



TRUTH, FEAR, AND VIRALITY: A CROSS-PLATFORM CONTENT ANALYSIS
OF HEALTH MISINFORMATION NARRATIVES ON SOCIAL MEDIA

Abdur Rehman Butt

Department of Media and Communication, UMT Sialkot Campus, Sialkot, Pakistan
abdur.rehman@skt.umt.edu.pk

Babar Hussain

Department of Sociology, University of the Punjab, Lahore, Pakistan
babar_wahlah@yahoo.com

Faiz Ullah

Department of Mass Communication and Media Studies, GIFT University, Gujranwala,
Pakistan
faizullah@gift.edu.pk

Shahbaz Aslam

Center for Media and Communication Studies, University of Gujrat, Gujrat, Pakistan
shahbaz_vu@yahoo.com

Rana Babar Sohail

IISAT Gujranwala, Pakistan
rana.babar@iisat.edu.pk

Abstract

Social media platforms have emerged as dominant conduits for health information, yet they simultaneously facilitate the accelerated diffusion of health misinformation with demonstrable consequences for public health outcomes. Despite a growing body of scholarship on the spread of misinformation, the mechanisms by which narrative and emotional content interact with platform-level algorithmic structures to produce differential virality remain undertheorized. This study addresses that gap through a systematic, cross-platform content analysis of 1,000 posts sampled from Twitter/X (n = 250), Facebook (n = 250), TikTok (n = 250), and YouTube (n = 250). Drawing on emotional contagion theory (Hatfield et al., 1993), algorithmic amplification frameworks (Gillespie, 2014), and misinformation diffusion models (Vosoughi et al., 2018), a theoretically grounded coding scheme was applied to assess misinformation typology, emotional tone, narrative framing, source credibility, and engagement metrics. Intercoder reliability was established at Cohen's $\kappa = .82$. Findings reveal that 48% of sampled content contained misinformation, with the highest prevalence on TikTok and Facebook. Fear-based narratives accounted for 62% of misinformation posts and generated 2.3 times as many shares and 1.8 times as many comments as equivalent factual content. Approximately 70% of misinformation originated from non-expert influencers, while medically credentialed sources contributed fewer than 15% of total posts. These patterns confirm that virality is not incidental but is structurally produced through the interaction of emotionally charged narrative content and engagement-optimizing algorithmic systems. The study contributes an integrated cross-platform analytical model to misinformation research and advances empirically grounded recommendations for platform governance, emotion-aware public health communication, and digital health literacy interventions.

Keywords: *health misinformation, virality, fear appeals, social media, content analysis, algorithmic amplification, emotional contagion, infodemic*

Introduction

In the contemporary information environment, social media platforms function simultaneously as the primary infrastructure for health information dissemination and as accelerators of health misinformation. With more than 4.9 billion social media users globally as of 2023 (Statista, 2023), platforms such as Twitter/X, Facebook, TikTok, and YouTube have effectively displaced traditional institutional channels, physicians, public health agencies, and academic journals, as the first point of contact between individuals and health information



(Chou et al., 2020). This structural transformation carries profound implications. The accessibility, speed, and participatory affordances of social media that make it a powerful resource for health communication also render it uniquely susceptible to the rapid, large-scale diffusion of false, misleading, and potentially harmful health claims.

Health misinformation—defined here as health-related information that is factually inaccurate, incomplete, or misleading in a manner capable of influencing health beliefs and behaviors (Vraga & Bode, 2020), has emerged as a defining challenge for public health systems worldwide. The COVID-19 pandemic made this challenge starkly visible. The World Health Organization (WHO, 2020) coined the term "infodemic" to describe the simultaneous epidemic of misinformation that accompanied the biological virus, documenting how false claims about the origins, transmission, treatment, and prevention of COVID-19 spread faster than the disease itself. Research conducted during the pandemic found that individuals exposed to misinformation demonstrated significantly reduced intention to vaccinate (Roozenbeek et al., 2020), diminished compliance with public health guidance (Pennycook et al., 2020), and increased engagement with ineffective or dangerous self-treatments (Tasnim et al., 2020). These effects were not confined to politically marginal communities but reached mainstream social media audiences at scale.

The central empirical puzzle motivating this study is one of asymmetry: why does health misinformation spread more effectively than factual health information across social media platforms? Early accounts of this phenomenon attributed differential spread primarily to individual cognitive factors—confirmation bias, motivated reasoning, and limited media literacy (Pennycook & Rand, 2019). While these individual-level mechanisms are empirically established, they do not fully account for the systematic and reproducible patterns of misinformation virality observed across platforms, populations, and health domains. A more complete account requires attention to the structural features of social media platforms themselves, and specifically to the interaction between the emotional and narrative properties of misinformation content and the engagement-optimizing logic of platform algorithms.

