



Veridonia: An Online Feed You Can Trust.

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Abstract

Veridonia is an experiment in building an online feed platform that redesigns how feeds are shaped. Rather than amplifying whatever drives clicks, it introduces a governance layer that lets communities decide what deserves visibility in the feed rather than relying on engagement-driven ranking, with the goal of improving the signal-to-noise ratio of what appears there. The system is designed to structure participation so that communities can surface material they find valuable through transparent procedures, randomised review, and accountable decision-making. Throughout this paper, Veridonia’s design is described using five foundational pillars (defined in Section 4): **sortition** (random participant selection), **consensus** (majority-based decisions), a **prediction-based rating system** (reputation from alignment with outcomes), a **multi-stage voting process** (sample-efficient publication decisions), and **transparency & auditability** (inspectable actions and updates). Together, these elements form a curation framework that differs fundamentally from engagement optimisation and offers a testable alternative for building healthier information spaces.

1. Introduction

The digital landscape today is dominated by engagement metrics such as views, likes, and shares, which serve as the primary indicators of content performance. This focus on the attention economy has led to the widespread prioritisation of sensationalist content over substantive information, contributing to the rapid spread of misinformation, the formation of ideological echo chambers, and a general decline in content quality. (1, 2, 3) Furthermore, opaque algorithms that dictate content visibility and maximise engagement at any cost have amplified mistrust and decreased accountability (4).

The current paradigm of social media platforms is increasingly misaligned with the broader interests of society. Rather than facilitating meaningful information exchange, these systems have evolved into attention-capture mechanisms engineered to maximise screen time. Their algorithms prioritise engagement through psychological manipulation, often at the expense of informative or socially valuable content. As a result, content with the highest emotional appeal—not necessarily the highest quality—achieves the greatest visibility, while important discourse is frequently relegated to the margins. In effect, emotionally charged noise is amplified, while informational signal is suppressed.

Chronological feeds are sometimes proposed as a corrective because they avoid engagement optimisation. This is a partial improvement, but it still leaves the core problem unsolved: attention remains scarce, and the burden of prioritisation is pushed almost entirely onto the user. In high-volume communities, “fair ordering” does not reliably produce “good allocation.”

Veridonia is conceived as a response to these challenges. Instead of relying on opaque engagement algorithms, it introduces a structure where communities themselves shape what rises to visibility in the feed through open, verifiable procedures. The emphasis is on rebuilding trust in how feed

curation happens – who participates, how decisions are made, and how influence is earned – rather than asserting any particular view of what information is correct.

2. Problem Statement

Most large-scale social platforms optimise feeds for engagement rather than informational value. Ranking functions are tuned to maximise clicks, reactions, and watch time, not to maximise how much reliable, context-rich information a user receives per unit of attention. This has several predictable, systemic consequences:

1. **Attention is steered toward noise:** Emotionally charged, sensational, or outrage-inducing posts generate more engagement than slower, context-heavy material, and are therefore amplified disproportionately (1, 2).
2. **Misinformation spreads more easily than verification:** False or misleading content is often cheaper to produce, more surprising, and more shareable than careful corrections, allowing it to propagate faster and further in engagement-driven systems (1).
3. **Filter bubbles and echo chambers emerge by design:** Personalisation concentrates a user’s feed around already-reinforced views, limiting exposure to high-signal disagreement and cross-cutting information while repeatedly resurfacing familiar, emotionally resonant material (2, 3).
4. **Curation is opaque and unaccountable:** Proprietary ranking algorithms and limited visibility into moderation decisions make it difficult for users, researchers, or policymakers to inspect how visibility is allocated or to contest systemic failures (4).
5. **There are downstream harms to individuals and society:** Feeds saturated with high-intensity, low-signal content correlate with elevated anxiety, distraction, and reduced well-being, particularly among younger users (5).

Chronological feeds avoid some of these distortions, but introduce different failures at feed scale:

1. **Prioritisation is offloaded to the user:** The feed becomes a firehose in high-volume communities, and users must supply constant attention and effort to find high-signal material.
2. **Visibility becomes path-dependent and unequal:** Early attention and posting time disproportionately shape outcomes; high-quality contributions can be buried by volume and timing rather than judged on their value to the community.

