Aligning incentives in cumulative cultural evolution (work in progress!)

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Abstract

We study the consequences for cumulative culture of a setting in which individuals choose whether to innovate or imitate on the basis of experienced rewards, rather than occupying fixed roles. Using a mathematical model, we show that a few reasonable assumptions about innovation difficulty and cost lead to misalignment between privately optimal behavioural probabilities and socially optimal role distribution, the modal outcome of which is cultural stagnation due to free-riding by imitators. We then show that a simple intervention—where copiers of a valuable trait pay some proportion of that value back to the trait's originator—can dramatically expand the proportion of parameter space over which free-riding is avoided. Results from a set of agent-based simulations illustrate how such a norm might emerge through a process of cultural group selection. Finally, we discuss possible contemporary and historical analogues of the model.

1 Introduction

Cumulative culture—that is, culture whose complexity or sophistication builds progressively over time—requires that two complementary processes occur within a population: the generation of novel improvements, and their diffusion via social learning. While both necessary, these two activities can present individuals with quite different 'returns on investment': innovators shoulder the costs and risks of discovery, while others may enjoy much of the same resulting value by simply copying what is discovered. This gives rise to a possible tension between, on one hand, the distribution of behaviours that is *individually* most rewarding; and on the other, the distribution required to sustain CCE. That tension

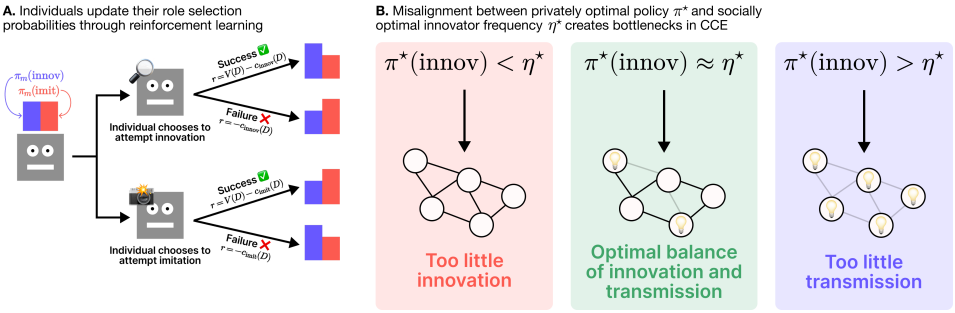


Figure 1: *If individuals choose how much to innovate or imitate, misalignment between individual payoffs and societal outcomes can limit cumulative cultural evolution.* **(A)** Individuals are modelled as rational agents that aim to maximize their payoffs by choosing 'innovator' or 'imitator' roles. **(B)** Illustrating three relationships between the payoff-maximising role-choice policy and the CCE-maximising distribution of roles within the population.

becomes particularly relevant if 'innovator' and 'imitator' are not fixed individual types, but rather transient roles resulting from an adaptive decision-making process. This creates a feedback dynamic: the evolution of a population's culture alters the environment in which its members learn how best to allocate their effort—between trying to discover novel solutions and exploiting solutions already found by others—with those learned allocations then shaping subsequent cultural change.

Explanations for the rarity (or even nonexistence) of CCE within nonhuman species have often proceeded by questioning those species' capacity either for faithfully transmitting novel traits, or for generating them in the first place (Dean et al., 2012). In particular, many have pointed to high-fidelity social learning as a key missing ingredient (Tennie et al., 2009), supported by evidence that apes tend to emulate outcomes rather than imitate specific behavioural procedures Nagell et al. (1993); Tomasello (1999); Horner and Whiten (2005); Whiten et al. (2009); Tomasello (1996). Others have focused on limitations in planning or in causal, analogical or technical reasoning (Vaesen, 2012; Osiurak et al., 2021; Vale et al., 2022; Stout and Hecht, 2017; Yaman et al., 2026).

Yet cumulative culture may fail to appear even when the cognitive capacities underlying these "dual engines" (Legare and Nielsen, 2015; Ehn and Laland, 2012; Dean et al., 2012) are present. It is not enough that a population simply be *capable* of generating and diffusing novel traits; these two processes must actually occur, in balance with one another, and there is no guarantee that the incentives governing individuals' choices must produce such a balance.

Recent work has begun to highlight this. Mesoudi et al. (2025) show how cost asymmetries between innovation and imitation can create a cooperative dilemma—reminiscent of Rogers' famous "paradox" (Rogers, 1988) in the non-cumulative setting—where social learners enjoy the benefits of novel traits without being subject to the costs involved in discovering them.

