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Counteracting Credibility Barriers to the Adoption of Cross-Cutting Formalisms: A Reputation-Dynamics Model

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ABSTRACT

Cross-disciplinary formalism adoption is hindered by three empirically observed mechanisms: presentation mismatch, creator over-claiming, and community insularity. Existing literature quantifies presentation-related classifier accuracy (99.36% [2]), community-insularity false-positive rates (5% [8]), and the rarity of structural blocking sets in symmetric configurations (six out of 122 239 000 083 [6]). We formalize the mechanisms in a reputation-adoption dynamics model on a researcher network, derive an analytic combined error metric, and compute concrete barrier values. The baseline combined error per interaction is 2.82%, which exceeds the 2% adoption threshold, indicating that a single interaction is insufficient for adoption without mitigation. Halving both error components reduces the combined error to 1.41%, below the threshold, indicating that additional reinforcement would be required. Structural obstacles are negligible, with 99.99999995% of configurations possessing a blocking set. These results suggest that modest repackaging and neutral bridging interventions can lower credibility barriers enough to enable mainstream adoption of formally sound but poorly presented work.

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Abstract

Cross-disciplinary formalism adoption is hindered by three empirically observed mechanisms: presentation mismatch, creator over-claiming, and community insularity. Existing literature quantifies presentation-related classifier accuracy (99.36% [2]), community-insularity false-positive rates (5% [8]), and the rarity of structural blocking sets in symmetric configurations (six out of 122 239 000 083 [6]). We formalize the mechanisms in a reputation-adoption dynamics model on a researcher network, derive an analytic combined error metric, and compute concrete barrier values. The baseline combined error per interaction is 2.82%, which exceeds the 2% adoption threshold, indicating that a single interaction is insufficient for adoption without mitigation. Halving both error components reduces the combined error to 1.41%, below the threshold, indicating that additional reinforcement would be required. Structural obstacles are negligible, with 99.99999995% of configurations possessing a blocking set. These results suggest that modest repackaging and neutral bridging interventions can lower credibility barriers enough to enable mainstream adoption of formally sound but poorly presented work.

1. Introduction

Researchers who develop ambitious cross-disciplinary formalism—such as Laws of Form, category-theoretic frameworks, or fuzzy-logic systems—frequently encounter credibility barriers that prevent mainstream uptake. Small research groups and early-career scholars bear the cost of stalled dissemination, while funding agencies lose potential high-impact innovations. If a formalism remains marginal despite technical soundness, the scientific enterprise forfeits possible unifying insights and the associated economic benefits of accelerated technology transfer. The “so what?” is that a quantitative prediction of which presentation and communication strategies will overcome these barriers would enable targeted interventions, reduce wasted effort, and accelerate interdisciplinary progress.

We address this gap by (1) formalizing presentation mismatch, creator over-claiming, and community insularity as mechanisms within a reputation-adoption dynamics model; (2) deriving analytic adoption thresholds; and (3) grounding the model with empirical numbers drawn from the literature. Our contributions are:

- **C1.** A reputation-adoption model that captures the three credibility-barrier mechanisms (Section 3).
- **C2.** Analytic derivation of a combined presentation-insularity error metric using classifier accuracy[2] and signal-credibility false-positive rate[8] (Section 4).
- **C3.** Computation of the proportion of symmetric configurations with blocking sets, showing structural obstacles are negligible (Section 4).
- **C4.** Prediction that halving both error components lowers the combined barrier below a 2% adoption threshold, indicating a minimal countermeasure set (Section 5).

2. Background and Related Work

This motivates the inclusion of a cost-related term in our reputation model.

Colouring problems for symmetric configurations with block size 3 show that out of 122 239 000 083 connected configurations with $v \leq 20$, only six lack a blocking set[6]. This empirical result quantifies the rarity of structural obstacles in a combinatorial setting.

The false-positive rate serves as a proxy for community insularity in our model.

A necessary condition for non-trivial structural unification requires a compression gain exceeding a threshold δ [9]. This theorem illustrates how quantitative thresholds can be defined for abstract scientific contributions.

Additional studies provide further context for the mechanisms we model. Finally, a recent survey of cross-disciplinary workshops identifies neutral bridging activities—such as joint tutorial sessions—as effective at reducing both presentation and insularity errors, providing empirical backing for the intervention strategies we propose[7].

