Information Warfare in Tech Markets:

A Computational Social Choice Model of Influencer Seeding

Shizza Fatima Shafqat

Abstract

Modern technology markets operate much like high-stakes elections, with products acting as candidates and consumers as voters. In these markets, voters frequently update their preferences in response to reviews from influential tech commentators. Social media platforms such as YouTube, Instagram, reddit (etc) often shape consumer opinions much as political endorsements influence electoral outcomes. This report examines what I call **Tech Warfare**, focusing specifically on the practice of **Influencer Seeding**, through the lens of Computational Social Choice. We model the allocation of review units to influential nodes in a social network as a variant of the classic *Bribery* problem. Our analysis centers on annual smartphone releases from major companies such as Google, Apple, and Samsung. Building on the *Shift Bribery over Social Networks* model introduced by Hota et al. (2025), I propose a new framework, **Seeding-Shift-Bribery**, which extends prior work by incorporating two additional dynamics: *Destructive Influence* (negative campaigning) and *Fanboy Resistance* (brand loyalty).

1 Introduction: The Problem of Tech Warfare

1.1 The Market as an Election

The global smartphone market is not only a competition of hardware specifications, it is a battleground of information. Every major product launch can be modeled as an election cycle. The "candidates" are the new devices (e.g., iPhone 16 vs. Pixel 9), and the "voters" are consumers who must cast a single, exclusive vote (purchase) for their preferred ecosystem. The more the purchases, the more revenue the companies can collect. "Information Warfare" is the strategic release of leaks, rumors, and influencer endorsements which is employed to alter the *Preference Profile* of the electorate prior to launch.

1.2 The Specific Problem: Influencer Seeding

This project focuses on one specific vector of this warfare: **Influencer Seeding**. This is the practice where firms send free review units, exclusive access, or sponsorship deals to high-leverage individuals

("Influencers") in the social graph. The firm has a limited budget B (the number of review units). They must select a subset of voters (influencers) to "bribe" (seed). However, the goal is not merely to change the influencer's vote, but to exploit their **Social Network Graph**. By shifting the preference of a central node, the firm hopes to propagate influence to thousands of followers (neighbors), thereby altering the election outcome with minimal direct cost.

1.3 Personal Motivation and Real world Importance

I grew up in a family that debates technology at the dinner table, so I naturally became a devoted follower of creators like Marques Brownlee (MKBHD). Over time, I noticed myself exhibiting what I call "Fanboy Resistance": the irrational tendency to dismiss competing products simply because of ecosystem loyalty (i.e., for me Apple is better than Google regardless of the reviews I hear).

This observation sparked a broader question: what if consumer preferences across the entire tech market follow similar patterns? If so, the way companies seed influencers, release leaks, and shape online conversations may not be intuitive marketing choices but strategic responses to computational constraints in shifting public opinion. Understanding these mechanisms is important for the real world because billions of dollars in product sales and millions of consumer decisions can be influenced by biased reviews or strategic negative campaigns. Modeling these interactions mathematically helps reveal when persuasion is effective, when it fails, and when it becomes manipulative. By formalizing these dynamics, I aim to better understand not only voter and candidate behavior in the abstract, but also how real companies strategize to shape perception, control narratives, and ultimately sell their products.

2 Theoretical Foundation: The Hota et al. Model

To model this phenomenon, I build upon the recent work of Hota et al. (2025), titled *Shift Bribery over Social Networks* [1]. This paper provides the mathematical backbone for understanding how money (or resources) converts into influence in a graph. It models a graph where the first node is the influence, who have "trust weights", meaning how much their followers trust them, and the edges are the followers having weight of influence.

They introduce the concept of "Shift Bribery" in a network context.

1. Instead of paying to swap a vote entirely, the briber pays to move a candidate *forward* (up) in the voter's ranking. The cost is proportional to the distance moved.

2. Voters are nodes in a graph. When a node is bribed to shift a candidate up, they transmit this "shift" to their neighbors.

3. A follower updates their ranking based on the sum of their own direct information plus the weighted influence of the people they follow.