The logical result of this dynamic is to reduce the level of innovation within the population, inhibiting cultural accumulation. Miu et al. (2024) go even further, suggesting that innovation (in their simulations, "refinement") may have a self-undermining quality: the introduction of novel improvements into the cultural pool at time t makes imitation at time $t+1$ more attractive, and might make further innovation at time $t+1$ costlier or more difficult (and thus less attractive).

It is worth clarifying that, in these models, imitation is not really equivalent to strict free-riding or defection in the sense of many other cooperative dilemmas. Without transmission, innovations cannot accumulate, and there is no CCE. The problem is one of proportion: a population benefits if individuals often imitate one another, but suffers if they always do.

Mesoudi et al. (2025) and Miu et al. (2024) establish that private and collective returns to innovation can diverge in a manner consequential for CCE. But they leave open the question of what happens when innovation and imitation are not fixed strategies or roles, and individuals instead learn from experience how to allocate effort between them. In this paper, we investigate this question. Within a simplified mathematical model of cumulative culture, we cast individuals as reinforcement learning (RL) agents that face repeated choices between innovation and imitation. We show that this creates a coupled dynamical system whose general outcome, under minimal assumptions, is the insufficient production of novel behaviours. We then show that this phenomenon can be mitigated—to an extent—by a simple payoff-modifying norm that allows successful innovators to reclaim some portion of the value that they create for imitators. To support our theoretical findings, we present results from agent-based simulations of three different CCE environments demonstrating that such a norm can evolve endogenously through a process of cultural group selection. We finish by discussing a few potential 'real-world' norms or institutions that might, at different points in human history, have served to approximate the simple value-capture mechanism explored in our models and simulations.

2 A simple model of cultural growth and decline

Before considering how individual strategy learning and cumulative culture interact, we must define a model of the latter. This model is intentionally simplistic, since we are interested specifically in the *interaction* between individual learning and CCE rather than a highly detailed exploration of either component.

Consider a population of M individuals, and at time t denote by D_t the 'complexity' of the population's culture (e.g. its number of accumulated improvements), and by η_t the proportion of individuals choosing to attempt innovation. The continuous change in this

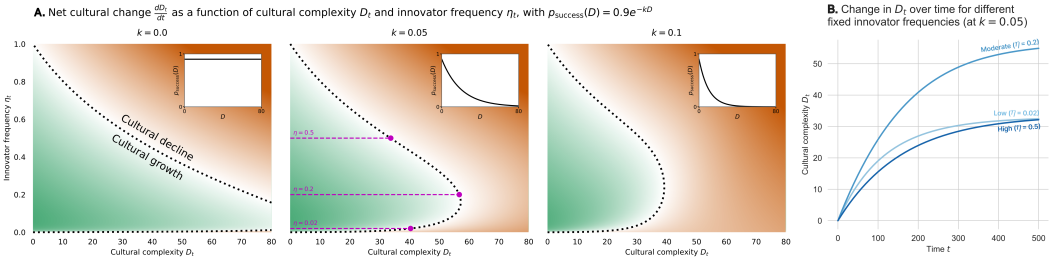


Figure 2: *Cultural progress is impeded when the innovator frequency η is too low or too high.* **(A)** Phase diagrams showing the regions of (D, η)-space for which $\frac{d}{dt}D_t$ [Equation (1)] is positive (green) vs negative (orange). Each panel corresponds to a particular setting of $p_{\text{success}}(D)$, the probability that an innovation attempt is successful. **(B)** Example cultural complexity timeseries for three fixed innovator frequencies, with $k = 0.05$.

population's cultural complexity can be expressed simply as

$$\frac{d}{dt}D_t = G(\eta_t, D_t) - L(\eta_t, D_t) \tag{1}$$

$$G(\eta, D) = \frac{1}{\frac{1}{\eta M p_{\text{success}}(D)} + T_{\text{diffusion}}(\eta)} \tag{2}$$

where G is the rate of cultural growth, L is the rate of cultural loss due to turnover (Henrich, 2004), and $p_{\text{success}}(D)$ gives the probability that a given innovation attempt is successful (details of the expressions chosen for $T_{\text{diffusion}}$ and L are given in the SI).

Equation (1) implies three different 'phases' that a population can occupy at any time: if $G(\eta_t, D_t) > L(\eta_t, D_t)$ then its culture is increasing in complexity; if $G(\eta_t, D_t) < L(\eta_t, D_t)$ it is declining; if $G(\eta_t, D_t) = L(\eta_t, D_t)$ it is stagnant. Sustaining CCE requires that a population stay within the first of these phases. If the incentives governing individual behaviour make doing so unlikely/difficult, this could help explain why cumulative culture is not more common across the animal kingdom.

