When Bad News Begets Bad News: Algorithmic Amplification and the Clustering of Negative News in India's Digital News Ecosystem

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Abstract

The digital news environment has transformed the way audiences encounter information. Instead of actively selecting individual news stories, users increasingly receive news through algorithmically curated feeds, recommendations, notifications, search results and social-media sharing. This transformation raises an important but insufficiently examined question: what happens to the information environment after a highly salient negative news event captures public attention? Do audiences simply encounter the original event repeatedly, or are they subsequently exposed to a wider cluster of similar negative events?

This paper examines the phenomenon conceptualised as negative news clustering: the temporal and thematic concentration of negative news stories following a high-salience negative event. It investigates the potential role of algorithmic amplification, user engagement, editorial imitation and platform recommendation in producing such clustering within India's digital news ecosystem. The study adopts a secondary-data and documentary research design, combining existing empirical research on news negativity and recommendation systems with Indian digital-news consumption data, platform-governance literature, regulatory documents, judicial principles and a contemporary Indian case illustration involving the viral Jamui incident and subsequent reporting of similar incidents in Bihar.

The evidence indicates that negative news possesses significant distributional advantages in digital environments. A large-scale 2024 study involving 95,282 news articles and 579 million Facebook and Twitter posts found that negative news articles were 1.91 times more likely to be shared on social media. Other experimental research has demonstrated that recommender systems can further amplify negative sentiment through repeated human-machine feedback loops. India's increasingly platform-dependent news environment provides a particularly important context: the 2026 Reuters

Institute Digital News Report reports that approximately 58% of its Indian respondents use YouTube for news, while social and video platforms have become central intermediaries between news producers and audiences.

The paper argues that negative-news clustering should not automatically be interpreted as proof of algorithmic manipulation. Similar clustering can arise from genuine increases in newsworthy events, editorial competition, audience demand, search behaviour, social sharing and recommendation algorithms simultaneously. The paper therefore proposes a Negative News Clustering Framework (NNCF) and a potential Negative News Clustering Index (NNCI) to distinguish event occurrence, media production, audience engagement and algorithmic distribution. The study concludes that algorithmic accountability in digital journalism must move beyond content removal and address the less visible question of what kinds of information are repeatedly made more visible.

Keywords: Algorithmic amplification, negative news, news clustering, algorithmic gatekeeping, news recommendation, digital journalism, platformisation, India, content moderation, media accountability

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1. Introduction

The contemporary news environment is no longer organised exclusively around the editorial decisions of newspapers, television channels or news websites. This development is part of a longer technological transition in which audiences have moved across increasingly interconnected media formats; Dwivedi and Kishore (2025a) identify technological change as a major force reshaping established media-consumption patterns. News now travels through a complex socio-technical environment in which journalists, news organisations, audiences, platforms, recommendation systems and engagement metrics interact continuously.

The transformation is particularly significant in India. Baghel and Dwivedi (2026), in their study of Generation Z news consumption in Indore, provide a relevant Indian foundation for examining the relationship between media convergence and subsequent news exposure. The 2026 Reuters Institute Digital News Report indicates that online and social-media consumption has become central to news access in India, with approximately 58% of surveyed respondents reporting YouTube as a source of news. The report also identifies the growing importance of video-led platforms, creators and regional-language digital news.

This means that the question of **what becomes news** is increasingly accompanied by another question:

What becomes repeatedly visible as news?

The distinction is important.

A traditional editorial system may decide that a crime, accident, political controversy or violent incident deserves front-page or prime-time treatment. In a platform-mediated environment, however, the visibility of that story can continue to evolve after publication. User clicks, watch time, shares, comments, searches and other engagement signals may affect subsequent distribution. Recommendation systems can then expose audiences to related stories.

This creates the possibility of a feedback loop:

Negative event → news coverage → audience engagement → algorithmic recommendation → similar news exposure → further engagement → increased visibility

The process may create what this paper terms **negative news clustering**.

Negative news clustering refers to a situation in which stories concerning similar negative themes, events or emotions become disproportionately concentrated in a user's or the wider digital news environment over a relatively short period.

For example, a major crime story may be followed by a sequence of reports about other crimes. A violent incident may be followed by stories of similar violence. A high-profile case involving women or children may be followed by increased visibility of other cases involving women or children.

The critical research problem is not simply whether these stories exist.

It is: **Why do they become visible together, and what role do algorithms play in that clustering?**

2. Background: From Editorial Gatekeeping to Algorithmic Distribution

The classic gatekeeping concept in media studies focused on the selection of information by editors and journalists. Digital platforms have not eliminated gatekeeping; they have redistributed it.

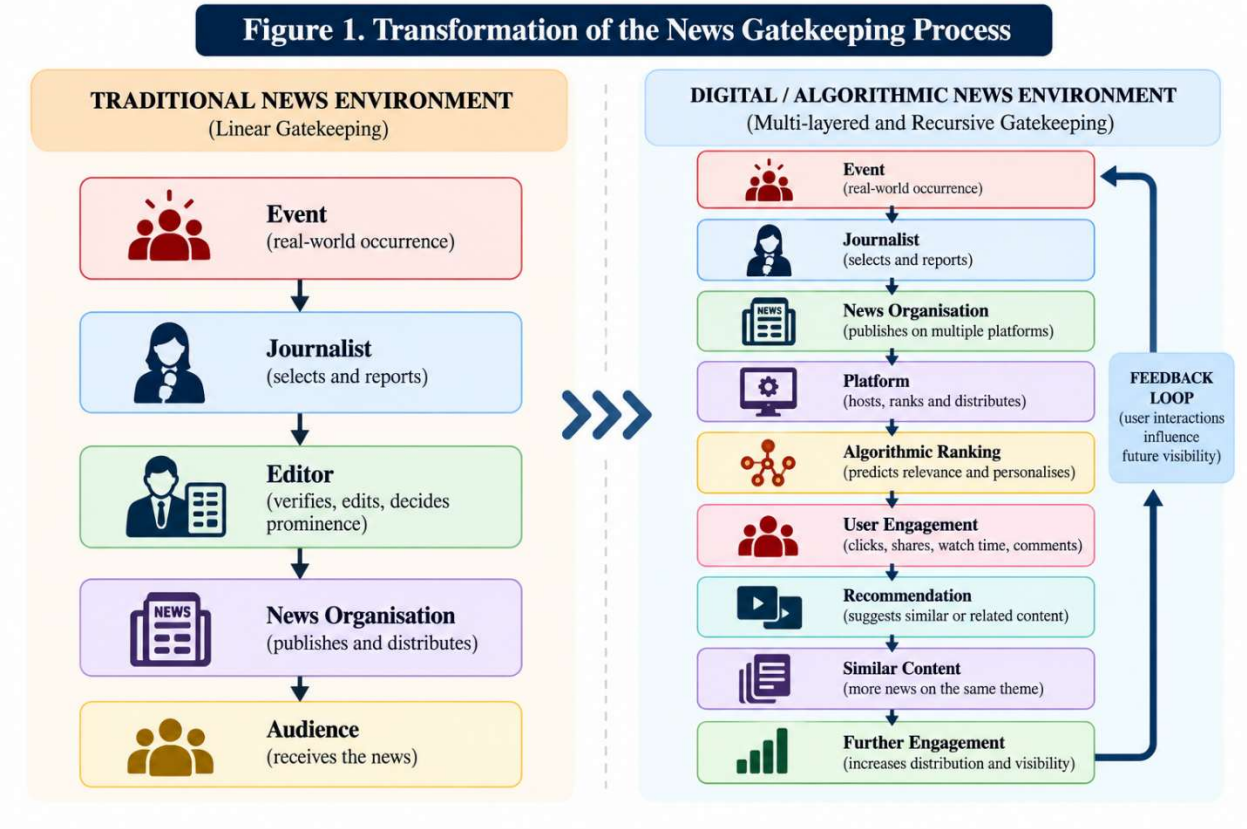
Contemporary news visibility can be understood as the outcome of several interacting gatekeepers:

Gatekeeper	Primary function	Example
Journalist	Selects and frames events	Decides what is worth reporting
News editor	Allocates prominence	Homepage, headline, push notification
Audience	Signals interest	Clicks, shares, comments, watch time
Platform	Distributes content	Feed/recommendation ranking
Algorithm	Predicts relevance	Recommends similar stories
Advertiser/market	Rewards attention	Engagement and monetisation
Regulator	Sets legal boundaries	Content obligations and takedown rules

News recommender systems have become a major research field because the abundance of digital content makes algorithmic selection increasingly necessary. This development is consistent with the broader movement from channel-specific consumption toward interconnected and multi-platform media use (Dwivedi & Kishore, 2025a; Dwivedi & Kishore, 2025b). Existing scholarship identifies collaborative filtering, content-based recommendation, neural recommendation and personalised recommendation as major approaches.

The transformation can therefore be conceptualised as:

Figure 1. Transformation of the News Gatekeeping Process



The algorithm does not necessarily create the original negative event. Instead, it may influence the **subsequent visibility and distribution** of content related to that event.

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3. Conceptualising Negative News Clustering

The present paper can therefore be situated within a coherent research trajectory: digital interface and usability (Dwivedi & Dubey, 2014) → changing media habits (Dwivedi & Nayak, 2021; Dwivedi, 2022) → technological transformation and multi-platform consumption (Dwivedi & Kishore, 2025a; 2025b) → media convergence and Generation Z news consumption (Baghel & Dwivedi, 2026) → algorithmic exposure and negative-news clustering (this study). The value of

this sequence is intellectual continuity: how technological change reshapes the relationship between media systems and audiences.

Research phase	Relevant publication	Contribution to current study
Digital interface	Dwivedi & Dubey (2014)	Digital interaction and information access
Audience habits	Dwivedi & Nayak (2021); Dwivedi (2022)	Changing media-consumption behaviour
Technology	Dwivedi & Kishore (2025a)	Technological transformation of media use
Multi-platform audiences	Dwivedi & Kishore (2025b)	Interconnected media consumption
Digital media ecosystem	Dwivedi & Kishore (2025c)	Fragmented/expanding digital environment
Media convergence	Baghel & Dwivedi (2026)	Indian Generation Z news consumption
Current study	Dwivedi (2026)	Algorithmic exposure and negative-news clustering

2.3 Research Trajectory and the Present Contribution

The author's later work on radio's continuing credibility in a fragmented digital audio landscape and on the transition from radio waves to digital screens further reflects the coexistence of legacy media and digital distribution (Dwivedi & Kishore, 2025c; Dwivedi, Choubey, & Das, 2026). These works are used here as contextual evidence about media transformation, not as evidence that algorithms amplify negative news.

Research on young audiences' media habits provides a longer-term context for the present inquiry. Dwivedi and Nayak (2021) examined podcast listenership among youngsters during the pandemic, while Dwivedi (2022) examined radio and podcast listenership in a changing media environment. Dwivedi (2022) also discussed changing preferences in the infotainment industry. These studies collectively point to a shift from scheduled, channel-specific consumption toward flexible and digitally mediated forms of media use.

2.2 Changing Audience Behaviour and the Question of Subsequent Exposure

This transition also reflects the movement from single-platform to multi-platform consumption. Dwivedi and Kishore (2025b), in their study of Generation Z and podcasting, examine how younger audiences increasingly navigate interconnected media formats. The relevance here is contextual rather than causal: multi-platform behaviour creates the environment within which recommendation systems can become intermediaries between published content and subsequent exposure.

The present study extends that line of inquiry. Earlier research asks how audiences consume news in a converged media environment; the present paper asks what may happen to subsequent news visibility when that environment is algorithmically organised. The proposed progression is: media convergence → fragmented digital consumption → algorithmic selection → personalised exposure → repeated exposure → news clustering.

The transformation of the news environment cannot be understood independently of media convergence. The movement from relatively distinct media channels toward interconnected digital platforms has altered how content is produced, distributed and encountered. Dwivedi and Kishore (2025a) examine technological catalysts and shifting media-consumption paradigms, while Baghel and Dwivedi (2026) specifically address media convergence and Generation Z news consumption in Indore. Together, these studies provide a useful starting point for understanding contemporary news consumption as an interconnected process rather than a series of isolated encounters.

2.1 From Media Convergence to Algorithmic Gatekeeping

This paper proposes **Negative News Clustering (NNC)** as an analytical concept.

Definition

Negative News Clustering is the temporal concentration of thematically or semantically related negative news stories following the emergence of a high-salience negative news event within a digital information environment.

The concept has four essential components:

1. **Trigger event**
2. **Temporal proximity**
3. **Thematic similarity**
4. **Negative valence**

A fifth dimension—**distributional amplification**—can then be added when platform-level evidence is available.

Table 1. Components of Negative News Clustering

Component	Operational meaning
Trigger event	A high-salience negative news event that generates substantial attention
Temporal proximity	Appearance of similar stories within a defined period after the trigger
Thematic similarity	Similarity in subject, event type, actors, location or narrative
Negative valence	Crime, violence, death, disaster, conflict, scandal, victimisation or other negative framing

Visibility	Placement, recommendation, sharing, reach or prominence
Amplification	Increase in distribution beyond baseline levels

The concept is intentionally broader than algorithmic amplification.

A cluster may emerge because **real-world events are clustered**, because journalists follow an emerging news trend, because audiences search for similar information, or because algorithms recommend similar stories.

Therefore:

Clustering is an observable phenomenon; algorithmic amplification is a possible mechanism.

This distinction is fundamental to the validity of the research.

