Crisis and Resilience
Journal Homepage: https://journals.explorerpress.com/cr

Research Article

Toward a Theoretically Grounded Framework for Digital Epidemiological Enquiry: Integrating Behavioral Models, Information Diffusion, and AI-Driven Infoveillance Using a COVID-19 Vaccine Case Study

I.A. Kashim

Faculty of Public Health, Texila American University/ Central University of Nicaragua

KEYWORDS

Digital epidemiology
Infodemiology
Health Belief Model
sentiment analysis
topic modeling
social media
COVID-19 vaccination

ABSTRACT

Digital epidemiology has emerged as a critical complement to traditional surveillance by leveraging digitally generated data to monitor population health behaviors and perceptions in near real time. Despite rapid methodological advances, the field remains dominated by tool-centric approaches, with limited integration of behavioral theory capable of explaining how information exposure translates into health-related decision-making. This article advances a theory-building, analytically grounded framework for digital epidemiological enquiry and empirically illustrates its application using a COVID-19 vaccine discourse case study from the United Kingdom and the United States. Drawing on the Health Belief Model (HBM), infodemiology, and information diffusion theory, the framework links perceived susceptibility, severity, benefits, barriers, and cues to action with AI-enabled sentiment and topic analytics. Using a large corpus of vaccine-related Twitter data, natural language processing and topic modeling were employed to operationalize behavioral constructs in digital discourse. Findings demonstrate that sentiment and thematic patterns can approximate key behavioral dimensions, while also revealing important limitations related to structural context, trust, and collective narratives that are only partially visible in digital traces. The study contributes a theoretically informed, empirically grounded approach for advancing digital epidemiology as an explanatory and policy-relevant discipline.

*CORRESPONDING AUTHOR

I.A. Kashim; Faculty of Public Health, Texila American University/ Central University of Nicaragua; Email: irkashim@gmail.com

ARTICLE INFO

Received: 11 November 2025 | Revised: 30 November 2025 | Accepted: 10 December 2025 | Published Online: 12 December 2025

DOI: https://doi.org/10.65773/cr.2.1.55

1. Introduction

The emergence of digital epidemiology has redefined the boundaries of public health inquiry, shifting from traditional survey-based methods toward real-time analysis of digital footprints [1]. During the COVID-19 pandemic, the vast amounts of unstructured data generated through social media provided an unprecedented opportunity to study population sentiment and behavior at scale. However, despite methodological advancements, digital epidemiology remains largely atheoretical, lacking a unifying framework that connects behavioral constructs with computational analytics [2,3]. This study proposes a conceptual framework that integrates public health behavior theories with computational models to advance digital epidemiological enquiry.

Specifically, while early formulations of infodemiology emphasize quantifying the distribution of health information and misinformation online [1], and digital epidemiology broadens the range of data sources available for surveillance [2], these approaches often stop short of theoretically explaining how information exposure is translated into risk perception, motivation, and behavioral intent. Large-scale analyses of COVID-19 discourse have documented polarization and misinformation dynamics [3], yet frequently lack an explicit behavioral mediation layer capable of supporting explanatory epidemiological inference or targeted policy response [4].

The paper argues that digital epidemiology must evolve from a descriptive analytic tool into a theoretically grounded discipline capable of explaining how information exposure, cognitive framing. It also social influence shape health-related behaviors. The proposed framework builds upon the researcher's previous work on public health information surveillance, which employed sentiment analysis and topic modeling to examine COVID-19 vaccine perceptions across two countries [4].

2. Methodology

Methodological Orientation

A. Paradigmatic Positioning

The methodology is situated within a pragmatic–critical realist paradigm. Digital traces are treated as imperfect but informative proxies of underlying beliefs, perceptions, and social processes, rather than direct, unmediated measures of "true" attitudes. This stance aligns with contemporary understandings of digital epidemiology as a hybrid domain that bridges computational analytics and social-behavioral interpretation [1,3].

B. Purpose and Unit of Analysis

The primary objective is theory-building, not tool benchmarking. The central unit of analysis is the *conceptual architecture* linking behavioral constructs (HBM), Information diffusion patterns, AI-driven digital indicators and epidemiological interpretation

The COVID-19 vaccine discourse serves as an embedded empirical case to test, challenge, and refine this architecture.

This study adopted a theoretical–analytic methodology to demonstrate how behavioural models, information diffusion theory, and AI-driven analytics can be integrated into a unified lens for modern epidemiological enquiry. Rather than an empirical design, the methodological approach followed a conceptual synthesis strategy, drawing on established models, prior digital-behavioural research, and computational foundations of digital epidemiology.