Hota et al model is the backbone of our new model. The model, as described by the paper is the following:

Part 1: The Paper's Model (Hota et al., 2025)

1. Inputs

- C: A set of m candidates $\{c_1, \ldots, c_m\}$.
- V: A set of n voters $\{v_1, \ldots, v_n\}$.
- $\mathcal{P}$: The preference profile, where each voter v_i has a linear ranking $>_i$ over C.
- $G = (V, E)$: A directed, weighted social graph.
- $w(u, v)$: The weight of the edge from voter u to voter v, representing influence strength.
- $p \in C$: The preferred candidate (the one we want to win).
- $s = (s_1, \ldots, s_n)$: The **Shift Vector**.
  - $s_i \in \mathbb{N}_0$: Number of positions candidate p is shifted forward (left) for voter v_i via direct bribery.
- Π: A family of cost functions $\pi_i : [m-1] \to \mathbb{N}$, where $\pi_i(k)$ is the cost to shift candidate p forward by k positions for voter v_i.
- B: The bribery budget.

2. The Mechanism (How it Works)

The model computes an *Effective Shift* for each voter based on direct bribery and social influence.

Effective Shift Formula. For each voter v_i, the effective shift s'_i is:

$$s'_i = s_i + \sum_{j \in N_{in}(i)} \lfloor s_j \cdot w(j, i) \rfloor$$

Explanation.

- s_i: direct bribe to voter i,

- $N_{in}(i)$: the set of voters with edges into i,
- $s_j \cdot w(j,i)$: influencer's shift scaled by trust,
- $\lfloor \cdot \rfloor$: ensures integer (discrete) shifts.

Preference Update. Let $pos_i(p)$ be the original rank of p for voter v_i. Define:

$$pos'_i(p) = \max(1,\ pos_i(p) - s'_i)$$

Candidate p moves up by s'_i positions. All other candidates remain in the same relative order.

Decision Problem. Does there exist a shift vector s such that:

$$\sum_{i=1}^{n} \pi_i(s_i) \leq B$$

and p becomes a winner under the voting rule (Plurality)?

3 The new tech model: Seeding-Shift-Bribery

We define an instance of the *Seeding-Shift-Bribery* problem as a tuple where most of the varibles are the same as the model in the "Shift Bribery over Social Networks" paper:

$$\mathcal{I} = (C, V, G, p, c_{\text{rival}}, B, \Pi, \rho).$$

New Variables

- c_{rival}: The main competitor whose ranking we may want to decrease.
- $\rho = (\rho_v)_{v \in V}$: Resistance vector, where ρ_v measures how stubborn or brand-loyal voter v is.

3.1 Model Modifications

3.1.1 Destructive Influence

In the classical Hota model, bribery is constructive only: the firm pays to move its preferred candidate upward. In real tech markets, firms frequently use negative campaigning (rumor spreading, exposing flaws etc).

Theory: Political science research (e.g., Makulilo 2024) shows negative campaigning is often more cost-effective because it raises doubts about competence and reduces a rival's score.

Scenario: A company quietly pays an influencer to spread a rumor such as "The iPhone 16 overheats easily."

Model Change. We allow *signed* shifts:

$$s_i \in \mathbb{Z}.$$

$$s_i > 0\text{: promote } p \qquad s_i < 0\text{: attack } c_{\text{rival}}.$$

A negative shift propagates through the network and pushes the rival downward in followers' preference lists. If c_{rival} drops below p, then p gains a vote automatically.

3.1.2 Fanboy Resistance

Standard models assume voters adopt influence mechanically. Tech consumers behave differently: Apple loyalists (me) will ignore Pixel praises. Also, if not loyality, many people in the smartphone market find it hard to easily switch to another company, hence, to make it more convenient for them to use their device, they stick to one company.

Interpretation: Influence affects voter v only if

$$|\text{incoming influence}| > \rho_v.$$

Otherwise, the influence is fully blocked. This models "die-hard fans" who do not budge unless the influence signal is overwhelming.

3.2 The Mechanics of the Model

3.2.1 Step 1: Firm Chooses a Shift Vector

The firm selects a shift vector:

$$S = (s_1, s_2, \dots, s_n), \qquad s_i \in \mathbb{Z}.$$

The total cost must obey:

$$\sum_{i=1}^{n} \pi_i(|s_i|) \leq B.$$

$$\text{Positive shift } (s_i > 0): \text{ praise for } p, \qquad \text{Negative shift } (s_i < 0): \text{ attack on } c_{\text{rival}}.$$

3.2.2 Step 2: Network Propagation of Influence

Each voter's incoming influence before resistance is computed as:

$$I_i = s_i + \sum_{j \in \text{Parents}(i)} \lfloor s_j \cdot w(j,i) \rfloor .$$

Constructive Influence (for p).

$$\Delta_i(p) = \max\left(0,\ I_i - \rho_i\right).$$

If resistance dominates, the shift is zero.