Taken together, these dynamics describe feeds with a chronically low signal-to-noise ratio: scarce human attention is repeatedly captured by vivid but low-information content, while slower, higher-signal contributions struggle to gain visibility. Addressing this requires intervening not just in individual pieces of content, but in the mechanisms that allocate visibility—how posts are selected, who participates in that selection, and how their influence is earned or withdrawn over time.

3. Design Goals: What a Better Feed Should Be

A feed is not just a ranking function. It is a system for allocating scarce collective attention under uncertainty. Veridonia’s technical design is meant to approximate the following properties; these define what “better” means in this paper and make the proposal testable. The mapping from these goals to Veridonia’s five pillars is given in Section 4.

3.1 Representative under uncertainty

Requirement: A feed should reflect what a community would broadly consider worth attention without requiring everyone to participate in every decision. Representation should be statistical, not exhaustive.

Why this matters: Chronological feeds offload all prioritisation onto the user; engagement feeds replace representation with behavioural prediction. Both fail differently.

Implications: For stable communities, decisions on what enters the feed should remain broadly consistent under repeated sampling, and should not depend on a small set of persistent decision-makers.

3.2 Resistant to capture, not dependent on trust

Requirement: A feed should remain usable even when some participants act strategically, maliciously, or in coordination. Safety should come from structure rather than assuming good behaviour.

Why this matters: Many platforms collapse because influence is either cheap to accumulate or permanent once acquired.

Implications: Successful capture should require sustained resources and coordination, with detectable traces in voting patterns and rating movements rather than silent, stable control.

3.3 Open to participation, selective in influence

Requirement: Anyone should be able to participate, but no one should have unlimited or permanent influence. Influence must be earned continuously.

Why this matters: “Low barrier to entry” and “quality control” are usually treated as opposites; a feed-scale system must separate voice from sustained weight.

Implications: New users can participate immediately, but high-impact roles should churn over time; sustained influence should correlate with sustained alignment rather than early accumulation.

3.4 Self-correcting over time

Requirement: A feed should be able to admit error, change its mind, and reallocate influence without manual intervention or regime change.

Why this matters: Engagement systems lock in early outcomes; moderator-centric systems ossify power.

Implications: Influence should be reversible: users (including editors) should be able to lose power through performance, and communities should be able to evolve norms without replacing governance.

3.5 Signal-prioritising by incentive, not intention

Requirement: A feed should not depend on users being wise, informed, or altruistic. It should reward behaviours that produce signal regardless of motive.

Why this matters: Systems that assume better norms will emerge tend to fail under adversarial incentives and scale.

Implications: Users seeking influence should be incentivised to invest effort in judgements that generalise across the community, not merely to maximise engagement or factional mobilisation.

3.6 Legible and contestable

Requirement: Participants should be able to form a mental model of why content appears or does not appear. Decisions should be challengeable without exiting the system.

Why this matters: Opacity destroys trust faster than disagreement.

Implications: Users should be able to answer “why did I see this?” and “why didn’t this appear?” with reference to concrete procedures, and appeals should be visible and tractable.

3.7 Fast enough for daily use

Requirement: A feed that is correct but slow is functionally unusable. Speed is a constraint, not a bonus feature.

Why this matters: Pure deliberation systems do not scale to feed-like latency and volume.

Implications: For typical communities, time-to-decision should fit into daily usage patterns, and per-user review load should stay bounded as content volume grows.

3.8 Procedural, not epistemic

Requirement: A feed should not claim to know what is true, important, or correct. It should claim only that its process is fair, inspectable, and adaptive.

Why this matters: This framing makes the system defensible in pluralistic and adversarial environments, where epistemic consensus is not available.

Implications: Disagreements should be addressable by disputing procedure (sampling, rules, appeals) rather than by appeals to authority or opaque optimisation.

4. Veridonia’s Proposed Solution

Veridonia introduces a community-driven approach to structuring visibility in its online feed. Instead of predicting what will maximise engagement, it delegates decisions about which posts appear in the feed to a sequence of transparent and well-defined steps that organise how participants review content. It does not presume that individual reviewers are free of bias; partiality and local perspective are treated as unavoidable features of human judgement. The design focus is therefore on how those judgements are sampled, combined, and rewarded. The design goals in Section 3 define the target properties of a “better feed”; the pillars below are the tools Veridonia uses to approximate them under online-feed constraints.