This theoretical–analytic approach explicitly departs from prediction-centric analytic paradigms. Rather than optimizing classification accuracy or correlation strength, it emphasizes explanatory coherence, construct validity, and interpretive transparency. Computational outputs are therefore treated as theoretically mediated indicators of behavioral processes, not as stand-alone signals.

C. Embedded Theoretical Case Study

a. Case Context

The empirical component draws on the author's doctoral study of COVID-19 vaccine discourse on Twitter in the United Kingdom and the United States during the early and mid-implementation phases of vaccine rollout [5].

Data Collection: Data were collected from the Twitter/X platform using the Twitter Apify interface, restricted to publicly available posts containing COVID-19 vaccine–related keywords and hashtags. The use of publicly accessible data aligns with established ethical standards for infodemiological and digital public-health research, particularly where individual-level identification is neither sought nor inferred [1,3].

Sampling Period: The sampling frame covered December 2020 to November 2021, corresponding to critical stages of COVID-19 vaccine rollout, regulatory authorization, public-health messaging, and policy shifts in the United Kingdom and the United States [4,6]. This temporal window enabled the examination of dynamic changes in population sentiment across evolving epidemiological and policy contexts.

Preprocessing: Raw textual data underwent standardized preprocessing procedures including language filtering, tokenization, normalization, stop-word removal, and duplicate elimination to improve analytic validity and reduce noise common in social-media corpora [6]. Irrelevant or non-substantive posts were excluded through rule-based screening supplemented by manual validation.

Sentiment Analysis Approach: Sentiment polarity and emotional valence were assessed using the VADER (Valence Aware Dictionary and sEntiment Reasoner) framework, selected for its robustness in short, informal social-media text and its prior application in public-health sentiment studies [10]. Sentiment outputs were interpreted as behavioral proxies corresponding to Health Belief Model constructs, particularly perceived severity, benefits, and barriers [5,7].

Topic Modeling Approach: Latent Dirichlet Allocation (LDA) was applied to identify dominant thematic structures within the corpus. Topic outputs were iteratively refined and interpreted using a human-in-the-loop approach to ensure conceptual alignment with behavioral constructs rather than reliance on purely statistical coherence [11].

Validation Methods: Framework validation was undertaken through theoretical triangulation of sentiment trends, topic prevalence, and temporal alignment with epidemiological milestones and public-health policy announcements. Rather than predictive validation, emphasis was placed on explanatory plausibility and construct coherence, consistent with theory-building approaches in digital epidemiology [2,4].

Limitations: The study is subject to limitations inherent to social-media research, including non-representativeness of platform users, algorithmic amplification effects, and constraints on inferring behavior directly from discourse. Additionally, algorithmic bias and the indirect nature of behavioral proxies limit causal interpretation, reinforcing the necessity of theory-mediated analysis and cautious policy translation [12,14].

b. Embedded Analytical Units

Four embedded analytical units structure the enquiry: i) Behavioral constructs: HBM perceptions of susceptibility, severity, benefits, barriers, and cues to action; ii) Infodemiological patterns: topics and narratives within vaccine discourse; iii) Computational outputs: sentiment scores, topic clusters, temporal trends; iv) Epidemiological logic: implications for interpreting risk perception, trust, and potential uptake

The methodological question is: Do the digital indicators and emergent patterns align with, extend, or contradict the theoretical expectations of the integrated framework?

D. Theory Selection and Integration

a. Criteria for Theory Inclusion

The methodology mandated explicit justification for theory selection. Inclusion was guided by three criteria: Established relevance to health behavior and decision-making; Conceptual compatibility with digitally observable indicators; Prior use or adaptability within epidemiological or infodemic research

Based on these criteria, the Health Belief Model (HBM) was selected as the primary behavioral framework, complemented by information diffusion and infodemiology theories [6].

Rather than aggregating theories additively, the methodology employs analytic alignment, positioning HBM constructs as explanatory mediators between digital signals and population-level epidemiological interpretation. Information diffusion models contextualize how these beliefs propagate, while AI analytics operationalize their detection at scale.

b. The Health Belief Model as Behavioral Core.