This interaction, between emotionally resonant content and algorithmically structured distribution, is the primary analytical focus of the present study. Building on Vosoughi et al.'s (2018) landmark finding that false news spreads faster and farther than true news on Twitter, and extending it through integrated theoretical attention to emotional contagion (Hatfield et al., 1993; Ferrara & Yang, 2015) and algorithmic amplification (Gillespie, 2014; Bucher, 2018), this study argues that the virality of health misinformation is not incidental to its falsity but is structurally produced by the specific emotional and narrative features that characterize misinformation content. Fear, urgency, and simplified causal narrative are not merely rhetorical strategies incidentally present in misinformation; they are functional mechanisms that exploit both the affective architecture of human social cognition and the engagement metrics through which algorithms determine content visibility.

This study addresses three specific research questions. First, what is the prevalence and typology of health misinformation across Twitter/X, Facebook, TikTok, and YouTube? Second, what emotional and narrative content characteristics are associated with high-engagement health misinformation, and how do these differ from the characteristics of factual health content? Third, how do platform-specific algorithmic structures mediate the relationship between content characteristics and virality?

These questions are addressed through a quantitative content analysis of 1,000 social media posts systematically sampled across the four target platforms, coded against a



theoretically grounded scheme assessing misinformation typology, emotional tone, narrative style, source type, and engagement metrics. The study's contributions are threefold: it provides systematic cross-platform prevalence data on health misinformation; it advances the theoretical integration of emotional contagion theory with algorithmic amplification frameworks; and it generates empirically grounded recommendations for platform governance and public health communication practice. The remainder of the paper is organized as follows. Section 2 reviews the relevant theoretical and empirical literature. Section 3 presents the integrated theoretical framework. Section 4 describes the methodology. Section 5 reports findings. Section 6 discusses implications, and Section 7 concludes.

Literature Review

2.1 Health Misinformation in Digital Environments

The study of health misinformation has undergone significant theoretical and methodological development over the past decade, moving from primarily definitional concerns toward a more integrated understanding of the structural conditions that produce and sustain misinformation ecosystems. Vraga and Bode (2020) provide one of the most widely adopted definitional frameworks, distinguishing health misinformation (false or inaccurate claims presented as health information) from disinformation (deliberately constructed false claims) and malinformation (accurate information deployed to cause harm). This conceptual precision is important because the conditions and mechanisms of spread differ across these categories, and effective interventions must be tailored accordingly.

A consistent finding across the empirical literature is that social media platforms amplify health misinformation at rates and scales that far exceed those achievable through traditional media channels. Vosoughi et al.'s (2018) analysis of twelve years of Twitter data—encompassing approximately 126,000 news stories shared by approximately three million users—found that false news diffused approximately six times faster, reached more people, penetrated deeper into information networks, and was retweeted more broadly than accurate information. Critically, this differential spread was driven primarily by human behavior rather than by bots, suggesting that false news possesses content characteristics that humans find inherently more compelling, a finding with direct implications for understanding how misinformation exploits affective mechanisms.

Platform-specific analyses have yielded important supplementary findings. A systematic review of health content on TikTok by Basch et al. (2021) found that a substantial proportion of high-engagement health videos contained inaccurate or misleading information, predominantly produced by non-medical creators whose presentation styles mimicked expert authority through the use of white coats, medical terminology, and clinical settings. Similar patterns have been documented on Facebook (Sharma et al., 2019) and YouTube (Li et al., 2020), with the common thread being that misinformation content systematically adopts credibility cues associated with expert knowledge while making claims that contradict evidence-based medicine. This mimicry of authority is analytically important because it suggests that the spread of misinformation is not simply a consequence of users' inability to evaluate evidence but is actively facilitated by the rhetorical and visual strategies through which misinformation content is constructed.

The literature has also documented significant variation in misinformation prevalence and typology across health domains. Vaccine hesitancy and anti-vaccination misinformation have received the most scholarly attention (Kata, 2012; Roozenbeek et al., 2020), and analyses of COVID-19 misinformation have generated an important body of knowledge about how



existing misinformation ecosystems were activated and amplified during acute public health crises (Cinelli et al., 2020; Sharma et al., 2020). However, misinformation about cancer treatments (Keown et al., 2019), mental health interventions (Aich et al., 2022), and chronic disease management (Hassona et al., 2021) has received comparatively less attention, suggesting significant gaps in the research agenda that the present study partly addresses.

2.2 Emotional Appeals and Fear-Based Narratives

The role of emotion in information processing and sharing behavior is theoretically well established and empirically robust. Drawing on the extended parallel process model (Witte, 1992) and the risk information seeking and processing model (Griffin et al., 1999), health communication scholars have long recognized that emotional appeals—and fear appeals in particular—exert powerful effects on health-related cognition and behavior. Fear appeals function by inducing threat appraisal, in which individuals evaluate the severity and personal relevance of a health threat, and coping appraisal, in which they assess the efficacy of available responses. When threat perception is high and coping efficacy is low, fear appeals tend to produce maladaptive responses, including avoidance, denial, and the acceptance of simplistic or pseudoscientific coping strategies (Witte, 1992)—precisely the behavioral patterns that health misinformation tends to promote (Aslam, Hayat, et al., 2020; Aslam, 2025; Aslam, Hussain, et al., 2025; Aslam et al., 2026; B. Hussain et al., 2025).

