Infodemic Intelligence for 2025 Infections: AIV, FMD, MPox, and HMPV

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Abstract. We present an AI-driven internet media surveillance approach that fuses multilingual posts from Twitter/X, Telegram, Facebook, Instagram, TikTok, news sites, and forums for four viral threats – foot-and-mouth disease (FMD), Avian Influenza virus (AIV), MPox, and Human metapneumovirus (HMPV). The timespan of the data is from 25 Dec 2024 to 15 Jul 2025. Results reveal policy-driven attention decay. Interest in AIV (A/H5N1) collapsed after US agencies stopped publishing extensive alerts. FMD outbreak discourse exhibited conspiracy spikes. We observed panic reactions and a persistent Global-North/South bias in the case of HMPV. The breakdown of different media usage shows the prevalence of social media in the case of HMPV discussion. Our study exemplifies the importance of the internet data analysis to assess the risk perception and reaction to governmental measures to improve containment management.

Keywords: Social Media Analysis · Infection control · and Natural Language Processing · One Health · Infodemiology · Foot-and-Mouth Disease · Avian Influenza · Human Metapneumovirus

1 Introduction

1.1 Infoveillance

Unconventional surveillance of One Health threats can be significantly enhanced by leveraging artificial intelligence (AI). Social media platforms offer rich, real-time data sources for tracking disease outbreaks, misinformation, and public sentiment [21]. Nowadays, researchers widely use online social and traditional media data to investigate the behavioral and affective dynamics of the public

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during the COVID-19 pandemic [14]; however, non-English languages are highly underrepresented, and other (i.e., non-human host) infections are almost not covered at all.

We note limitations of `epitweetr` (ECDC-based), for automated (now no longer available) monitoring of Twitter/X data to detect public health threats [8]; MEDISYS (EU Commission-based), which scrapes only traditional media [19]; and the inadequate coverage of Eastern European languages by EIOS (WHO-based), whose performance in early outbreak detection remains unclear [22].

1.2 Infodemiology

In an increasingly interconnected world, the rapid spread of information and misinformation during health crises poses significant challenges. This phenomenon, often called an "infodemic" [5, 20], requires sophisticated computational methods to understand and manage public discourse.

The broader concept of an infodemic, as an overwhelming spread of both accurate and false information during health crises, is central to the study's purpose. Effective infodemic [9] management requires systematic, evidence-based approaches to monitor and counter harmful information [27].

1.3 Related Works

The study resonates strongly with core concepts in communication theories. Agenda-setting theory suggests that the media not only inform us about what to think, but also influence how we think about it [18, 26]. When official sources reduce the salience of a topic, public and media attention tends to wane, demonstrating how communication policy can directly influence the public agenda. This dynamic underscores the importance of monitoring not just what is being said, but also what is not being said. Framing theory focuses on how information is presented or "framed" by the media, influencing public interpretation [7]. For AI systems and NLP techniques, recognizing these differing frames is critical for accurately assessing sentiment and identifying harmful narratives. Research indicates that media framing and selective exposure intensify misinformation spread, complicating effective communication. Uses and Gratifications Theory (UGT) shifts the focus from what media do to people to what people do with media [11]. UGT highlights that user motivations, such as altruism and socialization, influence engagement with distorted content, further eroding public trust. This theoretical lens suggests that AI systems should not only track content but also infer user motivations to better predict and mitigate misinformation cascades.

Integrating communication theories into the design and analysis of AI-driven surveillance systems can significantly enhance their ability to detect, interpret, and respond to viral infodemics.