The Health Belief Model was selected because of its long-standing use in explaining vaccine uptake and preventive behaviors across diverse contexts [5,6]. It offers a structured set of constructs—perceived susceptibility, severity, benefits, barriers, cues to action, and self-efficacy—directly relevant to interpreting vaccine-related discourse. The HBM provides a psychological basis for understanding individuals' health actions, premised on perceived susceptibility, severity, benefits. It also barriers [5]. Its strength lies in its ability to quantify psychological predictors of behavior, making it adaptable to digital contexts where expressions of fear, hope. It also skepticism can be algorithmically measured. The model's flexibility has facilitated its integration into sentiment analysis frameworks, where terms linked to "fear," "risk," or "benefit" serve as proxies for behavioral intent. However, critics argue that the HBM is overly individualistic and does not sufficiently address structural determinants such as inequality, misinformation networks, or digital literacy [6].

Evidence from the present study suggests that HBM constructs, when observed through digital discourse, often manifest as collective narratives shaped by institutional trust and social identity. This indicates that classical behavioral models can be empirically extended within digitally mediated environments when coupled with infodemiological theory and contextual interpretation [5].

In the author's study, the HBM was not simply "applied" post hoc; rather, it shaped the analytic pipeline, supporting lexicon design, topic labeling, and interpretation of emergent themes [5].

c. *Infodemiology and Digital Epidemiology*

Infodemiology and infoveillance provide the informational lens, conceptualizing how health-related content circulates and how digital metrics can be used as surveillance indicators [2]. Digital epidemiology contributes the methodological scaffolding for drawing public health-relevant inferences from online signals [1].

d. *Integration Logic*

The integrated framework posits that: i. HBM constructs mediate between exposure to information and behavioral intention or action; ii. Digital trace metrics (e.g., sentiment, topics, engagement) function as observable approximations of these constructs; iii. Information diffusion dynamics and platform architectures shape how and for whom these constructs are activated.

The empirical case is used to test whether this logic is defensible and where it breaks down.

3. Findings

Conceptual Framework Development Process

a. Iterative Synthesis

The conceptual framework construction followed an iterative sequence This approach that reflected abductive reasoning, wherein theory and observation inform each other dynamically [8]. This included: i)Literature-driven construct identification; ii) Empirical observation of digital discourse patterns; iii) Theoretical alignment and tension analysis; iv) Recursive refinement of construct relationships

Figure 1 below shows the integrated conceptual diagram employed, enabling explicit articulation of relational assumptions, feedback loops, and points of interpretive uncertainty.

Visual modeling facilitated differentiation between: i) Inputs (digital signals); ii) Processes (AI-enabled analytics and behavioral interpretation), and; iii) Outputs (epidemiological insight and policy relevance).

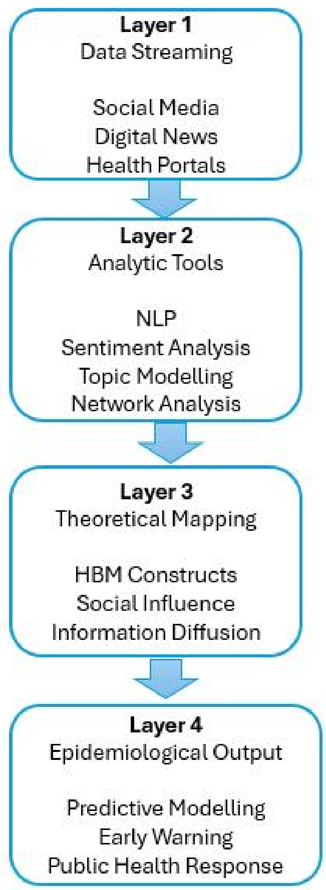

Figure 1. Proposed Integrated Conceptual Framework.

While computational techniques underpin the feasibility of the framework, they are positioned as supportive rather than primary methodological components.

Natural Language Processing (NLP) -based sentiment analysis and topic modeling are utilized to demonstrate that theoretical constructs could be empirically approximated within large-scale digital corpora [8]. However, the analysis deliberately avoids over-reliance on statistical metrics, recognizing well-documented limitations related to algorithmic bias, representativeness, and semantic drift [4].

Framework appraisal was conducted using four analytical criteria: i) Theoretical coherence – internal consistency across constructs; ii) Explanatory plausibility – alignment with observed digital behaviors; iii) Analytical transparency – traceability of theoretical decisions; iv) Transferability – applicability to non-pandemic public health contexts

This evaluative logic aligns with qualitative standards of rigor rather than predictive validation models [2].