4. Review of Existing Research

4.1 Negativity and News Sharing

One of the strongest empirical foundations for this research is the 2024 *Scientific Reports* study by Watson et al.

The researchers examined **95,282 news articles** from four US and UK news organisations and **579,182,075 Facebook and Twitter posts** linking to those articles. They found that users were **1.91 times more likely to share negative news articles**.

The study also found that accounting for reposts increased the effect of negativity on dissemination. The authors concluded that negative news has an important advantage in social-media distribution and warned that this could create incentives for journalists to produce more negative material.

Table 2. Major empirical evidence concerning negative-news amplification

Study	Dataset/Method	Major finding	Relevance
Watson et al. (2024)	95,282 articles; 579m+ social posts	Negative articles were 1.91× more likely to be shared	Strong evidence for negativity advantage
An et al.	News recommendation experiments	Sentiment can influence recommendation outcomes	Links sentiment and algorithms
Knudsen (2023)	Two online experiments	Recommendation systems can affect selective exposure	Supports recommendation-feedback perspective
Alam et al.	Recommender-system evaluation	Some recommenders showed a tendency toward negative sentiment	Supports algorithmic bias analysis

Treuillier et al. (2026)	News-recommender research	Accuracy-focused systems can constrain diversity	Supports accountability/diversity argument

The evidence does not prove that all platforms intentionally promote negative news. Instead, it demonstrates that **negative content has characteristics that can make it more distributable within engagement-driven environments**.

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5. The Algorithmic Amplification Mechanism

The most important question is how negative content moves from ordinary publication to amplified exposure.

Research on personalised news recommendation demonstrates that algorithmic systems learn from user interaction. Knudsen's research examines the conditions under which news recommender systems amplify or reduce selective exposure.

A particularly relevant study on sentiment manipulation reported that displayed news had substantially more negative sentiment than the original news set, while user click behaviour further strengthened the negative orientation. The researchers reported a **1.76-fold amplification of negative sentiment in top recommendation results** under their experimental conditions.

This suggests a potential feedback loop:

Figure 2. The Negative News Feedback Loop

NEGATIVE EVENT

↓

High newsworthiness

↓

High audience attention

↓

Clicks / shares / comments / watch time

↓

Engagement signal

↓

Recommendation system

↓

Similar or related stories recommended

↓

Repeated exposure

↓

Further engagement

↓

Higher distribution

↺

The important point is that **the algorithm need not have a programmed preference for negativity**.

A preference can emerge indirectly if:

negative content → more engagement → engagement optimisation → greater distribution.

Thus, algorithmic amplification may be an **emergent outcome of optimisation**, rather than an explicit editorial decision.

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6. India as a Significant Research Context

India offers a particularly important setting for studying this phenomenon because of the country's rapid transition toward platform-mediated news consumption.

The 2026 Reuters Institute Digital News Report describes a highly platformised Indian news environment in which video-based platforms and creators are increasingly important. Around **58% of surveyed Indian respondents reported using YouTube for news**. The report also highlights the growing significance of regional-language content, independent creators and social-video platforms.

The 2025 India report similarly identified YouTube, WhatsApp, Instagram and Facebook as important news-access channels among its predominantly English-speaking survey sample.

This creates an important structural condition:

The news audience is increasingly receiving information through systems that rank, recommend and personalise content.

Consequently, visibility becomes an important object of media research.

7. Research Gap

The existing literature provides substantial evidence concerning:

- negativity bias in news;
- social-media sharing of negative content;

- personalised news recommendation;
- selective exposure;
- algorithmic filtering;
- filter bubbles;
- platformisation of journalism.

However, a specific gap remains.

Existing studies commonly ask:

Does negative news receive more engagement?

or:

Do algorithms recommend similar content?

This paper asks a different question:

Does the emergence of a high-salience negative news event correspond with a subsequent temporal and thematic concentration of other negative news stories, and what mechanisms may explain that clustering?

The Indian context adds a further gap because research on algorithmic news exposure has not yet adequately connected:

event salience + news production + user engagement + recommendation + subsequent news clustering + platform accountability.

8. Objectives of the Study

The study has six objectives:

1. To conceptualise **negative news clustering** within India's digital news ecosystem.
2. To examine the relationship between negative news and digital dissemination.
3. To analyse the potential role of recommendation and engagement systems in amplifying similar negative stories.
4. To examine an Indian contemporary case cluster as an illustrative example of temporal and thematic news concentration.
5. To distinguish algorithmic amplification from editorial, audience and real-world event effects.
6. To propose an analytical framework and potential measurement index for future empirical research.

9. Research Questions

RQ1

Does a high-salience negative news event tend to be followed by an increase in thematically similar negative news coverage?

RQ2

What mechanisms may contribute to negative news clustering in India's digital news environment?

RQ3

What role can algorithmic recommendation and engagement optimisation play in amplifying such clustering?

RQ4

How can researchers distinguish algorithmic amplification from editorial imitation and genuine increases in negative events?

RQ5

What implications does algorithmically amplified negative-news visibility create for media diversity, audience autonomy and platform accountability?

RQ6

What legal and ethical accountability mechanisms are appropriate for algorithmically mediated news visibility?

10. Methodology

10.1 Research Design

The paper adopts a **secondary-data, documentary and case-study research design**.

It combines:

- published empirical research;
- publicly available digital-news datasets;
- platform and recommender-system literature;
- Indian regulatory documents;
- judicial decisions;
- contemporary news coverage;
- computational methods proposed for future empirical testing.

No primary survey is claimed in this paper.

This is important because it prevents the study from making unsupported claims about individual users' personalised feeds.

10.2 Proposed Data Sources

Table 3. Available secondary datasets and research resources

Source	Potential data	Application
GDELT 2.0	Global news/event data; themes, entities, emotions and events	News-volume and temporal analysis
GDELT Global Similarity Graph	Article-to-article similarity	Detecting related coverage
GDELT GKG	Entities, themes, locations and emotions	Semantic clustering
MediaCloud	News-story and source-level analysis	Indian media ecosystem mapping
Reuters Institute DNR	Audience news-use data	Indian news-consumption context
Platform transparency reports	Moderation/enforcement information	Platform governance
News websites	Headlines, publication time, topic	Event-cluster construction
Social platforms	Public engagement indicators where accessible	Distribution analysis

GDELT is especially useful because its GKG and event databases update at high frequency and process news across many languages. GDELT 2.0's GKG updates every 15 minutes, while its systems process large-scale global news data and provide thematic, entity and emotional metadata.

Its Global Similarity Graph is particularly relevant to this research because it calculates similarity between online news articles, creating an opportunity to identify clusters of semantically related coverage.

11. Proposed Operationalisation

A future empirical implementation can define a **trigger event window**.

For example:

T−72 **hours**
Baseline news environment

T0
Trigger event

T+24 **hours**
First post-event window

T+48 **hours**
Second window

T+72 **hours**
Third window

The researcher can then compare the frequency and similarity of negative stories.