Figure 2A visualises these phases for three example cases of $p_{\text{success}}(D) = 0.9e^{-kD}$: $k = 0$ (the chance of making a valuable discovery stays constant as cultural complexity rises), $k = 0.05$ (moderate exponential decay), and $k = 0.1$ (rapid exponential decay). At low complexity (D_t), almost any balance of innovation and imitation is observed to produce cultural growth. But as D_t increases, the range of innovator frequency η_t required to avoid stagnation becomes increasingly narrow, resulting in an 'inverse-U' relationship between η_t and cultural accumulation. For example, Figure 2B shows that for $k = 0.05$, a population at $\eta = 0.2$ achieves greater cultural complexity than one at either $\eta = 0.02$ or $\eta = 0.5$.

This inverse-U relationship is consistent with the idea that CCE requires sufficient levels of *both* innovation and transmission—its "dual engines" (Legare and Nielsen, 2015). In our model, more effort spent on one means less allocated to the other; as $\eta \to 1$ the population

becomes trapped in a repeated cycle where new traits are discovered, then lost as their originators die or migrate away, before being *re*discovered by the next generation, and so on. Maintaining cultural growth requires a distribution of roles that balances the introduction of new cultural products with their diffusion and retention.

3 Self-interested learning leads to underinnovation

In other words, CCE will be constrained when this distribution tilts too far in the direction of either innovation or imitation. What happens when we allow each individual to select their own role on the basis of reward feedback?

First let $V(D)$ give the individual value of obtaining a novel trait when the current cultural complexity is D. The expected rewards for each action can then be modelled as

$$r(\texttt{innov}; D) = p_{\text{success}}(D)V(D) - c_{\text{innov}}(D) \tag{3}$$

$$r(\texttt{imit}; D, \eta) = p_{\text{copy}}(D, \eta)V(D) - c_{\text{imit}}(D) \tag{4}$$

where p_{success} and p_{copy} give the probabilities of an innovation/imitation attempt succeeding, and $c_{\text{innov}}, c_{\text{imit}}$ are the costs associated with each strategy (see the SI for details of how p_{copy} is defined). Each individual begins life with an equal likelihood of choosing either role: $\pi_0(\texttt{innov}) = \pi_0(\texttt{imit}) = 0.5$. Over the course of their lifetime, they continually update these probabilities towards the distribution that maximises expected reward under the current values of D_t and η_t.

Intuitively, the collective outcome of this is that the population is moving at any given time towards an innovator frequency η that approximates (subject to turnover and decision noise) the individual-payoff-maximising probability of attempting innovation, which is governed by the difference

$$\Delta(D, \eta) = r(\texttt{imit}; D, \eta) - r(\texttt{innov}; D). \tag{5}$$

If avoiding cultural stagnation requires that η be kept within a certain window (Figure 2), the same must be true for Δ. In other words, if the difference in expected reward between innovation and imitation is either too high or too low, the individual probabilities of selecting each role will diverge from the population-level balance of roles required to sustain CCE.

To get a sense of how prevalent this misalignment is, we sampled instances of the coupled system across different combinations of innovation difficulty (controlled by k as before) and cost (controlled by c via $c_{\text{innov}}(D) - c_{\text{imit}}(D) = cD$). We then computed each system's equilibrium—that is, the point at which $\dot{D}_t = \dot{\eta}_t = 0$ and so cultural complexity is fixed—and compared it to the 'cultural ceiling' $D_{\max}$ (the complexity achievable by a population with optimal role allocation).

Figure 3A illustrates a few example equilibria. Figure 3B shows that when the difficulty

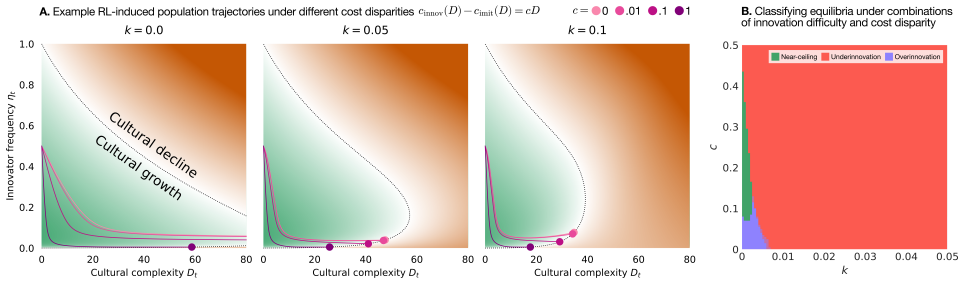


Figure 3: *Individual selection of roles via reinforcement learning generally leads to underinnovation.* **(A)** Example RL-induced trajectories of cultural complexity D_t and innovator frequency η_t under three values of the decay rate parameter k in $p_{\text{success}}(D) = 0.9e^{-kD}$. Coloured curves vary the cost disparity $c_{\text{innov}}(D) - c_{\text{imit}}(D) = cD$; circular markers indicate the equilibrium of each system (i.e. where $\dot{D} = \dot{\eta} = 0$). **(B)** Classifying equilibria across 10,000 combinations of k and c. For each combination, 100 systems were generated by randomly sampling the remaining model parameters; green tiles indicate points at which the mean complexity shortfall over these systems $\leq 10\%$. Tiles not meeting this threshold are coloured according to whether stagnation resulted more often from under- or overinnovation.

