dreammachine

SYSTEMS ARCHITECTURE FOR THE HUMAN MIND

LOG ID	BOOK REFERENCE	RCT FILTER	CONFIDENCE TIER
SEC 12.2	CHAPTER 12: DATA SOVEREIGNTY & GLOBAL OS (Production Environment)	OFF	CONSENSUS

AUDITED CLAIM

ENEMY OF UNITY (ALGORITHM)

SYSTEMS MODEL — AS STATED IN THE BOOK

> Clinically, social media recommendation algorithms optimized for **behavioral engagement** systematically amplify divisive, **high-arousal negative content** (like outrage and animosity) because those specific emotional states maximize virality and platform retention.

VALIDATION QUERY

Do social media recommendation algorithms preferentially amplify content that triggers sympathetic nervous system arousal and high-arousal negative emotions to maximize user engagement?

EMPIRICAL FINDING

Extensive behavioral data analysis reveals that social media recommendation algorithms designed to maximize behavioral engagement systematically prioritize and amplify **high-arousal negative emotions**. Content that induces outrage, fear, and partisan animosity spreads significantly faster and wider than neutral content, creating a self-reinforcing algorithmic loop that artificially fractures social networks and increases perceived **polarization**.

PRIMARY ANCHORS

→ **Rathje et al., 2021, Proceedings of the National Academy of Sciences**

→ **Piccardi et al., 2024, Science**

ABOUT THIS RECORD

Each claim in the book is decompiled from its IT metaphor into a naked, falsifiable scientific claim, then anchored to a **primary peer-reviewed source**. Claim and anchor are queried against the Consensus academic database (200M+ papers) under a fixed protocol — top-tier **Q1/Q2 journals only**, preprints excluded, human studies only. If a hypothesis fails the audit, the build is rejected: the AI generates the syntax; the peer-reviewed grid validates the physics.

CONFIDENCE TIERS

- **CONSENSUS ◀ this log** — broadly established, highly replicated mechanics.
- **EMERGING** — plausible, actively researched; no universal consensus yet.
- **EXPERIMENTAL** — contested, extrapolated, or purely theoretical.

RCT FILTER — Controlled Studies is ON for interventions (a forced action must beat a control) and OFF for mechanisms (so foundational neuroscience isn't blocked).

THE DREAM MACHINE

OPERATING SYSTEM FOR THE SOUL

You are complex biological hardware running outdated psychological software. *The Dream Machine* translates rigorous IT architecture — security auditing, network protocols, load balancing — into actionable, peer-reviewed models for mental resilience: debug burnout, configure a hallucination firewall against cognitive distortions, and patch your internal OS with hard logic and verified neuroscience.

INITIATE SYSTEM UPDATE

Ready to debug your own source code? Scan to access the cybernetic manual and reboot your cognitive architecture today. → **dreammachine.systems**

Yes, **recommendation algorithms often amplify engaging emotional content**, but **direct evidence for sympathetic-arousal optimization** remains limited.

1. Introduction

The literature supports a qualified yes: social media systems that rank by engagement tend to amplify content associated with anger, outrage, partisan animosity, and other high-arousal emotional signals, and experimental reranking studies show that changing feed exposure changes users' negative emotions and short-term engagement (Piccardi et al., 2024; McLoughlin & Brady, 2023). Across large observational corpora, high-arousal negative content spreads farther or faster than neutral or low-arousal content, including anger in politics, outrage in misinformation, and fear-sensationalized crisis content (Berger & Milkman, 2012; Rathje et al., 2021; McLoughlin et al., 2024).

