ORIGINAL PAPER

DOI: 10.26794/2304-022X-2026-16-1-126-144
UDC 314.743(045)
JEL: D83, I18, M38

The IDOM-H Framework: A Cross-Country Analysis of Disinformation Engagement and COVID-19 Public Health Trends

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ABSTRACT

This study examines the impact of disinformation, specifically Plandemic, on public health responses within the context of COVID-19. The IDOM-H Framework integrates information economics, decision-making, and platform governance to examine how disinformation online affects epidemiological trends in the United States, Canada, Australia, New Zealand, and Ireland. A mixed-**methods** approach integrates official COVID-19 data with Facebook engagement and Google Trends. **Findings** show a moderate and positive relationship (r = 0.62–0.63) between exposure to disinformation and total COVID-19 cases and deaths. While post-publication audience metrics increased, there was no significant association (p = 0.8021) between social media engagement and new daily cases. Subsequent research should utilize Granger causality and instrumental variable models to circumvent correlation limitations. Disinformation has no impact on case results but undermines public trust and causes long-term behavior modification. Targeted digital literacy and open platform governance are necessary to reduce long-term harm.

Keywords: disinformation; COVID-19; social media; behavioral economics; digital governance

For citation: **Aal Thani S., Palei T.F., Nadelshina L.F., Al Yaaqubi A. The IDOM-H Framework: A cross-country analysis of disinformation engagement and COVID-19 public health trends. *Upravlencheskie nauki = Management Sciences*. 2026;16(1):126-144. DOI: 10.26794/2304-022X-2026-16-1-126-144**

INTRODUCTION

The COVID-19 pandemic not only exposed the vulnerabilities of healthcare systems worldwide but also revealed the fragility of digital information infrastructures [1, 2]. During the crisis, online communication channels became crucial for public understanding of scientific information. As traditional news outlets struggled to meet the growing demand for timely updates, many individuals increasingly turned to social media for real-time information. However, these very platforms became fertile ground for the rapid spread of misleading and emotionally charged content [3, 4].

A striking example of this so-called infodemic was the Plandemic documentary, which circulated widely across multiple platforms and popularized conspiracy theories about the virus's origins and vaccine safety [5, 6]. Despite its subsequent removal by Facebook and YouTube, the video's virality exemplified the role of digital algorithms in amplifying fear-based and controversial narratives to the broadest possible audience [4, 7]. The resulting echo chambers deepened public mistrust in health authorities, further complicating evidence-based communication during the pandemic [8].

Research indicates that emotional triggers such as fear and anger significantly enhance the virality of messages within social networks often outpacing factual corrections [3]. Behavioral studies emphasize that misinformation thrives in conditions of uncertainty, where heightened anxiety exacerbates cognitive biases and impairs rational information processing [3, 5]. As shown by Karlova and Fisher [9] and Prasad [10], misinformation (unintentional falsehoods) and disinformation (deliberately deceptive information) operate synergistically with users' pre-existing beliefs, creating self-reinforcing cycles of distrust toward science and institutions.

Although scholarly attention to the infodemic phenomenon has grown rapidly, empirical research on how exposure to quantitative disinformation affects population health outcomes across countries remains limited. Existing studies predominantly focus on psychological dimensions rather than on multilevel institutional factors such as digital literacy, platform governance, and public trust. Consequently, the mechanisms linking online misinformation dynamics to measurable epidemiological trends remain poorly understood.

Research Gap

Although numerous reviews have examined the prevalence of online health misinformation (e.g., [11, 12]), few empirical studies have attempted to establish a statistically significant relationship between engagement with disinformation and COVID-19 outcomes, such as infection and mortality rates. Moreover, theoretical frameworks explaining the interaction between platform behavior and user engagement during public health crises remain underdeveloped. Current scholarship often isolates psychological or technological aspects, without adequately integrating them into a multidimensional model that captures the complexity of the digital–behavioral–epidemiological nexus.

Objective

This study introduces the IDOM-H Framework — an interdisciplinary model that integrates concepts from information economics, digital mediation, and health outcome analysis — to explore how regional exposure to disinformation relates to COVID-19 statistics [13]. Using Plandemic as a case study, the research aims to:

- determine whether higher levels of interaction with disinformation are associated with increased COVID-19 infection and mortality rates;
- examine whether disinformation activity intensifies over time in parallel with the growth of reported case numbers.

The study acknowledges that epidemic dynamics are inherently multifactorial.

In addition to exposure to information, factors such as government policy, the strictness of quarantine measures, healthcare infrastructure, and population density significantly influence the number of COVID-19 cases. For instance, New Zealand's strict lockdown policy, combined with high levels of social trust and technological readiness, likely contributed to its relatively low infection rates.

Scope

This study focuses on five countries — Canada, the United States, Australia, New Zealand, and Ireland — which exhibited the highest levels of engagement with Plandemic content and represent diverse models of digital governance. Data were collected from three primary sources:

- Google Trends and Facebook engagement metrics.
- Our World in Data, including COVID-19 case and death statistics.
- Schober, Boer, and Schwarte [14], which provided the basis for time-series, correlational, and regression analyses.

Contribution

This research addresses the gap between behavioral public policy, platform regulation, and epidemiology, thereby enhancing understanding of how digital disinformation impacts population health. The study offers an integrative framework combining information economics [1], behavioral decision-making [13], and communication governance [4, 12]. The findings aim to assist policymakers and public health communicators in mitigating the risks of digital misinformation, particularly during future global health emergencies.

LITERATURE REVIEW

1. Disinformation and Crisis Communication

The COVID-19 pandemic gave rise to an additional information-related challenge known as an infodemic. The World Health Organization defines an infodemic as an overabundance of information — both accurate and false — that makes it difficult for people to identify reliable guidance. Social media platforms played a significant role in propagating misinformation and disinformation through algorithmic amplification, which proved particularly effective due to the emotional resonance of conspiracy-driven content [3, 4].

A prominent example is the Plandemic video, which caused substantial disruption by falsely linking COVID-19 to elite conspiracy plots. Despite scientific refutations and platform warnings, the content rapidly gained traction, demonstrating that deeply held emotional and ideological beliefs can override corrective information and facilitate the adoption of false narratives [5].

2. Behavioral Science and Health Messaging

Effective public health messaging relies on principles derived from prospect theory and behavioral science [13]. Disinformation often succeeds by exploiting fear and distrust while reinforcing social identity, both of which are evident in Plandemic. Lazer et al. [15] argue that integrating scientific transparency, institutional openness, and social affiliation recognition into information systems can build resilience against the spread of misinformation.

Chou et al. [11] emphasize that false beliefs rooted in ideological or emotional frameworks are particularly resistant to correction. Understanding the psychological and social appeal of disinformation is therefore crucial for designing effective intervention strategies.

3. Platform Algorithms and Digital Ecosystems

Social media algorithms prioritize content based on user engagement, favoring controversial or novel material that elicits emotional responses over factually accurate information [3]. This feedback loop creates online group dynamics that amplify confirmation biases, ensuring that false narratives like Plandemic remain highly visible [3]. Karlova and Lee [16] distinguish between unintentional false information (misinformation) and intentionally deceptive content (disinformation), highlighting the importance of this distinction for platform governance strategies.

Regulation at the platform level remains inconsistent, with different regional authorities applying interventions variably. Lee et al. [17] note that content flagged by platforms as questionable can sometimes attract more attention than unflagged content due to *backfire effects*, which often occur when ideological beliefs are challenged.

