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# An attention economy model of co-evolution between content quality and audience selectivity

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# AN ATTENTION ECONOMY MODEL OF CO-EVOLUTION BETWEEN CONTENT QUALITY AND AUDIENCE SELECTIVITY

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## ABSTRACT

Human attention has become a scarce and strategically contested resource in digital environments. Content providers increasingly compete for visibility, often prioritizing attention-grabbing tactics over substantive quality. Despite extensive empirical evidence, few theoretical models explain the fundamental dynamics of the attention economy. Here, we develop a minimal mathematical framework for how content quality and audience attention coevolve under limited attention capacity. Using an evolutionary game approach, we model strategic feedback between providers, who decide how much effort to invest in production, and consumers, who choose whether to search selectively for high-quality content or engage passively. Analytical and numerical results reveal three characteristic regimes: collapse, boundary, and coexistence. Transitions between these regimes depend on how effectively audiences distinguish content quality. When audience discriminability is weak, both selective attention and high-quality production vanish, leading to informational collapse. When discriminability is sufficient and incentives are aligned, high- and low-quality content dynamically coexist through feedback between audience selectivity and provider effort. These findings identify two conditions for sustaining a healthy information ecosystem: adequate audience discriminability and sufficient incentives for high-effort creation. The model provides a theoretical foundation for understanding how institutional and platform designs can prevent the degradation of content quality in the attention economy.

***K*eywords** Attention economy · Adaptive feedback · Replicator dynamics

## Introduction

In today's digital society, the attention economy has become a central paradigm for understanding online information ecosystems. Human attention functions as a limited resource subject to intense competition [1, 2, 3, 4, 5, 6, 7]. This competition unfolds across digital media spaces, including news and social media platforms, video-sharing sites, and live-streaming environments [8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19], where user-generated and professional content continually vie for visibility. As digital platforms lower the barriers to content creation, the volume of online content

has surged. This expansion has intensified competition for user attention and enabled even low-quality material to spread widely [20, 21]. This imbalance between abundant content and users' limited capacity to process it highlights the fundamental scarcity of attention in online environments.

A widely observed pattern in such competitive environments is the proliferation of low-effort content, including clickbait, optimized to exploit platform algorithms and maximize short-term engagement [22, 23, 24]. Economic models show that competition for fragmented attention can depress information quality [25] and may even incentivize misinformation when short-term gains outweigh long-term credibility [26]. Recent advances in generative AI have amplified these pressures. They enable the rapid production of large volumes of text, images, and videos at minimal cost [27, 28, 29]. Although these strategies may be economically rational for individual providers, they collectively threaten the long-term viability of high-quality content and the informational health of online ecosystems. These observations raise a fundamental question: under what conditions can high-quality content remain sustainable in environments where limited attention is strategically distributed?

To address this question, it is essential to recognize that online information environments are shaped by the strategic adaptations of both content providers and consumers. Providers adjust their production strategies in response to competitive pressures and anticipated visibility. Consumers allocate their attention based on perceived credibility and content quality. These reciprocal adjustments create feedback loops that shape the evolving relationship between content production and attention allocation [30, 31, 32]. Previous studies have largely examined either collective attention patterns or individual attention decay [33, 34, 9, 35]. However, these approaches do not capture how providers and consumers jointly adapt under attention constraints. A theoretical framework that integrates their coadaptive behaviors and clarifies how such constraints shape long-term evolutionary outcomes is still lacking. In particular, many existing models treat attention allocation and content quality as exogenous, which limits their ability to capture the feedback between the two. As a result, how limited attention shapes the coevolution of quality provision and consumer behavior remains insufficiently understood.

Building on these observations, we develop a theoretical framework that explains when high-quality content can persist under limited attention. Unlike previous approaches that examine attention flows or individual behavior in isolation, our model jointly captures the strategic adaptation of content providers and consumers under explicit attention constraints. We construct a two-population evolutionary game with behavioral microfoundations, in which interactions under finite attention capacity generate a piecewise-smooth replicator system derived through a mean-field approximation. This formulation enables us to analytically identify the parameter thresholds that separate collapse, boundary, and coexistence regimes, providing a unified account of how attention constraints shape the long-term evolutionary dynamics of content quality.

Our analysis reveals that limited attention induces a fundamental divide in content dynamics: without sufficient discriminability, systems generically collapse into low-quality convergence, whereas boundary outcomes and stable coexistence arise only under specific combinations of attention capacity and providers' incentive strength. These evolutionary patterns clarify when high-effort content can persist in attention-driven environments and offer theoretical guidance for designing platforms that maintain informational quality. We formalize these mechanisms by introducing the evolutionary framework on which our analysis is based.

