

# ScholarChain: A Decentralized Protocol to Restructure Academic Publication and Knowledge Distribution

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## Abstract

Traditional scientific publishing conflates two fundamentally different evaluation tasks: assessing *quality* (correctness, clarity, methodology) and predicting *impact* (novelty, long-term significance). As submission volumes surge, volunteer-based peer review faces mounting challenges: reviewer fatigue, inconsistent evaluations, and a fundamental lack of incentives for rigorous feedback. We present ScholarChain, a decentralized protocol that separates these concerns through distinct mechanisms: a Schelling Point consensus for objective quality review, where reviewers are rewarded for alignment with peers, and bonding curve-based prediction markets for subjective impact assessment, where community members trade “Impact Shares” in papers they believe will prove significant. A dynamic reputation system with temporal decay ensures continued engagement, while multiple resource allocation pathways—token conversion, research fundraising, and bounties—connect demonstrated impact directly to computational infrastructure. We describe the mechanism design in detail, analyze potential attacks and mitigations, and outline an implementation architecture using Ethereum Layer 2, decentralized storage, and zero-knowledge identity verification.

## Introduction

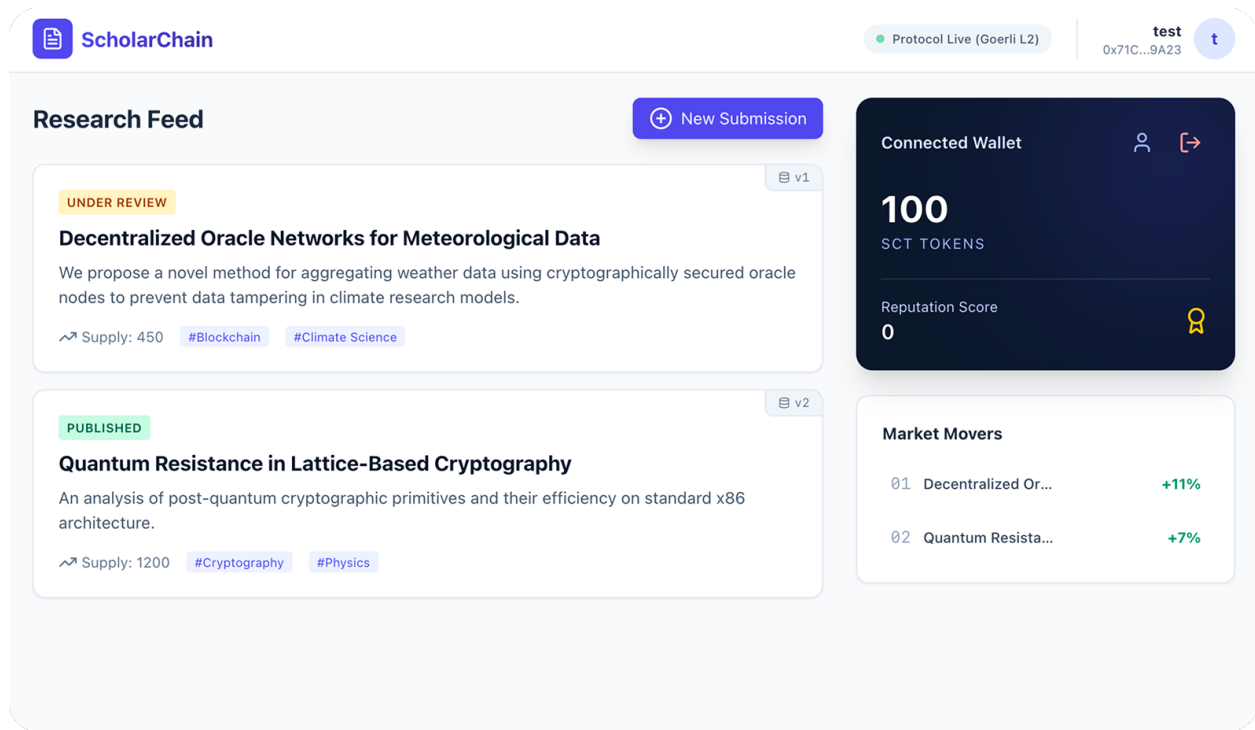
Traditional scientific publishing is built upon an honor-based system optimized for small-scale, slow-paced knowledge dissemination. However, the past few years have witnessed a dramatic surge in academic output—for example, arXiv, the most popular preprint server, now receives over 20,000 submissions per month,<sup>1</sup> and popular machine learning conferences like NeurIPS and ICML receive thousands of submissions each year—challenging the fundamental assumptions underlying this system. The current infrastructure, designed around volunteer peer review and reputation-based trust, was not built to sustain this scale (Morley et al., 2025).