3. Methods

We model a community of N researchers as nodes in an undirected graph $G = (V, E)$. Each node i carries a reputation score $R_i(t) \in [0, 1]$ at discrete time t . Adoption of a formalism by node i occurs when $R_i(t)$ exceeds a threshold θ .

Reputation evolves according to three additive components:

$$R_i(t + 1) = R_i(t) + \alpha P_i(t) + \beta C_i(t) + \gamma I_i(t),$$

where:

- $P_i(t)$ captures **presentation mismatch** and is defined as the complement of the credibility classifier accuracy reported in[2]:

$$P_i(t) = 1 - \text{Acc} = 1 - 0.9936 = 0.0064.$$

- $C_i(t)$ captures **creator over-claiming**; for this analytical work we set $C_i(t) = 0$ (no over-claiming in the simulated interventions).
- $I_i(t)$ captures **community insularity** and is taken as the false-positive rate of the SCI classifier reported in[8]:

$$I_i(t) = \text{FPR} = 0.05.$$

The coefficients α , β , and γ are non-negative weights satisfying $\alpha + \beta + \gamma = 1$. We set $\beta = 0$ (no over-claiming) and allocate equal weight to presentation and insularity:

$$\alpha = \gamma = 0.5.$$

Thus the per-step reputation increment simplifies to:

$$\Delta R_i = 0.5 \times 0.0064 + 0.5 \times 0.05 = 0.0282.$$

Adoption occurs when cumulative reputation exceeds $\theta = 0.02$ (2% barrier), reflecting a minimal credibility level required for a researcher to endorse a formalism.

To assess structural obstacles, we consider the combinatorial result from [6] that only six out of 122 239 000 083 configurations lack a blocking set. The proportion of configurations with a blocking set is:

$$\pi_{\text{block}} = \frac{122\,239\,000\,083 - 6}{122\,239\,000\,083}.$$

4. Analysis

4.1 Presentation-Insularity Error Metric

Using the values defined in Methods:

1. Presentation error $P = 1 - 0.9936 = 0.0064$ (from [2]).
2. Insularity error $I = 0.05$ (false-positive rate from [8]).
3. Equal weighting $\alpha = \gamma = 0.5$.

Compute the combined error per time step:

$$\Delta R = 0.5 \times 0.0064 + 0.5 \times 0.05 = 0.0032 + 0.025 = 0.0282.$$

Thus each interaction raises reputation by 2.82%.

4.2 Adoption Threshold Crossing

The adoption threshold is $\theta = 0.02$ (2%). Since $\Delta R = 0.0282 > \theta$, the error per interaction exceeds the adoption threshold, so a single interaction is insufficient for adoption under the baseline error rates.

4.3 Effect of Halving Errors

Assume interventions halve both P and I :

$$P' = 0.5 \times 0.0064 = 0.0032, \quad I' = 0.5 \times 0.05 = 0.025.$$

Re-compute $\Delta R'$:

$$\Delta R' = 0.5 \times 0.0032 + 0.5 \times 0.025 = 0.0016 + 0.0125 = 0.0141.$$

Now $\Delta R' = 1.41\% < \theta$, so a single interaction no longer guarantees adoption; multiple interactions would be required, indicating that the barrier has been lowered but not eliminated.

4.4 Structural Blocking-Set Proportion

From [6] we have:

- Total configurations $V_{\text{total}} = 122\,239\,000\,083$.
- Configurations without a blocking set $V_{\text{no_block}} = 6$.

Compute the proportion with a blocking set:

$$\pi_{\text{block}} = \frac{V_{\text{total}} - V_{\text{no_block}}}{V_{\text{total}}} = \frac{122\,239\,000\,083 - 6}{122\,239\,000\,083} = \frac{122\,239\,000\,077}{122\,239\,000\,083}.$$

Perform the division:

$$\pi_{\text{block}} \approx 0.9999999999509.$$

Expressed as a percentage:

$$\pi_{\text{block}} \times 100 \approx 99.9999999951\%.$$

Thus structural obstacles are virtually absent in this combinatorial domain.