In the social media context, the relationship between emotional content and sharing behavior has been extensively documented. Berger and Milkman (2012) found that content eliciting high-arousal emotions, including fear, anger, and awe, was more likely to be shared than content eliciting low-arousal states, regardless of its informational accuracy. Subsequent studies have confirmed and extended this finding specifically to misinformation contexts. Appraisal theory research by Myrick and Willoughby (2019) found that health misinformation consistently evoked higher levels of fear, anxiety, and disgust than equivalent factual health information, and that these emotional responses mediated the relationship between misinformation exposure and sharing intention.

Fear-based health misinformation is particularly effective because it exploits several well-documented features of human cognition. First, negative information generally commands disproportionate attentional resources—what Cacioppo and Gardner (1999) term the negativity bias—meaning that threatening content is more likely to be noticed, processed, and remembered than neutral or positive information. Second, fear-inducing content activates the availability heuristic (Tversky & Kahneman, 1973), making threats feel more probable and immediate than objective risk data would justify. Third, fear responses tend to compress the timescale of decision-making, generating urgency that bypasses deliberative evaluation and encourages rapid sharing behavior (Pennycook & Rand, 2019). Together, these mechanisms explain why fear-based misinformation achieves greater virality than even highly accurate fear-based information: its claims are typically simpler, more concrete, more emotionally intense, and more immediately actionable.

The concept of emotional contagion (Hatfield et al., 1993)—the process by which emotional states spread from individuals to others through behavioral mimicry and afferent feedback mechanisms—has been productively extended to digital contexts by Ferrara and Yang (2015), who documented that emotional signals embedded in social media content reliably produce corresponding emotional responses in subsequent users, which in turn predict engagement and resharing behavior. Kramer et al. (2014) demonstrated this dynamic experimentally in the context of Facebook's News Feed, showing that users exposed to



emotionally negative content produced more negative posts themselves, creating what they termed emotional contagion at scale. While the ethical dimensions of Kramer et al.'s experiment attracted significant criticism, its empirical findings have been widely replicated and have important implications for understanding how fear-based misinformation can propagate affective states through information networks.

2.3 Virality and Algorithmic Amplification

The virality of social media content is not a natural phenomenon but a structurally produced outcome of the interaction between content characteristics and the algorithmic systems through which platforms distribute content to users. Gillespie (2014) conceptualizes social media platforms as active curators of public discourse whose algorithmic systems embody specific commercial values and priorities, determining at scale which content receives visibility and which is rendered peripheral. The dominant commercial logic of major social media platforms—maximizing engagement in order to maximize advertising revenue—creates systematic incentives for algorithmic amplification of emotionally arousing content, irrespective of that content's accuracy or social value (Ahmad et al., 2021; Aslam, Iqbal, et al., 2025; Aslam, Yousaf, Raza, et al., 2025; S. Hussain et al., 2021; Jin et al., 2022).

The algorithmic architecture of each platform studied in this research instantiates this logic in platform-specific ways. Facebook's content ranking algorithm, as documented through internal research and regulatory testimony, prioritizes content that generates strong emotional reactions, as measured by reaction emoji usage and comment volume and tone (Horwitz & Seetharaman, 2021). TikTok's For You Page algorithm, arguably the most influential recommendation system of its generation, uses an extraordinarily granular set of engagement signals—including video completion rates, replays, shares, and search behavior following exposure—to construct individually calibrated recommendation feeds optimized for retention (Hern, 2022). YouTube's recommendation algorithm has been the subject of extensive research documenting its propensity to recommend progressively more extreme and emotionally intense content, a dynamic that has been specifically linked to the spread of health misinformation (Ribeiro et al., 2020). Twitter/X's algorithmic timeline, while historically less opaque than its competitors, similarly prioritizes high-engagement content, creating asymmetries in visibility that systematically favor emotionally provocative over informative content (Arif et al., 2017).

The consequence of these algorithmic structures is a systematic feedback loop in which emotional misinformation achieves high engagement, which signals quality or relevance to platform algorithms, which then amplify the content to larger audiences, which generates further engagement and further amplification. Cinelli et al. (2020) documented this dynamic in the context of COVID-19 misinformation, finding that misinformation spread through information cascades that were both broader and faster than those characteristic of factual content, and that algorithmic recommendation systems played a significant role in initiating and sustaining these cascades. Importantly, this dynamic is not a failure of platform algorithms but a predictable consequence of optimizing for engagement: platforms are functioning exactly as designed; it is the design itself that produces the amplification of misinformation.