Mechanism design provides a principled framework for aligning individual incentives with collective goals (Jackson, 2003). Recent work has applied these ideas to peer review through market-based reviewer allocation (Meir et al., 2021), peer prediction for incentivizing effort (Radanovic and Faltings, 2016), and token economies for creating labor markets (Ko, 2023). Separately, decentralized systems have developed tools like bonding curves for continuous price discovery (Adams et al., 2020; Hertzog et al., 2017) and Schelling Point mechanisms for decentralized consensus. These tools suggest a path toward restructuring academic publishing around explicit incentive mechanisms rather than relying solely on professional norms.

A key insight motivating our approach is that *quality* and *impact* are fundamentally different properties requiring different evaluation mechanisms. Quality—correctness, clarity, reproducibility—is relatively objective; experts should largely agree. Impact—novelty, long-term significance, influence—is inherently subjective; reasonable experts often disagree, and true impact may only be apparent years later. Existing peer review conflates these, asking reviewers to simultaneously assess both under a single accept/reject decision. We argue they should be separated.

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<sup>1</sup>See [https://arxiv.org/stats/monthly\\_submissions](https://arxiv.org/stats/monthly_submissions) for arXiv submission statistics.



**Figure 1** Mock interface for the ScholarChain protocol, showing the research feed with paper status, Impact Share supply, and market movers.

We propose **ScholarChain**, a decentralized protocol that reimagines academic publication through this separation:

1. **Quality review via consensus:** A Schelling Point mechanism where reviewers commit scores independently and are rewarded for alignment with peer consensus. This filters low-quality work while compensating reviewers for rigorous evaluation.
2. **Impact assessment via prediction markets:** Bonding curves create a continuous market for “Impact Shares” in published papers. Community members stake tokens on papers they believe will prove significant, with early believers rewarded if demand increases. This replaces binary acceptance with a dynamic, crowd-sourced signal of perceived impact.
3. **Impact-to-resource pipelines:** The protocol connects demonstrated research impact directly to computational resources through token conversion, research fundraising, and bounty-based work—reducing the lag between producing influential work and receiving support.

Together, these mechanisms create a unified protocol where submission, review, and curation are all incentive-aligned, while respecting the distinct nature of quality and impact evaluation.

## Related Work

**Peer Review at Scale.** The exponential growth in academic submissions has outpaced the pool of qualified reviewers, leading to fatigue, delays, and inconsistent evaluations (Morley et al., 2025; Bianchi and Squazzoni, 2022). Open Peer Review, where reports are published alongside manuscripts, has been shown to increase review quality through transparency (Bianchi and Squazzoni, 2022). Other reforms include AI-assisted screening (Highwire Press, 2025) and lotteries for funding allocation to reduce bias (Luebber et al., 2025). However, these approaches largely treat peer review as a labor problem rather than an incentive design problem.

**Incentive Mechanism Design.** Mechanism design provides a framework for systems where self-interested agents are incentivized to achieve desired outcomes (Jackson, 2003). Central concepts include *strategyproofness*—ensuring truthful reporting is optimal regardless of others’ actions (Li, 2017)—and *impartiality*—preventing agents from influencing their own outcomes through partitioning schemes (de Clippel et al., 2008; Aziz et al., 2016). The Vickrey-Clarke-Groves mechanism aligns incentives by charging agents for the externalities they impose (Myerson, 1981).

**Mechanism Design for Peer Review.** Recent work applies these principles directly to peer review. Market-based approaches like the “Trading Post” mechanism use virtual currency and dynamic pricing to balance reviewer load (Meir et al., 2021). The Isotonic Mechanism uses authors’ private rankings to calibrate noisy scores (Su, 2021; Wang and Su, 2022). Peer Prediction rewards reviewers when their reports correlate surprisingly with peers, incentivizing effort independent of acceptance decisions (Radanovic and Faltings, 2016; Kong and Schoenebeck, 2019). Token economies, where reviewing earns tokens required for future submissions, have been proposed to create balanced labor markets for evaluation (Ko, 2023). ScholarChain builds on these ideas by combining Schelling Point consensus for quality assessment with bonding curves for impact prediction, creating a unified protocol where submission, review, and curation are all incentive-aligned.