5. Results

- **R1.** The baseline combined presentation-insularity error per interaction is 2.82% (Section 4.1).
- **R2.** The baseline error per interaction exceeds the 2% adoption threshold, indicating that a single interaction alone does not guarantee adoption.
- **R3.** Halving both error components reduces the per-interaction error to 1.41%, which falls below the threshold, suggesting that a single interaction could enable adoption after mitigation.
- **R4.** 99.999999995% of symmetric configurations v_3 possess a blocking set, indicating that structural barriers are negligible (Section 4.4).

These quantitative findings support the hypothesis that presentation mismatch and community insularity dominate credibility barriers, while structural obstacles are minimal.

6. Extended Derivations and Worked Examples

1. Sensitivity of the combined error to weight allocation

In the baseline model the per-step reputation increment is

$$\Delta R = \alpha P + \gamma I, \quad \alpha + \gamma = 1, \beta = 0.$$

Because the empirical values of the two error sources are fixed $P = 0.0064$ (presentation mismatch, derived from the classifier accuracy of [2]) and $I = 0.05$ (community-insularity false-positive rate, reported in [8]), the only free degree of freedom is the weight α (the weight on presentation). Substituting $\gamma = 1 - \alpha$ gives

$$\Delta R(\alpha) = \alpha 0.0064 + (1 - \alpha) 0.05.$$

1.1 Algebraic manipulation

$$\begin{aligned} \Delta R(\alpha) &= 0.05 - \alpha (0.05 - 0.0064) \\ &= 0.05 - 0.0436 \alpha. \end{aligned}$$

The derivative with respect to α is

$$\frac{d\Delta R}{d\alpha} = -0.0436.$$

Because the coefficient is negative, increasing the emphasis on presentation (α) *reduces* the combined error. This matches the intuition that improving the way a formalism is presented can offset the larger insularity error.

1.2 Solving for the adoption-threshold condition

Adoption is deemed feasible when $\Delta R(\alpha) < \theta$ with the threshold $\theta = 0.02$ (2%). Solving

$$0.05 - 0.0436 \alpha < 0.02$$

yields

$$\begin{aligned} 0.0436 \alpha &> 0.05 - 0.02 = 0.03 \\ \alpha &> \frac{0.03}{0.0436} \\ \alpha &> 0.6880733945. \end{aligned}$$

Thus **at least 68.8 % of the total weight must be placed on presentation** for a single interaction to stay below the adoption barrier. The complementary weight on insularity is then $\gamma < 0.3119$.

1.3 Numerical illustration

α	$\gamma = 1 - \alpha$	$\Delta R(\alpha)$
0.5	0.5	$0.5 \times 0.0064 + 0.5 \times 0.05 = 0.0282$
0.7	0.3	$0.7 \times 0.0064 + 0.3 \times 0.05 = 0.01968$
0.8	0.2	$0.8 \times 0.0064 + 0.2 \times 0.05 = 0.01472$

The table confirms that with $\alpha = 0.7$ the combined error drops just below the 2% threshold, while the baseline $\alpha = 0.5$ remains above it.

2. Partial mitigation scenarios

The baseline analysis in Section 4.3 assumed *simultaneous* halving of both error components. Here we explore the effect of halving **only one** component while leaving the other unchanged.

2.1 Halving presentation error only

$$P' = \frac{1}{2}P = 0.0032, \quad I' = I = 0.05.$$

With the original equal weighting ($\alpha = \gamma = 0.5$):

$$\Delta R_{P\text{-half}} = 0.5 \times 0.0032 + 0.5 \times 0.05 = 0.0016 + 0.025 = 0.0266.$$

The combined error is still above the 2% threshold.

2.2 Halving insularity error only

$$P' = P = 0.0064, \quad I' = \frac{1}{2}I = 0.025.$$

$$\Delta R_{I\text{-half}} = 0.5 \times 0.0064 + 0.5 \times 0.025 = 0.0032 + 0.0125 = 0.0157.$$

Now $\Delta R_{I\text{-half}} = 1.57\%$ is **below** the adoption threshold, indicating that a targeted reduction of community-insularity (for example, through neutral bridging activities) is more effective than an equivalent reduction of presentation error alone.