1. Sortition (Randomized Participant Selection)

Random sampling broadens representation and limits coordinated control, ensuring that no fixed group consistently decides outcomes and that each decision reflects a changing cross-section of the community.

Design goal	Contribution
3.1 Representative under uncertainty	Samples a changing cross-section of the community rather than a fixed group
3.2 Resistant to capture, not dependent on trust	Makes targeted influence harder by making reviewer selection unpredictable
3.7 Fast enough for daily use	Avoids referenda-scale participation burdens

2. Consensus (Majority-Based Decision-Making)

Simple majority outcomes determine whether a piece of content advances, anchoring decisions in shared community standards rather than opaque algorithmic prediction.

Design goal	Contribution
3.1 Representative under uncertainty	Aggregates sampled judgements into a clear, legible outcome
3.5 Signal-prioritising by incentive, not intention	Keeps the optimisation target explicit and stable
3.6 Legible and contestable	Keeps outcomes contestable via reversible decisions (e.g., re-voting) under a clear rule
3.8 Procedural, not epistemic	Avoids hidden optimisation targets

3. Prediction-Based Rating System

A dynamic rating captures how reliably a participant’s past decisions have matched community outcomes and turns that history into a notion of reputation. This reputation signal governs who is eligible for which responsibilities across the system—for example, participation in higher-impact reviews, moderation roles, and looser throttling.

Design goal	Contribution
3.2 Resistant to capture, not dependent on trust	Makes long-term influence expensive to maintain without continued alignment
3.3 Open to participation, selective in influence	Converts historical alignment into conditional, revocable influence and enables rating-based throttling to limit high-volume low-alignment behaviour
3.4 Self-correcting over time	Reallocates influence after each decision, using zero-sum updates to prevent inflation and force trade-offs
3.5 Signal-prioritising by incentive, not intention	Rewards accurate anticipation of community outcomes rather than declared intentions
3.7 Fast enough for daily use	Reduces required sample size by concentrating decisions where they are most informative
3.8 Procedural, not epistemic	Grounds influence in outcomes rather than credentials

4. Multi-Stage Voting Process for Post Publication

Tiered voting structures how posts move toward publication in community feeds. Early checks expose posts to a broad, low-cost sample, while later checks use smaller panels drawn from higher-rated

participants to approximate the outcome of a much larger community vote with far fewer total ballots.

Design goal	Contribution
3.1 Representative under uncertainty	Approximates large-population outcomes with far fewer votes
3.2 Resistant to capture, not dependent on trust	Reduces attack surface by filtering volume early
3.3 Open to participation, selective in influence	Routes final decisions to reviewers with demonstrated track records without excluding broader participation
3.4 Self-correcting over time	Lets roles expand or contract dynamically as the rating distribution shifts
3.5 Signal-prioritising by incentive, not intention	Concentrates review capacity among participants who have repeatedly produced high-signal judgements
3.7 Fast enough for daily use	Approximates large votes with fewer ballots and less delay

5. Transparency and Auditability

Every moderation action, vote tally, and rating adjustment is publicly visible. This shifts trust away from assumptions about correctness and toward verifiable process, and allows communities to inspect how influence is earned and exercised.

Design goal	Contribution
3.2 Resistant to capture, not dependent on trust	Makes coordinated abuse more visible and investigable
3.6 Legible and contestable	Makes decisions, vote tallies, and rating changes inspectable
3.8 Procedural, not epistemic	Shifts legitimacy from assumed correctness to verifiable process

5. System Architecture

The following components detail the implementation of Veridonia’s five foundational pillars.

5.1 Submission & Review Pipeline

Veridonia evaluates each post that could appear in a community feed through a single, transparent pipeline that combines sortition (random sampling) and tiered majority voting. Random selection at each stage promotes fairness and diversity; tiering by rating concentrates final authority among proven reviewers without excluding broader participation. The mechanism scales with community size: as the population grows, random selection becomes harder to game; in very small communities the system collapses to a simpler single-stage vote.

The structure of this pipeline is chosen to balance three goals: keep decisions representative of the broader community, minimise the number of people who need to vote on any given post, and keep decision latency compatible with a live feed. The concrete stages below are a minimal arrangement that preserves diversity in early checks while concentrating later effort on a smaller set of participants who have demonstrated reliable judgement.