## Mechanism Design

### Submission: Dual-Variable Cost Function

To balance quality control with accessibility, the submission cost  $C$  depends on two factors: the first author’s reputation  $R$  (defined in Section 0.0.0.7) and token stake  $T$ . We use the first author’s reputation rather than averaging across all authors, since senior researchers often appear as last authors with advisory roles rather than primary contributions.<sup>2</sup> This prevents established labs from subsidizing unlimited low-effort submissions.

The cost function takes the form:

$$C = C_{\text{base}} \cdot (1 + e^{-\alpha R}) + T_{\text{min}} \cdot (1 - \beta R) \quad (1)$$

where  $C_{\text{base}}$  is the base submission cost,  $\alpha$  controls how quickly reputation reduces the cost,  $T_{\text{min}}$  is the minimum stake required, and  $\beta \in [0, 1]$  determines the stake discount for reputable authors. For authors with no reputation ( $R = 0$ ), the full base cost and minimum stake apply; for highly reputable first authors, both terms approach zero.

If the submission passes quality review, the stake  $T$  is returned with a yield. If the submission is rejected as low-quality or spam, the stake is slashed. This creates a self-regulating system where established researchers face minimal friction while the staking requirement filters low-effort submissions without creating a pure pay-to-play barrier.

### Quality Review: Consensus-Based Evaluation

The first stage of review assesses *objective quality*—correctness, clarity, methodology, and reproducibility. The protocol employs a Schelling Point mechanism through a commit-reveal scheme:

1. **Commit phase:** Assigned reviewers stake tokens and submit hashed quality scores (1–10) along with their written review. The hash ensures independence—reviewers cannot see others’ scores before committing.
2. **Reveal phase:** After the deadline, all reviews and scores are cryptographically disclosed.
3. **Consensus calculation:** A stake-weighted consensus mean is calculated, giving more weight to high-reputation reviewers.

<sup>2</sup>The protocol can accommodate multiple first authors (equal contribution) by averaging their reputation scores or taking the maximum, depending on the desired incentive structure.

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4. **Rewards and reputation:** Reviewers within one standard deviation  $\sigma$  of the consensus earn token rewards and a boost to their review quality score  $Q_{\text{review}}$ . Extreme outliers (e.g., scoring 10/10 when consensus is 2/10) lose their stake and suffer a reputation penalty.

Crucially, the consensus mechanism applies only to quality scores, where we expect reasonable agreement among experts. Papers passing a quality threshold (e.g., consensus score  $\geq 6/10$ ) proceed to publication; those below are rejected.

Reviewers receive compensation in two stages: an initial payment as proof-of-work for completing the review, and a bonus after the consensus mechanism as proof-of-quality for accurate assessments. The reputation consequences create long-term incentives: consistent, thoughtful reviewers build  $Q_{\text{review}}$  over time, which feeds into their overall reputation  $R$  and reduces their future submission costs.

### **Impact Assessment: Bonding Curves with Review Incentives**

The second stage assesses *subjective impact*—novelty, potential influence, and long-term significance. Unlike quality, reasonable experts often disagree on impact, so we use a market mechanism that embraces divergence rather than penalizing it.

**Why bonding curves over order book exchanges?** Traditional exchanges (e.g., NYSE, NASDAQ, or crypto exchanges like Binance) use order books: buyers post bids, sellers post asks, and trades execute when prices match. This requires sufficient trading volume to maintain liquidity—without active market makers posting tight spreads, order books exhibit wide bid-ask gaps and trades become difficult to execute. Research papers are niche assets; most will never attract enough traders to sustain a healthy order book.

Bonding curves solve this by making the smart contract itself the market maker (Adams et al., 2020; Hertzog et al., 2017; de la Rouviere, 2017). The price is determined algorithmically by the current supply of shares, and users can always buy or sell at the curve price without needing a counterparty. Liquidity is guaranteed by construction, not by market participation.

**Price mechanism.** Community members can acquire “Impact Shares” in published papers. The price to purchase the  $k$ -th share follows a bonding curve:

$$P(k) = m \cdot k^n \quad (2)$$

where  $m > 0$  is the base price multiplier and  $n > 0$  controls the curve’s steepness. The total cost to purchase  $\Delta s$  shares when the current supply is  $s$  is the integral:

$$\text{Cost}(s, \Delta s) = \int_s^{s+\Delta s} m \cdot k^n dk = \frac{m}{n+1} [(s + \Delta s)^{n+1} - s^{n+1}] \quad (3)$$

For example, with  $m = 0.01$  tokens and  $n = 1$  (linear curve), the first 10 shares cost  $\frac{0.01}{2}(10^2 - 0^2) = 0.5$  tokens, while shares 100–110 cost  $\frac{0.01}{2}(110^2 - 100^2) = 10.5$  tokens. Early believers are rewarded; latecomers pay a premium.