# Results

### Attention Economy Model

To formalize the coadaptive mechanisms discussed above, we construct a minimal evolutionary framework that captures how content quality and audience attention coevolve under limited cognitive resources. Digital environments are characterized by intense competition for visibility, which makes the incentives of providers and consumers inherently interdependent. The structure of the model is summarized in Fig. 1.

Content providers choose between two strategies. Under the high-effort strategy $H$, they produce high-quality content at a cost $c_H > 0$. Under the low-effort strategy $L$, they generate lower-quality content with no additional cost. We consider a fixed population of $m$ providers, each producing one item of content per period, regardless of strategy. Providers receive a reward $r > 0$ per view, so the payoff advantage of high-effort production depends on how consumers allocate attention across available items. The reward $r$ is identical for high- and low-quality items, reflecting platform environments, such as video-sharing platforms, where provider revenue is largely determined by view counts rather than intrinsic content quality.

Consumers also choose between two strategies. Under the active strategy $A$, they search for and selectively consume high-quality items while paying a per-period cost $c_A > 0$ that represents search and evaluation effort. Under the passive strategy $P$, they allocate their attention budget uniformly across all items produced. We consider a fixed population

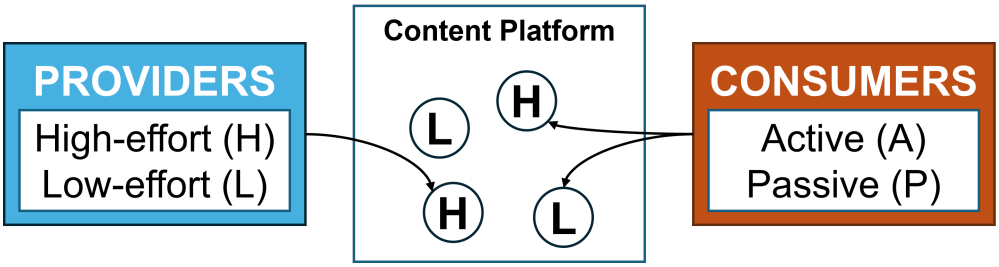



Figure 1: Conceptual diagram of the attention economy model. Providers invest high (H) or low (L) effort in content creation, while consumers allocate limited attention ($\sigma$) through active (A) or passive (P) viewing. Their strategic feedback determines the evolution of content quality and attention distribution.

Table 1: Summary of model parameters.

| Symbol | Description |
|---|---|
| $m$ | Number of content providers |
| $n$ | Number of content consumers |
| $\sigma$ | Attention capacity (fraction of attendable items) |
| $b_H$ | Benefit obtained from a high-quality item |
| $b_L$ | Benefit obtained from a low-quality item |
| $c_H$ | Cost of adopting the high-effort strategy |
| $c_A$ | Cost of adopting the active viewing strategy |
| $r$ | Reward per view received by providers |
| $x(t)$ | Fraction of high-effort providers at time $t$ |
| $y(t)$ | Fraction of active consumers at time $t$ |

of $n$ consumers, each with a limited attention capacity $\sigma \in (0, 1]$, which allows them to consume only a fraction $\sigma$ of items produced in each period. Consumer benefits from each item are additively separable.

Attention is treated as a scarce cognitive resource. The parameter $\sigma$ formalizes this constraint by limiting each consumer's attention budget, forcing providers to compete for inclusion within a narrow attention window. As a result, visibility becomes a key determinant of provider incentives and directly reflects consumer selection behavior. A key implication of this assumption is that attention scarcity enters payoffs directly, creating a qualitative shift in incentives depending on whether high-quality supply is sufficient to saturate consumers' attention budgets. The boundary $x = \sigma$ thus marks the point at which active consumers can fully satisfy their attention budgets using only high-quality items, eliminating any residual allocation to low-quality content and altering the payoff structure accordingly.

Given these incentives, the composition of strategies in each population evolves over time. Strategies adjust in proportion to their payoff differences, with higher-payoff strategies becoming more common. This replicator-like adjustment creates feedback between content quality and consumer selectivity.

Interactions in each period proceed as follows:

1. Providers produce one item according to their chosen strategy.
2. Consumers select $m\sigma$ items. Active consumers allocate their attention entirely to high-quality items when these are available in sufficient quantity. When the supply of high-quality items is insufficient, they consume all available high-quality items and then randomize over low-quality items to fill their remaining attention slots. Passive consumers sample uniformly from all items.
3. Providers receive reward $r$ per view.
4. Consumers obtain benefit $b_H$ from high-quality and $b_L$ from low-quality items, with $b_H > b_L > 0$.