2 Methods

We utilize infoveillance and infodemiology [9,17] techniques to monitor disease-related conversations across various platforms (Twitter/X, Telegram, Facebook, Instagram, TikTok, news websites, and forums) between 25 December 2024 and 15 July 2025. We have chosen four (re-)emerging viral infections significant for One Health and public health. Keywords (Table 1):

- **Foot-and-mouth disease** (English name of disease), FMD (international acronym), Pryszczyca (Polish), Maul- und Klauenseuche (German), Slintačka a krívačka (Slovak), Száj- és körömfájás (Hungarian): FMD is a highly contagious viral disease affecting cloven-hoofed animals, causing significant economic losses in livestock [23]. In early 2025, outbreaks were reported in Germany and in the SlovakiaHungary border region, triggering trade restrictions.
- **Avian influenza**, Bird flu (English names of the disease), AIV (international acronym of virus): Avian Influenza (particularly subtype A/H5N1) poses zoonotic risks and periodically causes mass die-offs among wild birds and poultry [25]. Since 2024, the United States has experienced outbreaks involving mammalian species (including humans), fueling strong negative sentiment and critiques of the national response [13].
- **Monkeypox** (older English name), MPox (international name of the disease): MPox is an infection caused by the MPXV (virus) in humans and has a reservoir in animals as well, historically endemic in parts of Africa, but with global spread observed in 2022 [2]. During 20242025, a Clade Ib outbreak in East Africa was observed.
- **Human metapneumovirus** (English), HMPV (international acronym of virus): HMPV causes respiratory infections in humans (the disease shares the virus name), particularly in children and the elderly, and typically surges in winter. In January 2025, a spike (not much different than in other seasons and regions) of cases appeared in China [1].

Table 1. Overview of mentions and reach related to selected diseases on Brand24

Infection	MPox	AIV	FMD	HMPV
Total mentions	50 773	134 220	55 682	137 810
Social media mentions	19 392	42 168	20 091	98 107
Non-social media mentions	31 381	92 052	35 591	39 703
Positive mentions	2 147	2 453	3 409	5 743
Negative mentions	2 712	14 959	6 093	4 292
Social media reach	211 294 605	586 290 333	145 357 097	1 954 165 470
Non-social media reach	172 685 192	758 814 850	241 273 010	326 196 588

Natural Language Processing (NLP) techniques applied by Brand24 [3] were used to extract data with keywords, and conduct sentiment analysis. These analyses were powered by deep learning and large pre-trained language models–especially recent multilingual models such as on-line ChatGPT, and locally-hosted Mistral, DeepSeek (designed for broad coverage including underrepresented languages in Eastern Europe) [6,10,28]. These models may classify content topics. In nomenclature "Mentions" refer to the number of posts, comments, articles, and multimedia items from both traditional and social media sources, while "reach" estimates the number of individuals potentially exposed to this content.

In this context negative sentiment may reflect fear, criticism, or opposition. This approach enables the detection of emerging threats, public concerns, and disinformation patterns in near real-time, offering valuable input for public health communication and epidemic preparedness frameworks [21,22].

3 Results

In terms of mentions number, we can distinguish pairs MPox and FMD (circa 55 k) as well as Avian Influenza and HMPV (circa 135 k) (Table 1, Fig. 1).