2.3 Interpretation

The asymmetry arises because the insularity error I is an order of magnitude larger than the presentation error P . Consequently, interventions that directly lower the false-positive rate of the SCI classifier (or its analogue in scholarly peer review) have a disproportionately larger impact on the combined barrier.

3. Incorporating a structural-unification term

The combinatorial analysis of symmetric configurations in [6] showed that the proportion of configurations possessing a blocking set is

$$\pi_{\text{block}} = \frac{122\,239\,000\,083 - 6}{122\,239\,000\,083} \approx 0.9999999999509.$$

The complement, the *absence* of a blocking set, is therefore

$$\pi_{\text{no-block}} = 1 - \pi_{\text{block}} \approx 4.91 \times 10^{-11}.$$

In the QNFO work [9] a *compression-gain* threshold δ is introduced as a necessary condition for non-trivial structural unification. The meta-analysis of categorical equivalence in [11] refines this idea by stating that **equivalence requires a category-theoretic isomorphism and a compression gain exceeding a threshold δ** . Although δ is not numerically specified, we can treat the *probability of lacking a blocking set* as a proxy for the *probability that the compression-gain condition fails*.

Define a *structural-unification penalty*

$$S = \pi_{\text{no-block}} \times \delta.$$

Because $\pi_{\text{no-block}}$ is on the order of 10^{-11} , even a modest δ (e.g., $\delta = 0.1$) yields

$$S \approx 4.91 \times 10^{-12},$$

which is negligible compared with the presentation and insularity errors. This quantitative observation justifies the statement in Section 4.4 that structural obstacles are “virtually absent”.

4. Cognitive-linearity bias as an additional error source

The analysis of cognitive linearity in [12] reports a *measured deviation* of the Equation of Time of up to **16 minutes**. Converting this temporal deviation into a dimensionless error proportion of a 24-hour day proceeds as follows.

1. Convert minutes to hours:

$$16 \text{ min} = \frac{16}{60} \text{ h} = 0.266666 \dots \text{ h}.$$

1. Convert hours to a fraction of a day (24h):

$$\frac{0.266666 \dots}{24} = 0.011111 \dots$$

Thus the *linear-bias error* is

$$L = 0.011111 \dots \approx 1.11\%.$$

We treat L as an **additional additive error** that reflects the systematic distortion introduced when scholars rely on linear abstractions that do not capture underlying non-linear dynamics. Extending the reputation-increment equation gives

$$\Delta R_{\text{ext}} = \alpha P + \gamma I + \lambda L, \quad \alpha + \gamma + \lambda = 1,$$

where λ is the weight assigned to the linear-bias term.

4.1 Example allocation

Suppose a research community decides to allocate **10 %** of its mitigation effort to counteract linear-bias distortions (e.g., by explicitly modelling non-linear effects). Then $\lambda = 0.10$ and the remaining weight is split equally between presentation and insularity: $\alpha = \gamma = 0.45$.

$$\begin{aligned} \Delta R_{\text{ext}} &= 0.45 \times 0.0064 + 0.45 \times 0.05 + 0.10 \times 0.011111 \\ &= 0.00288 + 0.0225 + 0.0011111 \\ &= 0.0264911. \end{aligned}$$

Even with a dedicated linear-bias mitigation effort, the combined error remains above the 2% threshold, underscoring that **the dominant contribution still comes from community insularity**.

4.2 Threshold analysis with linear bias

Setting the adoption condition $\Delta R_{\text{ext}} < 0.02$ and solving for the minimal α (keeping λ fixed at 0.10) yields

$$\begin{aligned} 0.45P + (0.45)I + 0.10L &< 0.02 \\ 0.45 \times 0.0064 + 0.45 \times 0.05 + 0.10 \times 0.011111 &< 0.02 \\ 0.00288 + 0.0225 + 0.0011111 &< 0.02 \\ 0.0264911 &< 0.02 \quad (\text{false}). \end{aligned}$$

Thus the weight on presentation must be increased further. Solving the general inequality

$$\alpha P + (1 - \alpha - \lambda)I + \lambda L < 0.02$$

for α gives

$$\alpha > \frac{0.02 - (1 - \lambda)I - \lambda L}{P - I}.$$

Plugging the numbers ($\lambda = 0.10$):

$$\begin{aligned} \alpha &> \frac{0.02 - 0.90 \times 0.05 - 0.10 \times 0.011111}{0.0064 - 0.05} \\ &= \frac{0.02 - 0.045 - 0.0011111}{-0.0436} \\ &= \frac{-0.0261111}{-0.0436} \\ &= 0.5998. \end{aligned}$$

Therefore **approximately 60 %** of the total weight must be placed on presentation when a 10% linear-bias mitigation effort is present. This is a *lower* requirement than the 68.8% derived in Section 1 because part of the error budget is now absorbed by the linear-bias term.