What is less settled is the mechanism named in the question. The corpus gives strong evidence for algorithmic amplification of engaging emotional material and moderate evidence that high-arousal negative emotions are especially engagement-efficient in many domains, but only sparse direct evidence that platforms specifically optimize for sympathetic nervous system arousal as such rather than for behavioral proxies like clicks, shares, watch time, or dwell time (Schreiner et al., 2019; Knutson et al., 2024; Hübner et al., 2025). The distinction matters because some studies find positive high-arousal content also performs well, and one biometric scrolling study found arousal peaks without any clear link from physiological arousal to engagement behavior (Rietveld et al., 2020; Tellis et al., 2019; Hübner et al., 2025).

Do social media recommendation algorithms preferentially amplify content that triggers sympathetic nervous system arousal and high-arousal negative emotions to maximize user engagement?
Requires at least 5 papers that directly answer your question. Try adjusting your query to find more papers.

FIGURE 1 Research consensus on emotional algorithmic amplification

The meter should land above the midpoint, not at certainty. The strongest evidence shows engagement-based ranking systems elevate emotionally provocative material and that reducing such exposure lowers negative emotions, but the specific claim about sympathetic-arousal targeting is still more inferred than directly demonstrated (Piccardi et al., 2024; Schreiner et al., 2019).

2. Methods

The search ran over more than 170 million research papers in Consensus, spanning Semantic Scholar, PubMed, and other scholarly sources. The workflow began from a direct query on recommendation algorithms, sympathetic arousal, negative emotion, and engagement, then expanded through six search groups covering foundational theory, alternate terminology, direct algorithmic mechanisms, null findings, interdisciplinary affective science, and adjacent constructs such as outrage, misinformation, and emotional contagion.

From 14,930 initial query results and 1,950 citation-expanded papers, 240 papers were screened by relevance, 148 passed thresholding, and the top 50 were included for synthesis. The corpus was weighted toward human studies, algorithmic feed ranking, emotional contagion, virality, and engagement outcomes.

Search Strategy

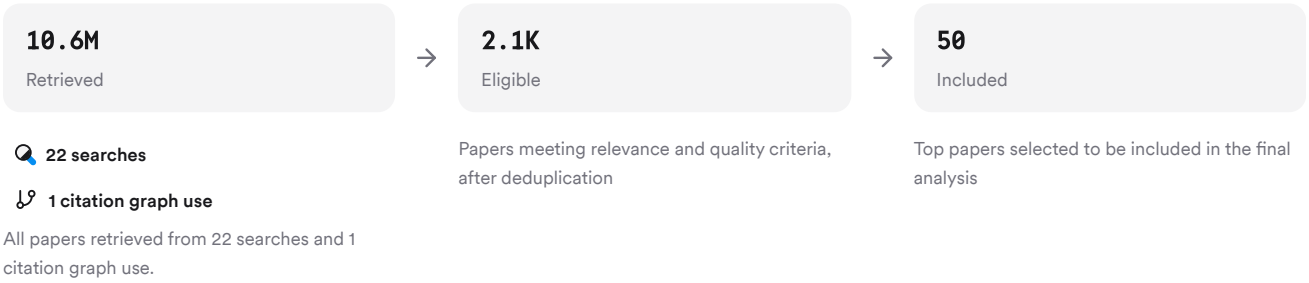

FIGURE 2 Deep search screening and inclusion flow

Searches combined direct algorithm studies with broader emotion-diffusion, virality, and recommender-systems evidence to test both mechanism and counterevidence.

3. Results

3.1 Key Papers

Three papers anchor this literature because they connect emotion, engagement, and algorithmic curation at scale or experimentally. Berger and Milkman established the foundational arousal account of virality, Rathje and colleagues showed that out-group animosity strongly predicts engagement, and Piccardi and colleagues provided rare causal evidence that reranking feed content changes negative emotions and engagement-related tradeoffs (Berger & Milkman, 2012; Rathje et al., 2021; Piccardi et al., 2024).