Process Flow

1. **Submit:** The author submits a post to a specific community.
2. **Stage 1: Initial Filter (lower 70% by rating):** A random sample from the lower 70% by rating within that community reviews the post for relevance, informational value, and community alignment.
Outcome:
 - If a simple majority approves, the post advances to Stage 2.
 - If a simple majority rejects, the post is rejected.**Rating:** After this decision, rating adjustments are applied to Stage-1 participants independently of Stage-2 outcomes.
3. **Stage 2: Final Decision (top 30% by rating):** A random sample drawn from the top 30% by rating issues the final decision by simple majority.
Outcome: The post either enters the community feed or does not, depending on the majority decision of the selected reviewers.
Rating: Rating adjustments are applied to Stage-2 participants after the final decision.
4. **Small-Population Mode:** For communities with fewer than 20 members, a single random sample is drawn from all available users. A simple majority decides whether to publish. Rating adjustments are applied to those participants.

Rationale and Manipulation Resistance

- **Sortition:** Random selection reduces the viability of targeted manipulation and collusion.
- **Tiering by rating:** Final decisions are made by users who have consistently shown good judgement in filtering for relevance and quality within the community’s scope, while keeping early checks broad to reflect community diversity and support scalability.
- **Efficiency under feed constraints:** For publication decisions about posts, Veridonia uses a two-stage pattern (Section 5.3) that approximates the decisions of a large one-stage community vote while keeping per-post latency and voter load compatible with a live feed.
- **Scalability:** Larger communities increase the entropy of selection, making coordinated capture more difficult.
- **Transparency:** All votes, outcomes, and subsequent rating changes are publicly logged for auditability.
- **Internal Echo Reduction:** Within a single community, the combination of random selection and majority outcomes tends to reward content that can attract support across factions. This pushes curation toward broadly acceptable signals and dampens the formation of narrow internal echo chambers, while still allowing distinct communities to maintain their own standards.

5.2 Prediction-Based Rating System

As one of Veridonia’s five foundational pillars, the prediction-based rating system reflects how consistently a participant’s prior decisions have matched the outcomes produced by their community. Over time, this identifies contributors whose votes are empirically predictive of full-community outcomes across many decision types. In practice, Veridonia implements this reputation score using an **ELO-style update rule**: after each decision, rating is transferred (zero-sum) from the losing side to the winning side, scaled by how “expected” the outcome was given each side’s

average rating. Higher-rated participants are invited into more consequential review stages, not as arbiters of correctness, but as members whose past participation suggests reliability in navigating the community’s expectations:

- **Dynamic Influence:** Users’ ratings reflect their track record of decisions relative to community outcomes. As these ratings rise, users become eligible for expanded responsibilities—such as participation in Stage-2 review for post publication decisions described in Section 5.3 or, where applicable, appointment as editors. These roles carry more weight in the curation pipeline that governs what appears in the community feed, are fully auditable, and remain conditional on continued performance.
- **Zero-Sum, Team-Weighted ELO Updates:** After the final decision, voters split into two teams: **winners** (their vote matches the outcome) and **losers** (their vote does not). Rating is reallocated zero-sum between these teams and weighted by their relative strength:
 1. Compute each team’s average ELO rating (`winners_avg`, `losers_avg`).
 2. For each participant, compute an update scaled by a constant **K** and the gap between team averages. Members of the **winners** gain rating, moving upward toward the opposing team’s average; members of the **losers** lose rating, moving downward toward the opposing team’s average.
 3. The sum of all gains equals the sum of all losses (zero-sum conservation).
 4. This team-weighted update reinforces effective group-level filtering, amplifying the influence of participants who align consistently with community outcomes and reducing that of those who do not.

Conserving total rating makes influence a scarce resource that can only be reallocated from less predictive to more predictive contributors, rather than inflated across the board. Weighting updates by team strength means that the size of each rating transfer depends on the gap between the average ratings of the winning and losing sides: when a lower-rated group wins against a higher-rated group, the adjustment is larger than when the higher-rated group wins as expected.