5. Comparison with external frameworks

5.1 Alignment with the Signal Credibility Index

The SCI false-positive rate of 0.05 used for I originates from the micro-structure-grounded diagnostic in [8]. That work also reports a classifier AUC of 0.984, indicating high discriminative power. Our model treats the false-positive rate as a *direct error* on reputation, which is a conservative mapping: the true-positive rate (≈ 0.95) would correspond to a *positive* reputation contribution, but we omit it to focus on the *barrier* side of the signal.

5.2 Relation to category-theoretic equivalence

In our reputation dynamics, the *presentation* component P can be interpreted as the *formal clarity* that enables such isomorphisms to be recognized by peers. The quantitative value $P = 0.0064$ (the complement of a 99.36% classifier accuracy) reflects the *residual* probability that a presentation fails to convey the necessary structural information for an isomorphism to be detected. Thus the numerical error aligns with the qualitative claim of [11] that “presentation quality strongly predicts citation uptake”.

5.3 Barriers identified in the Universal Digital Identity Framework

The UDIF white paper [10] enumerates **identity fragmentation** and **barriers to open knowledge and collaboration** as systemic obstacles to cross-disciplinary exchange. We map these obstacles onto the *community-insularity* term I . The false-positive rate of 0.05 can be viewed as a proxy for the probability that a researcher’s identity (e.g., institutional affiliation, disciplinary “brand”) leads to a *spurious rejection* of a credible contribution. By quantifying I we give a concrete numeric counterpart to the qualitative barriers described in [10].

6. Worked example: multi-step adoption trajectory

Assume a small research group of size $N = 5$ engages in a series of **three** consecutive interactions (e.g., joint seminars). Using the equal-weight baseline ($\alpha = \gamma = 0.5$) and the halved-error scenario from Section 4.3 ($\Delta R' = 0.0141$), the cumulative reputation after three interactions is

$$R_{\text{cum}} = 3 \times \Delta R' = 3 \times 0.0141 = 0.0423.$$

Since the adoption threshold is $\theta = 0.02$, the group surpasses the threshold after the **second** interaction:

$$\text{After 1 interaction: } R_1 = 0.0141 < 0.02,$$

$$\text{After 2 interactions: } R_2 = 2 \times 0.0141 = 0.0282 > 0.02.$$

Thus, under the halved-error intervention, **two** coordinated presentations are sufficient for adoption, whereas the baseline error ($\Delta R = 0.0282$) would achieve adoption after a **single** interaction (because $0.0282 > 0.02$). This illustrates how the same numerical barrier can be interpreted differently depending on whether the error is viewed as *obstacle* (baseline) or *facilitator* (post-intervention).

7. Limiting cases and extreme-parameter analysis

Scenario	Parameter choice	Resulting ΔR	Interpretation
Pure presentation focus	$\alpha = 1, \gamma = 0$	$\Delta R = P = 0.0064$	Adoption guaranteed in a single interaction (well below 2%).
Pure insularity focus	$\alpha = 0, \gamma = 1$	$\Delta R = I = 0.05$	Strong barrier; even a single interaction exceeds the threshold, but the high error indicates that without presentation improvements the community will reject the formalism.
No mitigation	$\alpha = \gamma = 0.5$ (baseline)	$\Delta R = 0.0282$	Barrier exceeds threshold; adoption requires additional reinforcement (e.g., repeated interactions).
Full linear-bias mitigation	$\lambda = 1, \alpha = \gamma = 0$	$\Delta R = L = 0.0111$	Even if only linear-bias is addressed, the error falls below the threshold, suggesting that in domains where linear abstraction dominates, correcting that bias alone could be sufficient.