Table 4. Proposed event-window model

Period	Purpose
T−72 to T−24	Baseline
T−24 to T0	Pre-event trend
T0	Trigger event
T0–T+24	Immediate response
T+24–T+48	Early clustering
T+48–T+72	Extended clustering
T+72 onward	Persistence/decay

12. Case Illustration: The Jamui–Bihar News Cluster

A contemporary Indian case illustrates why the proposed research question deserves empirical examination.

In September 2026, a video concerning the alleged harassment and assault of two minors in Jamui, Bihar, circulated widely online. Reporting indicates that the video generated substantial public and political attention, followed by police action, arrests and demands for investigation.

Importantly for this research, subsequent reporting began linking the Jamui case with other incidents.

For example, an *Indian Express* report published on 24 September 2026 was explicitly framed as **"Days after Jamui, another sexual harassment case from Bihar"**, describing another alleged incident in Samastipur.

Further reporting subsequently connected cases in Bihar's Gaya area with the earlier Jamui and Samastipur incidents. Other reporting referred to incidents in Jamui, Samastipur and Banka as a series that had generated public concern.

Table 5. Illustrative temporal news cluster

Stage	Event/news development	Media significance
1	Jamui incident/video becomes viral	High-salience negative trigger
2	Arrests/SIT/political reaction	Continued attention to trigger event
3	Samastipur incident reported	Similar thematic event appears in news cycle
4	Gaya-area incident reported	Further similar negative story
5	Banka and other Bihar cases enter discourse	Wider regional clustering

This sequence is analytically valuable—but it must be interpreted carefully.

What it demonstrates

It demonstrates **observable news clustering and editorial linkage**.

What it does NOT demonstrate

It does not, by itself, prove that:

"An algorithm caused the subsequent stories to appear."

There are several competing explanations:

1. Similar incidents may genuinely have occurred close together.
2. Journalists may have increased monitoring of similar incidents.
3. Editors may have recognised heightened audience interest.
4. Audiences may have searched for similar stories.
5. Social sharing may have increased their visibility.
6. Recommendation systems may have exposed users to related stories.
7. All of these mechanisms may have operated simultaneously.

This distinction is one of the central methodological contributions of the present study.

13. Case Study Interpretation

The Jamui sequence can therefore be represented as:

Figure 3. Possible News-Cluster Formation

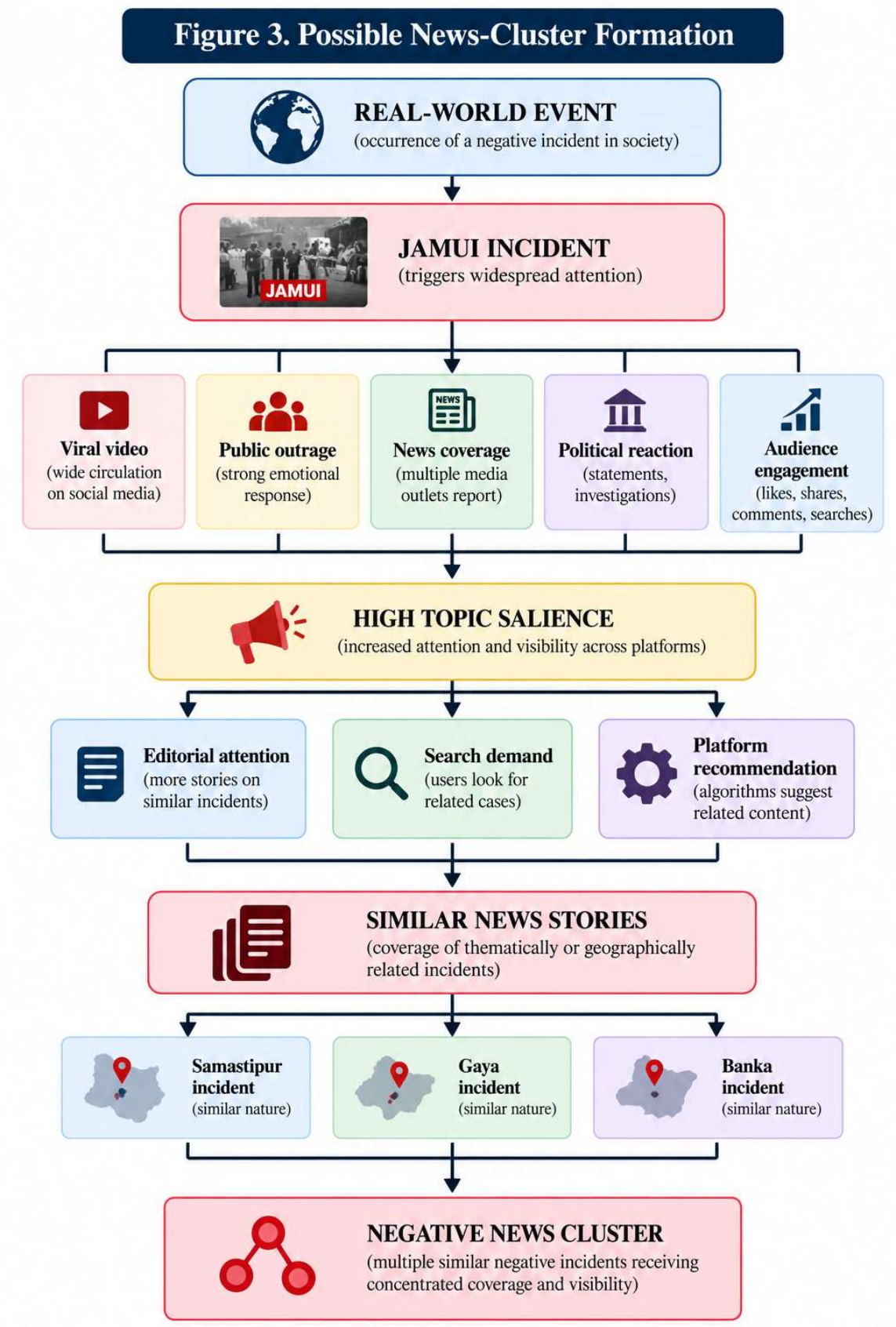
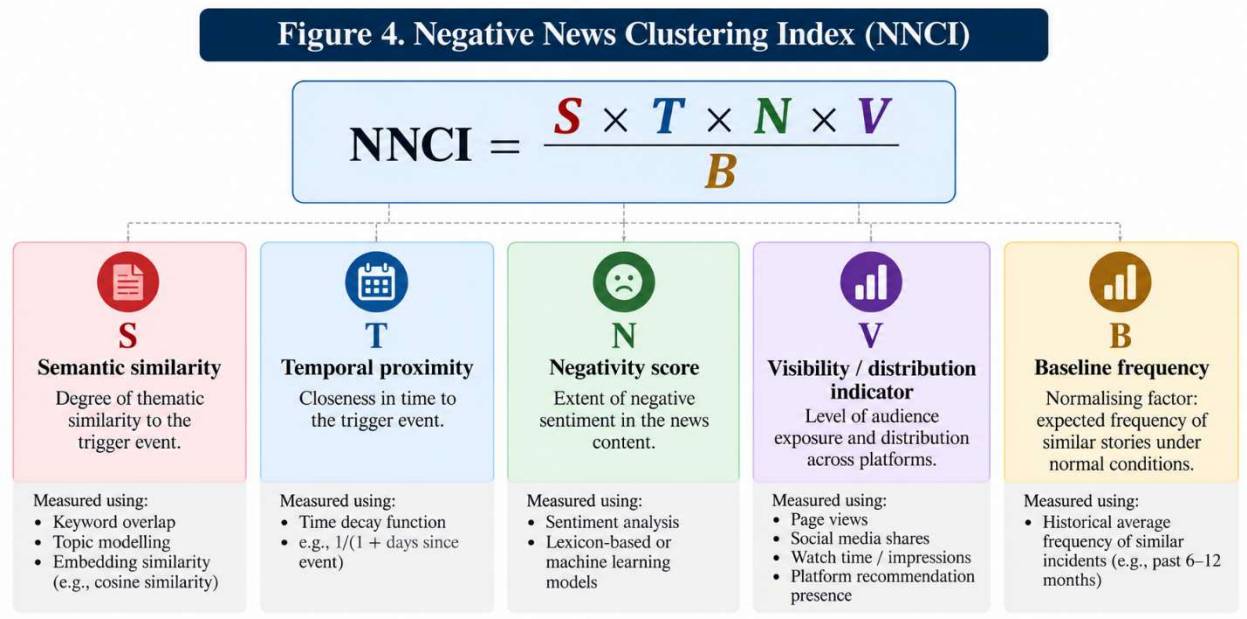