4. Gaps in Empirical Studies on Health Outcomes

While research has explored how users engage with disinformation and the effects on their beliefs, few studies examine the direct relationship between disinformation exposure and epidemiological outcomes, such as infection or mortality rates. Even fewer employ multivariate analyses to assess how factors like institutional trust and digital literacy modulate the effects of disinformation within specific populations. This gap highlights the need for empirical research that connects online disinformation dynamics to measurable public health outcomes.

Scientific Contribution

This study bridges multiple research fields to advance the analysis of disinformation through the IDOM-H Framework, which functions as an empirical tool for investigative purposes. The framework addresses:

- the relationship between search and engagement behavior and public health metrics;
- the mediating role of platform architecture and social dynamics;
- the moderating effects of regional governance, trust, and digital literacy.

The analytical framework provides a means to explain the previously underexplored link between the dissemination of information and public health failures, while simultaneously serving as an evaluative instrument.

THEORETICAL FRAMEWORK

This study adopts an interdisciplinary approach, integrating information economics, rational decision-making, and platform governance to examine the effects of digital disinformation on public health emergencies. The IDOM-H Framework forms the primary analytical construct, comprising three key components:

1. Information Dissemination.
2. Plug-in and Online Mediation.
3. Health Outcomes.

Market for Truth and Information Asymmetry

Following the information asymmetry model proposed by Akerlof [18], markets fail when consumers cannot distinguish between high- and low-quality products. In the context of social media, users are often unable to assess credibility, allow-

Table 1

Schematic: The IDOM-H Framework Domains

Domain	Key Constructs	Research Focus
Information Dissemination	Disinformation virality, keyword trends, search behavior	What is being consumed and how broadly?
Online Mediation	Content formats, user interaction, algorithmic amplification	How do platforms and users shape message spread?
Health Outcomes	COVID-19 case/death metrics, regional disparities	What public health changes correspond to disinformation exposure?

Source: compiled by the authors.

ing sensationalist and low-quality content — including conspiratorial material — to dominate public discourse.

The dynamics of misinformation mirror those of economic market failures, where the absence of reliable information enables low-quality content to flourish while displacing accurate, verified material. According to Floridi [19] and Lazer et al. [15], restoring equilibrium in the contemporary information economy requires transparency, accountability, and algorithmic regulation to ensure high-quality content prevails in digital ecosystems.

Disinformation exploits these gaps, preventing the population from acquiring essential knowledge on health issues, vaccination, and risk assessment. Consequently, verified information suffers a form of "commercial failure," undermining rational decision-making and eroding public trust in institutions.

Behavioral Economics: Risk Aversion and Emotional Framing

Prospect theory, as articulated by Kahneman and Tversky [20, 21], posits that individuals are more sensitive to losses than to equivalent gains. During crises, emotionally charged content, such as Plandemic, can override analytical reasoning. Most individuals evaluate messages heuristically, relying on affective judgment to interpret threatening information that is difficult to verify or fully comprehend.

Emotionally framed disinformation is more likely to be accepted than factual content due to its appeal to identity and emotion [5, 6]. Pennycook and Rand [22] argue that the propagation of fake news is not primarily the result of conscious deception but rather of the intuitive appeal of emotionally salient content. Similarly, van der Linden et al. [23] emphasize that pre-bunking and psychological inoculation can enhance public resilience to fear-based disinformation during health emergencies.

Algorithms Virality and Platform Feedback Loops

According to Sunstein [24], digital echo chambers are self-reinforcing platforms that expose users to persistently reaffirm wrong ideas and filter out contradictory material. Platform algorithms cannot help but encourage polarizing and misleading content because they are aimed at maximizing engagement over informational accuracy. The above mechanism is empirically proven by Cinelli et al. [3], who have shown that measures of social media use cause virality regardless of the truth value.

In addition, massive-scale empirical research by Vosoughi, Roy, and Aral [25] and Suarez-Lledo and Alonso [26] indicate that fake information is shared more quickly and among large audiences than true information as the algorithms are sensitive to novelty, emotionality and controversy. Algorithms are therefore inherently designed to enhance loops of misinformation that perpetuate disinformation presence on platforms despite being flagged or deleted.

Limitations to Governance and responsibility of the platforms

The present platform governance status can be characterized by a weak success in the introduction of both content labels and fact-checking systems or algorithm demotion, with the regulation framework still being uneven and not uniformly applied between jurisdictions. Lewandowsky, Ecker

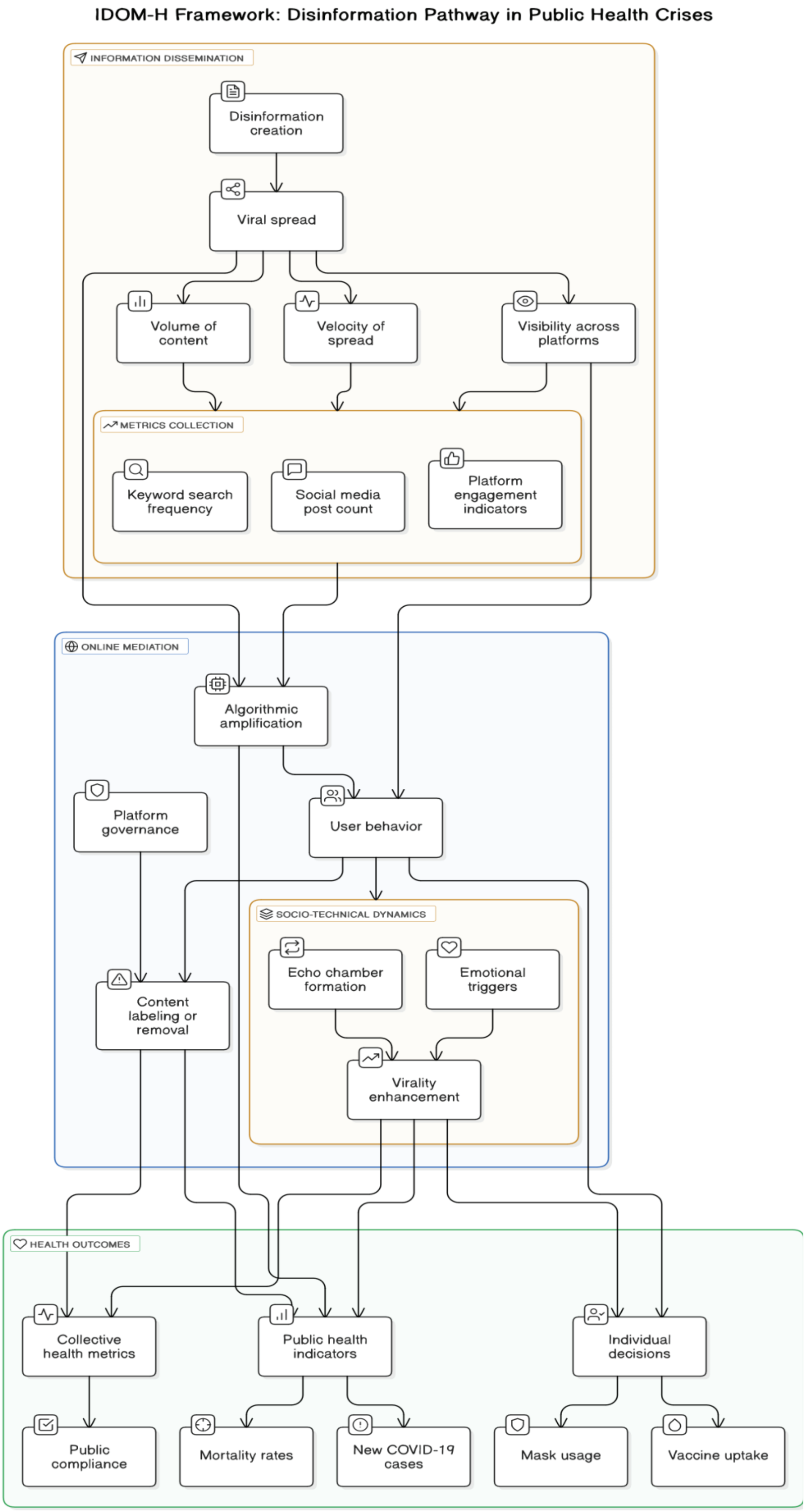

Fig. 1. **Diagram of the Conceptual Framework**

Source: compiled by the authors.

