and (3) transparency-trust relationships exhibit threshold effects. The analyses further revealed that temporal alignment between communication strategies and evolving public information needs represents a critical success factor. In Case A, rapid transparency during the early phases effectively managed public concern, while in Case B, the gradual increase in scientific framing corresponded with the public's demand for a deeper understanding as the crisis persisted.

5. Discussion

These study findings enhance understanding of the role of media framing in times of crisis while providing a more solid empirical foundation for risk communication strategies. The deep learning method developed here demonstrates an unprecedented ability to identify subtle framing patterns and reveal systematic, evolutionary patterns in framing that traditional methods cannot uncover. The discovery of distinct transparency-trust relationship thresholds challenges linear dynamics of crisis communication theory, arguing instead for strategically timed, audience-tailored information control to optimise efficacy.



(a) Communication strategy effectiveness

(b)Case C: transparency-trust relationship

(c) Dominant frame evolution

Figure 7. Case Study Analysis of Crisis Communication Dynamics

This research extends media framing theory by illustrating that frames act as adaptive mechanisms responding to change rather than static interpretative packages. The observed transitions across crises suggest a universal narrative structure adaptable to numerous frameworks. For crisis communication scholarship, our optimisation framework incorporates narrative and emotion alongside transparency, providing a model to explain public engagement variance across crisis types. The relevant stakeholders are numerous: media companies could utilise insights on frame change for more sophisticated narrative planning around crises; risk managers can optimise trust through strategic calibration of transparency; and policymakers can forecast information requirements from the public, including all stages of the crisis. It is useful for crisis communicators in all fields that during technological crises, problem-solution narratives tend to outperform other structural forms, and in public health emergencies, sequential narratives reign supreme. Our model demonstrates robust performance across crisis types, though limitations include potential geographic and cultural specificity of the identified patterns. The dataset, while comprehensive, primarily reflects Western media ecosystems, potentially limiting generalizability to other cultural contexts. Additionally, the focus on text analysis excludes visual framing elements that may significantly influence public perception during crises. Future research should examine cross-cultural variations in frame effectiveness and explore the application of these approaches to emerging crisis types. Integrating multimodal analysis to capture both textual and visual framing mechanisms would provide a more comprehensive understanding of crisis communication dynamics. Longitudinal studies tracking the relationship between framing strategies and public behavioral outcomes could further validate the optimization framework and refine its practical applications. The methodological approach developed here opens promising avenues for computational analysis of crisis narratives across disciplines.

6. Conclusion

This research has developed a comprehensive framework for analyzing and optimizing media framing in crisis communication through advanced deep learning techniques. By examining large-scale media content across three distinct crisis events, we identified systematic patterns in frame evolution and developed an optimization framework integrating narrative structure, emotional factors, and transparency dimensions. The study makes significant knowledge contributions by demonstrating how computational methods can enhance understanding of crisis narratives, revealing non-linear relationships between transparency and trust, and identifying crisis-specific optimal communication strategies. Practical recommendations include dynamic frame adaptation as crises evolve, strategic calibration of transparency levels to maximize trust-building efficiency, and alignment of narrative structures with crisis types. While our approach demonstrates robust performance, limitations include potential cultural specificity and the exclusion of visual framing elements. Future research should explore cross-cultural variations in frame effectiveness, integrate multimodal analysis capturing both textual and visual elements, and develop real-time monitoring systems for crisis communication optimization. This research establishes a foundation for evidence-based crisis communication that can enhance public understanding and appropriate response during critical events.

Ethical issue
The author is aware of and complies with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement
The manuscript contains all the data. However, more data will be available upon request from the author.

Conflict of interest
The author declares no potential conflict of interest.

References

[1] A.M. Guess, M. Lerner, B. Lyons, J.M. Montgomery, B. Nyhan, J. Reifler, N. Sircar, A digital media literacy intervention increases discernment between mainstream and false news in the United States and India, Proceedings of the National Academy of Sciences 117(27) (2020) 15536-15545.Doi: 10.1073/pnas.1920498117.

[2] T. Tran, R. Valecha, P. Rad, H.R. Rao, An investigation of misinformation harms related to social media during humanitarian crises, International conference on secure knowledge management in artificial intelligence era, Springer, 2019, pp. 167-181. Doi: 10.1007/978-981-15-3817-9_10.