Because rating is updated after every decision and across both stages of review, the boundary between lower- and higher-impact roles is permeable. Participants who begin in Stage-1 review can, through a sustained record of alignment with community outcomes, move into Stage-2 and eventually into editorial (moderation) roles, while those whose decisions repeatedly diverge from outcomes will see their influence contract. This continual re-evaluation stands in contrast to rigid, once-appointed moderator classes common on other platforms and is intended to support a more bottom-up, renewable form of authority.

The numerical example below illustrates how these small, bounded adjustments operate in a single vote.

Example: One Voting Stage

Suppose five users have been selected to vote on whether a suggested post A should be published to a community X.

Their initial ratings are **800, 755, 821, 798, and 804**.

Three vote **Yes** (users 1, 4, 5) and two **No** (2, 3). The majority outcome is **Yes**.

Step 1: Compute team averages

$$\mu_W = (800 + 798 + 804)/3 = 800.67$$

$$\mu_L = (755 + 821)/2 = 788.00$$

Step 2: Expected score for winners

$$E_W = \frac{1}{1 + 10^{(\mu_L - \mu_W)/400}} = \frac{1}{1 + 10^{(788.00 - 800.67)/400}} \approx 0.518$$

Step 3: Rating transfer

$$K = 32$$

$$\text{Total gain for winners} = K \times (1 - E_W) = 15.4$$

$$\text{Total loss for losers} = -15.4$$

Step 4: Distribution

Each winner gains $(+15.4/3 = +5.1)$

Each loser loses $(-15.4/2 = -7.7)$

After this round, the new ratings are approximately:

(805, 747, 813, 803, 809)

Although this example describes only one isolated voting stage, the same mechanism repeats continuously across many decisions and participants. Each round transfers small amounts of rating between participants whose votes align with the outcome and those that do not, and over time these micro-adjustments accumulate toward a stable equilibrium. In simulation over extended runs, the system self-organises into a characteristic distribution of ratings—most users cluster around the mean, with smaller groups at the extremes corresponding to more and less consistently predictive reviewers. The figure below shows this emergent pattern.

Local Rating & Elected Cross-Community Stewards (TBD)

Rating remains **strictly local to each community**. A user’s standing in one community neither boosts nor suppresses their standing in another, and no global rating is ever computed. This prevents the rise of “universal elites” and keeps influence contextual to demonstrated expertise.

In the future, Veridonia may introduce a small set of elected cross-community stewards (“chief editors”) with limited administrative powers (e.g., emergency takedowns, cross-community maintenance). Details of their election, scope, and accountability are **to be determined** and may draw inspiration from Wikipedia’s steward model. Crucially, these roles would not mix or merge community ratings, and routine content decisions would remain governed locally.

The rating system also encompasses onboarding and participation controls, detailed below:

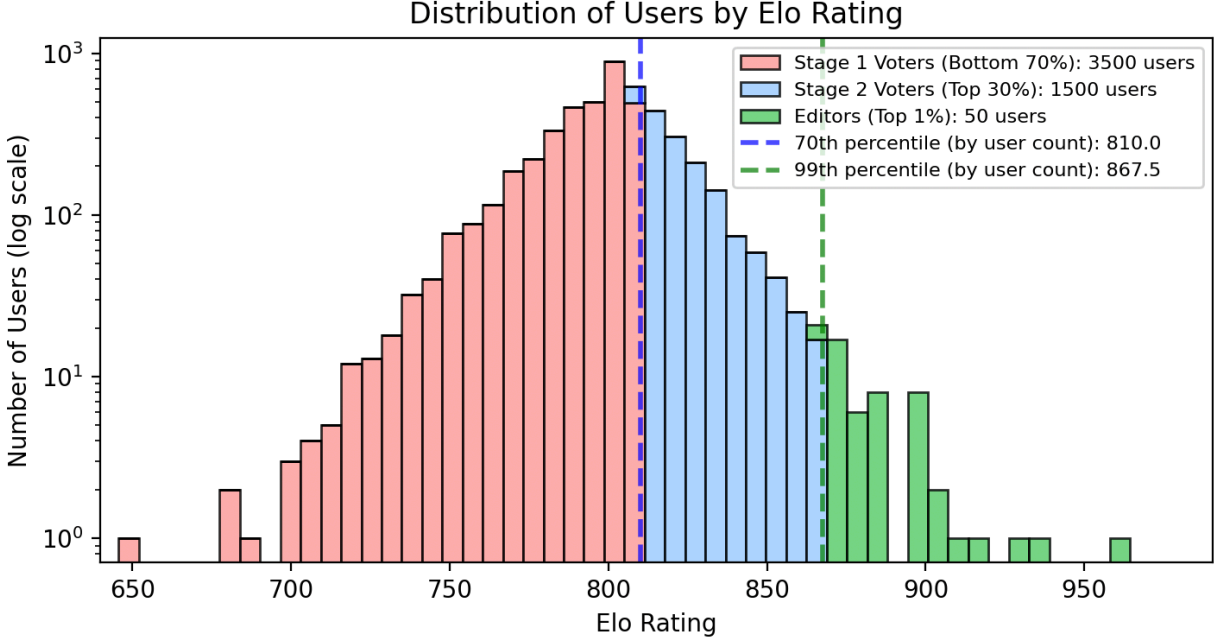


Figure 1: Distribution of Users by Rating. Simulation results showing the equilibrium state produced by repeated voting and rating updates. Most users cluster around the mean, with progressively smaller groups at higher and lower ratings corresponding to the initial and advanced decision groups. Dashed lines mark the 70th and 99th percentiles by user count.

5.2.1 User Onboarding and Baseline Attributes As a pragmatic defence against large-scale automated abuse, Veridonia currently couples initial user rating to an IP-level baseline while treating this mechanism as provisional rather than core to the system’s philosophy.

- **Initial Assignment:** If the IP address has no previous users, a default rating (e.g., 800) is used.
- **IP-Based Rating Inheritance:** To protect the platform from bot attacks and coordinated manipulation, all new users inherit the rating assigned to their IP address. After each voting stage, an IP address is updated to reflect the lowest rating among its associated users. For example, if users from an IP (e.g., 156.156.156.3) have ratings of 850, 700, and 1500, the IP is assigned a rating of 700. Any new users registering from this IP will begin with a rating of 700, capped at a default maximum (e.g., 800) for first-time IPs.

While this IP-based inheritance mechanism mitigates certain manipulation risks, it has clear limitations. Shared or dynamic IP addresses may produce unintended effects—including the penalisation of legitimate users employing privacy-preserving tools (e.g., Tor or VPNs). This mechanism is not foundational to Veridonia’s core philosophy; rather, it functions as an initial, pragmatic safeguard and is expected to evolve as the platform matures. Potential improvements under consideration include community-reviewed verification requests, whereby users could appeal or validate their onboarding status through review by top-rated participants (e.g., the top 30% or designated editors). The precise procedures and governance structures for such processes remain to be determined and will be shaped by community input and further research.

5.2.2 Rating-Based Throttling Mechanism Veridonia implements a throttling system that regulates users’ ability to post based on their rating. Concretely, users with lower rating can post less frequently and experience longer cooldowns between contributions, and as their rating improves these limits are progressively relaxed.

The throttling mechanism serves several critical functions:

1. **Quality Control:** By limiting the volume of content from users with lower rating scores, the system naturally increases the average signal relative to noise in visible content.
2. **Spam Prevention:** Rate limiting creates an effective barrier against automated spam and coordinated manipulation attempts.
3. **Incentivizing Quality:** The direct relationship between contribution privileges and rating motivates users to focus on thoughtful, community-aligned contributions rather than quantity.
4. **Self-Regulation:** The system creates a natural self-regulatory environment where users who consistently provide low-quality content have diminished impact on the community.
5. **Resource Management:** Throttling helps manage computational resources by preventing system overload from excessive low-quality submissions.

This mechanism reinforces Veridonia’s core principle that influence within the community should be earned through demonstrated alignment with community standards and quality contribution.

5.3 Multi-Stage Voting for Posts

Multi-stage voting is used specifically for publication decisions about posts that may enter community feeds. The central design question is how to approximate “what the whole community would decide” without asking a large share of the community to vote on every post.

As a reference point, one could imagine drawing a large random sample of the relevant community for each post and taking a single majority vote. This would provide a direct snapshot of average opinion but would be prohibitively expensive for a live online feed: decision latency would grow, and participants would be overwhelmed by constant review demands.