and/or cost of innovation increase with cultural complexity, by far the most frequent outcome across our sampled instances is premature cultural stagnation due to *underinnovation*. We note that both of these conditions have precedence in the cultural evolution and economics literatures. For example, rising innovation costs may reflect the time investment required to understand prior art sufficiently to build upon it (Mesoudi, 2011; Jones, 2009). Falling success probability could have a similar cause (Park et al., 2023), or simply be a product of growing search space size (Bloom et al., 2020) or of increasing friction between search space structure and innovators' cognitive biases (Thompson and Griffiths, 2021).

Interestingly, the bottom-left corner of Figure 3B reveals that, while much less common over the parameter ranges evaluated here, individual incentives can also disrupt CCE by making innovation *too* attractive rather than not attractive enough. When attempting innovation is both cheap and likely to succeed, individuals allocate insufficient effort to social learning, and so novel discoveries are unable to spread effectively.

4 Aligning incentives through value-capture norms

This analysis, while abstracted, suggests that a distributed process of individual role selection will generally not sustain the balance of innovation and transmission necessary for cumulative culture to flourish. How then can this problem be overcome, as our own species has apparently managed to do?

Numerous relevant ideas are offered by Mesoudi et al. (2025), who consider a setting where innovators can be either "open" (freely share information) or "closed" (attempt to

hoard their discoveries), and evaluate various mechanisms for their potential to prevent the extinction of open innovators from persistent free-riding by non-innovators. While this differs from our own construction, in which agents choose simply whether to innovate or imitate, the approaches evaluated are nevertheless worth touching on here. In one model, the authors suggest that a process of kin selection may lead to individuals being intrinsically motivated to share information with their offspring. In another model, each agent has a "reputation" that they increase by sharing information with others (especially their own innovations, in a form of priority advantage); agents with higher reputation are then more likely to have information shared with them in turn. Most directly relevant to the current work is their final model. This model shows that, given a high enough level of intergroup conflict, a simple form of cultural group selection—in which groups compete directly on the basis of cultural complexity—can also promote information sharing.

Notable about Mesoudi et al. (2025) is the authors' explicit framing of information-sharing in cultural evolution as a form of *cooperative dilemma*. This is reflected in their three proposed model extensions, which parallel classic mechanism families in the broader literature on the evolution of cooperation (e.g. strategy-based reciprocity and assortment through kin/group structure). However, another major strand in prior work on cooperative dilemmas has considered how groups of individuals can *actively* intervene on the payoff structure of their shared environment via norms and institutions. Many human cooperative systems are stabilised not only through assortment or repeated interaction, but by active incentive modification. For example, access to common goods may be made conditional on contribution to their maintenance, with defectors punished (Ostrom, 1990; Fehr and Gächter, 2002; Boyd et al., 2003; Kollock, 1998; Van Lange et al., 2013; Balliet et al., 2011).

This type of approach is particularly well-suited to our model, in which individuals' cultural-evolutionary roles are not fixed genetically but are instead chosen repeatedly based on within-lifetime learning. Similarly, rather than merely affecting selection for inherited behaviours, real-world norms and institutions operate by modifying the benefits and costs that people experience in relation to different behaviours. Here, such modifications are naturally expressed in terms of interventions on the reward functions given in Equations (3)–(4). This bears some relation to the RL community's concept of 'reward shaping', in which the aim is to make it easier for an individual agent to learn the optimal behaviour for some task without changing what that behaviour is (Ng et al., 1999). By contrast, we actually *do* want to change which behaviours yield high individual payoff; but only in service of making the CCE-maximising *population*-level distribution of role choices more accessible to decentralised learning. Similar approaches have previously been shown to improve collective outcomes in multi-agent RL (MARL) models of other social dilemmas (Vinitsky et al., 2023; Yaman et al., 2023; Hostallero et al., 2020; Wang et al., 2021).