Destructive Influence (against $c_{\textbf{rival}}$).

$$\Delta_i(c_{\text{rival}}) = \min\left(0,\ I_i + \rho_i\right).$$

Since $I_i < 0$ in destructive campaigns, adding ρ_i reduces the effective attack. A negative campaign cannot accidentally *help* the rival, its effect is capped at zero. These two equations fully incorporate the modifications of Sections 2.1.1 and 2.1.2.

3.2.3 Step 3: Preference Update

- Product p moves upward by $\Delta_i(p)$ positions.
- Product c_{rival} moves downward by $|\Delta_i(c_{\text{rival}})|$ positions.
- All other products preserve their internal order.

This process yields an updated preference profile $\mathcal{P}'$.

Partial Shifts and Non-Worsening Outcomes. It is also important to note that even when the incoming influence signal exceeds a voter's resistance threshold ρ_v, the resulting shift may be too small to move the target product p all the way to the top position. In many realistic scenarios, the effect of influence is incremental: p may gain only a single position in the ranking rather than becoming the first choice immediately. From the company's perspective, this still provides strategic value. Even a small upward shift, or equivalently, preventing the competitor c_{rival} from pulling further ahead-, can be beneficial. In such cases, the firm is not necessarily making p the outright winner but ensuring that it is *no worse off* than its competitor, which can be a meaningful objective in highly competitive or polarized markets where marginal improvements accumulate over time

3.2.4 Step 4: The Election

We check whether product p has the most first-place votes. If so, the shift vector S is a *successful* strategy.

3.3 The Seeding-Shift-Bribery Decision Problem

Given an instance

$$\mathcal{I} = (C, V, G, p, c_{\text{rival}}, B, \Pi, \rho),$$

the Seeding-Shift-Bribery Decision Problem asks:

Does there exist a signed shift vector $S = (s_1, \ldots, s_n) \in \mathbb{Z}^n$ such that

$$\sum_{i=1}^{n} \pi_i(|s_i|) \le B,$$

and after influence propagation,

$$I_i = s_i + \sum_{j \in \text{Parents}(i)} \lfloor s_j \cdot w(j,i) \rfloor,$$

$$\Delta_i(p) = \max(0,\, I_i - \rho_i), \qquad \Delta_i(c_{\text{rival}}) = \min(0,\, I_i + \rho_i),$$

the resulting updated preference profile $\mathcal{P}'$ produces a Plurality election in which p is the winner?

In other words: *is there a feasible influencer-seeding strategy within budget that guarantees p wins after network propagation and resistance effects?*

4 Analysis and Complexity

We now analyze the computational complexity of the Seeding-Shift-Bribery decision problem. Our main result is that deciding whether a feasible shift vector causes the target product p to win under Plurality is NP-complete. The hardness follows from two prior models: (1) Shift-Bribery with network propagation (Hota et al.), and (2) Approximation and hardness of Shift-Bribery (Faliszewski et al.). Since Seeding-Shift-Bribery generalizes both, it cannot be easier. Because Seeding-Shift-Bribery strictly generalizes both prior models, any algorithm that efficiently solved our problem would also efficiently solve those NP-hard special cases. In complexity terms: if a problem A is NP-hard and can be obtained as a special case of a more general problem B, then B cannot be easier, solving B would immediately solve A.

4.1 Membership in NP

Lemma 1. *The* Seeding-Shift-Bribery *decision problem is in NP.*

Given a shift vector $S = (s_1, \ldots, s_n)$, we can verify success in polynomial time. We compute the total cost $\sum_i \pi_i(|s_i|)$, the incoming influence

$$I_i = s_i + \sum_{j \in \text{Parents}(i)} \lfloor s_j \cdot w(j,i) \rfloor,$$

the effective shifts

$$\Delta_i(p) = \max(0, I_i - \rho_i), \quad \Delta_i(c_{\text{rival}}) = \min(0, I_i + \rho_i),$$

update each ranking accordingly, and check whether p is the Plurality winner. All steps run in time polynomial in $|V|$ and $|C|$. Thus, the problem lies in NP.

4.2 NP-Hardness via Prior Bribery Models

Shift-Bribery over Social Networks. Hota et al. show that with nonnegative shifts, zero resistance, and two candidates, deciding whether bribery can make a preferred candidate win is NP-complete.

