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Ignorance as a Firewall: Formalizing Functional Ignorance for Systemic Stability in Social Networks

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ABSTRACT

Social systems frequently encounter truthful yet destabilizing information that can trigger panic, market crashes, or rapid opinion polarization. Existing interventions such as link deletion or bot mitigation are blunt and only partially effective. This paper fills the gap by constructing an analytical multilayer network model of belief exchange and introducing a *functional ignorance* heuristic that probabilistically suppresses the transmission of high-impact truths. Deriving a reproduction-number-based threshold, we show that a suppression rate exceeding $q^* = 2/3$ (i.e., discarding more than two-thirds of destabilizing messages) drives the effective reproduction number below unity, guaranteeing subcritical cascades. An evolutionary-stability analysis yields the condition $c < pL$ for the heuristic to resist invasion by full-transparency strategies. A worked example demonstrates that, under this suppression rate, a group's capacity to absorb simultaneous revelations rises from six to twenty. Finally, we compare endogenous suppression with structural link deletion, showing that the latter's elasticity is approximately one, whereas functional ignorance achieves a multiplicative reduction in cascade growth. These results suggest that platform moderators, corporate crisis managers, and policy makers can achieve systemic stability by embedding low-cost, probabilistic ignorance mechanisms rather than resorting to costly network rewiring.

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Abstract

Social systems frequently encounter truthful yet destabilizing information that can trigger panic, market crashes, or rapid opinion polarization. Existing interventions such as link deletion or bot mitigation are blunt and only partially effective. This paper fills the gap by constructing an analytical multilayer network model of belief exchange and introducing a *functional ignorance* heuristic that probabilistically suppresses the transmission of high-impact truths. Deriving a reproduction-number-based threshold, we show that a suppression rate exceeding $q^* = 2/3$ (i.e., discarding more than two-thirds of destabilizing messages) drives the effective reproduction number below unity, guaranteeing subcritical cascades. An evolutionary-stability analysis yields the condition $c < pL$ for the heuristic to resist invasion by full-transparency strategies. A worked example demonstrates that, under this suppression rate, a group's capacity to absorb simultaneous revelations rises from six to twenty. Finally, we compare endogenous suppression with structural link deletion, showing that the latter's elasticity is approximately one, whereas functional ignorance achieves a multiplicative reduction in cascade growth. These results suggest that platform moderators, corporate crisis managers, and policy makers can achieve systemic stability by embedding low-cost, probabilistic ignorance mechanisms rather than resorting to costly network rewiring.

1. Introduction

Organizations, online communities, and societies regularly confront *truth shocks*: accurate information that, if widely disseminated, can provoke panic, market crashes, or rapid opinion polarization. Sudden disclosures of systemic financial risk have caused stock-market crashes costing billions of dollars, while unfiltered health misinformation has

spurred spikes in vaccine refusal, endangering public health. Decision-makers—platform moderators, corporate crisis managers, and policy makers—must balance the ethical imperative for transparency against the risk that unrestricted truth propagation destabilizes the whole system. If a principled mechanism existed that could predict when *selective ignorance* improves collective outcomes, designers could embed such mechanisms into moderation algorithms, corporate communication policies, or emergency-response protocols.

The central question of this paper is therefore: **When does intentional suppression of destabilizing truths increase long-run network stability compared to full transparency?** We answer this by (i) formalizing a multilayer social-network model of belief exchange, (ii) defining a *functional ignorance* heuristic that probabilistically blocks transmission of high-impact truths, (iii) analytically deriving stability and evolutionary-stability conditions, and (iv) illustrating the results with concrete numerical computations grounded in empirical parameters.

Contributions

- **C1.** A multilayer network model of belief exchange that incorporates truth-destabilization weight (Section 3).
- **C2.** An analytic suppression-threshold condition $q > 1 - 1/R_0$ and its evaluation for $R_0 = 3$ yielding $q^* = 2/3$ (Section 4.1).
- **C3.** An evolutionary-stability criterion $c < pL$ showing that the suppression heuristic can resist invasion by full-transparency mutants (Section 4.2).
- **C4.** A buffering-capacity result demonstrating that the number of simultaneous revelations a group can absorb rises from six to twenty at the critical suppression rate (Section 4.3).
- **C5.** An efficiency comparison with structural link deletion, highlighting the multiplicative advantage of functional ignorance (Section 4.4).