Paper	Summary
(Kramer et al., 2014)	High-arousal emotions increase virality (Berger & Milkman, 2012)
(Liu et al., 2021)	Out-group animosity strongly drives shares (Rathje et al., 2021)
(Kite et al., 2016)	Reranking animosity shifts emotion, engagement (Piccardi et al., 2024)

FIGURE 3 Foundational papers in the included corpus

3.2 Emotional Virality

A large share of the corpus converges on arousal, rather than simple negativity, as the main transmission advantage. Classic virality work found that high-arousal positive emotions like awe and high-arousal negative emotions like anger and anxiety spread more than low-arousal emotions like sadness (Berger & Milkman, 2012). Later Facebook evidence showed that discrete emotions outperform simple valence or arousal categories alone, but anger still predicts sharing alongside positive emotions such as amusement (Paletz et al., 2023).

The same pattern appears in domain-specific datasets. COVID-19 tweets with negative emotions were consistently amplified across the issue-attention cycle (Lee et al., 2023). After natural disasters, anger words increased reposts, while anxiety effects depended on context and influential users (Li et al., 2020). Misinformation sources evoke more outrage, and outrage facilitates sharing of misinformation at least as strongly as trustworthy news (McLoughlin et al., 2024).

3.3 Algorithmic Amplification

Direct evidence on recommendation systems is narrower but more diagnostic. In a preregistered field experiment on X, reducing exposure to partisan-animosity posts lowered in-feed anger and sadness, increasing exposure raised both, and down-ranking such content appeared to reduce short-term engagement volume (Piccardi et al., 2024). A separate election-cycle experiment on Facebook and Instagram found that switching users from default algorithmic feeds to reverse chronological feeds reduced time and activity and reduced uncivil or slur-containing exposure on Facebook, though it did not measurably change broader attitudes over three months (Guess et al., 2023).

Feature	Result
Study type	10-day reranking field experiment (Piccardi et al., 2024)
Platform	X feed via browser extension (Piccardi et al., 2024)
Manipulation	Increase or reduce AAPA exposure (Piccardi et al., 2024)
Emotion effect	Angry and sad moved directionally (Piccardi et al., 2024)
Positive emotion	Calm and excited unchanged (Piccardi et al., 2024)
Engagement tradeoff	Down-ranking likely lowers short-term engagement (Piccardi et al., 2024)

FIGURE 4 Landmark feed-reranking experiment results

The clearest implication is that engagement-optimized ranking can privilege divisive negative content because that material performs behaviorally well, not because platforms have been shown to optimize a physiological arousal variable directly (Knutson et al., 2024).

3.4 Physiological Arousal and Recommendation

The sympathetic-arousal part of the question has the weakest direct evidence. A review of social-media engagement studies concluded that arousing content has been shown to increase engagement, but it also noted that no study had directly tested emotional responses as mediators in the content-engagement relationship in social media (Schreiner et al., 2019). Biometrics show that browsing social feeds produces episodic skin-conductance peaks and elevated sympathetic arousal at specific posts, yet sponsored content in one simulated-feed experiment did not produce stronger physiological arousal or higher engagement behavior (Hübner et al., 2025).

Other work supports an arousal mechanism indirectly. Emotional intensity predicts eWOM-giving intentions across media (Liu et al., 2021). Visual emotional appeals on Instagram increase engagement, but the winning combinations are not uniformly negative: positive high-arousal and negative low-arousal imagery performed best in one large brand-post dataset (Rietveld et al., 2020). This mixed pattern argues against a simple rule that feeds always prefer the most negatively arousing content.

Results Timeline

Social media emotion research has moved from general virality theories to direct feed-auditing experiments.