2.4 Source Credibility, Authority Performance, and the Influencer Economy

A fourth dimension of the misinformation literature relevant to the present study concerns the role of source characteristics in misinformation spread. Source credibility—encompassing perceived expertise, trustworthiness, and goodwill—has long been recognized as a central determinant of persuasion in health communication contexts (Petty & Cacioppo, 1986). Traditional source credibility research assumed that credibility was primarily an



attribute of the source itself, derivable from institutional affiliation, educational credentials, and track record. Social media has complicated this picture considerably.

In the social media ecosystem, credibility is increasingly a performative and contextual achievement rather than an inherent source attribute. Non-expert health influencers construct credibility through the deliberate deployment of visual and verbal credibility cues—medical aesthetics, confident authoritative tone, selective citation of scientific-sounding terminology—that exploit audiences' heuristic processing of source quality (Basch et al., 2021). This performance of authority is particularly effective on platforms such as TikTok and Instagram, where the short-form video format rewards confident, simplified communication and penalizes the hedging and qualification that genuine scientific communication requires. The result is a systematic credibility inversion in which compelling non-expert communicators consistently outperform expert institutional communicators in terms of reach, engagement, and perceived trustworthiness among lay audiences (Sharma et al., 2019).

The influencer economy adds a further structural dimension: health misinformation can be commercially profitable. Influencers who build followings around health content—whether based on wellness culture, anti-establishment skepticism, or conspiracy-adjacent narratives—generate advertising revenue, sell branded products, and convert followers into customers for health-adjacent goods and services. This commercial logic creates direct financial incentives for the production and distribution of health misinformation that are structurally analogous to, and in some cases directly integrated with, the engagement incentives of platform algorithms (Aslam, Ali, et al., 2020; Aslam, Yousaf, & Raza, 2025; Aslam & Ahmad, 2019; Faizullah et al., 2021).

Theoretical Framework

The present study integrates three complementary theoretical traditions to provide a multi-level account of health misinformation virality. Each tradition captures a distinct level of analysis; it is their integration that enables a comprehensive explanation of how misinformation content, user behavior, and platform structure interact to produce the systematic patterns documented in the empirical literature.

3.1 Emotional Contagion Theory

Originally developed by Hatfield et al. (1993) in the context of face-to-face interaction, emotional contagion theory proposes that emotions spread between individuals through processes of behavioral mimicry and afferent feedback, such that exposure to another person's emotional expression tends to elicit a corresponding emotional state in the observer. Extended to digital environments by Ferrara and Yang (2015) and empirically validated in social media contexts (Kramer et al., 2014), the theory provides the foundational micro-level mechanism through which health misinformation's emotional properties generate engagement and propagation. Specifically, fear-inducing content activates threat-oriented emotional processing in recipients, which motivates the social transmission of warning signals—a behavioral pattern with deep evolutionary roots that social media platforms' viral mechanics effectively exploit and amplify.

3.2 Algorithmic Amplification Theory

Gillespie's (2014) framework of algorithmic curation conceptualizes social media platforms not as neutral information conduits but as active editorial systems whose design choices produce structured inequalities in content visibility. Complemented by Bucher's (2018) analysis of the "if...then" logic of algorithmic power, this framework explains how the engagement metrics that platforms use as proxies for content quality—likes, shares, comments,



dwelt time—systematically favor emotionally provocative content. This meso-level theoretical resource connects the micro-level dynamics of emotional contagion to the macro-level structural outcomes of misinformation spread, explaining why individual-level affective responses aggregate into population-level misinformation epidemics.

3.3 Misinformation Diffusion Theory

Drawing on Vosoughi et al.'s (2018) empirical account and the broader network diffusion literature (Watts & Dodds, 2007), misinformation diffusion theory addresses the network-level dynamics through which false information spreads. The key theoretical contribution of this perspective is the demonstration that misinformation possesses structural properties—novelty, emotional intensity, simplified narrative, actionable implication—that make it particularly well adapted to diffusion through social networks irrespective of its accuracy. This macro-level framework provides the systemic context within which emotional contagion and algorithmic amplification operate.

3.4 Integrated Conceptual Model

These three theoretical pillars are integrated into a sequential and mutually reinforcing conceptual model that specifies the mechanisms through which health misinformation achieves disproportionate virality. The model proceeds through four stages. In the first stage, narrative content characterized by fear-based emotional framing, causal simplification, and urgency cues activates emotional threat responses in audiences, consistent with emotional contagion theory. In the second stage, this emotional activation translates into high engagement behavior—sharing, commenting, liking—that signals content relevance to platform algorithms. In the third stage, algorithmic amplification systems, operating on engagement signals as proxies for content quality, redistribute the emotionally engaging content to larger audiences, initiating or expanding information cascades. In the fourth stage, the expanded reach generates further engagement, completing a feedback cycle that produces the exponential virality characteristic of health misinformation episodes. This model generates the specific testable propositions examined in this study: that fear-based content will achieve higher engagement than neutral or positive content; that misinformation will be disproportionately associated with fear-based framing; and that these relationships will be moderated by platform-specific algorithmic characteristics.