Equations (3)–(4) specify that, of the total value created by a novel innovation, the

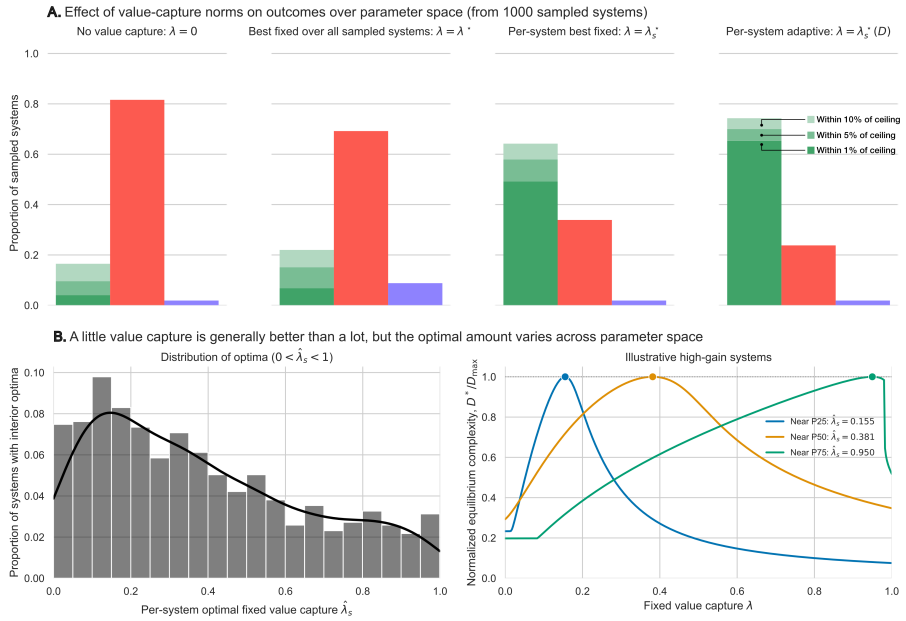


Figure 4: *Letting innovators capture more of their discoveries' total value can mitigate underinnovation from RL-guided role selection.* **(A)** under different value-capture regimes, the distribution of equilibrium outcomes from 1000 randomly sampled parameter combinations. As in Figure 3, red and blue indicate under- and overinnovation respectively; green shades partition near-ceiling outcomes by increasing proximity to the cultural ceiling. **(B)** a histogram of the best-performing fixed value-capture rate $\hat{\lambda}_s$ for each of the 1000 sampled systems, accompanied by curves for three example systems of achievable cultural complexity vs λ.

innovator's share is exactly the same as that of any imitator. A simple way to adjust the balance of expected rewards, then, is to allow the innovator to 'capture' some additional proportion of the value resulting from their efforts. To formalise this, suppose that, if an innovation diffuses, it is eventually used by K individuals (the innovator plus $K-1$ imitators). We will define K in terms of imitator frequency as $K(\eta) = 1 + (1-\eta)(M-1)$. The *total* value created is then equal to $K(\eta)V(D)$. With $\lambda \in [0,1]$ controlling the 'rate' of capture, the expected rewards become

$$r(\texttt{innov}; D, \eta) = p_{\text{success}}(D)\Big[1 + \lambda\big(K(\eta) - 1\big)\Big]V(D) - c_{\text{innov}}(D) \tag{6}$$

$$r(\texttt{imit}; D, \eta) = (1-\lambda)p_{\text{copy}}V(D) - c_{\text{imit}}(D). \tag{7}$$

So when $\lambda = 0$, innovators capture no additional value; when $\lambda = 1$, innovators capture *all* of the total value (and imitators get nothing); when $0 < \lambda < 1$, innovators capture some additional value without reducing imitator payoffs to zero.

Table 1: Overview of the three search environments used in our agent-based model simulations

	Binary trait environment	Refinement bandit environment	Compositional tech tree environment
Source	Mesoudi et al. (2025)	Miu et al. (2024)	Original
Complexity	Low	Medium	High
Cultural trait	Binary value	Refined bandit arm	Unit of technological know-how
D metric	Median(number of traits unlocked)	Median(highest known arm value)	Median(highest technology level unlocked)

To evaluate the effect of this mechanism on our theoretical model, we again sample random combinations of model parameters. For each of the resulting systems, we compute its equilibrium cultural complexity under different values of the value-capture rate λ. Figure 4A shows that the simple intervention specified in Equations (6)–(7) can substantially improve the alignment between individual incentives and population-level cultural outcomes. It also reveals that the most effective rate of value capture varies both between and within systems. Imposing the same value of λ across all sampled parameter combinations (second panel from the left) produced only a modest effect, whereas allowing λ to vary between systems (third panel) yielded much larger gains, with a smaller additional benefit from letting it change over time as $\lambda_t = \arg\max_\lambda \frac{dD_t}{dt}(\lambda)$ (final panel). This is further evidenced by Figure 4B, which shows a very broad distribution of optimal value-capture rates. Finally, we find an inverse-U relationship between λ and equilibrium cultural complexity, echoing Figure 2

In other words, a social norm or institution that rewards innovators by granting them a share of the value they create for others can significantly widen the range of parameter space over which CCE is viable.