The two-stage process is an optimisation of this baseline. Stage 1 uses a broad, randomly selected group drawn from the bulk of the community to filter out clearly off-scope or low-value submissions at low cost, preserving diversity and representation while reducing volume. Stage 2 then applies the same majority rule to a much smaller group of higher-rated reviewers whose ratings reflect a history of aligning with past community outcomes. Because these participants have repeatedly demonstrated that their judgements track what the broader community tends to decide, their votes serve as a sample-efficient proxy for a much larger community poll.

In expectation, this arrangement allows Veridonia to achieve outcomes that are comparable to, and on harder or more context-dependent posts potentially better than, those of a single large undifferentiated vote, while requiring far fewer total votes per decision and keeping latency compatible with an online feed. Other decision types—such as editors voting on maintenance proposals—may use a single stage, with each eligible participant carrying equal weight in that vote, while still relying on rating to determine eligibility and to update ratings after the fact.

6. Transparency and Self-Governance

Veridonia is designed to be an open and self-regulating ecosystem:

- **Public Auditability:** All voting records, rating adjustments, and moderation actions affecting what appears in the feed are logged and accessible for independent review, emulating blockchain-like transparency.
- **Decentralised Moderation:** Governance is vested in the community, with every member empowered to contribute, vote, and shape content standards for their feeds. Moderation rights are held by approximately the top 1% of users in a community by rating, who are able to soft-delete posts from the feed to uphold standards. Every moderation action can be appealed by the broader community through a randomized jury voting process.

Privacy by Design and Data Control:

Veridonia does not require sign-up to participate and does not track users across the web. The system only uses minimal signals necessary for fairness—for example, new accounts inherit the lowest rating from their IP to discourage bot farms. Beyond this, rating is tied entirely to actions within the platform: voting, posting, and how those decisions align with the community.

At the same time, users retain full control of their data. All activity histories can be accessed and verified without compromising security, reinforcing both transparency and individual privacy.

7. Additional Core Principles

Independence from Advertiser Influence: Veridonia is free from advertiser funding, ensuring that feed curation is not driven by advertiser incentives and is dictated solely by community standards. The platform will never employ advertising as a monetisation strategy. Instead, future revenue models may involve subscriptions or donations, but public benefit content—such as community feeds—will always remain free to access. Only private benefit features may be offered as paid options, balancing sustainability with Veridonia’s commitment to open access and public good.

8. Conclusion

Veridonia is an experiment in community-guided online feeds. By pairing sortition and tiered voting with a prediction-based rating model (ELO-style), it replaces engagement optimisation with incentives that reward careful participation. Contributions that repeatedly fall outside the community’s standards carry rating and throttling costs, while steady, attentive decisions expand a participant’s role in shaping what the community sees in its feeds. The expectation is that such incentives produce feeds that feel more deliberate, legible, and aligned with the community’s own preferences, with a healthier balance of signal over noise than engagement-driven alternatives.

The next step is empirical: testing the system under real conditions and deliberate stress. We will evaluate how feeds distribute attention between substantive contributions and noise, as well as overall content quality and capture resistance. We will also examine decision latency versus judgement alignment and the fairness of IP-based inheritance to refine both the model and its parameters.

To keep the claims in Section 3 falsifiable, we will measure (a) representativeness under uncertainty via outcome stability across repeated random samples and the concentration of decision power over time (Goals 3.1, 3.3), (b) capture resistance via the cost of influence acquisition, detectable coordination signatures in voting records, and the persistence of any captured state under continued participation (Goal 3.2), (c) self-correction via rating mobility, role churn, and reversibility of high-impact roles after shifts in community outcomes (Goal 3.4), (d) legibility/contestability via audit

usage and appeal outcomes (Goal 3.6), and (e) daily usability via time-to-decision distributions and per-user review load under realistic volume (Goal 3.7). The procedural rather than epistemic framing constrains success criteria to these process-level properties rather than claims of objective correctness (Goal 3.8).

A second question is sustainability. We will evaluate whether a non-advertising model – driven by voluntary support or subscriptions – can fund operations without distorting incentives, while keeping core public-benefit features open.

Ultimately, Veridonia is a falsifiable proposal. If outcomes under real use do not beat practical baselines—or if funding compromises the aims—it should be revised or retired. If they do, the system may be worth iterating on. We invite researchers and communities to test, critique, and adapt these ideas.

9. References

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