Methodology

4.1 Research Design

This study employs a quantitative content analysis design. Content analysis is the methodological approach of choice for systematically examining patterns in large volumes of media content, enabling the reliable, replicable quantification of content characteristics in ways that permit statistical analysis and theoretical inference (Krippendorff, 2018; Neuendorf, 2017). A quantitative, deductive approach was adopted in preference to qualitative methods because the primary research objectives—establishing prevalence estimates, identifying correlations between content characteristics and engagement, and comparing patterns across platforms—require the statistical generalizability that only systematic, large-sample, reliably coded data can provide. The cross-platform design enables comparative analysis of how the relationship between content characteristics and virality is moderated by platform-specific algorithmic and cultural environments.

4.2 Population, Sampling Frame, and Procedure

The target population for this study comprised health-related social media posts published between January 2022 and December 2023 on four platforms: Twitter/X, Facebook,



TikTok, and YouTube. This two-year sampling window was selected to ensure coverage of both ongoing COVID-19 misinformation dynamics and the emergence of post-pandemic health misinformation trends, while avoiding the methodological complications of the acute pandemic period (2020–2021), during which platform moderation policies were unusually active and non-routine.

Health-related posts were identified using a theoretically grounded keyword search strategy. Keywords were selected to cover the five highest-volume health misinformation domains identified in the extant literature (Chou et al., 2020): vaccine safety, cancer treatments, COVID-19, mental health interventions, and nutritional health claims. For each domain, a set of fifteen to twenty keywords was developed through consultation of the misinformation typology literature and pilot testing, yielding a final keyword list of eighty-two terms. To ensure that sampling captured both misinformation and factual content for comparative analysis, keywords were not restricted to known misinformation terms but encompassed the full landscape of health discourse in each domain.

A stratified random sampling procedure was applied, with platform constituting the stratification variable. Within each platform stratum ($n = 250$), posts were sampled proportionally across health domains to ensure domain diversity. For Twitter/X, Facebook, and YouTube, posts were sampled using platform APIs and third-party data access tools. TikTok data were collected using TikTok Research API access and manual verification. Content sampling was limited to publicly available posts, and no personally identifying information was collected or retained, consistent with the ethical guidelines of the Association of Internet Researchers (Franzke et al., 2020).

4.3 Coding Scheme

A deductive coding scheme was developed from the theoretical framework described in Section 3 and operationalized through extensive review of prior content analysis instruments used in health misinformation research (Basch et al., 2021; Vraga & Bode, 2020). The scheme comprises five variable categories. Misinformation type was coded as one of four categories: false or unverified cure claim, conspiracy or anti-institutional claim, misleading statistical or risk claim, or factually accurate. Emotional tone was coded as primarily fear-based, primarily hope-based, primarily anger-based, or primarily neutral, using operational definitions adapted from valence and arousal frameworks in affective computing (Russell, 1980). Narrative style was coded as personal testimonial, expert or authority claim, sensationalist or alarmist framing, or informational. Source type was coded as medical professional, scientific or academic institution, mainstream news organization, non-expert influencer, or anonymous or unknown. Engagement metrics—total shares or retweets, comments, and platform-specific reaction counts—were recorded as continuous variables.

All coding categories were operationally defined in a detailed codebook developed through an iterative process of codebook construction, piloting, and revision. An initial codebook was developed by the research team, piloted on a random subsample of 60 posts (15 per platform), and revised to resolve ambiguities and improve operational precision. A second pilot ($n = 40$) was conducted following codebook revision to verify that operational definitions were reproducible across coders.

4.4 Intercoder Reliability

Two trained coders independently coded a stratified random subsample of 200 posts (20% of the total corpus, 50 per platform) to establish intercoder reliability. Prior to independent coding, coders completed eight hours of training using a dedicated training set of



80 posts not included in the reliability subsample. Cohen's kappa coefficients were calculated for each coding variable following completion of the reliability subsample. Kappa values were as follows: misinformation type, $\kappa = .84$; emotional tone, $\kappa = .81$; narrative style, $\kappa = .79$; source type, $\kappa = .85$. The composite kappa across all variables was .82, indicating strong intercoder agreement by the established standards of the field (Landis & Koch, 1977). Disagreements on the reliability subsample were resolved through discussion and consensus, and the agreed codes were used in subsequent analyses.

4.5 Analytic Strategy

Descriptive statistics were calculated for all coding variables to establish prevalence distributions. Chi-square tests of independence were used to assess associations between categorical variables, including between misinformation type and emotional tone, and between source type and misinformation prevalence. Independent samples t-tests and one-way analyses of variance (ANOVA) were used to compare engagement metrics across content type and emotional tone categories. Effect sizes were calculated using Cohen's d for pairwise comparisons and eta-squared (η^2) for ANOVA models. Platform was included as a moderating variable in all primary analyses, with platform-stratified results reported to assess the generalizability of cross-platform patterns. Analyses were conducted in IBM SPSS Statistics Version 28 and R Version 4.3.1. Statistical significance was assessed at $\alpha = .05$ for all tests.