Figure 3. Possible News-Cluster Formation
REAL-WORLD EVENT
(occurrence of a negative incident in society)
JAMUI
JAMUI INCIDENT
(triggers widespread attention)
Viral video
(wide circulation on social media)
Public outrage
(strong emotional response)
NEWS
News coverage
(multiple media outlets report)
Political reaction
(statements, investigations)
Audience engagement
(likes, shares, comments, searches)
HIGH TOPIC SALIENCE
(increased attention and visibility across platforms)
Editorial attention
(more stories on similar incidents)
Search demand
(users look for related cases)
Platform recommendation
(algorithms suggest related content)
SIMILAR NEWS STORIES
(coverage of thematically or geographically related incidents)
Samastipur incident
(similar nature)
Gaya incident
(similar nature)
Banka incident
(similar nature)
NEGATIVE NEWS CLUSTER
(multiple similar negative incidents receiving concentrated coverage and visibility)

The framework demonstrates why a simple observation such as “bad news follows bad news” cannot be automatically attributed to artificial intelligence.

14. Negative News Clustering Index

To advance beyond descriptive observation, this paper proposes the **Negative News Clustering Index (NNCI)** as a potential measurement framework.



The formula is conceptual and requires empirical validation.

A more rigorous version could assign standardised values to each component.

Table 6. Proposed NNCI dimensions

Variable	Possible measurement
Semantic similarity	Sentence embeddings / cosine similarity
Temporal proximity	Hours from trigger event
Negative sentiment	Sentiment model/manual coding
News volume	Number of related articles
Visibility	Homepage placement/recommendation/share indicators
Engagement	Shares/comments/views where available
Source diversity	Number of independent outlets
Geographic spread	Number of locations
Event similarity	Common event type/actors/themes

The index would allow researchers to compare:

Normal news conditions vs. post-trigger news conditions.

15. Distinguishing Algorithmic Amplification from Media Amplification

One of the most important contributions of this paper is the proposed distinction between **four amplification mechanisms**.

Table 7. Four mechanisms of negative-news amplification

Mechanism	Explanation	Evidence required
Event amplification	More real-world events actually occur	Police/government/event data
Editorial amplification	Newsrooms publish more similar stories	Article volume and editorial analysis
Social amplification	Users share similar stories more frequently	Engagement/share data
Algorithmic amplification	Recommendation/ranking systems increase exposure	Feed/recommendation or platform-level evidence

A fifth mechanism may also be relevant:

Search amplification

A major event causes people to search for related terms, causing search/news systems to surface more related material.

Therefore:

Observed clustering ≠ algorithmic causation.

This is perhaps the most important methodological caution for researchers studying platform algorithms.

16. Theoretical Framework

The paper integrates five established theoretical perspectives.

16.1 Gatekeeping Theory

News organisations traditionally act as gatekeepers by selecting which events become news.

16.2 Agenda-Setting Theory

High-volume coverage can influence which issues audiences perceive as important.

16.3 Negativity Bias

Negative information often attracts stronger attention and engagement.

16.4 Selective Exposure

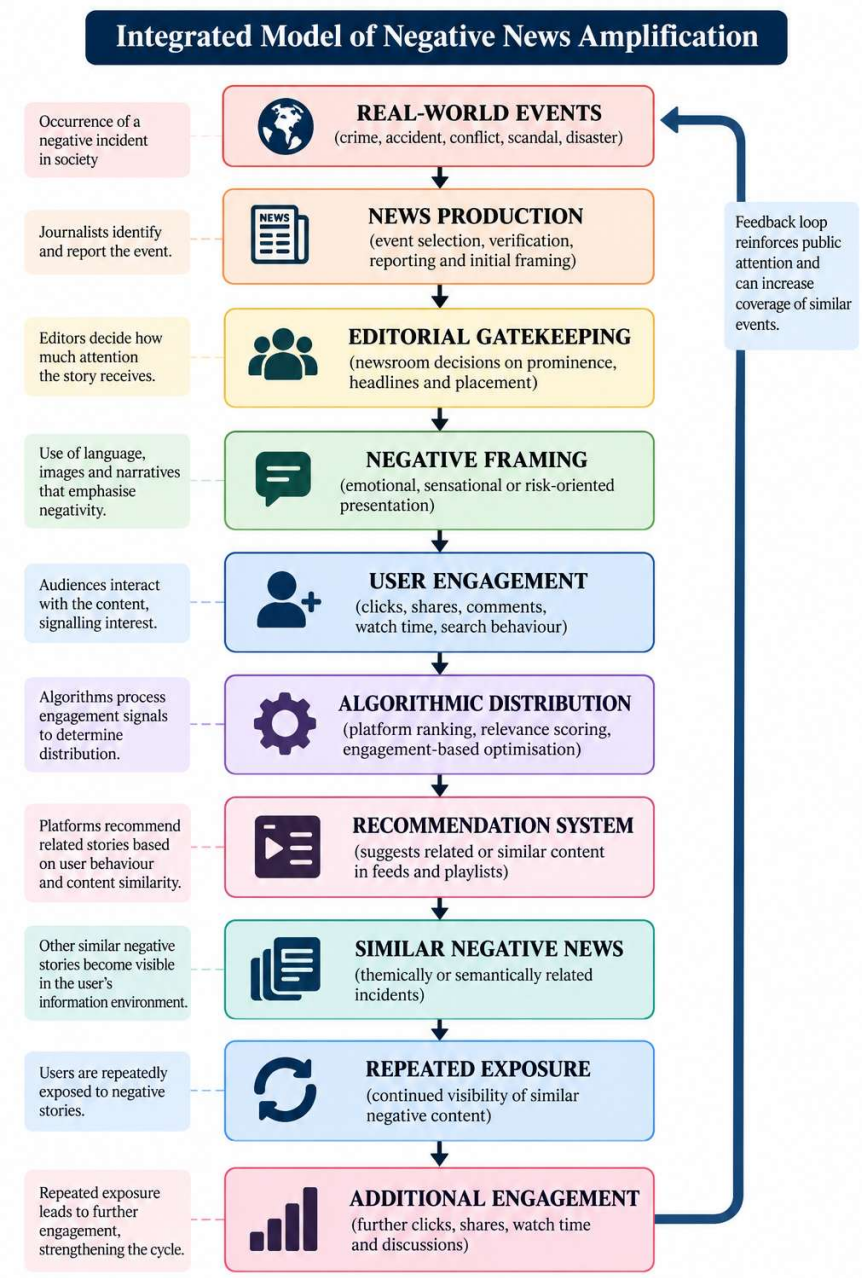
Users may choose information that confirms their existing interests or emotional preferences.