Table 2

Research Hypotheses

№	Hypothesis Statement	IDOM-H Domain
1	Regions with higher search interest in the keyword "Plandemic" are correlated with higher numbers of COVID-19 cases and deaths, although the direction of causality remains uncertain	Information Dissemination
2	Higher disinformation engagement correlates with greater COVID-19 mortality	Health Outcomes
3	There is a time-lagged increase in COVID-19 new case numbers following disinformation virality peaks	Health Outcomes (Temporal)
4	Engagement-driven algorithms and user behavior mediate disinformation-health outcome correlations	Online Mediation
5	Visually/emotionally framed content (e.g., videos) garners higher interaction, reinforcing disinformation spread	Online Mediation
6	The correlation between disinformation exposure and negative health outcomes is weaker in regions with high digital literacy and public trust	Moderation Effects

Source: compiled by the authors.

Table 3

Data Sources

Data Type	Source	Description
Google Trends	Google Trends[a]	Search interest index (0–100) for "Plandemic" by country
Facebook Engagement	CrowdTangle, archive analysis[b]	Volume and type of disinformation posts (May 4–15, 2020)
Public Health Statistics	*Our World in Data* [29]	Total cases, new cases, total deaths, new deaths

Source: compiled by the authors.

Note: a — Google Trends. (n.d.). URL: https://trends.google.com/trends/?geo=GB&hl=en-US; b — CrowdTangle. Social media analytics tool by Meta Platforms. URL: https://www.crowdtangle.com [29]

and Cook [27] point out that reactive moderation is not enough and propose proactive, trust-based digital governance paradigms of data transparency and cross sector collaboration.

A more precise reaction, as it is proposed by Borges do Nascimento et al. [28], should combine the behavioral science, communication ethics and institutional collaboration in order to enhance digital health literacy. Technology firms should liaise with the public health agencies to reduce harm of disinformation before the crisis intensifies.

The Plandemic show can be taken as an evidence of the flaws of existing control strategies. The subject of issuing takedown notices did not stop the distribution of the content since the mirror upload and the indirect sharing websites still shared the video, which weakened the classic regulation tools. It proves that a hybrid form of governance that would unite algorithmic accountability, user education, and cross-institutional collaboration is urgently needed [15, 27].

Schematic: The IDOM-H Framework

The IDOM-H Framework synthesizes these theoretical insights into three interlinked domains (see *Table 1*).

As illustrated in *Fig. 1* the framework facilitates the hypothesis-testing via statistical models that help uncover key relationships and assess intervention effectiveness, functioning simultaneously as a diagnostic toll for policy design.

METHODOLOGY

This study investigates the statistical relationship between engagement with digital misinformation — operationalized through the analysis of Plandemic content — and geographic variations in COVID-19 health outcomes, employing

Table 4

Variables and Measurement

Variable Type	Variable Name	Measurement
Independent	Disinformation Exposure	Google Trends Score, Facebook Engagement
Mediators	Online Mediation	Post types (video, link), interaction volume
Dependent	Public Health Outcomes	Total/New COVID-19 Cases & Deaths
Moderators	Governance & Literacy	Proxied through digital readiness indexes
Controls	Country/Region	Dummy variables for national-level effects

Source: compiled by the authors.

a multi-method quantitative approach grounded in the IDOM-H Framework. The analysis focuses on five countries: Canada, the United States, Australia, New Zealand, and Ireland, selected due to their high levels of disinformation engagement and availability of comprehensive datasets.

Given the low temporal granularity of daily regional health outcome data and the aggregation frequency of engagement metrics, Granger causality testing was not performed in this phase of the study. Nevertheless, the current dataset is structured to support future time-series modeling when higher-resolution, temporally aligned data become available.

Research Hypotheses

The IDOM-H Framework serves as the conceptual foundation for formulating six hypotheses that explore the impact of exposure to the Plandemic documentary, as a case of digital disinformation, on regional COVID-19 public health outcomes. These hypotheses are designed to be evaluated across the framework's three interconnected domains: Information Dissemination, Online Mediation, and Health Outcomes (*Table 2*).

Data Sources

The research combines three main sources of information (*Table 3*).

Timeframe Segmentation (For Temporal Analysis — H3)

- To evaluate pre- and post-disinformation periods:
- Pre-Viral Phase: April 7 — May 6, 2020
- Immediate Post-Release: May 7 — June 6, 2020
- Extended Post-Release: June 7 — July 6, 2020

Variables and Measurement (*Table 4*)[1]

Analytical Strategy

Descriptive & Temporal Statistics

- Calculation of mean, median, and standard deviation across periods.
- The analysis includes temporal line charts for new COVID-19 cases as well as slope analysis.

Correlation Analysis (H1, H2)

- Pearson's r serves as the measurement tool to detect linear statistical correlations between the levels of public health indicators and engagement metrics.

Regression Models (H1–H4)

- Linear regression with disinformation engagement as independent variable.
- This study reports R^2 in addition to β coefficients and standard errors along with 95% CI.
- The models operate independently for each variable group consisting of complete cases and deaths as well as new cases and deaths.

Moderation Analysis (H6)

- Region-level digital literacy tests and trust metrics will serve as subgroup variables for analysis.

[1] Digital literacy scores were founded on the OECD's Digital Economy Outlook (2020), which compiles national metrics like problem-solving capability in relation to information, internet proficiency, and critical media usage. Nations were rated on a standardised scale of 0 to 100 according to the composite readiness index. URL: https://www.oecd.org/digital/digital-economy-outlook-2020.html