5 Evidence from agent-based simulations

So far, we have evaluated the effect of value capture on CCE by looking at how it changes the equilibrium of our theoretical model (Figure 4). But since we have been describing individual behaviour in terms of reinforcement learning (RL), a natural next step is to test what happens when our abstract expressions for $\frac{dD}{dt}$ and $\frac{d\eta}{dt}$ are replaced by 'real' RL environments. To avoid tying our results too closely to a particular ABM implementation, we report results from three different simulation environments (Table 1). Two of these are adapted from prior work discussed in previous sections (Mesoudi et al., 2025; Miu et al., 2024); the third is original, and is intended to capture a cultural setting with richer structure and a more complex search landscape. Detailed descriptions of all three are given in the SI.

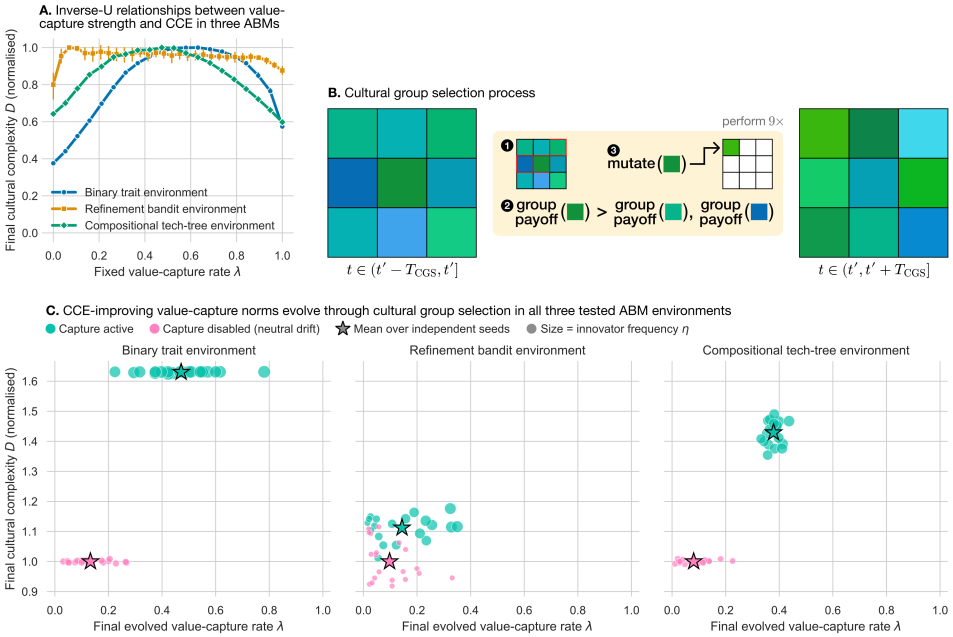


Figure 5: *Effective value-capture norms can evolve through cultural group selection between populations of simulated agents.* **(A)** For the three environments listed in Table 1, the effect of fixed value-capture rate on final cultural complexity. **(B)** An illustration of the cultural group selection (CGS) process used in our agent-based simulations, showing one iteration: every T_{cgs} timesteps, the current cultural complexity D is recorded for each of the population's 9 groups. Tournament selection (with $k = 3$) decides the 'parent' for each group in the next 'generation'; parents' λ values are then mutated with Gaussian noise. **(C)** For the same three environments, differences in relative cultural complexity, value-capture rate, and innovator frequency between populations with value capture active vs disabled, following CGS. Scatterplots show 20 independent seeds per environment x condition; each simulation ran for $T = 2500$ timesteps.

We first ran simulations under different fixed value-capture rates (Figure 5A). All three environments exhibited the qualitative effect predicted by our theoretical model (Figure 4B)—that is, an inverse-U effect of λ on final cultural complexity (though with substantial variation in both peak location and height).

A more interesting test is whether beneficial value-capture norms can evolve endogenously within simulated populations, rather than simply being imposed. Mesoudi et al. (2025) previously explored cultural group selection (CGS) as a potential solution to the information-hoarding problem, suggesting that a group of innovators that freely share information among themselves ought to outcompete either a group of non-sharing innovators or a group of non-innovators. We adapt their approach: rather than acting directly on individuals' behavioural strategies, we propose that CGS could drive the evolution of group-wide value-capture norms, with those norms then influencing individuals' learned choices. We explore this idea by simulating a process of CGS in which value-capture strength undergoes selection and mutation through competition between groups occupying a shared environment. Details of our CGS procedure are given in the SI; Figure 5B illustrates the general approach.