16.5 Algorithmic Gatekeeping

Platforms increasingly mediate the visibility of content through computational ranking and recommendation.

These can be combined into a new model:

Figure 4. Integrated Theoretical Model



The model treats algorithmic amplification as **one part of a larger socio-technical system**, rather than as an autonomous cause.

17. Platformisation and the Changing Meaning of News Visibility

The 2026 Digital News Report describes a wider shift toward social and video platforms as major routes to news consumption globally, with platforms becoming increasingly important intermediaries between audiences and publishers.

This transformation creates an important distinction between:

Availability

Whether a news story exists online.

and

Visibility

Whether an audience is likely to encounter it.

A story may remain available but become practically invisible because:

- it is not recommended;
- it is ranked below competing stories;
- it receives less distribution;
- it is not included in personalised feeds;
- it loses search prominence;
- similar content dominates the user's information environment.

This is why the paper argues that contemporary media accountability should not focus exclusively on **removal**.

It must also consider:

amplification, ranking, recommendation and visibility.

18. Legal and Regulatory Dimensions in India

The algorithmic distribution of news intersects with Indian intermediary regulation and constitutional principles concerning speech and press freedom.

The Information Technology (Intermediary Guidelines and Digital Media Ethics Code) Rules, 2021 impose due-diligence obligations on intermediaries. The rules also provide mechanisms

relating to removal/disablement, grievance redressal and, for significant social-media intermediaries, technology-based measures.

The regulatory framework is primarily concerned with unlawful or harmful content and intermediary due diligence. It does not, however, mean that every algorithmic recommendation is legally equivalent to publication by the platform.

This distinction matters.

Table 8. Legal questions created by algorithmic amplification

Issue	Legal question
Recommendation	Should platforms explain why particular content is recommended?
Downranking	Does reduced visibility require procedural transparency?
Content removal	What notice and appeal rights apply?
Viral harmful content	How quickly should platforms respond?
Child-related content	What additional protections apply?
Algorithmic bias	What accountability should apply to systematic amplification?
News diversity	Should recommendation systems preserve informational diversity?
Government requests	What procedural safeguards exist for state-directed restrictions?

The Indian framework has also evolved toward stronger grievance and safety mechanisms. MeitY materials describe expedited procedures for specified categories of harmful content, including content involving nudity, sexual material and impersonation.

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19. Freedom of Expression and Algorithmic Visibility

Indian constitutional jurisprudence provides an important foundation for thinking about digital visibility.

In *Anuradha Bhasin v. Union of India*, the Supreme Court addressed restrictions on internet access and emphasised that restrictions affecting Article 19 rights must satisfy legal and reasonableness requirements.

The broader constitutional principle is significant for algorithmic environments because information access increasingly depends upon digital infrastructure and platforms.

The question for future legal scholarship is therefore not necessarily:

“Is an algorithm censoring speech?”

but potentially:

"What level of procedural and substantive accountability should apply when privately operated ranking systems materially affect the visibility of lawful expression?"

This is an emerging legal and policy question rather than a settled proposition of Indian law.

20. Content Involving Children: The Jamui Case and Platform Responsibility

The Jamui example also demonstrates the difficult intersection between virality, public interest, victim protection and platform responsibility.

The Protection of Children from Sexual Offences Act, 2012 contains specific provisions concerning media reporting and procedures involving children. Section 23 is expressly identified as dealing with the procedure for media.

The IT Rules also provide specific obligations concerning certain categories of sexually explicit or privacy-invasive content.

Therefore, a viral video involving minors creates a dual problem:

Public-interest value

The video may expose an alleged offence and mobilise public attention.

Victim-protection risk

Repeated republication may:

- expose victims;
- increase trauma;
- facilitate identification;
- create permanent digital traces;
- encourage voyeuristic consumption;
- reproduce harmful material;
- increase secondary victimisation.

This illustrates why **algorithmic amplification is not merely a technological problem**. It is simultaneously a media ethics, legal, child-protection and platform-governance problem.

21. Intellectual Property and the Viral-News Problem

The IPR dimension is also important.

A video becoming viral does not automatically mean that everyone acquires the right to reproduce it commercially.

Potential rights and interests can include:

- copyright in the original recording;

- ownership/control of the recording;
- platform licence terms;
- journalistic fair dealing/public-interest considerations;
- privacy and personality interests;
- statutory protections concerning children;
- evidentiary preservation requirements.

The situation becomes particularly complicated when a platform algorithm repeatedly recommends copies of the same video.

Thus:

Virality and copyright are separate questions.

High visibility does not extinguish intellectual-property rights.

At the same time, enforcement of copyright should not be considered independently from victim-protection and public-interest reporting.

For a future paper, this creates another interesting research direction:

How should platforms reconcile copyright enforcement, public-interest journalism and victim-protection obligations when algorithmically amplified content concerns alleged criminal activity?

22. Findings

Based on the secondary evidence reviewed, the study identifies seven major findings.

Finding 1: Negative news possesses a measurable distributional advantage

Large-scale empirical evidence demonstrates that negative news is more likely to be shared socially. The 2024 study found a 1.91-fold increase in sharing likelihood for negative articles.