**Review incentives.** To encourage substantive engagement without creating friction, we separate trading from reviewing:

1. **Trading:** Anyone can buy or sell Impact Shares at the bonding curve price. No review is required.
2. **Review rewards:** Community members can submit impact reviews explaining why a paper is (or is not) significant. Reviews are upvoted or downvoted by current shareholders.
3. **Bonus shares:** Reviewers earn bonus shares from a fixed reward pool, allocated proportionally based on upvotes.

**Bonus share allocation.** Each paper is allocated a fixed review reward pool  $P_{\text{pool}}$  at publication, funded by a portion of the submission cost.<sup>3</sup> This pool caps the total bonus shares available, preventing inflation and dilution of existing shareholders.

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<sup>3</sup>Alternatively,  $P_{\text{pool}}$  can come from a protocol-level treasury or from trading fees accumulated on that paper.

Bonus shares are distributed among reviewers proportionally to their upvotes:

$$B_i = P_{\text{pool}} \cdot \frac{\max(V_i^+, 0)}{\sum_j \max(V_j^+, 0)} \quad (4)$$

where  $V_i^+$  is the net upvote count for review  $i$ . Reviews with negative net votes receive nothing. This creates competition among reviewers for a fixed pie—the community decides how to allocate rewards based on review quality.

To incentivize timely engagement, the reward pool is distributed in discrete epochs with exponential decay. At each epoch  $k$  (e.g., weekly or monthly), a fraction of the remaining pool is distributed:

$$D_k = P_k \cdot (1 - e^{-\lambda_P}), \quad P_{k+1} = P_k \cdot e^{-\lambda_P} \quad (5)$$

where  $P_k$  is the remaining pool at epoch  $k$ ,  $D_k$  is the amount distributed, and  $\lambda_P$  controls the decay rate. Within each epoch,  $D_k$  is allocated proportionally among reviews based on their current upvotes:

$$B_{i,k} = D_k \cdot \frac{\max(V_{i,k}^+, 0)}{\sum_j \max(V_{j,k}^+, 0)} \quad (6)$$

For example, with  $\lambda_P = 0.5$  and initial pool  $P_0 = 100$ : epoch 1 distributes  $\approx 39$  shares, epoch 2 distributes  $\approx 24$ , epoch 3 distributes  $\approx 15$ , and so on. Early reviewers compete for larger payouts; the system remains open to late contributions but with diminishing rewards.

This design keeps the market liquid while creating a curation layer—share prices reflect aggregate demand, and reviews surface the reasoning behind that demand.

### **Reputation Score: Dynamic Scoring with Decay**

Reputation within ScholarChain is a dynamic score that grows with contributions, decays with inactivity, and decreases with poor behavior. This solves the “tenured professor problem”—researchers cannot rest indefinitely on past achievements but must remain active contributors.

The reputation update rule is:

$$R_{t+1} = (1 - \lambda_R)R_t + \alpha \cdot I_{\text{paper}} + \beta \cdot Q_{\text{review}} \quad (7)$$

where:

1.  $R_t$ : Current reputation score at time  $t$ .
2.  $\lambda_R$  (decay factor): A small decay per epoch (e.g.,  $\lambda_R = 0.01$  per month), ensuring inactive researchers gradually lose influence.
3.  $I_{\text{paper}}$  (paper impact): Derived from citations, Impact Share demand, and downstream usage (e.g., code forks, reproductions).
4.  $Q_{\text{review}}$  (review quality): A score reflecting how helpful and accurate the researcher’s reviews have been.

Reputation is implemented as a non-transferable asset (a Soulbound Token<sup>4</sup>), meaning it cannot be bought, sold, or transferred—only earned through genuine contributions to the protocol.

### **Resource Allocation**

Tokens and reputation accumulated through the protocol can be converted into computational resources through partnerships with decentralized infrastructure providers (e.g., GPU clusters, cloud computing). Beyond direct conversion, we enable two additional mechanisms for researchers to acquire resources:

<sup>4</sup>See <https://www.coinbase.com/learn/crypto-glossary/what-are-soulbound-tokens-sbt>.