Results

5.1 Prevalence and Typology of Health Misinformation

Of the 1,000 posts analyzed, 480 (48.0%) were coded as containing health misinformation, with a further 52 (5.2%) coded as ambiguous and excluded from primary misinformation-focused analyses. The remaining 468 (46.8%) were coded as factually accurate health content. Misinformation prevalence varied significantly across platforms, $\chi^2(3, N = 948) = 47.3, p < .001$. TikTok exhibited the highest misinformation prevalence (58.4%, $n = 146$), followed by Facebook (54.8%, $n = 137$), Twitter/X (41.2%, $n = 103$), and YouTube (38.8%, $n = 97$). These platform-level differences were robust and consistent with the hypothesis that short-form video platforms, characterized by lower barriers to content creation and more opaque moderation systems, create conditions particularly conducive to misinformation spread (Basch et al., 2021).

Among misinformation posts, false or unverified cure claims constituted the largest typological category (38.5%), followed by misleading statistical or risk claims (27.9%), conspiracy or anti-institutional claims (22.1%), and other or unclassifiable misinformation (11.5%). The distribution of misinformation typologies was not uniform across platforms: conspiracy content was disproportionately prevalent on Twitter/X (34.0% of that platform's misinformation content), while false cure claims dominated on TikTok (47.3%) and Facebook (42.3%).

Table 1

Misinformation Prevalence and Typology by Platform

Platform	Total Posts	Misinformation (%)	False Cure (%)	Conspiracy (%)	Misleading Risk (%)
Twitter/X	250	41.2	28.2	34.0	24.3
Facebook	250	54.8	42.3	18.2	27.4



Platform	Total Posts	Misinformation (%)	False Cure (%)	Conspiracy (%)	Misleading Risk (%)
TikTok	250	58.4	47.3	15.1	29.5
YouTube	250	38.8	36.1	20.6	31.9
Total/Mean	1,000	48.0	38.5	22.1	27.9

Note. Percentages for typology columns reflect proportion of misinformation posts within each platform.

5.2 Emotional Tone Distribution

Analysis of emotional tone across the full sample revealed a markedly asymmetric distribution in which fear-based content was substantially over-represented among misinformation posts relative to factual content. Among misinformation posts, fear-based emotional tone was coded in 61.9% of cases, anger-based tone in 9.8%, hope-based tone in 8.7%, and neutral tone in 19.6%. By contrast, among factual health posts, neutral tone predominated (62.4%), with hope-based tone accounting for 22.1%, fear-based tone for 12.8%, and anger-based tone for 2.7%. The association between misinformation classification and emotional tone was highly significant, $\chi^2(3, N = 948) = 312.7, p < .001$, Cramér's $V = .57$, indicating a large effect.

Platform-level analysis of emotional tone distribution revealed that fear-based framing was most prevalent among TikTok misinformation posts (68.5%), followed by Facebook (64.2%), YouTube (58.7%), and Twitter/X (54.3%). These differences may reflect platform-specific norms around affective communication style, as well as differences in content format: short-form video, which dominates TikTok and increasingly Facebook and YouTube, affords greater use of paralinguistic emotional cues—facial expression, tone of voice, music—that may enhance the emotional impact of fear-based narratives (Myrick & Willoughby, 2019).

5.3 Virality and Engagement Patterns

The central hypothesis of this study—that fear-based misinformation would achieve disproportionately high engagement relative to neutral or factual content—was strongly supported by the engagement data. Fear-based misinformation posts generated a mean share count 2.31 times higher than factually accurate content with neutral tone ($M = 8,247$ vs. $M = 3,572$ shares, $t(624) = 11.43, p < .001, d = 0.84$), and a mean comment count 1.82 times higher ($M = 1,936$ vs. $M = 1,063$ comments, $t(624) = 7.29, p < .001, d = 0.55$). These effect sizes are classified as large and medium-to-large respectively, indicating practically significant as well as statistically significant differences.

Within misinformation posts, emotional tone emerged as the strongest predictor of engagement, explaining a substantially greater proportion of variance in share count ($\eta^2 = .31$) than misinformation typology ($\eta^2 = .12$) or source type ($\eta^2 = .09$). This finding has important implications for intervention design: it suggests that the emotional register of health misinformation is more important than its specific topical or typological content in determining its spread, and therefore that emotional approaches—including inoculation theory-based interventions (Roozenbeek et al., 2022) and emotion regulation strategies—should be central components of counter-misinformation efforts.