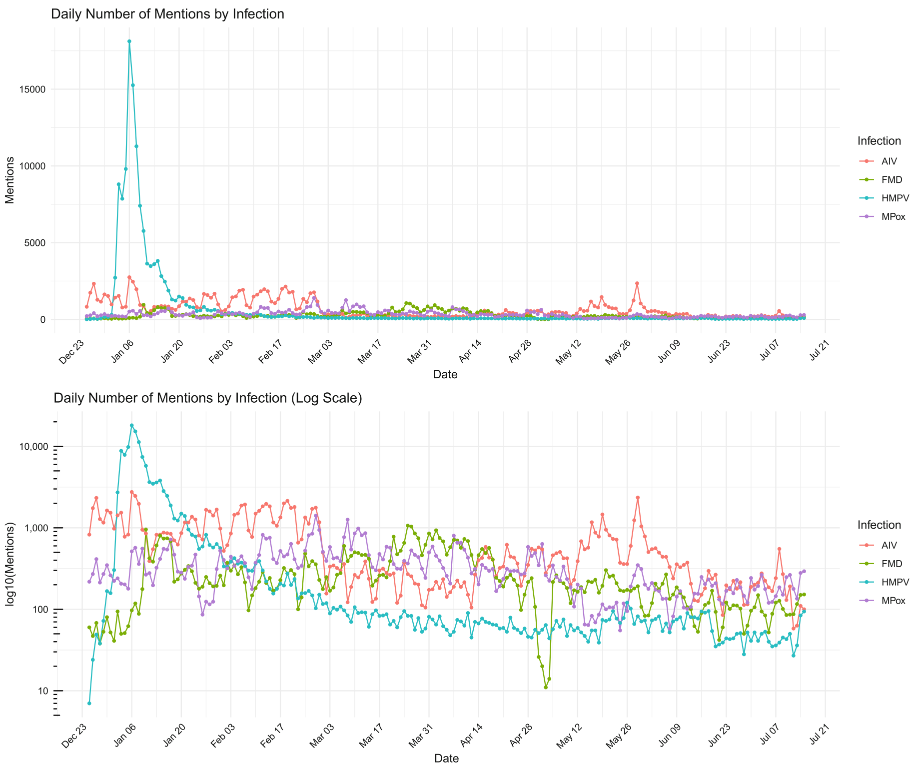

Fig. 1. Time evolution of mentions counts. Upper: linear. Lower: log scale

However, HMPV generates much greater reach (especially in social media) than any other infection) - even it concentrates only in January 2025. Mostly animal host diseases Avian Influenza and FMD/MPox (but to a lesser extent), have better traditional media penetration than social media.

During outbreaks of FMD and Avian Influenza, when the U.S. government took controversial actions, the share of negative emotions increased (Fig. 2).

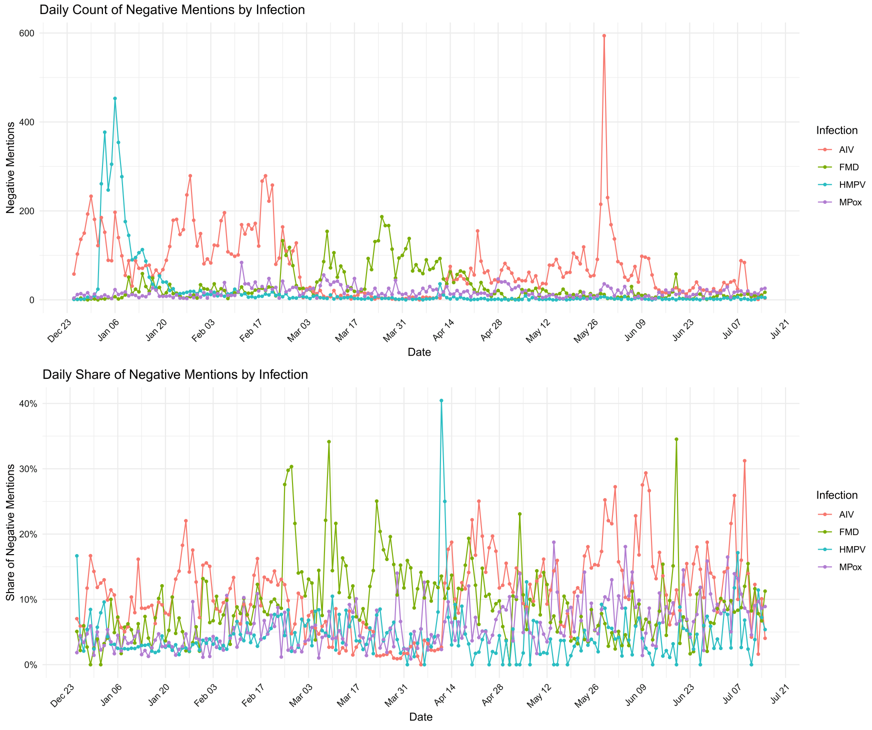

Fig. 2. Negative sentiment. Upper: counts. Lower: share

3.1 Foot-and-Mouth Disease (FMD)

We observe an increase in interest and a greater share of negative emotion around outbreaks in Germany (January) and Slovakia/Hungary (March/April). Peaks occur on each country's detection day as well as when restrictions are introduced. Social media played only a minor role; economic concerns dominated traditional media. We see the propagation of fake news about suspected farms, with key conspiracy theories revealed by topic modeling with LLMs:

– FMD as a lab-engineered virus (paralleling accusations against biolabs in Ukraine [12]).