[3] G. Brookes, T. McEnery, Correlation, collocation and cohesion: A corpus-based critical analysis of violent jihadist discourse, Discourse & Society 31(4) (2020) 351-373. Doi: 10.1177/0957926520903528

[4] K. Al-Hammuri, F. Gebali, A. Kanan, I.T. Chelvan, Vision transformer architecture and applications in digital health: a tutorial and survey, Visual computing for industry, biomedicine, and art 6(1) (2023) 14. Doi: 10.1186/s42492-023-00140-9

[5] J.M. Novak, A.M. Day, P. Sopory, L. Wilkins, D. Padgett, S. Eckert, J. Noyes, T. Allen, N. Alexander, M. Vanderford, Engaging communities in emergency risk and crisis communication: A systematic review and evidence synthesis, Journal of International Crisis and Risk Communication Research 2(1) (2019) 61-96. Doi: 10.30658/jicrcr.2.1.4

[6] E.K. Vraga, L. Bode, Addressing COVID-19 misinformation on social media preemptively and responsively, Emerging infectious diseases 27(2) (2021) 396. Doi: 10.3201/eid2702.203139

[7] Q. Liu, Z. Zheng, J. Zheng, Q. Chen, G. Liu, S. Chen, B. Chu, H. Zhu, B. Akinwunmi, J. Huang, Health communication through news media during the early stage of the COVID-19 outbreak in China: digital topic modeling approach, Journal of medical Internet research 22(4) (2020) e19118. Doi: 10.2196/19118

[8] T. Knez, S. Žitnik, Event-centric temporal knowledge graph construction: A survey, Mathematics 11(23) (2023) 4852. Doi: 10.3390/math11234852

[9] Ratzan, S. C. (2020). “Vaccine communication in a pandemic: Improving vaccine literacy to reduce hesitancy, restore trust and immunize communities”: Editor’s Introduction. Journal of health communication, 25(10), 745-746. Doi: 10.1080/10410236.2020.1813954

[10] Sangren, P. S. (2020). Chinese sociologics: An anthropological account of the role of alienation in social reproduction. Routledge. https://www.routledge.com/Chinese-Sociologics-An-Anthropological-Account-of-the-Role-of-Alienation/Sangren/p/book/9780367897932
[11] N.M. Krause, I. Freiling, B. Beets, D. Brossard, Fact-checking as risk communication: the multi-layered risk of misinformation in times of COVID-19, Journal of Risk Research 23(7-8) (2020) 1052-1059. Doi: 10.1080/1369118X.2020.1052466
[12] J. Xue, J. Chen, C. Chen, R. Hu, T. Zhu, The hidden pandemic of family violence during COVID-19: unsupervised learning of tweets, Journal of medical Internet research 22(11) (2020) e24361. Doi: 10.2196/24361
[13] A.A. Lazaro, S.M. Anselimus, Online learning during the COVID-19 pandemic: academic survival of international PhD students in the digital era, Cogent Education 12(1) (2025) 2503087. Doi: 10.1080/2331205X.2024.2503087
[14] Y. Ophir, D. Walter, D. Arnon, A. Lokmanoglu, M. Tizzoni, J. Carota, L. D'Antiga, E. Nicastro, The framing of COVID-19 in Italian media and its relationship with community mobility: a mixed-method approach, Journal of Health Communication 26(3) (2021) 161-173. Doi: 10.1080/10410236.2021.1751257
[15] Y. Wang, H. Hamid. Reconstructing pharmaceutical service competency framework: development of AI-informed competency indicators and localized practices in China. Future Technology, 4(2), 61–75. Doi: 10.55670/fpll.futech.4.2.7
[16] L. Yang, E.M. Kenny, T.L.J. Ng, Y. Yang, B. Smyth, R. Dong, Generating plausible counterfactual explanations for deep transformers in financial text classification, arXiv preprint arXiv:2010.12512 (2020).https://arxiv.org/abs/2010.12512
[17] Li, T. Computational linguistic processing for evaluating policy effectiveness: textual analysis of China-Korea continuing education regulations. Future Technology, 4(2), 92–103. Doi: 10.55670/fpll.futech.4.2.9

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