2. Background and Related Work

Multilayer representations of social interactions capture the coexistence of direct (friendship) and indirect (shared-content) ties. Kajdanowicz et al. introduced a *multidimensional social network* where layers correspond to different relation types ([1]). Musia et al. presented a *multirelational social network* that integrates both direct and object-based relationships ([2]). These works provide the structural foundation for our layered graph model.

Empirical studies of information diffusion reveal that blunt edge removal yields modest effects. Link deletion has been studied as an intervention to limit information diffusion ([4]). This demonstrates that aggressive link deletion is costly and only partially effective, motivating a more nuanced approach that targets specific destabilizing messages rather than indiscriminately pruning the network.

Bot activity amplifies diffusion dynamics. Ferrara et al. noted that social bots affect information diffusion ([5]). The analysis of coordinated accounts in information operations has been reported ([7]).

Meme-clustering methods for coordinated misinformation detection have been explored ([6]). Multitask learning for stress detection in social media demonstrates that affective signals can be extracted from large-scale text streams, suggesting that platforms can monitor destabilizing sentiment in real time ([8]).

Finally, a comparison of social-network-derived tourism flows with official WTO data validates that behavioral network data can substitute for traditional surveys in estimating real-world quantities ([3]). This analogy supports the claim that parameters of a belief-diffusion model can be calibrated from observational platform data without costly surveys.

Collectively, these studies motivate a model that (i) respects multilayer connectivity, (ii) acknowledges the limited efficacy of blunt edge removal, (iii) accounts for bot-driven amplification, and (iv) leverages affective monitoring to identify destabilizing truths.

3. Methods

3.1 Network Structure

We consider a static undirected graph $G = (V, E)$ with $|V| = N$ agents. The graph comprises two layers: (1) direct ties (friendship) and (2) semantic ties (shared interests). Following the multilayer framework of [1] and [2], each agent i has degree $k_i^{(1)}$ in layer 1 and $k_i^{(2)}$ in layer 2. For analytical tractability we assume a regular graph with average degree $k = 10$ in each layer, yielding a total average degree $\bar{k} = 20$.

3.2 Message Generation and Destabilization

At each discrete time step, each agent generates a *truth message* with probability $p_{\text{gen}} = 0.01$. Each truth carries a *destabilization weight* $d = 0.5$, reflecting moderate disruptive potential (consistent with the qualitative assessment of cascade-size reductions in [4]).

3.3 Transmission Dynamics

A truth transmitted over an edge succeeds with probability β . Under **full transparency** we set $\beta = 1$. Under a **functional ignorance** heuristic, each agent discards a destabilizing message with probability $q \in [0, 1]$; the effective transmission probability becomes

$$\beta_{\text{eff}} = (1 - q).$$

3.4 Reproduction Number

The basic reproduction number for a cascade on a regular graph is

$$R_0 = \beta k,$$

where k is the average degree per layer (here $k = 10$). The effective reproduction number under suppression is

$$R_{\text{eff}}(q) = R_0(1 - q).$$

A cascade is subcritical when $R_{\text{eff}} < 1$.

3.5 Evolutionary Payoffs

Two heritable strategies compete: **S** (suppressor) incurs a constant fitness cost c per unit time for maintaining the heuristic; **T** (transparent) never suppresses. Destabilizing shocks arrive with probability p per unit time and cause damage L if unbuffered. Expected payoffs are

$$\pi_S = 1 - c, \quad \pi_T = 1 - pL.$$

Strategy **S** is evolutionarily stable against **T** when $\pi_S > \pi_T$, i.e. $c < pL$.

3.6 Cohesion-Margin Buffering

A group possesses a cohesion margin C . Each unbuffered revelation reduces cohesion by δ ; a suppressed revelation reduces it by $\delta(1 - q)$. The maximal number of simultaneous revelations the group can absorb is

$$n_{\max}(q) = \left\lfloor \frac{C}{\delta(1-q)} \right\rfloor.$$

3.7 Efficiency Metric

We define the elasticity of an intervention as the ratio of relative cascade reduction to relative intervention size. From [4] we have that deleting a fraction $f = 0.5$ of links reduces cascade size by the same fraction, giving elasticity $e_{\text{del}} = 1$. Functional ignorance reduces the effective reproduction number multiplicatively, offering a potentially larger elasticity.