- Political cover-ups (declaring states of emergency to conceal economic crises).
- Hidden agendas involving meat-market distortions aimed at facilitating the Mercosur agreement (between the EU and several South American countries).

Using selected keyword searches in traditional media, we found that conspiracy-theory mentions constituted only 1.4% in German, while in Slovak and Hungarian they accounted for 2.4% and 4.2% (Table 2).

Table 2. FMD: Conspiracy rate by language in traditional media

Language	conspiracy rate (%)	Total mentions in languages
slk	2.365	3890
pol	0.941	4675
deu	1.426	5259
hun	4.207	5467
eng	4.322	8468

3.2 Avian Influenza (AIV)

Mainly A/H5N1 in mammals, with primary outbreaks in the USA. Infections among mammals increased notably. Substantial negative sentiment was attributed to criticisms of U.S. policy responses (Fig. 2) and to egg shortages (e.g., around the Easter holidays and again in June). For example, when the U.S. Department of Health canceled a contract for an H5N1 vaccine solution, the share of negative emotions increased sharply. Interest has decreased since U.S. authorities such as the Departments of Agriculture and Health stopped communicating alerts (Fig. 1). The last major federal update was issued in March 2025 [24], focusing on milk safety rather than outbreak containment. From that point on, human and animal H5N1 infection data were no longer provided as standalone updates. Consequently, media and expert attention declined, partly due to the removal of high-profile alerts and regular briefings.

3.3 MPox

Occurrences continue in African conflict zones, mostly clade Ib but occasionally the clade II pandemic lineage detected in 2022. Online discourse remains stable, but it is far less intense than when the disease was present outside Africa [4]. Negative sentiment share increases linearly (Fig. 2) by 0.98 percent point monthly (p-Value$= 2.2 \times 10^{-16}$).

3.4 Human Metapneumovirus (HMPV)

Global interest was sparked by the outbreaks in China, leading to a sharp surge in online activity in early January 2025 (Fig. 1). This pattern resembles a typical single-event (impulse) excitation phenomenon. Furthermore, the proportion of negative emotions was comparable to that for other diseases, except during the very first week at the turn of 2024/2025 (Fig. 2).

3.5 Various Media Composition and Interpretation

Table 3. Comparison of series features

Infection	SD	Skewness	Significant peaks	Half-life (days)	7-day seasonality
AIV	578.90	1.30	12	3	0.303
FMD	219.08	1.46	14	4	0.225
MPox	217.29	1.64	11	2	0.323
HMPV	2237.43	5.23	8	3	0.066

Daily series of mentions differ substantially among each-other. We selected features (Table 3) describing behavior.

- **SD**: Daily variability of interest (Standard Deviation).
- **Skewness**: Asymmetry (high values sharp spikes such as in HMPV case).
- **Significant Peaks**: Number of days with value mean + 2 × SD.
- **Half-life**: Median number of days until interest falls below 50 % of Significant Peak.
- **7-d Seasonality**: Strength of weekly cycle scaled to 0 (no seasonality)—1 (strict seasonality) range computed via STL (SeasonalTrend decomposition using Loess) decomposition with period 7. We extract the seasonal component $S_t^{(7)}$ and residual R_t, then calculate $\mathrm{Var}(S_t^{(7)})/(\mathrm{Var}(S_t^{(7)}) + \mathrm{Var}(R_t))$. HMPV exhibits the weakest weekly seasonality trend.