Results from our three environments are shown in Figure 5C. Since λ can't go below zero, any upward trend could simply be the result of neutral drift. To account for this, we repeated every simulation run with all value capture disabled regardless of each group's λ; the CGS dynamics, though left unchanged, thus operated on an entirely meaningless parameter. A one-sided paired permutation test revealed that final λ values in the 'active' condition were significantly higher than those in the 'disabled' condition for the binary trait (mean paired difference 0.338, $p < .001$) and tech-tree (mpd 0.298, $p < .001$) environments, but not for the refinement bandit environment (mpd 0.0465, $p = 0.0577$). Active-condition final cultural complexity was significantly higher in all three environments (all $p < .001$), as was final innovator frequency (all $p < .001$).

6 Discussion

Our results highlight a distinct constraint on cumulative culture. Even when individuals are *capable* of both innovation and social learning, the way they choose to divide their time/effort may not generate the population-level balance of these "dual engines" (Legare and Nielsen, 2015) that is required for sustained accumulation. Indeed, if increases in cultural complexity raise the cost or difficulty of innovation, CCE can progressively push individual incentives towards imitation, thereby undermining its own future growth. Crucially, our work can complement existing cognitive and demographic accounts of CCE, which determine *what* individuals are able to discover and transmit, as well as to *whom*. Incentive structures then influence whether they expend effort on each activity, and to what extent.

Our results further illustrate that resolving this constraint does not require that a

population simply suppress imitation or maximise innovation. This distinguishes CCE from many canonical cooperative dilemmas: although imitators can appear to free-ride on the efforts of innovators, they fulfil an essential function by enabling both the diffusion and retention of novel traits. Instead, the problem lies in maintaining an appropriate balance between two complementary activities. Accordingly, interventions that increase the private returns on attempting innovation can help strike this balance when such attempts are rare, but become counterproductive when applied too strongly.

This perspective also suggests a potentially important role for norms and institutions, which need not determine behaviour directly, but can instead alter the rewards that individuals experience as a result of their choices. This differs from accounts in which socially beneficial behaviour must itself be genetically or culturally inherited as a fixed strategy, and allows populations to retain flexible reward-sensitive learners while culturally evolving the incentive environment in which that learning takes place. Our agent-based simulations offer a demonstration that such incentive structures can themselves become targets of cultural evolution. Across three simulated CCE environments, allowing between-group variance in value-capture rate led to greater cultural complexity relative to matched controls (with capture disabled). We do not take these simulations to establish cultural group selection as the uniquely—or even most—plausible driving force behind the existence of such norms/institutions; what they do show is that group-level competition can, under the right conditions, produce rules that realign individual payoffs towards collective cultural success.

6.1 Real-world mechanisms of value capture

If active incentive alignment is to play any part in an account of cumulative culture, what might it look like in the 'real world'? Our value-capture model is intentionally abstract; we are not trying to claim that human societies literally redistribute a fixed proportion of each new discovery's total value to its originator. Instead, it provides a common functional description for institutions that reward the production of useful/valuable innovations without preventing their diffusion. Contemporary intellectual property (IP) law offers one particularly obvious example; earlier and less formal systems may have operated on the basis of prestige, reputation, or other forms of social incentive.

6.1.1 Patents and copyright

Economists have long recognised the problem of "appropriability": asymmetry between the costs involved in producing vs *re*producing new goods or knowledge can mean that innovators capture very little of the total value resulting from their efforts, weakening the private incentive towards attempting such innovation in the first place (Arrow, 1962; Levin et al., 1987). Patent systems are an attempt to address this problem, through the granting of temporary exclusion rights which (in principle) enable the rights-holder to claim a greater

share of the economic return generated by their creative output (Levin et al., 1987; Hall and Harhoff, 2012).