Finding 2: Recommendation systems can reinforce sentiment patterns

Experimental evidence indicates that recommendation systems may reproduce and intensify sentiment biases already present in user interaction data.

Finding 3: Human and algorithmic amplification are interdependent

Algorithms learn from user behaviour, while user behaviour is itself influenced by the information presented to users.

Finding 4: India is highly exposed to platform-mediated news

YouTube and other social/video platforms are increasingly important news sources in India.

Finding 5: Negative-news clustering is observable, but causality is difficult to establish

The Jamui–Samastipur–Gaya/Banka sequence provides an illustrative example of thematic and temporal clustering in contemporary Indian news coverage.

Finding 6: Algorithmic amplification should not be confused with editorial amplification

Newsrooms may increase coverage because an issue becomes salient independently of platform recommendation.

Finding 7: Accountability must include visibility

Existing content-governance debates frequently focus on removal. The evidence suggests that **ranking, recommendation, downranking and amplification** deserve equal analytical attention.

23. Discussion

The central argument of this paper is that digital journalism has created a new form of gatekeeping that operates through **visibility rather than only selection**.

Traditional journalism asks:

What should we publish?

Digital platforms add:

What should this user see next?

The second question can have profound consequences.

Suppose a user encounters one negative event. If that interaction becomes an engagement signal, the platform may recommend similar stories. The user then interacts with those stories, generating more signals.

The result may be:

[Negative\ Event \rightarrow Engagement \rightarrow Recommendation \rightarrow Similar\ News \rightarrow Engagement]

This can produce a **negativity feedback loop**.

Importantly, the loop does not require malicious intent.

A system designed to maximise relevance or engagement can unintentionally create a more negative information environment.

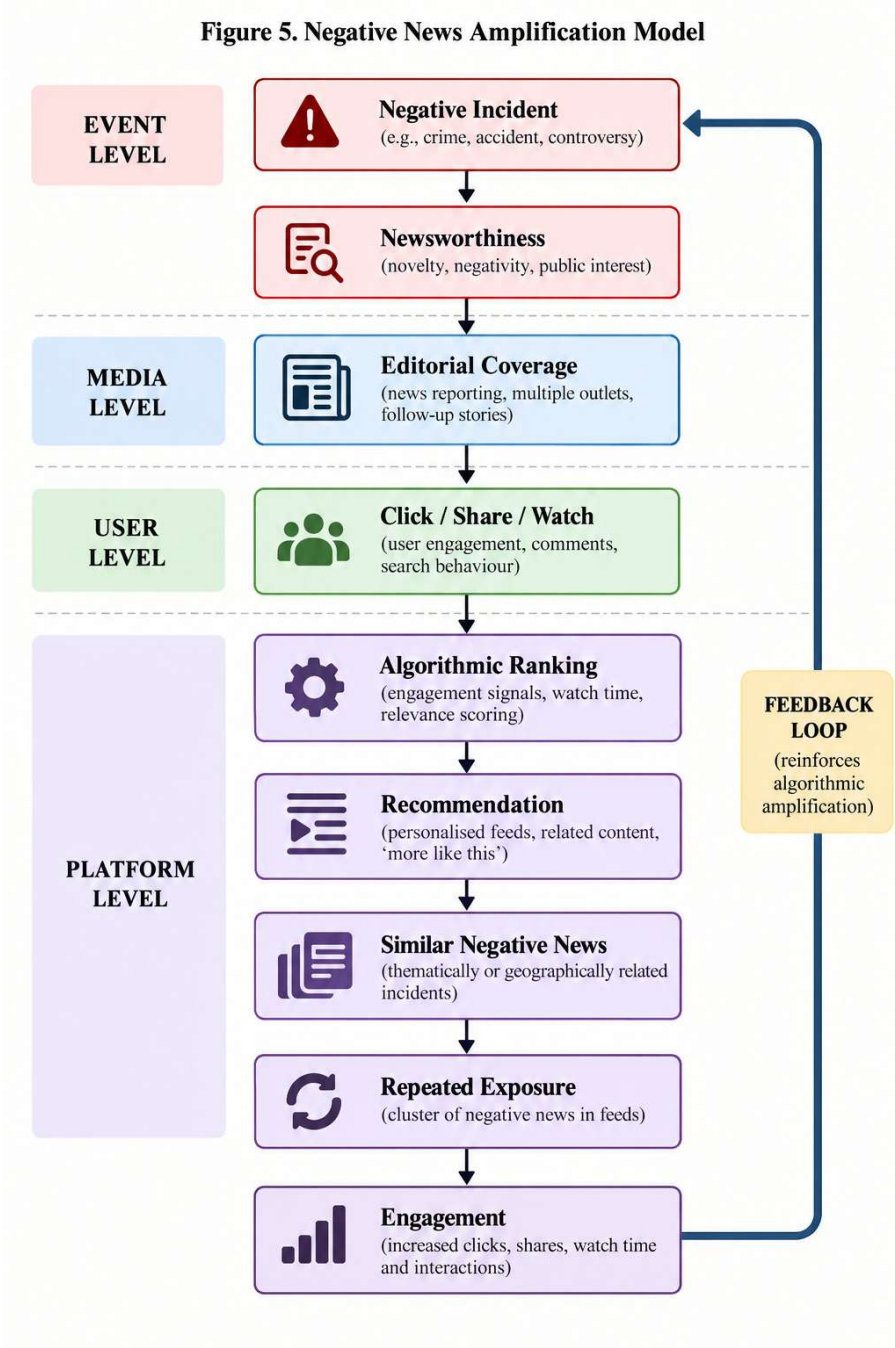
This is consistent with broader research showing that news recommender systems can create risks for diversity and selective exposure.

24. Proposed Negative News Amplification Model

The paper proposes the following model:

Figure 5. Negative News Amplification Model

Figure 5. Negative News Amplification Model



The model therefore identifies **three distinct forms of amplification**:

Production amplification

More stories are produced.

Distribution amplification

Existing stories are distributed more widely.

Recommendation amplification

Users are presented with increasingly similar stories.

Future empirical studies should measure all three separately.

25. Implications for Journalism

The findings have several implications for journalists and news organisations.

25.1 Engagement should not become the sole editorial metric

If negative news consistently generates greater engagement, an engagement-only newsroom may unintentionally increase negativity.

25.2 Editors should monitor repetition

A major incident can create pressure to publish every similar incident.

25.3 Context should accompany clustering

If several similar incidents are reported, journalists should explain whether the apparent increase reflects:

- a genuine increase in incidence;
- improved reporting;
- increased visibility;
- or heightened audience attention.

25.4 Newsrooms should distinguish virality from public importance

A story becoming viral does not necessarily make it more socially important than other stories.

26. Implications for Platform Governance

Platforms should move toward greater transparency concerning recommendation systems.