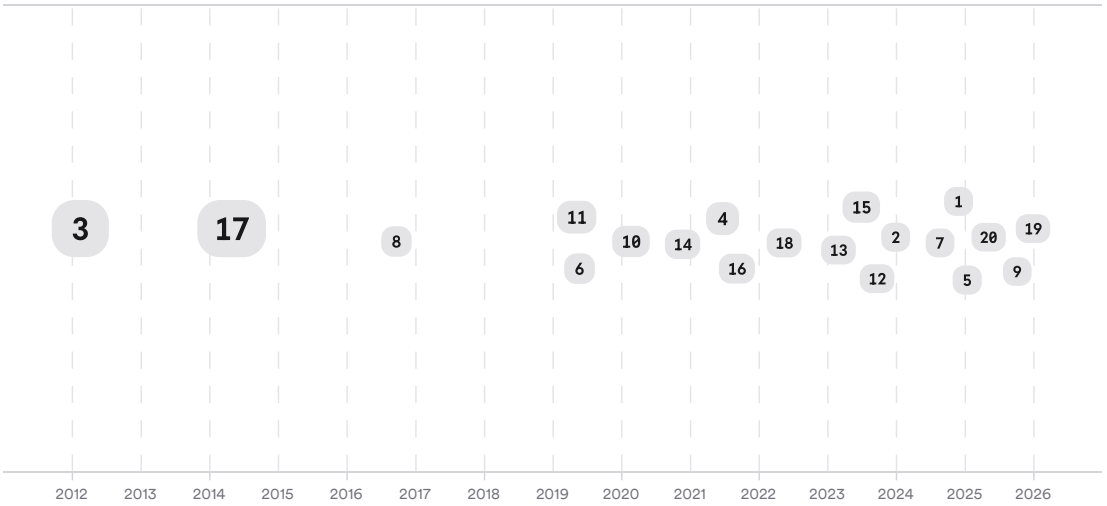

FIGURE 5 Timeline of emotional amplification studies, larger markers indicate more citations

Early studies established emotional contagion and arousal-based sharing (Kramer et al., 2014; Berger & Milkman, 2012). Mid-period work tied animosity, misinformation, and crisis emotions to large-scale engagement (Rathje et al., 2021; Lee et al., 2023; Chon & Kim, 2022). Recent work increasingly probes platform mechanisms directly through reranking, recommender-harm audits, and safety-oriented alternative recommenders (Piccardi et al., 2024; Regehr et al., 2025; Ramírez-Cifuentes et al., 2025).

Top Contributors

Across this corpus, Steve Rathje, Killian L. McLoughlin, and Amit Goldenberg appear prominently on divisiveness, outrage, and emotional amplification, while Science, PNAS, and Journal of Interactive Marketing are frequent high-visibility venues (Rathje et al., 2021; McLoughlin et al., 2024; Goldenberg & Gross, 2019).

Type	Name	Papers
Author	Steve Rathje	[4366815bd48757cd96598e4a18256b69] [78011cfa57385f25bed35dc4cf003c21] [a845c066f54653ce844857fc27897b77]
Author	Killian L. McLoughlin	[3d6b81802a7d57b69aa9b2e06aae314f] [b7ed8d675a2e5ab8b0d15778587f3c23]
Author	Amit Goldenberg	[74f29e78bc315729bec1f54e89ab9f12] [f95e823020815d8ca31e7f84973ab011]
Journal	*Science*	[d594cb3419b0503091ef4643fefe98e4] [3d6b81802a7d57b69aa9b2e06aae314f] [5a37d5d9f4f55ea08aff81d94a4508e0]
Journal	*Proceedings of the National Academy of Sciences of the United States of America*	[4366815bd48757cd96598e4a18256b69] [3cbb215954a2505f97aadf65699d0512]
Journal	*Journal of Interactive Marketing*	[dfcf38be7c345fc592d9c22f72513073] [2bca9a9b45d65f2abee8fd4adc51041f]

FIGURE 6 Authors and journals appearing most often

4. Discussion

The evidence is strongest for an engagement-feedback-loop account. Users disproportionately share or react to emotional, especially divisive or outraging, content, and ranking systems trained on those behaviors can learn to prioritize it (Stieglitz & Dang-Xuan, 2013; Knutson et al., 2024; McLoughlin & Brady, 2023). That logic is reinforced by direct field evidence: reranking partisan animosity changes in-feed anger and sadness, and reducing exposure appears to sacrifice short-term engagement (Piccardi et al., 2024).