Table 2
Mean Engagement Metrics by Content Type and Emotional Tone

Content / Tone	Mean Shares	Mean Comments	Mean Reactions	Cohen's d vs. Factual Neutral
Misinformation – Fear	8,247	1,936	12,483	0.84
Misinformation – Anger	5,614	2,281	9,102	0.61
Misinformation – Hope	4,109	1,187	7,834	0.42
Misinformation – Neutral	3,981	1,025	6,249	0.38
Factual – Fear	4,723	1,294	7,126	0.47
Factual – Hope	3,895	1,108	6,412	0.34
Factual – Neutral	3,572	1,063	5,984	–

Note. All comparisons with factual neutral content are significant at $p < .001$ unless otherwise indicated.

5.4 Source Characteristics

Non-expert influencers—defined as individuals with substantial follower counts who produce health content without recognized medical or scientific credentials—were identified as the source of 69.4% of misinformation posts, compared to 38.1% of factual health posts, $\chi^2(4, N = 948) = 84.3, p < .001$. Medical professionals accounted for 14.2% of factual posts but only 6.1% of misinformation posts. Scientific or academic institutions produced 18.7% of factual posts and 4.4% of misinformation posts. Mainstream news organizations accounted for a similar proportion of factual (18.3%) and misinformation (11.8%) content, consistent with prior research documenting that traditional media sometimes amplify health misinformation through sensationalized or oversimplified health reporting (Sumner et al., 2014).

The association between source type and engagement was complex. Non-expert influencers achieved the highest mean engagement metrics overall, reflecting their large pre-existing follower bases and their optimization for platform-specific engagement norms. However, when follower count was controlled as a covariate in a hierarchical regression model, emotional tone remained a significant independent predictor of engagement ($\beta = .28, p < .001$), while source type influence was substantially reduced (β from .41 to .19), suggesting that emotional narrative characteristics drive engagement over and above the distributional advantages associated with influencer status.

Discussion

6.1 Fear as a Structural Driver of Virality

The findings of this study compellingly confirm and extend prior theoretical and empirical accounts of fear's role in health misinformation virality. The strength of the



association between fear-based emotional framing and engagement metrics—particularly the large effect size for the fear misinformation versus factual neutral comparison ($d = 0.84$)—is consistent with the predictions of emotional contagion theory (Hatfield et al., 1993; Ferrara & Yang, 2015) and with Berger and Milkman's (2012) foundational work on emotion and sharing. Importantly, however, our findings go beyond establishing that fear content engages: they demonstrate that fear-based content is disproportionately concentrated within misinformation rather than factual information, and that this concentration is systematic rather than incidental. This suggests that the emotional properties of health misinformation are not merely rhetorical decoration but are functional features of a content type specifically adapted—whether by intentional design or evolutionary selection—to exploit the affective architecture of social media sharing.

The finding that emotional tone accounts for more variance in engagement than misinformation type or source type ($\eta^2 = .31$ vs. $.12$ and $.09$, respectively) has direct implications for both theory and practice. Theoretically, it suggests that affective mechanisms occupy a more central position in misinformation diffusion than either content-level factors (what kind of false claim is being made) or source-level factors (who is making it). This finding supports a conceptual reframing of health misinformation virality as fundamentally an affective phenomenon—one whose explanation must be centered on emotional dynamics rather than cognitive evaluation or source credibility heuristics, as traditional persuasion models might suggest (Petty & Cacioppo, 1986).

6.2 Algorithmic Amplification as Structural Complicity

The cross-platform variation in misinformation prevalence and engagement—with TikTok and Facebook consistently showing higher prevalence and higher engagement multiples for fear-based content—provides important evidence for the moderating role of platform-specific algorithmic structures in health misinformation virality. These differences are not readily explicable by demographic or cultural variation across platform user bases alone; they reflect the distinct recommendation logics and engagement optimization strategies that characterize each platform's algorithmic infrastructure (Gillespie, 2014; Hern, 2022).

TikTok's particularly high misinformation prevalence (58.4%) and the elevated engagement multiplier for fear-based content on that platform are consistent with published analyses of the For You Page algorithm's sensitivity to emotional signals and its tendency to surface emotionally intense content regardless of source credibility (Basch et al., 2021; Hern, 2022). Facebook's similarly elevated prevalence (54.8%) is consistent with internal research leaked by whistleblowers and subsequently reported in the academic literature (Horwitz & Seetharaman, 2021), which documented that Facebook's engagement-weighting algorithm was associated with the amplification of misinformation and divisive content.

A critical implication of this analysis is that platform algorithmic systems are not passive conduits for user-generated misinformation but active participants in its amplification. The engagement-maximization logic embedded in platform algorithms creates what amounts to a structural subsidy for emotionally provocative content, systematically increasing the reach and impact of misinformation relative to accurate information. This framing challenges the common platform narrative that misinformation spread is primarily a demand-side problem—a consequence of what users want—rather than a supply-side structural condition that platforms actively create through their algorithmic design choices (Cinelli et al., 2020).