A meaningful accountability framework should include:

Principle	Suggested requirement
Transparency	Explain broad categories of recommendation signals
Contestability	Allow users to challenge certain recommendation decisions
Diversity	Measure whether recommendations become excessively homogeneous
Safety	Detect harmful amplification loops
Auditability	Enable independent research under privacy safeguards
Victim protection	Reduce repeated circulation of sensitive material
Child protection	Apply stronger safeguards to content involving minors

Research access	Provide qualified researchers with meaningful data access
Accountability	Publish meaningful information about ranking and recommendation systems

This does not imply that platforms should reveal proprietary algorithms or source code.

Rather:

Algorithmic accountability should concern observable effects and governance processes, not necessarily disclosure of proprietary code.

27. Proposed Algorithmic Accountability Matrix for Negative News

Table 9. Negative News Algorithmic Accountability Matrix

Dimension	Key question	Possible indicator
Exposure	Is similar negative content repeatedly shown?	Recommendation frequency
Diversity	Are alternative topics presented?	Topic-diversity score
Transparency	Does platform explain recommendation logic?	Disclosure score
Contestability	Can users influence recommendations?	User-control mechanisms
Harm	Does repeated exposure create foreseeable risk?	Safety assessment
Child protection	Are minors adequately protected?	Detection/removal measures
Auditability	Can researchers examine effects?	Research access
Correctability	Can harmful recommendations be reduced?	Feedback mechanism
Accountability	Is platform performance independently evaluated?	Audit/reporting

28. Limitations

The paper has five major limitations.

First

The available empirical evidence on negativity and sharing is not India-specific. The major 2024 dataset analysed US and UK news organisations.

Second

Platform recommendation systems are largely proprietary.

Third

Observed clustering does not establish algorithmic causality.

Fourth

Newsroom behaviour and user behaviour can produce patterns that resemble algorithmic amplification.

Fifth

Publicly observable recommendation outputs are not equivalent to the underlying ranking model.

Therefore, future research should combine **large-scale news data with controlled platform-audit experiments**.

29. Future Research Design

A full empirical study can be conducted in five stages.

Stage 1: Identify trigger events

Select 20–30 high-salience negative events in India.

Stage 2: Construct event windows

Collect news:

72 hours before → event → 72/168 hours after

Stage 3: Detect similarity

Use NLP/semantic embeddings to identify similar news stories.

Stage 4: Measure sentiment

Classify stories as:

- positive;
- neutral;
- negative.

Stage 5: Compare amplification

Compare:

[Post-event\ clustering]

against

[Pre-event\ baseline]

The resulting dataset could contain:

Variable	Example
Event ID	E001
Trigger date	DD/MM/YYYY
News category	Crime
Headline	Text
Publication time	Timestamp

Sentiment	−1 to +1
Similarity	0–1
Source	News organisation
Location	District/state
Engagement	Shares/views
Platform	YouTube/X/Instagram/etc.
Recommendation evidence	Yes/No
Time from trigger	Hours

This would allow statistical modelling of whether negative-news clustering increases after high-salience events.

30. Proposed Hypotheses for the Future Empirical Phase

H1

High-salience negative news events are followed by a statistically significant increase in thematically similar negative news coverage.

H2

The volume of similar negative news decreases as temporal distance from the trigger event increases.

H3

Negative stories receiving higher engagement are more likely to be followed by increased distribution of thematically similar content.

H4

News clusters with higher engagement demonstrate greater persistence than low-engagement clusters.

H5

Algorithmically mediated environments exhibit greater thematic concentration of negative news than non-personalised news environments.

H6

Higher negative-news clustering is associated with lower topic diversity in subsequent news exposure.

H5 and H6 would require direct platform-level or experimental evidence and should **not** be treated as established findings from the present documentary study.

31. Conclusion

The digital transformation of journalism has changed the meaning of news exposure. This transformation can be situated within a longer trajectory documented in the author's previous work, from digital usability (Dwivedi & Dubey, 2014), through changing radio and podcast habits (Dwivedi & Nayak, 2021; Dwivedi, 2022), to multi-platform and converged media consumption (Dwivedi & Kishore, 2025b; Baghel & Dwivedi, 2026).

In the traditional media environment, a negative event could become a major story because journalists and editors considered it important. In the platformised environment, its trajectory can continue through social sharing, audience engagement, search behaviour, recommendation systems and algorithmic ranking.

The result may be a phenomenon in which:

one negative event creates the conditions for greater visibility of other negative events.

This paper conceptualises that phenomenon as negative news clustering.

Existing empirical evidence provides strong support for the proposition that negative news has a distributional advantage. Large-scale research has demonstrated greater social sharing of negative news, while recommender-system research indicates that user behaviour and algorithmic recommendation can reinforce sentiment patterns.

India provides a particularly significant environment for examining this process because social and video platforms have become important routes through which citizens encounter news.

The Jamui-related news sequence demonstrates how a high-salience negative event can be followed by a series of thematically related reports. Yet the sequence also demonstrates why researchers must resist technological determinism. Similar news can cluster because of real-world events, editorial decisions, audience interest, search behaviour and algorithms simultaneously.

The central contribution of this paper is therefore a conceptual shift:

The problem is not only what platforms remove. It is also what platforms repeatedly make visible.

Algorithmic accountability in digital journalism should consequently expand beyond questions of content deletion and unlawful material. It should also address ranking, recommendation, amplification, repetition, diversity and visibility.

The proposed Negative News Clustering Index (NNCI) provides one possible direction for future empirical research. By combining temporal proximity, semantic similarity, sentiment, volume and visibility, researchers can move from anecdotal observations of “bad news following bad news” toward measurable analysis.

Ultimately, the question is not whether algorithms are solely responsible for negativity.

The more important question is:

When human attention, newsroom incentives and algorithmic recommendation continuously reinforce one another, does the digital news ecosystem gradually become better at showing us what is most important—or merely what keeps us looking?

That question deserves systematic investigation in India's rapidly platformised news environment.

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Research Integrity Note

Self-citation integrity: The author's previous publications are cited only where their stated topics provide contextual or conceptual support. They are not presented as empirical evidence for algorithmic amplification, negative-news clustering or platform causation. The central empirical claims remain bounded by the external evidence and by the proposed, not yet executed, empirical protocol.

This manuscript is deliberately written as a **secondary-data analytical/conceptual paper with documented evidence**, rather than fabricating primary survey results or platform-experiment findings. The Jamui sequence is presented as an **illustrative contemporary case**, not as proof that an algorithm caused subsequent incidents to appear.

For journal submission, the next empirical stage should ideally operationalise the proposed **Negative News Clustering Index (NNCI)** using GDELT/news datasets and a defined sample of Indian events. That would convert the current manuscript from a strong conceptual-secondary-data paper into a substantially stronger **empirical research article**.