The model parameters are listed in Table 1.

Let $x(t)$ denote the fraction of high-effort providers and $y(t)$ the fraction of active consumers at time $t$. These state variables summarize the population-level state. We capture the resulting feedback through a two-population replicator framework, with the full mathematical formulation provided in the Materials and Methods section.

Table 2: Summary of equilibrium types and their stability conditions in the attention-quality dynamics.

| Type of equilibrium | Fixed point $(x^*, y^*)$ | Stability condition |
|---|---|---|
| Collapse equilibrium | $(0, 0)$ | Always stable |
| Boundary equilibrium | $\left(\frac{rn\sigma}{c_H}, 1\right)$ | $\begin{cases} rn\sigma < c_H < rn, \\ \frac{c_A}{m\sigma(b_H - b_L)} + \frac{rn\sigma}{c_H} < 1 \end{cases}$ |
| Coexistence equilibrium | $\left(1 - \frac{c_A}{m\sigma(b_H - b_L)}, \frac{c_H}{rn\sigma}\left(1 - \frac{c_A}{m\sigma(b_H - b_L)}\right)\right)$ | $\begin{cases} m\sigma(1-\sigma)(b_H - b_L) > c_A, \\ \frac{c_A}{m\sigma(b_H - b_L)} + \frac{rn\sigma}{c_H} > 1 \end{cases}$ |

To clarify how attention constraints shape the coevolution of content quality and viewing behavior, we analyze the qualitative behavior of this replicator system. We first characterize all equilibria and derive the parameter thresholds that determine their stability. We then perform numerical integration of the system to examine trajectories and basins of attraction, illustrating how the system responds to changes in attention capacity and incentive strength.

Across these analyses, the dynamics organize into three characteristic regimes that govern long-run outcomes of attention and quality. In the collapse regime, both selective attention and high-effort provision vanish, and the system converges to a low-quality, non-selective state. In the boundary regime, consumers remain selective but providers exert only intermediate effort, leading to partially improved yet fragile information environments. In the coexistence regime, high-effort providers and selective consumers persist together with damped oscillations, maintaining quality through mutual adaptation. In the following sections, we characterize the parameter conditions under which each regime arises and analyze their dynamical and policy implications.

**Analytical characterization of stable equilibria**

We begin by analyzing the stability of the three equilibria identified in the replicator system: (i) the collapse equilibrium at the origin, (ii) the boundary equilibrium on $y = 1$ with $0 < x^* < 1$, and (iii) an interior coexistence equilibrium in which both high-effort providers and active consumers persist. As summarized in Table 2, the stability of these equilibria is governed by the interplay between attention capacity, the cost of active consumption, and the effective reward for high-effort provision.

The origin $(x, y) = (0, 0)$ is always locally stable, representing a collapse regime where both selective attention and high-effort provision disappear. In particular, this equilibrium becomes the only attractor when the following condition holds:

$$m\sigma(1 - \sigma)(b_H - b_L) < c_A. \tag{1}$$

The derivation of this threshold is provided in the SI Appendix. Intuitively, the term $\sigma(1-\sigma)$ indicates that discrimination is weakest when attention is either too scarce or too dispersed, making selective viewing unprofitable and preventing high-quality content from gaining traction. In this parameter region, no nontrivial equilibria exist, and all trajectories converge to the origin regardless of initial conditions. In such environments, consumers find it unprofitable to engage in selective attention, and low-effort content dominates in the steady state.

In contrast, when $m\sigma(1 - \sigma)(b_H - b_L) > c_A$, nontrivial equilibria become possible. Which equilibrium stabilizes depends on the ratio of the effective reward to the production cost, $rn\sigma/c_H$. If

$$\frac{c_A}{m\sigma(b_H - b_L)} + \frac{rn\sigma}{c_H} > 1, \tag{2}$$

the interior coexistence equilibrium is locally stable. In this regime, both high-effort providers and active consumers persist at positive levels, sustaining quality endogenously through mutual reinforcement. In contrast, if the opposite inequality holds,

$$\frac{c_A}{m\sigma(b_H - b_L)} + \frac{rn\sigma}{c_H} < 1, \tag{3}$$

the boundary equilibrium becomes stable: all consumers remain active ($y \to 1$), but providers exert only intermediate effort. This state represents a partially functional but not fully self-sustaining information environment.