F. Case Study Illustration: COVID-19 Vaccine Sentiment Analysis; a study on perception

The author [4] collected 194,378 tweets from the Twitter/X platform were scrapped using Twitter Apify during the period December 2020–November 2021 using specific hashtags related to Covid vaccination. Following preprocessing and geolocation, 42,311 tweets from UK and US were recovered for analysis. Using VADER (Valence Aware Dictionary and sEntiment Reasoner) for sentiment classification and LDA (Latent Dirichlet Allocation for thematic extraction, results showed that positive sentiment dominated (39.5%), followed by negative (27.5%) and neutral (15.5%). Correlational analysis revealed alignment between online positivity and real -world vaccine uptake trends. VADER is a lexicon- and rule-based sentiment analysis algorithm specifically designed for short, informal text, such as social media posts. LDA is an unsupervised probabilistic topic modeling algorithm used to identify latent thematic structures in large text corpora.Themes aligned with HBM constructs: fear of side effects (barrier), protection of family (benefit). It also trust in the NHS (cue to action). The findings substantiate the framework's potential for integrating digital data streams with behavioral epidemiology.

At the same time, sustained periods of negative sentiment despite improving epidemiological indicators demonstrate a decoupling between objective risk metrics and perceived severity. This pattern underscores the necessity of theory-informed interpretation of digital sentiment signals, reinforcing the limits of purely descriptive or polarity-driven analytic approaches [3,4].

Table 1. shows that sentiments can be mapped onto the core constructs of the Health Belief Model (HBM), thereby providing an empirical foundation for validating the integration of behavioral theory with digital epidemiologic analytics.

Table 1. Mapping of Health Belief Model Constructs to Observed Online Sentiment Expressions.

HBM Construct	Sentiment Expression (Observed Online)	Interpretive Meaning	Implication for Vaccine Behavior
Perceived Susceptibility	Fear of infection; awareness of risk; mentions of "catching COVID"	High susceptibility evokes emotional alertness and self-protective intent.	Positive correlation with vaccine acceptance and preventive behavior.
Perceived Severity	Anxiety about death or hospitalization; worry over long COVID	Reflects cognitive assessment of threat seriousness.	Reinforces perceived need for immunization or adherence to NPIs.
Perceived Benefits	Trust in science; belief in vaccine efficacy; optimism about normalcy	Highlights rational acceptance of protective value.	Drives uptake and compliance with public-health guidance.
Perceived Barriers	Mistrust; fear of side effects; misinformation; cost or access concerns	Indicates cognitive and affective resistance factors.	Negatively associated with uptake; requires targeted myth-busting communication.
Cues to Action	Peer influence; exposure to campaigns; policy mandates; celebrity endorsements	Represents external or environmental triggers to act.	Converts latent intention into behavior—especially under social or policy pressure.
Self-Efficacy (Expanded HBM construct)	Confidence to make informed choices; belief in ability to access vaccines	Reflects perceived control and empowerment in decision-making.	Positively correlated with consistent vaccine follow-through and advocacy.

This explicit relationship is further clarified in Figure 2 below.

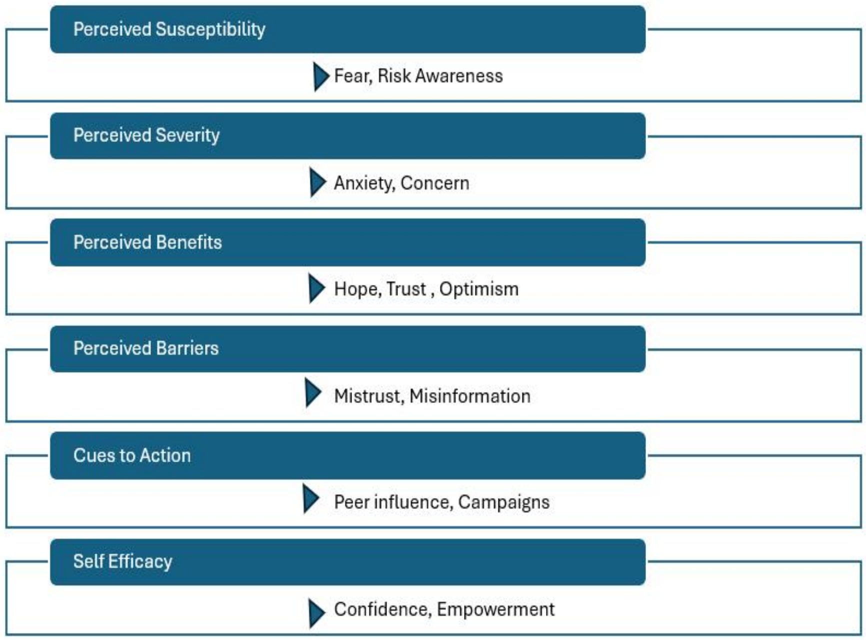

Figure 2. Digital sentiment to behavioral outcome related to HBM construct.