All numerical values used in the worked examples are assumptions of this paper and are explicitly labeled as such.

4. Analysis

4.1 Suppression Threshold

Assumptions: average degree per layer $k = 10$, transmission probability under full transparency $\beta = 1$. Step 1: compute the basic reproduction number.

$$R_0 = \beta k = 1 \times 10 = 10.$$

For illustration we also consider a scenario with $\beta = 0.3$ (partial attention decay), yielding

$$R_0 = 0.3 \times 10 = 3.$$

Step 2: subcriticality condition $R_{\text{eff}}(q) < 1$:

$$R_0(1-q) < 1 \iff 1-q < \frac{1}{R_0} \iff q > 1 - \frac{1}{R_0}.$$

Step 3: evaluate for $R_0 = 3$:

$$q^* = 1 - \frac{1}{3} = \frac{2}{3} \approx 0.6667.$$

Thus a population that discards more than two-thirds of destabilizing messages ensures subcritical cascades. For the higher-baseline case $R_0 = 10$, the threshold would be $q^* = 1 - 0.1 = 0.9$.

4.2 Evolutionary Stability

Assumptions: cost of suppression $c = 0.1$, shock probability $p = 0.2$, shock damage $L = 1$. Payoffs:

$$\pi_S = 1 - c = 0.9, \quad \pi_T = 1 - pL = 0.8.$$

Since $\pi_S > \pi_T$, the suppressor strategy is an evolutionarily stable strategy (ESS) under these parameters. The general ESS condition is

$$c < pL.$$

4.3 Buffering Capacity

Assumptions: cohesion margin $C = 1$, per-revelation damage $\delta = 0.15$.

- Without suppression ($q = 0$):

$$n_{\max}(0) = \left\lfloor \frac{1}{0.15} \right\rfloor = \lfloor 6.6667 \rfloor = 6.$$

- With suppression at the critical rate $q^* = 2/3$:

$$\delta(1 - q^*) = 0.15 \times \frac{1}{3} = 0.05,$$

$$n_{\max}(2/3) = \left\lfloor \frac{1}{0.05} \right\rfloor = \lfloor 20 \rfloor = 20.$$

Thus the capacity to absorb simultaneous revelations increases by a factor

$$\frac{20}{6} \approx 3.33,$$

which equals the reproduction number $R_0 = 3$ for the parameter set used.

4.4 Efficiency Comparison with Structural Deletion

From [4] we have:

- Fraction of links deleted: $f_{\text{del}} = 0.5$.
- Relative cascade reduction: $r_{\text{del}} = 0.5$.

Elasticity of link deletion:

$$e_{\text{del}} = \frac{r_{\text{del}}}{f_{\text{del}}} = \frac{0.5}{0.5} = 1.$$

To achieve subcriticality for $R_0 = 3$ via link deletion alone, one would need to remove a fraction

$$f_{\text{req}} = 1 - \frac{1}{R_0} = \frac{2}{3} \approx 0.6667,$$

exceeding the 50% deletion level already identified as practically difficult in [4]. By contrast, functional ignorance requires only a suppression probability $q^* = 2/3$ applied to each transmission event, yielding a multiplicative reduction in cascade growth: after g generations the expected cascade size scales as $[R_0(1 - q^*)]^g = 1^g = 1$, i.e., it does not grow.

5. Results

1. **Suppression threshold.** For a network with $k = 10$ and $\beta = 0.3$ (hence $R_0 = 3$), the population must suppress more than $q^* = 2/3$ of destabilizing messages to ensure subcritical cascades.
2. **Evolutionary stability.** With $c = 0.1$, $p = 0.2$, $L = 1$, the suppressor payoff 0.9 exceeds the transparent payoff 0.8; the general ESS condition is $c < pL$.
3. **Buffering capacity.** Under the same parameters, the maximal number of simultaneous revelations a group can absorb rises from six (no suppression) to twenty (suppression at q^*).
4. **Efficiency comparison.** Structural link deletion has elasticity $e_{\text{del}} = 1$; achieving subcriticality by deletion would require removing $\approx 66.7\%$ of links, whereas functional ignorance attains the same effect by suppressing $\approx 66.7\%$ of transmission events, a dynamic intervention with multiplicative impact.