These analytical results indicate two hierarchical thresholds that shape the sustainability of quality under limited attention. The first threshold, $m\sigma(1 - \sigma)(b_H - b_L) = c_A$, separates collapsed from non-collapsed systems and depends solely on consumers' ability to distinguish between high- and low-quality content. The second threshold, determined

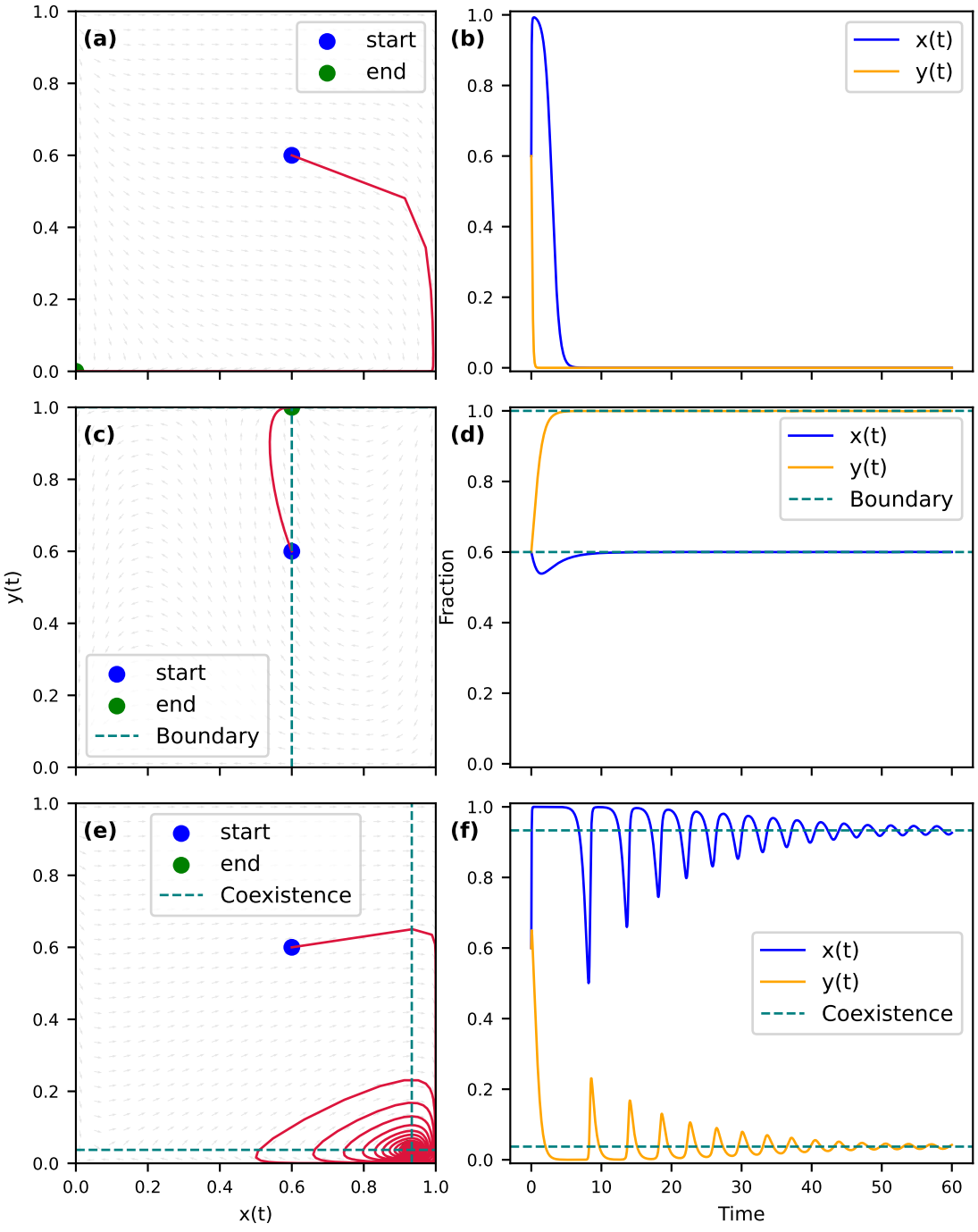



Figure 2: Representative trajectories of the replicator dynamics under three parameter regimes. Parameters were chosen to satisfy the corresponding stability conditions: (a,b) Collapse: $m = 20$, $n = 100$, $\sigma = 0.5$, $r = 1$, $b_H - b_L = 1$, $c_A = 10$, $c_H = 2$. (c,d) Boundary: $m = 1$, $n = 10$, $\sigma = 0.5$, $r = 0.12$, $b_H - b_L = 10$, $c_A = 1$, $c_H = 1$. (e,f) Coexistence: $m = 20$, $n = 100$, $\sigma = 0.5$, $r = 1$, $b_H - b_L = 3$, $c_A = 2$, $c_H = 2$. The green dashed lines mark the equilibrium.

by the balance between reward and cost parameters, divides the non-collapsed region into boundary and coexistence regimes. Together, they show that maintaining high-quality information requires not only sufficient discriminability among consumers but also an adequate incentive structure for providers.