6.3 Authority Performance and the Credibility Inversion

The finding that 69.4% of misinformation posts originated from non-expert influencers, while medical professionals contributed only 6.1%, instantiates at scale the credibility inversion dynamic theorized by Basch et al. (2021) and Sharma et al. (2019). This pattern reflects a fundamental structural mismatch between the communication norms required for accurate scientific health information—qualification, uncertainty acknowledgment, causal complexity—and the communication norms rewarded by platform engagement metrics—confidence, simplicity, emotional impact, and narrative resolution.

The hierarchical regression finding that emotional tone retains significant predictive power over engagement after controlling for follower count reinforces this interpretation. It suggests that health communicators with genuine medical expertise who adopt emotionally engaged, narratively compelling communication styles may be able to partially bridge the engagement gap with misinformation content—a finding with actionable implications for public health communication training and practice. However, the systemic scale of the credibility inversion documented here suggests that individual communication style adjustments, while potentially valuable, are insufficient as a primary response strategy.

6.4 Public Health and Governance Implications

The findings of this study have several concrete implications for public health practice, platform governance, and digital literacy intervention design. For public health communicators, the evidence that emotional tone is the primary driver of engagement—and that fear-based narratives specifically outperform neutral informational approaches—suggests the value of systematically integrating emotional engagement strategies into health communication design, while avoiding the fear-based framing that characterizes misinformation (Witte, 1992). Inoculation-theory-based approaches (Roozenbeek et al., 2022), which preemptively expose audiences to weakened forms of misinformation strategies, have shown particular promise in building emotional resilience to fear-based health claims.

For platform governance, the structural complicity finding argues for regulatory frameworks that go beyond requiring platforms to remove specific pieces of misinformation content, and instead address the algorithmic design features that systematically amplify emotionally engaging misinformation. Specific proposals with evidence support include algorithmic friction interventions (Pennycook et al., 2020), in which platforms introduce low-cost interventions—accuracy prompts, sharing delays, credibility labels—that activate deliberative processing before sharing; engagement metric reforms that deweight metrics most susceptible to emotional manipulation; and systematic algorithmic auditing requirements that would make it possible for independent researchers and regulators to assess the extent to which recommendation systems amplify versus suppress misinformation (Ribeiro et al., 2020).

6.5 Limitations

Several limitations of this study warrant acknowledgment. First, the cross-sectional design precludes causal inference: while the associations between fear-based framing, misinformation, and engagement are robust, the directionality of these relationships cannot be definitively established from content analysis data alone. Longitudinal or experimental designs would be necessary to establish causal claims. Second, the sampling window (2022–2023) and the keyword-based sampling strategy may not fully capture the diversity of health misinformation content, particularly highly niche or community-specific misinformation that would not appear in general keyword searches. Third, the coding of emotional tone, while established with strong intercoder reliability ($\kappa = .81$), necessarily involves interpretation that



may not fully capture the complex, mixed, and contextually variable emotional responses that content elicits in different audiences. Fourth, the cross-platform comparison is complicated by significant differences in the demographic composition, use patterns, and cultural contexts of each platform's user base, which may confound platform-level algorithmic effects with user-level and cultural-level variation.

Conclusion

This study has demonstrated that the virality of health misinformation on social media is not an incidental or random phenomenon but a structurally produced outcome of the systematic interaction between the emotional and narrative properties of misinformation content and the engagement-optimizing algorithmic architectures of social media platforms. Fear-based narratives are disproportionately associated with health misinformation and achieve substantially higher engagement than factual health content, generating more than twice the shares and nearly twice the comments. These effects are consistent across platforms, though modulated by platform-specific algorithmic characteristics, with TikTok and Facebook showing the most pronounced amplification dynamics.

The study's theoretical contribution—the integration of emotional contagion theory, algorithmic amplification frameworks, and misinformation diffusion models into a unified sequential conceptual model—advances the explanatory framework available to misinformation researchers by specifying the mechanisms through which content properties, user behavior, and platform structure interact to produce population-level misinformation epidemics. The concept of structural virality—virality as a produced rather than emergent outcome—represents a reframing with significant implications for how responsibility for misinformation harm is distributed between individual actors, platform corporations, and regulatory systems.

Addressing the health misinformation crisis requires interventions at multiple levels simultaneously. Platforms must accept responsibility for the amplification effects their algorithmic design choices produce and implement evidence-based modifications to engagement optimization logic. Public health communicators must develop more sophisticated, emotionally intelligent communication strategies that can compete for attention in algorithmically structured information environments without sacrificing accuracy or resorting to the fear-based manipulation that characterizes misinformation. Policymakers must develop regulatory frameworks capable of addressing structural platform dynamics rather than merely requiring post-hoc content removal. And digital health literacy education must equip users to recognize not merely the claims of misinformation but the emotional and algorithmic mechanisms through which misinformation achieves its disproportionate impact. The findings of this study provide an empirical and theoretical foundation for each of these intervention directions.

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