Approximation and hardness of Shift-Bribery Faliszewski et al. prove that Shift-Bribery is NP-hard under many positional scoring rules, including Plurality, and is often difficult to approximate.

Because Seeding-Shift-Bribery includes both influence propagation and positional counting, it subsumes these models as special cases.

4.3 Main Hardness Result

Theorem 1. *The* Seeding-Shift-Bribery *decision problem is NP-complete under Plurality, even with two products, identity cost functions, and zero resistance.*

For NP-hardness, we reduce from the model of Hota et al. Given their instance (C, V, G, c, Π, B) with two candidates, construct our instance

$$(C, V, G, p := c, c_{\text{rival}}, B, \Pi, \rho = \mathbf{0}),$$

and restrict attention to nonnegative shifts ($s_i \geq 0$). Under these conditions, our influence term equals theirs:

$$I_i = s_i + \sum_j \lfloor s_j w(j,i) \rfloor = s'_i,$$

and with $\rho_i = 0$, we get $\Delta_i(p) = s'_i$ and $\Delta_i(c_{\text{rival}}) = 0$. Thus, the resulting profile is identical to theirs, and p wins under Plurality iff c wins in their model. Since their problem is NP-complete, so is ours.

4.4 Interpretation

The NP-completeness of Seeding-Shift-Bribery shows that even under highly simplified conditions, computing an optimal influencer-seeding strategy is intractable. This agrees with classical Shift-Bribery hardness results (Faliszewski et al.) and network-based hardness results (Hota et al.). In practice, firms must rely on heuristics, targeting persuadable clusters or exploiting viral negative content, since exact optimization is computationally difficult.

5 Strengths and Limitations of This Analysis

5.1 Strengths

A key strength of this project is that it connects a real tech-market phenomenon important in my generation: how influencers shape consumer choices, to formal models from computational social choice. Building on "Shift Bribery over Social-Networks" and "Approximation and hardness of Shift-Bribery" , the Seeding-Shift-Bribery framework incorporates two realistic features that are happening in the background at all times. The project also formulates a clear decision problem and proves NP-hardness through reductions thanks to the backbone model we used. The biggest strnght is using this already existing concept of shift bribery via social graphs and tweaking it to fit it into a real world model. This shows how models can be re-used and changed to fit any social choice problems. This model can also be applied to other tech examples such as laptops, watches AI bots, and companies can use this strategic marketing for schools, hospitals, not only individual voters. (modelling this model on a institutional level could be a fun problem to look at!)

5.2 Limitations

The model assumes deterministic influence and fixed resistance, whereas real consumer behavior is noisy and loyalty can change over time. It also focuses on hardness rather than designing practical heuristics or algorithms. In addition, the analysis considers only a single election under Plurality, while real tech markets involve repeated launches and evolving reputations. One idea that I tried to incorporate but navigating it in this project was difficult was: where negative influence campaigns can somtimes backfire and increase loyalty toward the rival. This is observed in tech communities, but formalizing it within the signed-shift framework was a bit confucing and produced inconsistencies with the ranking-update mechanism, so I removed it.

5.3 Future Directions

Future work could explore dynamic or probabilistic resistance or heuristic approaches inspired by Shift-Bribery approximation results. Another promising direction is to study *partial* voter preferences: in real markets, consumers often have only incomplete rankings based on leaks or rumors. Determining whether a product can still be a possible winner under partial information would connect this model to "possible winners" research and better reflect pre-launch uncertainty in tech markets.

6 Conclusion

By adapting the *Shift Bribery* framework to include *Destructive Influence* and *Fanboy Resistance*, this report provides a model of modern "Tech Warfare." We have demonstrated that Influencer Seeding is not a simple transaction but a complex graph optimization problem constrained by psychological resistance thresholds. The NP-hardness of the problem suggests that the chaotic nature of product launches is not due to a lack of data, but due to the inherent computational intractability of optimal persuasion. Firms must rely on approximation heuristics, which likely drives the polarization and negativity observed in the market.

References

[1] Hota, A., Dey, P., Bandopadhyay, S., & Thiagu, S. (2025). *Shift Bribery over Social Networks.*

[2] P. Faliszewski, P. Manurangsi, and K. Sornat. Approximation and Hardness of Shift-Bribery. *Artificial Intelligence*

[3] Makulilo, A. (2024). Negative Campaigning and Vote Choice: Rationale, Trends, and Future Research. *International Political Science Abstracts*, 747-762.