### Dynamic behavior across three regimes

Next, we examine how system trajectories approach these equilibria under varying parameter regimes. Figure 2 presents representative vector fields and time evolutions for the three regimes: collapse, boundary, and coexistence. These trajectories were generated by numerically integrating the replicator equations with a standard adaptive Runge–Kutta method (RK45), using parameter values chosen to satisfy the stability conditions of each regime.

When the active-consumption cost $c_A$ is high or the quality gap $b_H - b_L$ is small, consumers lack sufficient motivation to search for high-quality content. Selective viewing fails to emerge ($y \to 0$), and providers lose incentives to exert high effort ($x \to 0$), leading both populations to a state dominated by low-quality content and non-selective behavior.

In the boundary regime, consumers sustain selective attention ($y \to 1$), but the effort level of providers remains moderate, with $x$ converging to an intermediate value. This regime represents an environment where demand for quality exists, yet the reward for high-effort provision is inadequate to sustain full-quality production.

In the coexistence regime, both providers and consumers persist at positive equilibrium levels ($x > 0, y > 0$), yet convergence toward this steady state is not monotonic. The trajectories exhibit mild oscillations around the equilibrium, reflecting feedback between supply and selection. When the share of low-quality content increases, consumers become more selective ($y$ rises), which restores incentives for high-effort creation and raises $x$. As high-quality content becomes abundant, the need for active searching decreases, and $y$ gradually falls. This in turn reduces $x$, generating a slow cyclical adjustment. Because these adjustments weaken as the system approaches the fixed point, the feedback loses strength over time, producing damped rather than persistent oscillations.

This damped cycle reflects adaptive consumer behavior: selectivity increases only when necessary, allowing consumers to minimize active-consumption costs while supporting the persistence of high-quality supply. Thus, the coexistence regime represents a dynamically maintained state in which high-effort provision and selective attention reinforce one another.

### Basins of attraction across regimes

Having examined the typical trajectories within each regime, we next investigate how their basins of attraction vary across parameter settings. The size and structure of these basins differ substantially between the boundary and coexistence regimes.

Figure 3 shows the final equilibrium reached from systematically varied initial conditions $(x_0, y_0)$. Red regions denote initial conditions that converge to the coexistence or boundary regime, while gray regions correspond to trajectories converging to the collapse regime. Arrows in the background indicate the vector field of the replicator dynamics.

When the boundary equilibrium is stable (left panel), the region of initial conditions leading to coexistence is limited. Without a sufficiently large initial fraction of high-effort providers or active consumers, the system collapses to $(x, y) \to (0, 0)$. This indicates that the boundary regime is highly sensitive to initial conditions: quality and selectivity must already be present at appreciable levels for the system to avoid degeneration.

In contrast, when the internal coexistence equilibrium is stable (right panel), the basin of attraction expands substantially. Even when both $x$ and $y$ start from low levels, the feedback between effort and attention drives the system back toward coexistence. This result indicates that the coexistence regime is robust across a wide range of initial conditions, whereas the boundary regime emerges only when selective attention or high-effort provision is already prevalent.

### Determinants of collapse and policy implications

The key bifurcation of the system separates the collapse regime, where both strategies vanish, from the non-collapsed regimes, where at least partial coexistence of high- and low-quality content persists. This transition primarily depends on consumers' ability to discriminate between quality levels, which is characterized by $m\sigma(1-\sigma)(b_H - b_L) = c_A$. Here, $\sigma(1-\sigma)$ captures a nonlinear effect of attention capacity: discrimination weakens when attention is either too scarce or too dispersed. If this balance between discriminability and active-consumption cost fails to exceed this threshold, selective engagement does not emerge, and high effort cannot be sustained. In this case, the system collapses regardless of initial conditions.