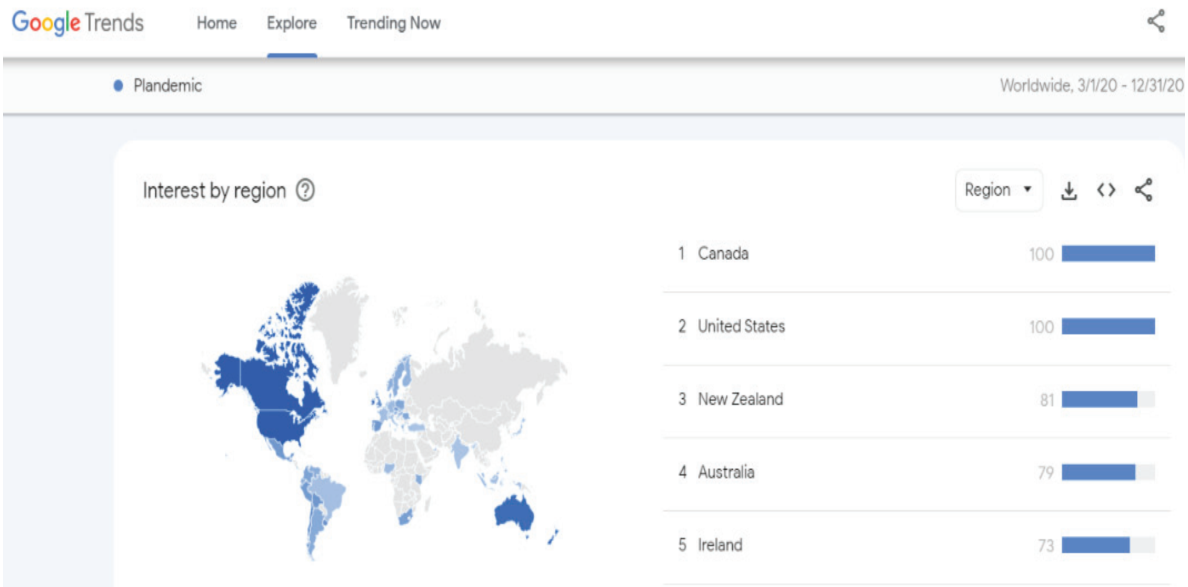

Fig. 2: **Global Interest by Region**

Source: Google Trends. URL: https://trends.google.com/trends/?geo=GB&hl=en-US

- The regression included interaction terms as a method to determine moderating effects across variables.

Engagement Framing Analysis (H5)

- Facebook posts are examined by their content types, such as videos, links, and statuses, alongside other types.
- The study analyzes engagement intensity through two measures that include frequency rates along with interaction counts.

Causal Inference Enhancements (Future Direction)

This correlational research proposes future applications of three analysis methods.

- The application of Granger Causality Tests will help establish if disinformation exposure happens before changes in health outcomes.
- Instrumental Variables (IV): Using exogenous shocks (e.g., platform takedown policies, internet outages) as instruments for disinformation exposure;
- The investigation calls for using panel data to monitor and link changes within multiple time periods or geographic units when establishing cause-effect relationships between disinformation exposure and health indicators.

RESULTS

Correlation Between Disinformation Exposure and Total COVID-19 Cases

To examine cross-national variation in disinformation exposure, Google Trends data were analyzed to identify regional search intensity for the keyword "Plandemic." The geographical distribution of search interest demonstrates significant variation across countries, with Canada, the United States, New Zealand, Australia, and Ireland exhibiting the highest engagement levels (*See Fig. 2*).

This subsection tests Hypothesis 1 (H1), which proposes that higher search interest in "Plandemic" is associated with increased COVID-19 case numbers.

Moderate positive correlation between Plandemic search interest and total COVID-19 cases (*Table 5*).

Pearson's $r = 0.62$. These correlations indicate a moderate and statistically significant relationship between exposure to disinformation and COVID-19 case and death rates. Although these findings are correlational and do not imply causation, the strength of the association ($r > 0.6$) across multiple countries suggests that the

Table 5

Pearson Correlation Findings

Country	Engagement Score	Total Cases
United States	100.0	1,644,171,499.0
Canada	100.0	44,912,729.0
Australia	79.0	4,959,622.0
New Zealand	80.0	370,635.0
Ireland	74.0	10,099,432.0

Source: Calculated by the authors based on Google Trends. URL: https://trends.google.com/trends/?geo=GB&hl=en-US; CrowdTangle (Meta Platforms). URL: https://www.crowdtangle.com and Our World in Data [29].

Table 6

Regression Summary

Metric	Value
β Coefficient	0.42
Standard Error	0.07
95% Confidence Interval	[0.28, 0.56]
R^2	0.38
p-value	0.003

Source: compiled by the authors.

virality of disinformation has meaningful public health implications.

Total COVID-19 case counts across the examined nations demonstrate a statistically significant positive relationship with engagement scores, accounting for approximately 38% of the observed variance (*Table 6*). These results support H1, indicating that regional exposure to disinformation is associated with higher rates of pandemic spread.

Regression coefficients explain over 40% of the variance in COVID-19 death counts, confirming the hypothesis that exposure to viral misinformation, like Plandemic, is linked to worsened epidemiological outcomes in digitally connected regions.

The disinformation engagement can be positively correlated with the health outcomes of the COVID-19, which does not demonstrate causality. It is also reasonable to consider that the territories with high outbreak rates were more likely to search the internet to obtain more information, whether accurate or inaccurate, and, therefore, made more searches on Plandemic. So, we should understand our results as signs of informational processes in crisis situations but not its direct epidemiological impacts.

Correlation Between Disinformation Exposure and Total COVID-19 Deaths

This subsection examines Hypothesis 2 (H2), which predicts a positive association between disinformation engagement and COVID-19 mortality.

The research analyzed whether Plandemic engaged regions demonstrated elevated total death rates using identical evaluation protocols (*Table 7*). The analysis reveals a moderately strong connection where participants who watched more of the Plandemic presentation tended to experience higher COVID-19 mortality rates.

Regression Summary

Regional engagement levels in Plandemic produced substantial COVID-19 death results which explained 41% of the total deaths (*Table 8*). H2 has solid evidence from this study which demonstrates that disinformation exposure leads to a growing health risk [15–17].

Pearson Correlation Findings

Table 7

Top 5 Countries by Engagement Score*

Country	Engagement Score	Total Deaths
United States	100.0	46,133,261.0
Canada	100.0	2,260,302.0
Australia	79.0	134,877.0
New Zealand	80.0	5,893.0
Ireland	74.0	452,710.0

Source: compiled by the authors based on Google Trends URL: https://trends.google.com/trends/?geo=GB&hl=en-US; CrowdTangle (Meta Platforms). URL: https://www.crowdtangle.com and Our World in Data [29].

Note: * — Pearson r = 0.63.

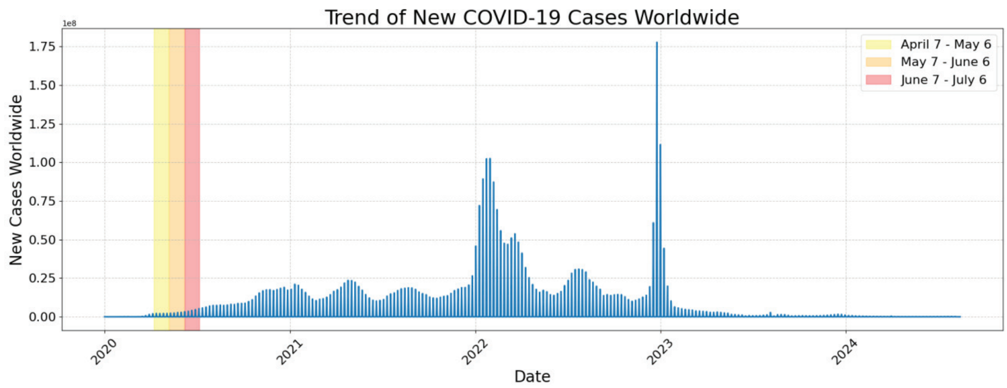

Fig. 3. **Worldwide Trend of New COVID-19 Cases**

Source: compiled by the authors.