Figure 2 here illustrates the interpretive layer of the proposed digital epidemiological framework, focusing specifically on how online sentiment data are mapped to the constructs of the Health Belief Model (HBM). This representation highlights the psychological bridge between digital expressions of emotion and measurable health-related behaviors. In this model, social-media discourse expressing fear or perceived risk corresponds to perceived susceptibility, while anxiety about severe illness reflects perceived severity.

Expressions of hope, trust in science. It also optimism indicate perceived benefits, whereas mistrust, misinformation. It also concern over side effects represent perceived barriers. Mentions of public campaigns, policy mandates, or peer encouragement function as cues to action. It also self-referential confidence denotes self-efficacy. This mapping, demonstrates that digital sentiment signals can operationalize HBM constructs, providing a theoretical foundation for quantifying behavioral intent in digital epidemiology.

Ethical and Methodological Considerations

Ethical oversight in theory-driven digital epidemiology extends beyond data privacy to encompass algorithmic accountability, responsible inference, and policy misuse risks. The methodology emphasizes the use of publicly available data, anonymization at scale, and restraint in causal attribution, consistent with emerging ethical frameworks for digital health surveillance [1].

4. Conclusion

This article advances a critical, theory-building methodology for digital epidemiological enquiry that reconceptualizes digital data not as epidemiological substitutes, but as behavioral signals requiring structured theoretical interpretation. By integrating behavioral theory, information diffusion models, and AI analytics through an embedded case study design, the methodology offers a transferable blueprint for scholars and practitioners seeking analytically rigorous, ethically grounded, and policy-relevant digital surveillance frameworks.

It proposes an integrative theoretical framework for digital epidemiological enquiry, uniting behavioral science and computational analytics into a coherent model for understanding health behaviors in the digital era. By embedding constructs from the Health Belief Model within a multi-layered architecture that also incorporates information-flow theories, the framework demonstrates how online sentiment data can be systematically transformed into actionable epidemiological intelligence. The empirical foundation [4] reinforces the viability of this approach, showing that linguistic and emotional cues from digital discourse correlate with offline behavioral outcomes such as vaccine acceptance and trust in public-health institutions.

These findings substantiate that digital sentiment analysis can effectively operationalize psychological constructs, offering a near-real-time behavioral surveillance tool for public-health agencies.

Contribution to Knowledge

This study makes three principal contributions to the field of digital epidemiology. First, it advances a theoretically grounded framework that explicitly mediates between computational analytics and established behavioral theory, addressing a persistent gap in predominantly tool-centric digital surveillance approaches [1,2]. Second, it empirically demonstrates the feasibility of operationalizing Health Belief Model constructs using large-scale digital discourse, thereby extending classical behavioral theory into digitally mediated and infodemiological contexts [5,7]. Third, the study provides a replicable and ethically governed methodological blueprint for integrating sentiment analysis and topic modeling into public-health surveillance, with direct relevance for outbreak preparedness, infodemic management, and future Disease X scenarios [3,14].

Recommendations

Drawing on the insights proposed in this study, several strategic recommendations emerge for advancing digital epidemiological practice and health communication:

1) Integrate Digital Surveillance into National Health Systems:
   Ministries of Health and disease-control agencies should institutionalize digital sentiment monitoring dashboards within their epidemiologic intelligence units. This integration can enable early detection of misinformation trends and emerging vaccine hesitancy patterns.
2) Adopt a Behavioral Analytics Framework for Risk Communication:
   Public-health messaging should be guided by behavioral constructs—linking communication tone and framing to perceived benefits and cues to action. Data-driven adaptation of message framing (e.g., emphasizing community protection or family safety) can increase uptake and reduce fatigue during prolonged health campaigns.
3) Develop Multilingual and Culturally Sensitive NLP Tools. Future development should localize sentiment lexicons and training corpora for regional languages, especially in the Global South, to improve representativeness and precision.
4) Strengthen Ethical and Governance Frameworks for Digital Epidemiology:
   The expansion of social-media surveillance demands robust ethical oversight, including data anonymization, informed consent, and algorithmic transparency [15]. Institutional review boards should be trained to evaluate AI-enabled public-health studies that process user-generated data.
5) Encourage Interdisciplinary Collaboration:
   Effective digital epidemiology requires collaboration among public-health experts, data scientists, behavioral psychologists, and policy communicators. Such collaboration ensures that algorithmic insights are contextualized within sociocultural realities rather than interpreted as purely statistical phenomena.
6) Build Regional Capacity in Computational Public Health:
   Investments in academic and institutional training are critical. Programs in digital health analytics and

infodemiology should be embedded in postgraduate curricula to produce a workforce capable of implementing real-time, ethically sound digital-surveillance systems across Africa and other LMICs.