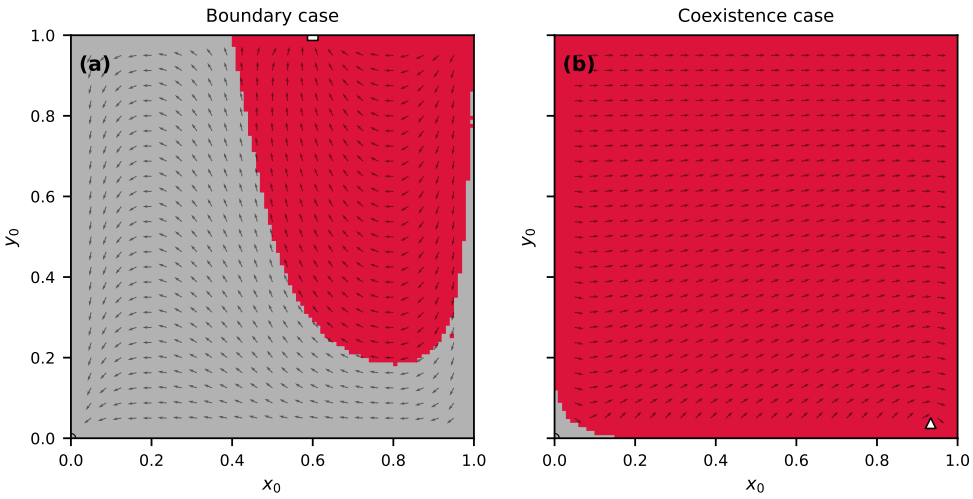



Figure 3: Basins of attraction under two parameter regimes. Left: parameter setting where the boundary equilibrium is stable. Right: setting where the coexistence equilibrium is stable. Red regions indicate initial conditions converging to non-collapsed equilibria, whereas gray regions indicate collapse. Background arrows show the replicator vector field. Basins were computed on a $100 \times 100$ grid of initial conditions.

Figure 4 shows this boundary in the $(b_H - b_L, c_A)$ and $(\sigma, c_A)$ planes. A larger quality gap or lower active-consumption cost reduces the collapse region. The non-collapsed region is maximized near $\sigma = 0.5$ and shrinks as $\sigma \to 0$ or $\sigma \to 1$. In smaller markets with fewer providers ($m$ small), preventing collapse requires stronger support for discrimination (reducing $c_A$) or a larger quality gap.

Importantly, this collapse boundary is independent of the reward parameters $(r, c_H, n)$ that govern providers' incentives. The first-order condition for sustaining quality lies in the consumers' motivation to differentiate content. Once this condition is met, the specific equilibrium that stabilizes within the non-collapsed domain is determined by the ratio $rn\sigma/c_H$: higher ratios favor the coexistence equilibrium, whereas lower ratios yield boundary-type stability.

These results suggest a two-step design principle for sustaining high-quality digital ecosystems. First, collapse must be avoided by ensuring sufficient discriminability. This can be achieved by (i) reducing active-consumption cost $c_A$ through improved search, labeling, or recommendation systems, (ii) enlarging the quality gap $b_H - b_L$ by suppressing low-quality exposure or penalizing manipulative content, and (iii) optimizing attention capacity $\sigma$ by limiting excessive information exposure. Second, once collapse is avoided, maintaining coexistence requires increasing the effective reward ratio $rn\sigma/c_H$ by improving incentives for high-effort production or reducing creation costs.

Overall, the model demonstrates that sustainable content quality does not rely on favorable initial conditions but on an institutional balance between discriminability and incentive design.

## Discussion

To understand how content quality and audience attention coevolve under limited attention, we developed a minimal theoretical framework that captures the strategic feedback between providers and consumers. The model reveals that content dynamics fall into three regimes separated by a fundamental bifurcation determined by $m\sigma(1-\sigma)(b_H - b_L) = c_A$. This threshold clarifies the role of consumers' discriminability, with $\sigma(1-\sigma)$ indicating that both excessive and insufficient attention undermine quality selection. Thus, simply increasing exposure does not necessarily improve the content environment.

Our contribution is to show that these dynamics emerge from a simple coadaptive mechanism linking selective attention and content effort under explicit attention constraints.