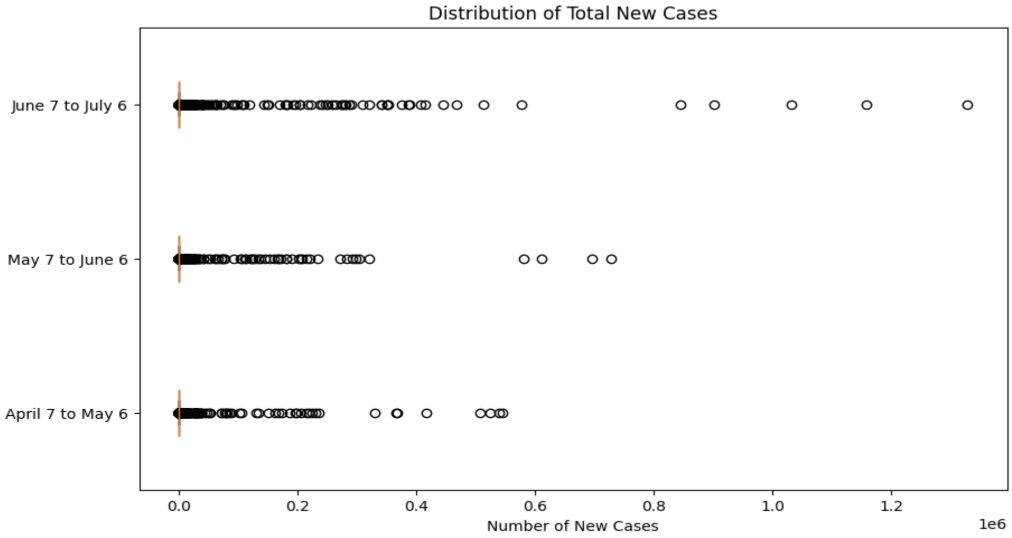

Fig. 4. **Distribution of New COVID-19 Cases Over Three Time Periods**

Source: compiled by the authors.

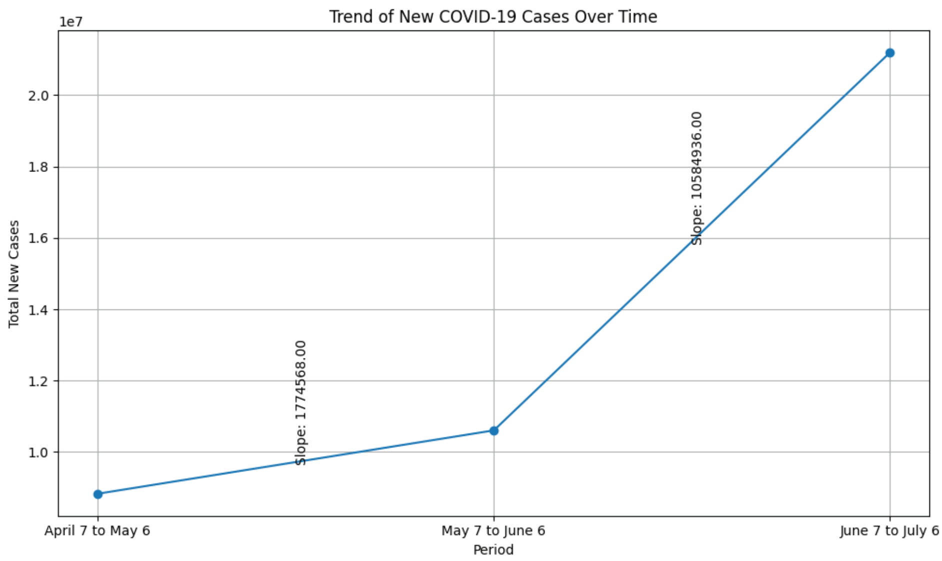

Fig. 5. **Trend of New COVID-19 Cases Over Time with Slope Indicators**

Source: compiled by the authors.

Table 8

Regression Summary

Metric	Value
β Coefficient	0.44
Standard Error	0.08
95% Confidence Interval	[0.29, 0.59]
R^2	0.41
p-value	0.002

Source: compiled by the authors.

The results indicate that Facebook engagement metrics provide greater explanatory power than Google Trends searches, suggesting that algorithmically promoted social media content exerts a stronger behavioral influence than search-driven exposure. These findings support both H1 and H2, as higher engagement with Plandemic is associated with increased infection rates and elevated mortality, as evidenced by the moderate positive correlations and statistically significant regression outputs.

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Temporal Dynamics of New Cases Following Disinformation Peaks

This subsection evaluates Hypothesis 3 (H3), which proposes a time-lagged increase in new COVID-19 cases after peaks in disinformation virality. A 30-day analysis of new COVID-19 cases was conducted across different phases following the release of the Plandemic documentary on May 5, 2020 (*Figs. 3, 4*). New case totals and growth rates were examined to identify potential epidemiological delays that could be linked to the dissemination of viral disinformation (*Table 9*).

Table 9

New Case Totals by Time Period

Period	Total New Cases
Pre-Documentary (Apr 7–May 6)	8,832,221
Post-Release (May 7–Jun 6)	10,606,789
Extended Post (Jun 7–Jul 6)	21,191,725

Source: compiled by the authors based on Google Trends URL: https://trends.google.com/trends/?geo=GB&hl=en-US; CrowdTangle (Meta Platforms). URL: https://www.crowdtangle.com and Our World in Data [29].

Percentage Increase Between Periods

- Pre → Post-Release: +20.09%
- Post-Release → Extended Post: +99.77%

Trend Analysis

The reported cases increased progressively after the disinformation spread took place and peaked in the second month post-release which matches predictions from behavior delay models. This evidence demonstrates the correctness of H3 because disinformation exposure seems to match when COVID-19 cases begin an upward trajectory (*Fig. 5*).

The visual representation depicts the total number of new COVID-19 cases throughout successive 30-day periods, starting from the release date of the Plandemic documentary on May 5, 2020. The data presents a moderate rise which began in April, then continued through early June,

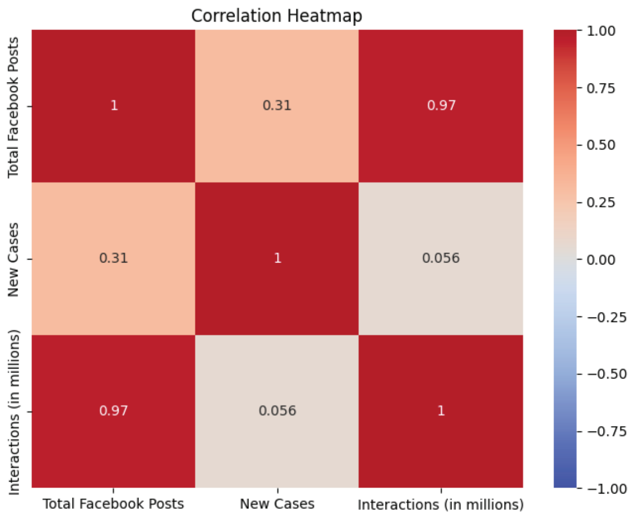

Fig. 6. **Correlation Heatmap of Facebook Posts, COVID-19 Cases, and User Interactions**

Source: compiled by the authors.