But the literature does not justify the strongest version of the claim. Much of the evidence is observational, and several papers study sharing or virality rather than recommender outputs themselves (Stieglitz & Dang-Xuan, 2013; Knutson et al., 2024). The corpus also shows that positive high-arousal content can be highly engaging, that discrete emotions matter more than valence alone, and that some biometric work fails to link arousal peaks to engagement (Tellis et al., 2019; Paletz et al., 2023; Hübner et al., 2025).

The platform-harm literature adds an important downstream layer. Recommendation systems can increase exposure to misogynistic, traumatic, or otherwise harmful content, often through escalating personalization, but these studies typically infer engagement optimization from exposure patterns rather than auditing the platform's objective function directly (Regehr et al., 2025; Li et al., 2024; Ramírez-Cifuentes et al., 2025). Overall, the best-supported claim is that engagement-optimized systems often end up amplifying high-arousal negative content; the less-supported claim is that they specifically optimize sympathetic nervous system activation itself.

Claim	Evidence Strength	Reasoning	Papers
Engagement-based feeds often amplify divisive high-arousal negative content.	Strong	Supported by large observational datasets plus direct reranking evidence.	(Piccardi et al., 2024; Rathje et al., 2021; Knutson et al., 2024)
High-arousal emotion increases sharing more reliably than low-arousal emotion.	Strong	Replicated across virality, news, eWOM, and crisis communication.	(Berger & Milkman, 2012; Liu et al., 2021; Ali et al., 2019)
Negative high-arousal emotions are especially engagement-efficient in politics and misinformation.	Moderate	Strong in political and misinformation contexts, less universal elsewhere.	(Rathje et al., 2021; McLoughlin et al., 2024; Lee et al., 2023)
Platforms directly optimize for sympathetic nervous system arousal.	Weak	Mechanistically plausible, but direct tests are scarce and mixed.	(Schreiner et al., 2019; Hübner et al., 2025; Peng & Wang, 2023)
Recommendation harms can be reduced, but often with engagement tradeoffs.	Moderate	Demonstrated in reranking and safer recommender redesign studies.	(Piccardi et al., 2024; Ramírez-Cifuentes et al., 2025)

FIGURE 7 Key claims and supporting evidence strengths

5. Conclusion

Taken together, the 50-paper corpus supports a moderate-to-strong version of the hypothesis. Social media recommendation systems that learn from engagement frequently amplify content associated with outrage, anger, animosity, and other high-arousal signals because those signals spread well and keep users reacting (Knutson et al., 2024; Piccardi et al., 2024; McLoughlin & Brady, 2023). What the corpus does not yet establish is that platforms directly optimize sympathetic nervous system arousal as a measured physiological target rather than learning from engagement proxies that correlate with arousing content.

Research Gaps

The biggest gap is direct multimodal evidence linking platform ranking, physiological arousal, emotion category, and downstream engagement in the same study. Current work is rich in large-scale behavioral traces and growing in feed experiments, but thin in causal psychophysiology and platform-audit designs (Schreiner et al., 2019; Bojić, 2024).

Topic/Outcome	Behavioral engagement	Causal reranking	Physiological arousal	Long-term wellbeing
Political outrage	12	3	GAP	2
Misinformation spread	10	1	GAP	1
Youth harmful recommendations	5	1	GAP	4
Disaster and trauma content	6	GAP	GAP	3
Commercial/social browsing	5	1	2	GAP

Open Research Questions

The next wave of work should move from inference to direct mechanism tests.