Each regime has a natural interpretation. In the collapse regime, low-quality and non-selective behaviors dominate, resembling environments saturated with repetitive, manipulative, or clickbait content [22, 23, 24]. The coexistence regime represents a dynamic balance in which temporary declines in quality heighten selectivity, restoring providers' incentives and generating self-correcting oscillations. The boundary regime arises when consumers remain selective but

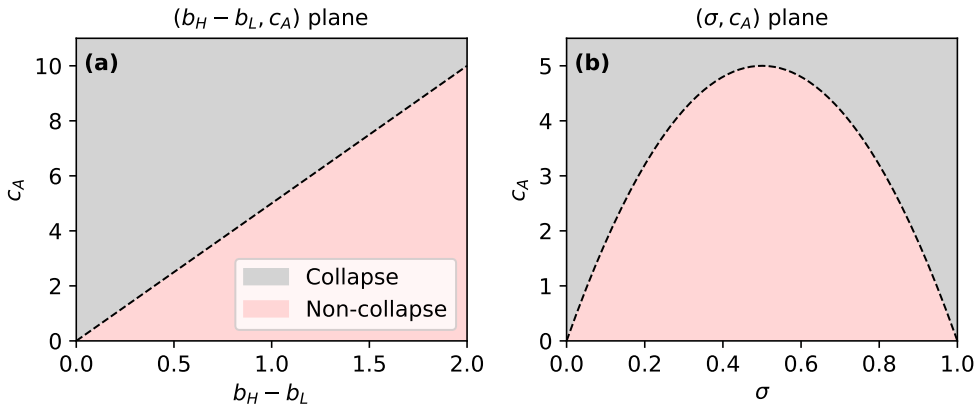



Figure 4: Regimes of collapse and non-collapse. (a) Regimes on the $(b_H - b_L, c_A)$ plane for fixed $\sigma = 0.5$. The dashed line $c_A = m\sigma(b_H - b_L)(1 - \sigma)$ separates collapse (gray, above) from non-collapse (white, below). (b) Regimes on the $(\sigma, c_A)$ plane for fixed $b_H - b_L = 1$. The non-collapsed region is widest around $\sigma \approx 0.5$ and shrinks as $\sigma \to 0$ or $\sigma \to 1$.

high-effort production is only moderately profitable, a situation characteristic of expert or niche domains. Our basin analysis shows that coexistence is robust to a wide range of initial conditions, whereas boundary outcomes require already favorable levels of selectivity or quality. This asymmetry highlights the importance of interventions that support discriminability before content quality deteriorates.

A related implication concerns recent developments in generative AI. By enabling the rapid creation of large amounts of content, such tools may increase the volume of material competing for users' attention. This can heighten the cognitive effort required to identify reliably high-quality items, effectively raising the functional cost $c_A$ in our model. While this remains a tentative interpretation, it highlights a potential mechanism through which content proliferation may move platforms closer to the collapse boundary when discrimination does not improve accordingly.

These findings offer a two-stage framework for policy and platform design. First, avoiding collapse requires sustaining sufficient discriminability, which can be achieved by lowering cognitive search costs, enlarging the quality gap, or optimizing attention capacity. Importantly, the system performs best in an intermediate range where $\sigma(1 - \sigma)$ is maximized; increasing attention indiscriminately is not always beneficial. Second, once collapse is avoided, stabilizing coexistence requires improving the effective reward ratio $rn\sigma/c_H$ through transparent incentives, lower production costs, or appropriately regulated content throughput. Sustaining content quality thus depends less on initial conditions than on an institutional balance between discriminability and incentives.

The present model abstracts many features of real digital ecosystems. It assumes homogeneous consumers and providers, fixed market size, and simplified functional forms for discrimination and rewards. Relaxing these assumptions could reveal richer dynamics such as multistability or path dependence. Empirically evaluating the model's predictions will require data on selective engagement and content production across platforms. Future extensions may also incorporate cases where low-quality content yields subjective or identity-based utility, such as misinformation, sensationalism, or partisan narratives. Integrating media literacy, trust, and informational health into the model could further clarify how attention and quality interact under algorithmic amplification [36, 37, 38].

Overall, the model indicates that sustaining high-quality content hinges not on favorable initial conditions but on preserving discriminability while maintaining incentives for high-effort creation.

# Material and Methods

## Replicator formulation

We now develop the analytical formulation of the evolutionary dynamics. Let $x(t)$ denote the fraction of high-effort providers and $y(t)$ the fraction of active consumers. The incentive to invest in effort increases with the prevalence of active consumers, while the value of being active rises with the share of high-quality providers. This bidirectional feedback generates a coevolutionary dynamic process in the pair $(x(t), y(t))$.

In each period, every provider produces one item, and each consumer can attend to a fraction $\sigma$ of the items produced. We analyze the system at the population level by adopting a mean-field framework, in which providers and consumers are randomly matched and individual fluctuations are smoothed by averaging. The parameter $\sigma$ thus determines whether the system operates in an attention-saturated or attention-limited regime, depending on whether the fraction of high-quality content $x$ is large enough to meet the attention capacity $\sigma$. Accordingly, the payoff structure differs between these regimes, leading to a piecewise-defined form of the expected payoffs that captures the transition between attention-saturated and attention-limited environments. This distinction arises because active consumers may or may not be able to fill their attention budgets with high-quality items, causing the payoff differences to take distinct functional forms across regimes.