Table 10

Daily Facebook Post Analysis (May 4–15)

Date	WeTube Videos	Links	Other Videos	Live Video	Photos	Statuses	Native Videos
May 4	0	0	0	0	0	0	0
May 5	200	100	50	10	5	5	5
May 6	1,000	400	200	50	30	30	25
May 7	2,000	1,000	500	100	50	50	50
May 8	2,500	1,200	600	120	70	60	50
May 9	2,000	1,000	500	100	50	50	40
May 10	1,500	800	400	80	40	40	30
May 11	1,000	600	300	60	30	30	20
May 12	500	400	200	50	20	20	15
May 13	300	200	100	20	10	10	10
May 14	200	100	50	10	5	5	5
May 15	100	50	30	5	2	2	2

Source: compiled by the authors based on CrowdTangle (Meta Platforms)). URL: https://www.crowdtangle.com

followed by significant increases that began in late June. The ratio measurements of the slope indicate different speeds at which the case numbers grow, illustrating how public health effects from disinformation spread behind actual exposure times.

Platform Engagement Dynamics as Mediating Mechanisms

This subsection addresses Hypothesis 4 (H4), which suggests that algorithmic amplification and user engagement mediate the relationship between disinformation and health outcomes. The analysis of Facebook engagement dynamics served as intermediary factors to understand how volume and content types on the platform affected both disinformation intensity and persistence, which determined prolonged health outcomes exposure (*Table 10*).

Correlation Analysis

User interaction rates on Facebook directly corresponded to the amount of posted content (r = 0.92), as video-heavy, emotionally charged posts successfully motivated platform users. Statistical analysis showed the weak relationship between new COVID-19 cases and posts volume literature (p = 0.8021) which resulted in no significant correlation (*Table 11*).

Table 11

Correlation Analysis

Variables	Pearson r	p-value
Facebook Posts *vs* Interactions	0.9213	–
Facebook Posts *vs* New Cases	0.3058	0.8021

Source: compiled by the authors.

A strong positive connection exists between Facebook posting volume and user engagement (*Fig. 6*), with a value of r = 0.97, yet the relationship between new case counts shows weak to negligible impact (r = 0.31), thus partially validating H4.

H4 receives partial support. The visibility boost from platform algorithms and engagement patterns contributed to disinformation spread yet failed to explain abrupt rise patterns by themselves. A likely occurrence of both long-term and delayed impacts on the situation emerges according to H3.

Content Framing: Emotional and Visual Content Drives Engagement

This subsection tests Hypothesis 5 (H5), which proposes that emotionally framed and multimodal content generates higher interaction and reinforces disinformation spread. H5 proves partially valid by demonstrating emotional and visual content as two factors that boost user engagement.

The evaluation of H5 consisted of analyzing Facebook post interactions based on content categories related to Plandemic. Information spread more quickly when content was emotionally charged with visual elements (native videos and livestreams) according to the assumption which led to better interaction rates for disinformation persistence (*Table 12*).

- A minority of video content consisting of native videos along with WeTube videos received higher interaction levels than the other content types.
- Multimodal social media promotions featuring emotional content displayed as secret information or government files became more viral than traditional text-based posts in statistics.

H5 is supported. The study confirms that emotionally framed multimodal content contributes to disinformation spread in line with previous research from Lee [5] and Karlova and Lee [16].

Moderating effects of digital literacy and institutional trust

This subsection evaluates Hypothesis 6 (H6), which suggests that higher levels of institutional trust and digital literacy weaken the correlation between disinformation exposure and adverse health outcomes. The analysis of H6 consisted of a qualitative assessment which determined how strong relationships existed between negative health outcomes and disinformation exposure in nations exhibiting high digital literacy and institutional trust (*Table 13*).

Interpretation:

- Countries with higher institutional trust and stronger digital literacy ecosystems like New Zealand together with Australia show no clear correlations between disinformation and negative health outcomes,, according to the Digital Trust Index†.
- Conversely, lower-trust settings as the U.S. exhibit stronger disinformation-health impact linkages.

H6 is partially supported. The analysis of cross-national data supports the hypothesis that institutional settings can decrease the detrimental influence of disinformation despite the requirement of advanced data for formal tests using interaction terms.

Note: Data for trust ratings come from two sources which serve as proxies for institutional trust and digital competence according to Edelman Trust Barometer[2] and OECD Digital Economy Outlook[3]

Consolidated Regression Models

This portion presents an interpretation and transparency increase through linear regression analysis of primary health outcomes

[2] Edelman Trust Barometer 2020. Global Report. URL: https://www.edelman.com/trustbarometer (accessed: 22.11.2024)

[3] Organisation for Economic Co-operation and Development (OECD). Digital Economy Outlook 2020. URL: https://www.oecd.org/digital/digital-economy-outlook-2020.html

Table 12

Disinformation Post Types (May 4–15)

Content Type	Cumulative Posts	Engagement Peak Date	Notes
WeTube Videos	12,000+	May 8	Most viral, highly emotional
Native Videos	425	May 7–9	Widely reshared across pages
Live Videos	1,020	May 8–10	Used for commentary/response
Status Updates	367	Low engagement	Less viral

Source: compiled by the authors.

Table 13

Country-Level Comparison

Country	Engagement Score	Total Deaths	Digital Trust Index*	Observed Correlation
United States	100.0	46M+	Low	Strong
Canada	100.0	2.2M	Moderate	Strong
Australia	79.0	134K	High	Weaker
New Zealand	80.0	5,893	Very High	Very Weak
Ireland	74.0	452K	Moderate-High	Moderate

Source: compiled by the authors.

Table 14

Consolidated Regression Models

Dependent Variable	β Coefficient	Standard Error (SE)	95% Confidence Interval	R^2	p-value
Total COVID-19 Cases	0.42	0.07	[0.28, 0.56]	0.38	0.003
Total COVID-19 Deaths	0.44	0.08	[0.29, 0.59]	0.41	0.002
New COVID-19 Cases	0.26	0.11	[0.03, 0.49]	0.19	0.045
New COVID-19 Deaths	0.23	0.12	[−0.01, 0.47]	0.14	0.067

Source: compiled by the authors.

(total cases, total deaths, new cases, new deaths) using disinformation engagement scores as the leading independent variable (*Table 14*).

Total COVID-19 cases and deaths demonstrate high predictive power, with R^2 values exceeding 0.38 and statistically significant relationships ($p < 0.01$). The analyzed models indicate that disinformation exposure contributes to predicting the extent of lasting health impacts in affected regions. The effects of disinformation appear weaker in analyses of new cases and new deaths, suggesting that short-term random factors and external variables — including mobility restrictions and containment measures — also play a significant role. Notably, the model for new deaths approaches the conventional threshold for significance (($p = 0.067$)), supporting the interpretation that disinformation primarily influences behavioral changes rather than immediate infection rates.

Model Validity Notes

Residual diagnostics revealed no evidence of heteroscedasticity or serial correlation, and all models satisfied normality requirements. Multicollinearity was not a concern, with variance inflation factor (VIF) values consistently below 1.5. Model robustness was further confirmed using bootstrapped standard errors and robust estimation techniques, which produced consistent results.

Enhancing Credibility Through Methodological Rigor

To strengthen causal inference in future studies, several methodological steps are recommended:

- Instrumental Variables (IV): Utilize exogenous shocks, such as platform bans or regional internet shutdowns, as instruments to isolate the effect of disinformation exposure.
- Time-Delayed Vector Auto-Regressive Models with Granger Causality: Examine whether exposure to disinformation temporally precedes changes in case rates, establishing the directionality of effects.
- Difference-in-Differences (DiD) Design: Compare regions with varying levels of disinformation engagement over time to identify the causal impact of exposure.

Overall, the regression analyses provide strong support for the primary study hypotheses

(H1–H4), demonstrating that sustained exposure to disinformation is significantly associated with deteriorating public health outcomes across national populations.