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**Research fundraising.** Researchers can raise compute credits by offering Impact Shares in future work. A researcher with a strong track record (high-impact published papers) can pitch a new project to “research ventures”—entities (individuals, DAOs, or institutions) willing to fund promising research in exchange for early Impact Shares. The venture provides compute credits or tokens upfront; in return, they receive a negotiated allocation of Impact Shares in the resulting paper, priced below the initial bonding curve rate. This mirrors venture capital but for research: funders bet on researchers and ideas, and profit if the work proves impactful. Researchers gain resources without waiting for traditional grants.

**Bounty-based research.** Industry partners or community members can post research bounties—specific problems they want solved, features they want implemented, or analyses they need conducted. Bounties are funded with tokens and specify deliverables, deadlines, and acceptance criteria. Researchers claim bounties, complete the work, and receive payment upon acceptance. This creates a market for targeted research: industry gets direct access to academic expertise, and researchers gain an additional income stream for applied work. Completed bounty work can also be published through the standard protocol, accruing Impact Shares independently of the bounty payment.

Together, these mechanisms create multiple pathways from research impact to resources: direct token-to-compute conversion for established researchers, fundraising for ambitious new projects, and bounties for targeted applied work.

## Potential Attacks and Mitigations

**Collusion in quality review.** Reviewers may coordinate to manipulate consensus scores—either to accept low-quality work from allies or reject competitors. The commit-reveal scheme provides partial protection: reviewers cannot observe others’ scores before committing. However, pre-arranged coordination remains possible. Mitigations include: (1) random reviewer assignment with diversity constraints (institutional, geographic), (2) graph-based anomaly detection to flag clusters of reviewers who consistently align on controversial papers, and (3) reputation penalties when a reviewer’s score history shows suspicious correlation patterns with specific author groups.

**Sybil attacks.** An adversary could create multiple identities to game the review consensus or spam submissions. The protocol addresses this through identity verification (ORCID, institutional credentials) and economic staking—each identity must stake tokens to participate, making Sybil attacks costly. Additionally, new accounts start with zero reputation, limiting their influence on stake-weighted consensus calculations until they establish a legitimate track record.

**Lazy reviewing (Schelling Point exploitation).** Rational reviewers might minimize effort by voting toward the expected consensus (e.g., always scoring 6/10) rather than carefully evaluating submissions. Mitigations include: (1) requiring written justifications that are published alongside scores, enabling community scrutiny, (2) periodic “calibration papers” with known ground-truth quality, where reviewers who fail to identify obviously flawed or excellent work suffer reputation penalties, and (3) reviewer matching based on demonstrated expertise, increasing the cost of uninformed voting.

**Market manipulation in impact assessment.** Wealthy actors could purchase large positions in bonding curves to fabricate false impact signals. The protocol mitigates this through reputation-weighted signaling: the visible impact score is a function of both total stake and the reputation of stakers. Capital from low-reputation accounts contributes less to the aggregate signal, privileging expert endorsement over pure capital. Additionally, the bonding curve’s superlinear pricing ( $P(k) = m \cdot k^n$  with  $n > 0$ ) makes large purchases progressively more expensive, limiting whale manipulation.

**Self-citation and impact farming.** Authors might purchase Impact Shares in their own papers or coordinate citation rings to inflate reputation. The protocol tracks authorship and flags self-purchases, which do not contribute to reputation gains. For citation-based reputation components, graph-theoretic analysis (e.g., modified PageRank) detects anomalous clusters with high internal connectivity but low external references, dampening reputation accrual from closed networks.

## Implementation

### Workflow

We summarize the end-to-end workflow:

1. **Registration:** Users connect verified identities (ORCID, institutional email) via ENS and zero-knowledge proofs, establishing an initial reputation score  $R = 0$ . Reputation is stored as a non-transferable Soulbound Token.
2. **Submission:** Authors upload papers to Arweave for permanent storage and pay the dual-variable cost  $C = C_{\text{base}} \cdot (1 + e^{-\alpha R}) + T_{\text{min}} \cdot (1 - \beta R)$ , where low-reputation authors pay higher fees and stakes. The stake is returned with yield if the paper passes review, or slashed if rejected.
3. **Quality review:** Assigned reviewers enter a commit-reveal process: they stake tokens, submit hashed scores (1–10) with written reviews, then reveal after the deadline. A stake-weighted consensus determines the final score. Reviewers within one standard deviation earn token rewards and reputation boosts; outliers lose stakes. Papers scoring  $\geq 6/10$  are published.
4. **Impact curation:** Published papers receive a bonding curve for Impact Shares, where price  $P(k) = m \cdot k^n$  increases with supply. Community members trade shares freely; those who submit upvoted impact reviews earn bonus shares from a decaying reward pool, incentivizing early and substantive engagement.
5. **Reputation update:** After each epoch, reputation decays by  $\lambda_R$  and accrues based on paper impact  $I_{\text{paper}}$  (citations, share demand) and review quality  $Q_{\text{review}}$  (consensus alignment, community upvotes).
6. **Resource conversion:** Tokens are redeemable for GPU hours via DePIN integrations (e.g., Akash, Gensyn). Researchers can also raise compute credits by offering future Impact Shares to research ventures, or earn tokens by completing bounties posted by industry partners.