Let $\pi$ denote the expected payoff for each strategy under the mean-field approximation. Subscripts $H$ and $L$ refer to high- and low-effort providers, respectively, while $A$ and $P$ denote active and passive consumers, respectively. Superscripts "prov" and "cons" denote the provider and consumer populations.

**(i) Case 1: high-quality supply sufficient ($x \geq \sigma$).**

$$\begin{aligned}
\pi_H^{\text{prov}}(x,y) &= -c_H + rn\sigma\left((1-y) + \frac{y}{x}\right), \\
\pi_L^{\text{prov}}(x,y) &= rn\sigma(1-y), \\
\pi_A^{\text{cons}}(x,y) &= -c_A + m\sigma b_H, \\
\pi_P^{\text{cons}}(x,y) &= \sigma m\left(xb_H + (1-x)b_L\right).
\end{aligned} \tag{4}$$

**(ii) Case 2: high-quality supply insufficient ($x < \sigma$).**

$$\begin{aligned}
\pi_H^{\text{prov}}(x,y) &= -c_H + rn\left(\sigma(1-y) + y\right), \\
\pi_L^{\text{prov}}(x,y) &= rn\left[\sigma(1-y) + y\frac{\sigma - x}{1-x}\right], \\
\pi_A^{\text{cons}}(x,y) &= -c_A + m\left(xb_H + (\sigma - x)b_L\right), \\
\pi_P^{\text{cons}}(x,y) &= \sigma m\left(xb_H + (1-x)b_L\right).
\end{aligned} \tag{5}$$

These expressions are derived by conditioning on whether active consumers can fully satisfy their attention budgets with high-quality items. Detailed derivations are provided in the SI Appendix.

Both providers and consumers adapt their strategies through a finite rationality imitation process. Individuals observe the payoffs of others in their population and switch strategies with a probability proportional to the payoff difference. Thus, the evolution of the population shares is described by a two-population replicator system:

$$\begin{aligned}
\dot{x} &= x(1-x)\left[\pi_H^{\text{prov}}(x,y) - \pi_L^{\text{prov}}(x,y)\right], \\
\dot{y} &= y(1-y)\left[\pi_A^{\text{cons}}(x,y) - \pi_P^{\text{cons}}(x,y)\right].
\end{aligned} \tag{6}$$

As the payoff functions are piecewise defined at $x = \sigma$, the resulting vector field constitutes a piecewise-smooth dynamical system. Substituting the regime-specific payoff functions into the replicator equations yields the following piecewise-smooth system:

$$\dot{x} = \begin{cases} (1-x)\left(rn\sigma y - c_H x\right), & (\sigma \leq x), \\ x\left(rny(1-\sigma) + c_H(x-1)\right), & (\sigma > x), \end{cases} \tag{7}$$

$$\dot{y} = \begin{cases} y(1-y)\left(bm\sigma(1-x) - c_A\right), & (\sigma \leq x), \\ y(1-y)\left(bmx(1-\sigma) - c_A\right), & (\sigma > x), \end{cases} \tag{8}$$

where $b = b_H - b_L$ denotes the benefit differential between the high- and low-quality items. This piecewise structure arises because the payoff differences are represented differently across the two regimes. For $x \geq \sigma$, active consumers are fully saturated with high-quality items, eliminating any dependence on low-quality allocations. For $x < \sigma$, partial substitution toward low-quality items introduces additional linear terms.

Equilibrium points are obtained by solving $\dot{x} = \dot{y} = 0$. In this model, the dynamics yield exactly three stable equilibria: a collapse equilibrium at $(0,0)$, a boundary equilibrium at $y = 1$ with $0 < x^* < 1$, and a single interior coexistence equilibrium. These equilibria represent potential long-run steady states of the evolutionary dynamics. Local stability was evaluated using the eigenvalues of the Jacobian matrix computed at each equilibrium. The explicit equilibrium coordinates and stability conditions are provided in the SI Appendix, and their qualitative implications are discussed in the Results section.

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## Author contributions statement

F.T. and H.Y. designed the research; M.C. and I.O. developed and analyzed the model; M.C. performed numerical analysis; M.C., D.L., I.O., H.Y., and F.T. discussed and interpreted the results; and M.C. wrote the paper. All authors reviewed and approved the final manuscript.

## Competing interests

The authors declare no competing interests.

## Data availability

No external datasets were used in this study.

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