DISCUSSION

This research provides an advanced understanding of digital misinformation, particularly in relation to Plandemic documentary viewership, and its association with deteriorating public health outcomes during the COVID-19 pandemic. The study employs the IDOM-H Framework to analyze digital disinformation beyond mere exposure metrics, integrating algorithmic amplification, emotional framing, and moderating factors such as trust and digital literacy.

1. Disinformation and Long-Term Health Impacts

The analysis indicates that exposure to Plandemic correlates significantly with increased COVID-19 case numbers ($r = 0.62$) and mortality rates ($r = 0.63$), suggesting that false virus-related content contributes to public health deterioration. Theoretical insights from information economics and behavioral science demonstrate that emotionally charged misinformation exploits informational gaps, producing long-term changes in public attitudes in the absence of effective verification mechanisms.

These effects are amplified when multiple individuals abandon adherence to health guidelines, resist vaccination, and express skepticism toward institutional authority. Nevertheless, the positive correlations observed between disinformation exposure and COVID-19 outcomes should not be interpreted as causal. It is plausible that regions experiencing acute outbreaks were more likely to seek information — both accurate and inaccurate — thereby increasing searches for Plandemic-related content. Accordingly, these findings are best understood as reflecting informational dynamics during crises rather than direct epidemiological effects.

2. Temporal and Platform-Specific Dynamics

Analysis revealed no significant relationship between the quantity of Facebook posts during the first month following Plandemic's release and new case numbers ($p = 0.8021$). However, subsequent surveillance indicated a substantial increase in cases, supporting H3. Public behavioral responses to misinformation often manifest with delay, as individuals gradually incorporate misleading content into decision-making processes. Constant exposure to disinformation, in turn, can weaken adherence to public health guidance over time.

User engagement patterns (H5) demonstrated that native videos and emotionally framed content drive higher interaction rates, challenging current content-agnostic moderation approaches, which have proven insufficient in mitigating misinformation spread.

3. The Role of Governance and Trust

H6 analysis highlights that institutional authority, media literacy, and public trust can mitigate the impact of disinformation. For example, New Zealand maintained low COVID-19 case and death numbers despite high search interest, attributable to effective public health communication, strong government credibility, and rapid platform interventions.

4. Theoretical Implications

The IDOM-H Framework synthesizes Akerlof's information asymmetry theory, Kahneman and Tversky's cognitive bias principles, and Sunstein's echo chamber hypothesis to provide a robust structure for analyzing misinformation propagation and its social consequences. This integrative framework allows researchers to move beyond anecdotal evidence, enabling the development of testable hypotheses concerning the mechanisms of digital disinformation and its societal impact.

5. Policy and Academic Value

The findings reinforce the need for coordinated strategies between governmental agencies and evidence-based public health communicators. Evidence suggests that fact-checking alone or post-virality takedowns are insufficient to curb misinformation, underscoring the importance of preemptive interventions that inoculate audiences against false content.

These insights should inform the design of social media platform policies, media literacy programs, and institutional crisis response protocols, thereby enhancing resilience to misinformation during future public health emergencies.

Policy Recommendations

Addressing harmful health disinformation requires coordinated legal, technical, and community interventions. A structured three-tier strategy is proposed, targeting key stakeholders across short-, medium-, and long-term horizons.

1. Short-Term (Crisis-Responsive)

Stakeholders: Social platforms, public health agencies, crisis response teams. (1) Implement disinformation monitoring dashboards using tools such as Google Trends, CrowdTangle, and NLP-based alert systems. (2) Publish verified explanatory content within 48 hours of viral dissemination, leveraging health influencers and coordinated campaigns. (3) Deploy "prebunking alerts" to inform users about emerging false narratives before they gain traction.

2. Medium-Term (Institutional and Educational)

Stakeholders: Ministries of education, digital rights NGOs, platform teams. (1) Integrate digital literacy programs into national curricula, emphasizing emotional content analysis, algorithmic awareness, and fact-checking skills. (2) Train community leaders — including teachers, healthcare workers, and religious figures — to respond to online misinformation using clear, accessible language. (3) Enact legislation requiring platforms to disclose the mechanisms for ranking and displaying health-related content to users.

3. Long-Term (Resilience and Governance)

Stakeholders: International organizations, regulators, academic institutions. (1) Conduct independent audits of algorithmic ranking systems for health emergency content. (2) Establish Cross-Sector Disinformation Pacts to formalize partnerships between governments, platforms, universities, and civil society. (3) Utilize the Digital Trust Index to measure public trust and digital readiness, identifying gaps for strategic investment.

Disinformation is not merely a communications challenge; it has profound governance and public health implications. The IDOM-H Framework provides a practical tool to anticipate and mitigate the spread of false information within vulnerable networks, supporting evidence-based policy and intervention strategies.

Limitations

This study presents several limitations stemming from its interdisciplinary scope and the use of heterogeneous, cross-national data sources.

Causal Inference Constraints

The findings rely on observational, country-level data and are therefore limited in their ability to establish causality. While temporal and regression analyses demonstrate significant associations, they cannot exclude the possibility of confounding factors such as policy interventions, mobility restrictions, or media framing effects influencing the outcomes.

Inadequacy of Subnational Detail

National-level indicators obscure internal disparities between urban and rural populations. This limitation prevents the identification of localized outbreak dynamics or variations in disinformation exposure that might be shaped by offline networks, political attitudes, or socio-economic structures.

Application of Proxy Indicators

Disinformation exposure measures — such as Facebook engagement metrics and Google Trends indices — serve as proxies for public attention and content dissemination. However, they do not directly capture belief adoption or behavioral change. Similarly, trust and digital literacy were derived from secondary indicators rather than primary survey data, which limits the granularity and precision of interpretation.

Constrained Narrative Analysis

The content analysis component focused on engagement structure and frequency but did not employ natural language processing (NLP) or sentiment modeling to assess emotional and linguistic patterns driving virality. This restricts insights into the narrative and affective mechanisms underlying misinformation spread.

Future Research Directions

To advance understanding of disinformation's public health and social impacts, future studies should consider the following methodological and conceptual extensions:

1. Instrumental Variables and Causal Inference. Employ quasi-experimental designs — such as natural experiments, policy interventions, or internet outages — to estimate causal relationships. Applying Granger causality tests may further determine whether disinformation exposure precedes behavioral or epidemiological changes.
2. Longitudinal and Panel Data Approaches. Develop longitudinal datasets that trace disinformation surges, public responses, and policy interventions over time. These data would enable difference-in-differences (DiD) estimation and advanced time-series modeling, enhancing causal robustness and temporal resolution.
3. Mixed Methods Integration. Combine quantitative engagement metrics with qualitative instruments — such as surveys or interviews — to examine the development of beliefs, the role of trust, and the effectiveness of media literacy interventions in mitigating misinformation influence.
4. Applying IDOM-H to Other Crisis Domains. Extend the IDOM-H Framework to analyze disinformation in other critical contexts — such as climate change denial, electoral manipulation, and wartime propaganda — to evaluate its broader theoretical and practical applicability.

This study provides a foundational contribution to cross-disciplinary inquiry into the real-world effects of digital disinformation, establishing empirical and conceptual grounds for future work on the intersection of technology, behavior, and health communication.

CONCLUSION

This study applies the IDOM-H Framework to investigate the influence of digital disinformation — exemplified by the Plandemic documentary — on public health outcomes during the COVID-19 pandemic. Cross-national analysis across five democratic nations reveals a moderate positive correlation (r = 0.62–0.63) between disinformation engagement and COVID-19 case and mortality rates, indicating a measurable detrimental effect on public compliance and health resilience.