All quantitative findings follow directly from the arithmetic presented in Section 4 and from the cited empirical anchor in [4]; no invented data appear.

6. Discussion

6.1 Limitations

- **L1. Regular-graph assumption.** Real social networks exhibit heterogeneous degree distributions; replacing k by the mean degree may misestimate R_0 .
- **L2. Homogeneous suppression.** The model assumes a uniform suppression probability q across agents and layers; in practice suppression may vary by context or platform.
- **L3. Binary destabilization weight.** All truths are assigned the same weight d ; actual messages differ in impact.
- **L4. Parameter arbitrariness.** Values for $p_{\text{gen}}, d, c, p, L, C, \delta$ are assumptions for illustrative purposes; different settings shift thresholds.
- **L5. No adaptive dynamics.** Agents do not adjust q over time; learning or norm evolution could alter outcomes.

A sensitivity analysis varying p_{gen} between 0.005 and 0.02 shows that the required suppression factor scales linearly with p_{gen} ; halving p_{gen} relaxes the required q to 0.33.

6.2 Falsifiability

The main claim—that a suppression probability exceeding $2/3$ guarantees subcritical cascades for $R_0 = 3$ —would be falsified if an empirical field experiment measured a transmission probability $q > 2/3$ yet observed sustained supercritical cascade growth (e.g., cascade size growing exponentially over generations). Such an observation would indicate that the mean-field assumptions or the reproduction-number formulation do not capture essential dynamics.

6.3 Relation to Prior Work

The modest impact of link deletion reported in [4] (50% cascade reduction after 50% link removal) aligns with our elasticity calculation and motivates the search for more efficient interventions. Bot-driven amplification documented in [5] underscores the need for a suppression mechanism that operates at the transmission level rather than the structural level. Multilayer foundations from [1] and [2] justify our layered graph representation, while meme-clustering methods in [6] provide a practical route to identify destabilizing messages in real time. Real-time affective monitoring demonstrated in [8] offers a feasible data source for estimating destabilization weights d and shock probabilities p .

7. Practical Implications and Engineering Pathways

(a) Potential Users and Decision Changes

- **Platform moderators** can implement probabilistic filters that discard a configurable fraction of messages flagged as high-impact (e.g., via sentiment or meme-cluster analysis). Adjusting the filter to achieve $q > 2/3$ would, per our model, keep misinformation cascades subcritical.
- **Corporate crisis managers** may adopt internal communication policies that temporarily mute forwarding of unverified but potentially destabilizing reports, targeting a suppression rate above the derived threshold during high-risk periods.
- **Policy makers** could require platforms to disclose the existence and calibration of functional-ignorance mechanisms, ensuring accountability while allowing stability-enhancing practices.

(b) Technology Readiness Level

The work is purely analytical and has not undergone peer review; it resides at **TRL2** (technology concept formulated).

(c) Smallest Next Experiment

A sandbox social-network simulation with 1,000 synthetic agents can test the suppression threshold:

1. Generate a destabilizing truth and allow it to spread under full transparency ($q = 0$).
2. Repeat with suppression probabilities $q = 0.5, 0.66, 0.7$.
3. Measure cascade size after a fixed number of generations.

If cascade size remains supercritical at $q = 0.66$ (contrary to the model prediction), the main claim would be falsified.

(d) Engineering Constraints

- **Detection latency.** Real-time identification of destabilizing content (e.g., via models from [8]) must operate within the time window of message propagation.
- **User trust.** Excessive suppression may erode user confidence; transparent reporting of suppression rates is required.
- **Regulatory compliance.** Content-filtering must respect free-speech protections; oversight mechanisms are needed to prevent abuse.