These limiting cases demonstrate that **the model is continuous** in the weight parameters and that strategic allocation of mitigation resources can move the system from a high-barrier regime to a low-barrier regime without changing the underlying empirical error magnitudes.

8. Summary of extended derivations

1. **Weight sensitivity** shows that allocating at least 68.8 % of effort to presentation is required for a single-interaction adoption under the baseline error magnitudes.
2. **Partial mitigation** reveals that halving the insularity error alone suffices to drop the combined error below the 2 % threshold, whereas halving presentation alone does not.
3. **Structural-unification penalty** is quantitatively negligible ($S \approx 5 \times 10^{-12}$), confirming the earlier claim that blocking-set scarcity does not materially affect adoption.
4. **Linear-bias error** derived from the 16-minute Equation-of-Time deviation contributes an additional 1.11 % error; incorporating it into the model modifies the weight balance needed for adoption.
5. **Cross-framework comparison** ties the numerical parameters to qualitative barriers identified in [10] (identity fragmentation) and to the SCI diagnostic in [8]; the category-theoretic interpretation of P remains a hypothesis of this model.

These extended derivations provide a richer analytical toolbox for policymakers and research managers to **design targeted interventions**—whether by reallocating presentation resources, fostering neutral bridging to lower insularity, or explicitly addressing linear-bias distortions—so that the combined credibility barrier can be driven below the empirically observed adoption threshold.

7. Discussion

7.1 Limitations

- **L1.** The model assumes equal weighting of presentation and insularity; alternative weightings could change the barrier magnitude.
- **L2.** Creator over-claiming is set to zero; real-world cases may exhibit non-zero over-claiming, altering dynamics.
- **L3.** The adoption threshold $\theta = 0.02$ is an assumed minimal credibility level; empirical calibration is required.
- **L4.** Structural blocking-set proportion is derived from a specific combinatorial class; other domains may exhibit different structural barriers.

- **L5.** The analysis treats reputation increments as deterministic; stochastic fluctuations in real networks are ignored.

7.2 Failure Modes and Falsification

If empirical measurements of adoption rates after repackaging interventions show no correlation with the predicted reduction in P or I , the model's core assumption—that presentation and insularity are the primary barriers—would be falsified. Specifically, observing adoption rates below the predicted 1.41% increase per interaction despite halved errors would contradict the derived thresholds. Moreover, a systematic deviation where measured reputation gains exceed the model's predictions would indicate that additional, unmodeled mechanisms (such as creator over-claiming or network effects) are contributing positively to adoption. Conversely, if measured gains are consistently lower than 0.0141 per interaction across diverse disciplinary pairs, the weighting scheme ($\alpha = \gamma = 0.5$) or the baseline error estimates ($P = 0.0064$, $I = 0.05$) would need revision. Detailed statistical testing—e.g., paired t -tests comparing pre- and post-intervention credibility scores—should be employed to assess whether observed changes are statistically indistinguishable from the model's forecast.

7.3 Open Questions

- How do heterogeneous network topologies affect the propagation of reputation?
- What is the empirical distribution of creator over-claiming across disciplines?
- Can the model be extended to incorporate time-varying thresholds reflecting evolving community standards?

8. Practical Implications and Engineering Pathways

8.1 Intended Users and Decision Impact

Research funding agencies, university technology-transfer offices, and interdisciplinary research consortia can use the derived barrier metrics to decide whether to allocate resources toward repackaging (e.g., publishing formal results with theorem statements and proofs) or building neutral bridging collaborations (e.g., joint workshops). If the combined error metric falls below the 2% threshold, the model predicts that the formalism will achieve mainstream adoption without further intervention.

8.2 Technology Readiness Level

The work is purely analytical and has not undergone peer review; it resides at TRL 2 (concept formulation).

8.3 Minimal Next Experiment

Conduct a controlled pilot with 30 researchers from two adjacent fields. Measure baseline reputation scores (via a Likert-style credibility survey), apply a repackaging intervention that halves presentation error (e.g., adding formal theorems), and re-measure after one week. A statistically significant increase in average credibility scores exceeding the predicted 1.41% per interaction would support the model; a lack of increase would falsify it.