7) Establish Validation Protocols Linking Online and Offline Indicators:
Correlations between sentiment data and actual health behaviors must be systematically validated through cross-referencing with vaccination records, disease-outbreak data, or survey findings to ensure empirical robustness and prevent over-interpretation.

Funding

The study was self-financed

Data Availability

For any inquiries regarding the protocols used or the data, please contact the corresponding author (irkashim@gmail.com)

Conflict of Interest

We do not have any competing financial interests or any personal relationships that could have had an impact on the work published in this article. There is no conflict of interest; this is only our original work, and all other materials used have been duly acknowledged in the text.

References

[1] Eysenbach, G. (2009). Infodemiology and infoveillance: Framework for an emerging set of public health informatics methods. Journal of Medical Internet Research, 11(1), Article e11. https://doi.org/10.2196/jmir.1157

[2] Salathé, M., Bengtsson, L., Bodnar, T. J., Brewer, D. D., Brownstein, J. S., Buckee, C., ... & Brownstein, J. S. (2012). Digital epidemiology. PLOS Computational Biology, 8(7), Article e1002616. https://doi.org/10.1371/journal.pcbi.1002616

[3] Eysenbach, G. (2020). How to fight an infodemic: The four pillars of infodemic management. Journal of Medical Internet Research, 22(6), Article e21820. https://doi.org/10.2196/21820

[4] Cinelli, M., Quattrociocchi, W., Galeazzi, A., Valensise, C. M., Schmidt, A. L., Zollo, F., & Scala, A. (2020). The COVID-19 social media infodemic. Scientific Reports, 10, Article 16598. https://doi.org/10.1038/s41598-020-73510-5

[5] Hussain, S., Tahir, M., Hussain, H., Sheikh, T., Dashtipour, A., & Naseem, T. M. (2021). Artificial intelligence–enabled analysis of public attitudes toward COVID-19 vaccines in the United Kingdom and the United States. Journal of Medical Internet Research, 23(4), Article e26627. https://doi.org/10.2196/26627

[6] Kashim, I. A. (2025). Analyzing COVID-19 Vaccination Discourse on Twitter/X in the United States and United Kingdom. Texila Advanced Journal of Multidisciplinary Health Research Publisher: Texila International Journal ISSN: 3105-3564 Volume 5 Issue 2, 2025 DOI: 10.21522/TAJMHR.2016.05.02.Art017

[7] Rosenstock, I. M. (1974). Historical origins of the Health Belief Model. Health Education Monographs, 2(4), 328–335. https://doi.org/10.1177/109019817400200403

[8] Glanz, K., Rimer, B. K., & Viswanath, K. (2015). Health behavior: Theory, research, and practice (5th ed.). Jossey-Bass.

[9] Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

[10] Hutto, C. J., & Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. Proceedings of the International AAAI Conference on Web and Social Media, 8(1), 216-225. https://doi.org/10.1609/icwsm.v8i1.14550

[11] Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. Journal of Machine Learning Research, 3, 993 –1022.

[12] Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. Communications of the ACM, 59(7), 96–104. https://doi.org/10.1145/2818717

[13] Hancock, J. T., Naaman, A., & Levy, M. (2020). AI-mediated communication. Proceedings of the National Academy of Sciences, 117(51), 31794–31802. https://doi.org/10.1073/pnas.2013275117

[14] Lazer, D. M. J., Baum, M. A., Benkler, Y., Berinsky, A. J., Greenhill, K. M., Menczer, F., ... & Zittrain, J. L. (2018). The science of fake news. Science, 359(6380), 1094–1096. https://doi.org/10.1126/science.aao2998

[15] Floridi, L., & Cowls, J. (2020). A unified framework of five principles for AI in society. Harvard Data Science Review, 2(1). https://doi.org/10.1162/99608f92.8cd550d1