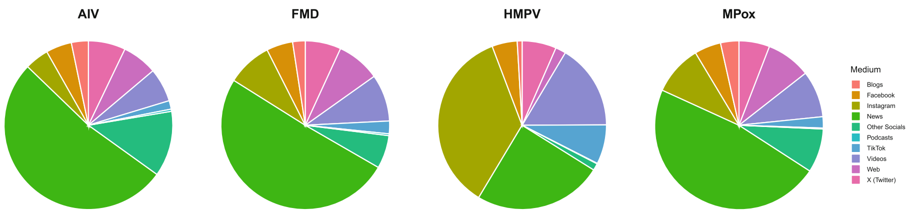

Fig. 3. Various medium composition

We observe how the detection of new or re-emerging disease cases (e.g., FMD, HMPV) shapes media dynamics. HMPV goes viral on social media, getting a high fraction of mentions on platforms such as Instagram or YouTube (Fig. 3) and very high reach (Table 1). The media composition of HMPV differs significantly from that of other infections (Table 4). In the case of Avian Influenza, media interest appears to be strongly influenced by political factors. The examples of MPox and FMD (both are endemic outside of rich countries) further illustrate that unless a disease emerges in the Global North, it tends to receive limited media coverage.

Table 4. Pairwise χ^2 test p-values for medium independence (standard p-Value and Bonferroni-adjusted p-Value). *An algorithmic proxy of 0 in double precision floating-point arithmetic, **An algorithmic proxy of 1 after transformation

Pair	p-value	Adj. p-value
AIV vs FMD	0.898	1**
AIV vs HMPV	0*	0*
AIV vs MPox	0.929	1**
FMD vs HMPV	2×10^{-5}	1.2×10^{-4}
FMD vs MPox	0.999	1**
HMPV vs MPox	2×10^{-5}	1.2×10^{-4}

4 Conclusions

Our findings underscore the importance of AI-driven social media monitoring [16] in both One and Public Health contexts, and advocate for its integration into epidemic preparedness frameworks.

In our study, we observe a clear instance of the agenda-setting phenomenon: a decrease in interest in Avian Influenza (A/H5N1) occurred after U.S. agencies halted alerts. The cessation of regular briefings and the removal of high-profile alerts by authorities like the U.S. Departments of Agriculture and Health led to a decline in media and expert attention, suggesting a strong influence of communication policy on the public agenda. Also, seasonality (the effect of the day of mention within the weekly cycle) is clear in each series except HMPV (Table 3, Fig. 1).

While professional traditional media dominated in the case of FMD, focusing on the economic concerns of the disease, we saw the emergence of conspiratorial "frames" [15] portraying the virus as lab-engineered or linked to political cover-ups (Table 2). This differentiation in narratives across media platforms highlights how various frames can impact public sentiment, as evidenced in our study by an increase in negative emotions during FMD outbreaks.

The dramatic surge in reach for Human Metapneumovirus, particularly on social media platforms like Instagram and YouTube, and the “irrational online panic” it triggered in early January 2025, exemplify the rapid, though sometimes misleading, spread of viral content. Unlike mainly animal-host diseases such as Avian Influenza and FMD, which had better penetration in traditional media, HMPV “went viral” on social media, underscoring the role of these platforms in the dynamic dissemination of information, especially when it concerns human infections.

Finally, this study sheds light on the broader issue of Global NorthSouth media bias in health communication. Observations of MPox and FMD show that, unless a disease establishes in the Global North, it tends to receive limited media coverage. The relatively stable–yet far less intense–online discourse about MPox now that it is largely confined to East Africa, compared with the surge during its global spread in 2022 [2], underscores this disparity.

This study has several limitations. First, the amount of noise varies across datasets; for example, the FMD dataset contains some acronyms unrelated to the disease, so careful post-collection data curation is essential. Second, the usage of disease and virus names differs by country and language: while “HMPV” is internationally standardized, “FMD” can appear in multiple forms depending on the locale. Additionally, the Brand24 filtering and sampling algorithms are out of our control (collection bias).

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