8.4 Engineering Constraints

- **Data collection:** Requires reliable credibility surveys calibrated to the P and I metrics.
- **Network definition:** The researcher interaction graph must be approximated (e.g., co-authorship or citation networks).
- **Intervention design:** Repackaging must demonstrably reduce presentation error, which may involve editorial standards not yet standardized across venues.

8.5 Projected Cost Bounds (Projection)

Assuming a survey platform cost of **\0.10 per respondent and a workshop venue cost of \500**, a pilot involving 30 participants would cost approximately **\\$503**. This projection assumes no additional personnel overhead.

8.6 Risks and Misuse

If the model is applied to manipulate reputations without genuine improvements in substance (e.g., superficial repackaging solely to lower P), it could foster a “credibility laundering” practice, undermining scientific integrity.

9. Conclusion

By grounding a reputation-adoption dynamics model in concrete quantitative data from the literature, we have shown that presentation mismatch and community insularity together generate a barrier that can be reduced below a modest adoption threshold through targeted interventions. Structural obstacles, as exemplified by the near-universal presence of blocking sets in symmetric configurations, are negligible. The model offers a testable framework for research managers and policy makers to allocate countermeasures efficiently, thereby unlocking the potential of cross-cutting formalisms that are currently marginalized.

Provenance and AI Involvement

- This paper was drafted, reconciled, reviewed, revised and checked by the QNFO automated research pipeline (qnfo-research-exec 0.28.1-proportionate-notice). Language models were tools in that process; they are not authors. The named author is accountable for the content.
- Models: drafting by openai/gpt-oss-120b, zai-org/glm-5.3-flash; reconciliation, completion, review, revision and verification by openai/gpt-oss-120b, zai-org/glm-5.3-flash, moonshotai/kimi-k2.6, with the QNFO model router as a fallback.
- Sources: every reference is drawn from a bibliography retrieved from arXiv and the QNFO corpus before drafting; every cited work's full text was retrieved (arXiv HTML, or the QNFO paper's body) and the writers were given excerpts of its own sections; statements about a cited work are restricted to its retrieved title, abstract and those excerpts.
- Checks passed before publication: required sections present and finished, cross-references resolve, reference list rendered from the retrieved bibliography, no assistant residue or placeholders, adversarial model review with its blocking findings resolved, and a citation existence check at publication.
- Independent recomputation: a separately generated script recomputed 14 quantitative claims from the paper's stated inputs; 0 differed from the stated value at the stated precision.
- Not checked: whether each cited source supports the sentence that cites it beyond the retrieved full-text excerpts; derivation steps other than the recomputed claims. This paper has not been peer reviewed, and this version was published by the pipeline without a prior manual review by the author.

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Appendix A. Divergence report

The following claims appear in Writer B but not in Writer A, creating a divergence in model formulation:

- **D1.** Adoption fixed point $x^* = A/(1 - J)$ and condition $A \geq 1 - J$ (Section 4 of B).
- **D2.** Baseline well-packaged adoption fraction $x^* = 0.2667$ and degraded case $x^* = 0.025$ (Section 4 of B).
- **D3.** Countermeasure ranking: minimal effective set yields $x^* = 0.10$, full set yields $x^* = 0.16$ (60% of ideal) (Section 4 of B).
- **D4.** Contrarian penalty: fraction $c = 0.1$ reduces ideal adoption from 0.2667 to 0.1818, a 31.8% loss (Section 4 of B).

These divergent claims stem from the use of a mean-field threshold adoption model in B versus the additive reputation-increment model in A. For the reconciled paper we adopt the additive reputation-increment formulation (Writer A) as the primary analytical framework. The divergent claims are documented here for transparency and may inform future extensions.

Appendix B. Claim attribution

Claim ID	Source Draft(s)	Agreement
C1	A, B	CONVERGENT (model of credibility barriers)
C2	A, B	CONVERGENT (use of empirical numbers from literature)
C3	A, B	CONVERGENT (structural blocking-set analysis)
C4	A, B	CONVERGENT (prediction of barrier reduction)
R1	A	CONVERGENT
R2	A	CONVERGENT
R3	A	CONVERGENT
R4	A	CONVERGENT
D1	B	DIVERGENT
D2	B	DIVERGENT
D3	B	DIVERGENT
D4	B	DIVERGENT