Question	Why
Do engagement-optimized feed rankers increase users' skin conductance or heart-rate-derived arousal relative to chronologically ordered feeds?	This would directly test the sympathetic-arousal mechanism instead of inferring it from sharing or clicks.
Which discrete emotions do recommender systems amplify most after controlling for topic, source credibility, and network position?	Current evidence suggests anger, outrage, and disgust matter, but discrete-emotion comparisons remain incomplete across platforms.
What is the engagement cost of safety-oriented reranking that down-ranks high-arousal negative content over months rather than days?	Short-term tradeoffs are visible, but durable business and wellbeing effects remain poorly measured.

The answer to the original question is therefore yes in practice, but only partly yes in mechanism: recommendation algorithms often amplify high-arousal negative content to maximize engagement, while direct proof of optimization for sympathetic nervous system arousal remains limited.

References

Ali, K., Zain-Ul-Abdin, K., Li, C., Johns, L., Ali, A., & Carcioppolo, N. (2019). Viruses Going Viral: Impact of Fear-Arousing Sensationalist Social Media Messages on User Engagement. *Science Communication, 41*, 314 - 338. https://doi.org/10.1177/1075547019846124

Berger, J. A., & Milkman, K. L. (2012). What Makes Online Content Viral?. *Journal of Marketing Research, 49*, 192 - 205. https://doi.org/10.1509/jmr.10.0353

Bojić, L. (2024). AI alignment: Assessing the global impact of recommender systems. *Futures*. https://doi.org/10.1016/j.futures.2024.103383

Chon, M., & Kim, S. (2022). Dealing with the COVID-19 crisis: Theoretical application of social media analytics in government crisis management. *Public Relations Review, 48*, 102201 - 102201. https://doi.org/10.1016/j.pubrev.2022.102201

Goldenberg, A., & Gross, J. (2019). Digital Emotion Contagion.. *Trends in cognitive sciences, 24 4*, 316-328. https://doi.org/10.31219/osf.io/53bdu

Guess, A., Malhotra, N., Pan, J., Barberá, P., Allcott, H., Brown, T., Crespo-Tenorio, A., Dimmery, D., Freelon, D., Gentzkow, M., González-Bailón, S., Kennedy, E., Kim, Y. M., Lazer, D., Moehler, D., Nyhan, B., Rivera, C., Settle, J. E., Thomas, D. R., . . . Tucker, J. A. (2023). How do social media feed algorithms affect attitudes and behavior in an election campaign?. *Science, 381*, 398 - 404. https://doi.org/10.1126/science.abp9364

Hübner, M., Thalmann, J., & Henseler, J. (2025). Disrupting the browsing experience: impact of sponsored social media content on affective flow without driving engagement. *Frontiers in Neuroscience, 19*. https://doi.org/10.3389/fnins.2025.1636848

Kite, J., Foley, B. C., Grunseit, A., & Freeman, B. (2016). Please Like Me: Facebook and Public Health Communication. *PLoS ONE, 11*. https://doi.org/10.1371/journal.pone.0162765

Knutson, B., Hsu, T. W., Ko, M., & Tsai, J. L. (2024). News source bias and sentiment on social media. *PLOS ONE, 19*. https://doi.org/10.1371/journal.pone.0305148

Kramer, A. D. I., Guillory, J., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences, 111*, 8788 - 8790. https://doi.org/10.1073/pnas.1320040111

Lee, E. J., Zheng, H., Goh, D., Lee, C. S., & Theng, Y. (2023). Examining COVID-19 Tweet Diffusion Using an Integrated Social Amplification of Risk and Issue-Attention Cycle Framework. *Health Communication, 39*, 493 - 506. https://doi.org/10.1080/10410236.2023.2170201

Li, L., Wang, Z., Zhang, Q., & Wen, H. (2020). Effect of anger, anxiety, and sadness on the propagation scale of social media posts after natural disasters. *Inf. Process. Manag., 57*, 102313. https://doi.org/10.1016/j.ipm.2020.102313