This maps quite closely onto the abstract intervention represented in our model by λ. While a patent does not *literally* transfer a fixed proportion of every imitator's benefit back to the relevant innovator, it may allow value capture through monopoly commercialisation, sale of the patent, or—most directly analogous—licensing agreements under which royalties are paid in exchange for usage rights. An important feature of patent institutions is that, when working correctly, they increase appropriability without valuable information being permanently withheld. Patent law has thus been characterised in terms of a *balance* between appropriation and diffusion (Levin et al., 1987). And while patents are most typically associated with technological innovation, similar arguments have been made for copyright in the context of artistic or other creative works. Landes and Posner (1989) frame copyright as balancing the benefit of allowing creators to recover the costs of artistic production against the benefit of inexpensive access and reuse. These framings fit nicely with our model's explicit distinction of individually- vs socially-optimal role allocation, and are echoed in our inverse-U results (Figures 4B,5A)

However: the earliest reported precedent for modern IP law dates to around 500 BCE (Athenaeus, 2010; Raustiala and Sprigman, 2006). By contrast, recent work from Paige and Perreault (2024) uses evidence of stone tool complexity to suggest that human cultural evolution became meaningfully cumulative around 600,000 years ago. So either value capture mechanisms played no role in >99% of human cultural history, or they did so through a less obvious route.

6.1.2 Prestige

What might such a route look like? In an influential paper, Henrich and Gil-White (2001) theorised that prestige evolved in response to a selective milieu that favoured more discerning social learners; i.e. those whose attention is typically directed toward demonstrators with better-than-average knowledge or skill. Since competence is often difficult or costly to assess directly, the story goes, these pressures led to the use of prestige cues as more accessible markers of demonstrator quality in valued domains such as hunting or foraging. A key component of H&GW's theory is that prestigious individuals become the beneficiaries of 'freely-conferred' deference behaviours (e.g. resource gifts, grooming), performed in exchange for access to valuable learning opportunities. Importantly, this provides a means by which nonmaterial status can translate to material benefits.

Consider, for a moment, a hypothetical society in which prestige-biased social learning and deference gifting are widespread. This society already has social norms governing which activities are deemed worthy of prestige. Now imagine that a new norm emerges, specifying that innovation itself—divorced from any specific domain—is prestigious. Individuals that

innovate successfully achieve greater prestige; this in turn translates to rewards in the form of resource gifts or exemption from certain tasks. Clearly, this would represent a much less direct form of value capture than e.g. royalty payments, but if these prestige-mediated benefits scale with the total value of an innovator's output, it could approximate our λ model.

There are multiple reasons to find this idea attractive. First, it assumes little in the way of additional social or psychological machinery. If people already possess mechanisms for assigning, tracking, and being motivated by prestige, then the novel ingredient is simply a culturally transmitted rule specifying that successful innovation is among the achievements that merit prestige. In this way it might be thought of as a partial *exaptation* of prestige: a system that originally facilitated selective social learning may also have helped incentivise the production of learnable innovations. Second, prestige is well-suited to capture the delayed and diffuse benefits that characterise cumulative culture: the value of an innovation may only become apparent once others extend or refine it; reputational credit can allow benefits to flow back to earlier contributors over longer timescales. Finally, a norm that causes innovators to be considered prestigious may accelerate not only the production of innovations but also their *diffusion*, via its interaction with prestige-biased social learning.

6.2 Limitations and future work

We believe that our results highlight a relatively underexplored element of the discussion around uniqueness of human cumulative culture: the potential role of social norms and institutions in aligning individually rewarding patterns of behaviour with those necessary to sustain the cultural ratchet. Nevertheless, it is worth highlighting some limitations of the current work. First, the underlying model of CCE used to produce our theoretical results is, in many regards, very simplistic. This is by design, since it allows us to focus on the qualitative interactions between individual RL and population-level cultural outcomes; but... For instance, we treat 'cultural complexity' as a scalar quantity, whereas in reality of course culture is extremely multidimensional. Relaxing this construction would allow innovators to specialise in different domains of cultural production, perhaps developing uneven capacity for success due to domain-specific experience. Another simplifying assumption of our theoretical model involves the cultural decline term L (see SI), which assumes that a higher cultural complexity always means a greater rate of loss. We don't have to look far within our own history for examples of innovations that have the opposite effect: the printing press made it less likely that someone's ideas would die with them, an effect that has only been amplified by more recent information technologies like the world wide web.

Beyond the underlying CCE dynamics, another limitation is that we only consider a single type of payoff-modifying norm/institution, based on the idea of value capture. In principle, similar results could be achieved by ... such as awarding a flat subsidy to would-be

innovators or sanctioning agents that only ever imitate. In addition to this, neither our theoretical models nor our simulations engage with the details of how a value-capture norm would be 'implemented' in practice—e.g. how would compliance be enforced, what sort of body would be responsible for collection and distribution, etc.

Finally, our approach to cultural group selection represents one end of the spectrum of demographic processes that can underlie CGS. In our simulations, groups compete with and replace one another directly, such as may happen through military conflict or resource competition. But group-level cultural change can also emerge more gradually through selective migration or transmission at the individual level, Boyd and Richerson (2009); Molleman et al. (2013).

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