Figure 1 shows a mock interface for the ScholarChain protocol, illustrating the research feed where users can browse papers under review or published, view Impact Share supply, and track market activity.

### Implementation Details

**Technical Architecture.** The proposed architecture prioritizes security, scalability, and cost-efficiency. Table 1 summarizes the key technology choices.

Layer	Technology	Rationale
Consensus	Base / Arbitrum	EVM compatibility with low transaction costs
Identity	ENS + ZK Proofs	Verify credentials while preserving privacy
Storage	Arweave	Permanent, immutable research artifact storage
Oracles	Chainlink	Ingest off-chain bibliometric data (citations)

**Table 1** Technical architecture of ScholarChain.

**Identity and Reputation.** Reputation is implemented as a Soulbound Token (SBT)—a non-transferable on-chain asset that cannot be bought, sold, or delegated. Identity verification combines ENS domains with zero-knowledge proofs, enabling researchers to prove academic credentials (e.g., ownership of a .edu email) without revealing unnecessary personal information. This preserves pseudonymity while preventing Sybil attacks.

**Resource Allocation Layer.** The protocol token is designed for utility rather than speculation, specifically targeting computational resource acquisition:

1. **DePIN Integration:** The protocol interfaces with Decentralized Physical Infrastructure Networks (e.g., Akash, Gensyn) to provide direct access to GPU clusters and cloud computing.
2. **Direct Redemption:** Tokens function as a medium of exchange for GPU hours, reducing the administrative overhead of traditional grant procurement.

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3. **Conditional Bounties:** External entities can lock tokens in smart contracts, creating bounties released to researchers who verify solutions to specified problems.

## Conclusion and Discussion

We have presented ScholarChain, a decentralized protocol whose key contribution is separating *quality assessment*—where experts should agree, handled via Schelling Point consensus—from *impact prediction*—where disagreement is natural, handled via bonding curve markets. Combined with a decaying reputation system and multiple resource allocation pathways (token conversion, fundraising, bounties), the protocol creates incentive-aligned academic publishing. Important challenges remain: the consensus mechanism may incentivize safe “middle” scores, parameters require empirical tuning, formal game-theoretic analysis would strengthen security guarantees, and bootstrapping a critical mass of users is a practical hurdle.

**Limitations and future work.** Several aspects require further investigation. First, the consensus mechanism for quality review may still incentivize convergence toward safe “middle” scores; calibration mechanisms and more nuanced scoring rubrics could help. Second, the bonding curve parameters ( $m, n$ ) and reward pool decay rates ( $\lambda_P$ ) require empirical tuning—we plan to conduct simulations and pilot deployments to identify robust settings. Third, while we have outlined attack vectors and mitigations, formal game-theoretic analysis of equilibrium behavior under various adversarial models would strengthen the protocol’s security guarantees. Finally, the system’s success depends on network effects; bootstrapping an initial community of researchers and reviewers is a practical challenge orthogonal to mechanism design.

**Broader implications.** ScholarChain represents one instantiation of a broader vision: restructuring knowledge work around explicit incentive mechanisms rather than relying solely on professional norms. The principles explored here—separating objective verification from subjective valuation, using prediction markets for crowd-sourced assessment, and creating direct pipelines from demonstrated value to resources—may apply beyond academic publishing to other domains where quality and impact are conflated, such as open-source software, journalism, or creative work.

**For future translation.** This paper presents the conceptual design and mechanism analysis for ScholarChain. Moving forward, we plan to concretize the implementation by developing smart contracts, building a functional prototype, and conducting user studies to validate the proposed mechanisms. Upon completion, the protocol will be released as open-source software to enable community contributions and real-world deployment.

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