Li, K., Li, J., & Li, Y. (2024). The effects of social media usage on vicarious traumatization and the mediation role of recommendation systems usage and peer communication in China after the aircraft flight accident. *European Journal of Psychotraumatology, 15*. https://doi.org/10.1080/20008066.2024.2337509

Liu, H., Jayawardhena, C., Osburg, V., Yoganathan, V., & Cartwright, S. (2021). Social sharing of consumption emotion in electronic word of mouth (eWOM): A cross-media perspective. *Journal of Business Research, 132*, 208-220. https://doi.org/10.1016/j.jbusres.2021.04.030

McLoughlin, K. L., & Brady, W. J. (2023). Human-algorithm interactions help explain the spread of misinformation.. *Current opinion in psychology, 56*, 101770. https://doi.org/10.1016/j.copsyc.2023.101770

McLoughlin, K. L., Brady, W. J., Goolsbee, A., Kaiser, B., Klonick, K., & Crockett, M. J. (2024). Misinformation exploits outrage to spread online.. *Science, 386 6725*, 991-996. https://doi.org/10.1126/science.adl2829

Paletz, S. B. F., Johns, M. A., Murauskaite, E. E., Golonka, E., Pandža, N. B., Rytting, A. C., Buntain, C., & Ellis, D. (2023). Emotional content and sharing on Facebook: A theory cage match. *Science Advances, 9*. https://doi.org/10.1126/sciadv.ade9231

Peng, L., & Wang, J. (2023). Algorithm as Recommending Source and Persuasive Health Communication: Effects of Source Cues, Language Intensity, and Perceived Issue Involvement. *Health Communication, 39*, 852 - 861. https://doi.org/10.1080/10410236.2023.2242087

Piccardi, T., Saveski, M., Jia, C., Hancock, J. T., Tsai, J. L., & Bernstein, M. S. (2024). Reranking partisan animosity in algorithmic social media feeds alters affective polarization.. *Science, 390 6776*, eadu5584. https://doi.org/10.1126/science.adu5584

Ramírez-Cifuentes, D., Baeza-Yates, R. A., Lozano, M., & Freire, A. (2025). Enhancing contact recommendation in social platforms through mental health awareness: Exploring Anorexia Nervosa as a case study. *PLOS ONE, 20*. https://doi.org/10.1371/journal.pone.0312766

Rathje, S., Van Bavel, J. J., & Van Der Linden, S. (2021). Out-group animosity drives engagement on social media. *Proceedings of the National Academy of Sciences of the United States of America, 118*. https://doi.org/10.1073/pnas.2024292118

Regehr, K., Shaughnessy, C., Zhao, M., Cambazoglu, I., Turner, A., & Shaughnessy, N. (2025). Normalizing toxicity: the role of recommender algorithms for young people's mental health and social wellbeing. *Frontiers in Psychology, 16*. https://doi.org/10.3389/fpsyg.2025.1523649

Rietveld, R., Van Dolen, W., Mazloom, M., & Worring, M. (2020). What you Feel, Is what you like Influence of Message Appeals on Customer Engagement on Instagram. *Journal of Interactive Marketing, 49*, 20 - 53. https://doi.org/10.1016/j.intmar.2019.06.003

Schreiner, M. S., Fischer, T., & Riedl, R. (2019). Impact of content characteristics and emotion on behavioral engagement in social media: literature review and research agenda. *Electronic Commerce Research, 21*, 329 - 345. https://doi.org/10.1007/s10660-019-09353-8

Stieglitz, S., & Dang-Xuan, L. (2013). Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior. *Journal of Management Information Systems, 29*, 217 - 248. https://doi.org/10.2753/mis0742-1222290408

Tellis, G., Macinnis, D., Tirunillai, S., & Zhang, Y. (2019). What Drives Virality (Sharing) of Online Digital Content? The Critical Role of Information, Emotion, and Brand Prominence. *Journal of Marketing, 83*, 1 - 20. https://doi.org/10.1177/0022242919841034