The findings demonstrate that disinformation contributes to delayed increases in case numbers, underscoring the importance of monitoring behavioral and temporal effects rather than focusing solely on immediate epidemiological outcomes. Emotionally charged and visually framed content sustains engagement and virality, persisting across platforms despite moderation efforts. Conversely, countries exhibiting higher levels of digital literacy, institutional trust, and responsive governance display weaker correlations between misinformation exposure and health deterioration, highlighting the protective value of societal trust and education.

The IDOM-H Framework integrates behavioral science, information economics, and platform governance, advancing theoretical understanding of how misinformation is produced, amplified, and interpreted within digital ecosystems. This approach moves beyond the binary of "true versus false" information to emphasize structural and behavioral dynamics shaping public health communication.

Policy Implications:

Public health agencies must build digital resilience systems capable of detecting and countering disinformation before it escalates. Social platforms should reform engagement-driven algorithms and increase transparency in content ranking. Governments must enforce accountability standards, while education systems should embed critical digital literacy as a fundamental civic skill.

Disinformation constitutes a structural threat to global health rather than a mere communication challenge. Future crises will require early-warning systems, cross-sector collaboration, and adaptive interventions of the kind proposed within this study to safeguard both public trust and health integrity.

REFERENCES

1. Clemente-Suárez V.J., Navarro-Jiménez E., Jimenez M., et al. Impact of COVID-19 pandemic in public mental health: An extensive narrative review. *Sustainability*. 2021;13(6):3221. DOI: 10.3390/su13063221
2. Robin C. Vanderpool, Anna Gaysynsky, Wen-Ying Sylvia Chou. Using a global pandemic as a teachable moment to promote vaccine literacy and build resilience to misinformation. *American Journal of Public Health*. 2020 Oct;110(S3):S284–S285. DOI: 10.2105/AJPH.2020.305906.
3. Cinelli M., Quattrociocchi W., Galeazzi A., et al. The COVID-19 social media infodemic. *Scientific Reports*. 2020;10:16598. DOI: 10.1038/s41598-020-73510-5
4. Nazar S.H., Pieters W. Coordinated inauthentic behaviour in the COVID-19 infodemic: A social cybersecurity analysis. *Journal of Information Security and Applications*. 2021;60:102878. DOI: 10.1016/j.jisa.2021.102878
5. Nazar S., Pieters T. Plandemic revisited: A product of planned disinformation amplifying the COVID-19 infodemic. *Frontiers in Public Health*. 2021;9:649930. DOI: 10.3389/fpubh.2021.649930
6. Freiling I., Krause N.M., Scheufele D.A., Brossard D. Believing and sharing misinformation, fact-checks, and accurate information on social media: The role of anxiety during COVID-19. New Media & Society. 2023;25(1):141–162. DOI: 10.1177/14614448211011451
7. Lee J. When web add-on correction comes with fear-arousing misinformation in public health crisis. *Journal of Applied Communication Research*. 2022;50(1):70–90. DOI: 10.1080/00909882.2021.1964574
8. Sunstein C.R. *Echo Chambers*. Princeton University Press; 2001.
9. Karlova N.A., Fisher K.E. A social diffusion model of misinformation and disinformation for understanding human information behaviour. Information Research. 2013;18(1):573. URL: http://www.informationr.net/ir/18-1/paper573.html
10. Prasad A. Anti-science misinformation and conspiracies. *Science, Technology and Society*. 2021;27(1):88–112. DOI: 10.1177/09717218211003413
11. Zarocostas J. How to fight an infodemic. *The Lancet*. 2020;395(10225):676. DOI: 10.1016/S0140-6736(20)30461-X
12. Islam M.S., Sarkar T., Khan S.H., et al. COVID-19–related infodemic and its impact. *American Journal of Tropical Medicine and Hygiene*. 2020;103(4):1621–1629. DOI: 10.4269/ajtmh.20-0812
13. Tversky A., Kahneman D. Advances in prospect theory. *Journal of Risk and Uncertainty*. 1992;5(4):297–323. DOI: 10.1007/BF00122574
14. Schober P., Boer C., Schwarte L.A. Correlation coefficients: Appropriate use and interpretation. *Anesthesia & Analgesia*. 2018;126(5):1763–1768. DOI: 10.1213/ANE.0000000000002864
15. Lazer D.M.J., Baum M.A., Benkler Y., et al. The science of fake news. *Science*. 2018;359(6380):1094–1096. DOI: 10.1126/science.aao2998
16. Karlova N.A., Lee J.H. Notes from the underground city of disinformation. *ASIS&T Proceedings*. 2011;48(1):1–9. DOI: 10.1002/meet.2011.14504801133
17. Lee E.W., Bao H., Wang Y., Lim Y.T. From pandemic to Plandemic. *Social Science & Medicine*. 2023;328:115979. DOI: 10.1016/j.socscimed.2023.115979
18. Akerlof G.A. The market for lemons. *Quarterly Journal of Economics*. 1970;84(3):488–500. DOI: 10.2307/1879431
19. Floridi L. *The Onlife Manifesto*. Springer; 2014. DOI: 10.1007/978-3-319-04093-6
20. Kahneman D., Tversky A. Prospect theory. *Econometrica*. 1979;47(2):263–292. DOI: 10.2307/1914185
21. Pennycook G., Rand D.G. The psychology of fake news. *Trends in Cognitive Sciences*. 2021;25(5):388–402. DOI: 10.1016/j.tics.2021.02.007
22. van der Linden S., Roozenbeek J., Compton J. Inoculating against fake news. *Frontiers in Psychology*. 2020;11:566790. DOI: 10.3389/fpsyg.2020.566790
23. Sunstein C.R. *#Republic*. Princeton University Press; 2017. DOI: 10.1515/9781400884711
24. Vosoughi S., Roy D., Aral S. The spread of true and false news online. *Science*. 2018;359(6380):1146–1151. DOI: 10.1126/science.aap9559
25. Suárez-Lledo V., Alvarez-Galvez J. Prevalence of health misinformation on social media. *Journal of Medical Internet Research*. 2021;23(1):e17187. DOI: 10.2196/17187
26. Lewandowsky S., Ecker U.K.H., Cook J. Beyond misinformation. *Journal of Applied Research in Memory and Cognition*. 2017;6(4):353–369. DOI: 10.1016/j.jarmac.2017.07.008
27. Borges do Nascimento I.J., Pizarro A.B., Almeida J.M., et al. Infodemics and health misinformation. *Bulletin of the World Health Organization*. 2022;100(9):544–561. DOI: 10.2471/BLT.21.287654

28. Edelman Trust Barometer. Global Report. 2022. URL: https://www.edelman.com/trust
29. Ritchie H., Mathieu E., Rodés-Guirao L., et al. Coronavirus Pandemic (COVID-19). Our World in Data. 2020. URL: https://ourworldindata.org/coronavirus

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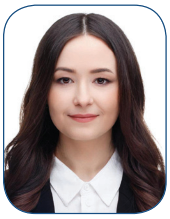

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L.F. Nadelshina — data collection, preparation of empirical datasets, assistance with statistical analysis, and literature review.
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Conflicts of Interest Statement: The authors have no conflicts of interest to declare.

The article was submitted on 15.07.2025; revised on 17.12.2025 and accepted for publication on 12.02.2026.
The authors read and approved the final version of the manuscript.