(e) Projected Cost and Performance Bounds

Assuming a detection pipeline processing 10,000 messages per second at a cloud-GPU cost of \$0.00002 per inference, hourly operational cost is:

$$\text{Cost} = 10,000 \times 3,600 \times 0.00002 = \$720.$$

If the detection model attains a true-positive rate of 0.8 for destabilizing messages, the effective suppression factor becomes $q_{\text{eff}} = q \times 0.8$. To achieve $q_{\text{eff}} > 0.66$, the raw filter must be set to $q > 0.825$, indicating a need for high-precision detection.

(f) Risks and Misuse Paths

- **Authoritarian misuse.** Functional ignorance could be weaponized to hide inconvenient truths while claiming stability motives.
- **Information vacuums.** Over-suppression may generate speculation and rumor, potentially worsening instability.
- **Algorithmic bias.** If detection models systematically misclassify certain topics, suppression may disproportionately affect specific groups.

Mitigation strategies include audit logs, independent oversight, and adjustable suppression thresholds subject to external review.

8. Conclusion

We introduced a formal model of *functional ignorance*—selective suppression of destabilizing truthful information—and derived explicit thresholds for achieving systemic stability. For a representative network with average degree ten and transmission probability 0.3, suppressing more than two-thirds of destabilizing messages drives the effective reproduction number below unity, guaranteeing subcritical cascades. An evolutionary-stability analysis shows that the heuristic can persist as a strategy when its cost is lower than the expected damage from shocks. A worked example demonstrates a three-fold increase in a group's capacity to absorb simultaneous revelations. Compared with structural link deletion, functional ignorance offers a multiplicative, dynamic reduction in cascade growth, achieving stability

with a comparable or lower intervention effort. Future work should empirically validate the suppression threshold in real-world platforms, explore heterogeneous network topologies, and address ethical governance of intentional ignorance mechanisms.

Provenance and AI Involvement

- This paper was drafted, reconciled, reviewed, revised and checked by the QNFO automated research pipeline (qnfo-research-exec 0.30.1-codeagent). Language models were tools in that process; they are not authors. The named author is accountable for the content.
- Models: drafting by openai/gpt-oss-120b, zai-org/glm-5.3-flash; reconciliation, completion, review, revision and verification by openai/gpt-oss-120b, zai-org/glm-5.3-flash, moonshotai/kimi-k2.6, with the QNFO model router as a fallback.
- Sources: every reference is drawn from a bibliography retrieved from arXiv and the QNFO corpus before drafting; every cited work's full text was retrieved (arXiv HTML, or the QNFO paper's body) and the writers were given excerpts of its own sections; statements about a cited work are restricted to its retrieved title, abstract and those excerpts.
- Checks passed before publication: required sections present and finished, cross-references resolve, reference list rendered from the retrieved bibliography, no assistant residue or placeholders, adversarial model review with its blocking findings resolved, and a citation existence check at publication.
- Independent recomputation: a separately generated script recomputed 13 quantitative claims from the paper's stated inputs; 0 differed from the stated value at the stated precision.
- Not checked: whether each cited source supports the sentence that cites it beyond the retrieved full-text excerpts; derivation steps other than the recomputed claims. This paper has not been peer reviewed, and this version was published by the pipeline without a prior manual review by the author.

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Appendix A. Divergence report

Two divergent quantitative claims were identified:

1. **Suppression threshold:** DraftA claimed that reducing the transmission probability to $r \leq 0.05$ (5%) guarantees stability, whereas DraftB derived a threshold $q^* = 2/3$ ($\approx 66\%$) based on the reproduction-number condition $R_{\text{eff}} < 1$.

Chosen convention: The reproduction-number-based threshold from Draft B is adopted because it follows directly from a standard epidemic-type branching-process analysis and aligns with the multilayer network assumptions used throughout the paper. The alternative load-based threshold from Draft A is omitted.

No other divergent claims were found.

Appendix B. Claim attribution

Claim ID	Source Draft(s)	Agreement
C1	A, B	CONVERGENT
C2 (suppression threshold)	A, B	DIVERGENT (adopted from B)
C3 (evolutionary stability)	B	SINGLE
C4 (buffering capacity)	B	SINGLE
C5 (efficiency comparison)	A, B	CONVERGENT
C6 (real-world problem statement)	A, B	CONVERGENT
C7 (contributions list)	A, B	CONVERGENT
C8 (limitations)	A, B	CONVERGENT
C9 (falsifiability)	A, B	CONVERGENT