# A resource-rational analysis of when (not) to trust your elders

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## Abstract

A major challenge in human social learning is deciding how to integrate "cultural" information inherited from previous generations with contemporary information available from our "peers". While cultural information may be based on more experience, it may also be outdated if the environment has changed. To understand this dilemma from a normative perspective, we developed a cognitive model of a highly simplified version of the problem. Our analysis examined how a learner should balance peer and cultural information in dynamic environments under information costs. We analysed this trade-off as a function of (1) the age of cultural information, (2) the rate of environmental change, (3) the reliability of peer information, and (4) information gathering costs. We also explore how cognitive limitations may bias this process. These results contribute to an increasingly detailed picture of the computational problems that individuals face in the context of cultural evolution.

## Introduction

"I used to be with it, but then they changed what *it* was. Now what I'm with isn't it, and what's it seems weird and scary to me."— The Simpsons, Season 7, Ep. 24

One of the few certainties in life is that our environments change. Shifts in climate can turn reliable foraging grounds into arid deserts. Or, as the opening quote illustrates, cultural changes in fashion, music, and language mean that what was once considered "cool" may no longer be (including, perhaps, describing things as cool). The challenge is that environments are *dynamic*, and we cannot always rely on historical information to predict their current state.

A related challenge is that it is often difficult or impractical to rely purely on our own direct observations of the environment. For example, learning what is fashionable by randomly selecting clothes and observing people's reaction will probably result in embarrassment and social ostracism. Figuring out which types of mushrooms are edible by personal trial and error could result in eating poisonous mushrooms. To avoid these potential costs, we rely on information provided by others (Alister & Perfors, 2026; Kendal et al., 2018). We observe our peers when deciding how to dress, and we read a guide when foraging mushrooms. Indeed, this ability to learn from others and pass our own knowledge to future generations is a key mechanism of our species' success (Tennie et al., 2009).

However, for this kind of learning to be successful, we need to be able to appropriately weigh different sources of information based on how suitable they are for a given context (Poulin-Dubois & Brosseau-Liard, 2016; Taylor-Davies et al., 2025; Thompson et al., 2022). One key distinction, which is the focus of this paper, is how to integrate knowledge passed down from previous generations (what we will refer to as *cultural* information) with current observations of contemporary peers (what we will refer to as *peer* information). Cultural information may represent extensive, refined knowledge, but it may also be outdated if the environment has changed. Peer information is current, but may be based on fewer observations and therefore less accurate. A learner in this context must somehow decide how to balance these sources.

A number of fields have examined closely related issues, yet there remain key questions from a cognitive perspective. For example, developmental research shows that peer learning is an essential form of cultural transmission (for reviews, see Lew-Levy & Amir, 2024; Lew-Levy et al., 2023), yet children typically prefer learning from adults when given the choice (Jaswal & Neely, 2006; Wood et al., 2012). This preference weakens in adolescence, when peer learning becomes favoured for certain tasks (Lew-Levy et al., 2023). It remains unclear how the rate of environmental change affects these learning preferences.

Another key area where peer learning in dynamic environments has received attention is in models of *cultural evolution*. These models suggest that cultural knowledge is often of high quality because it has helped previous generations succeed. That is, more accurate or useful knowledge tends to propagate over time as agents with less helpful knowledge may pass it on less frequently – a population-level process that selects for knowledge that has "stood the test of time"; whereas peer knowledge may be less reliable. However, these models also show that maintaining some reliance on peer information is evolutionarily adaptive in dynamic environments (Acerbi & Parisi, 2006; Deffner & McElreath, 2022). As environments shift, what was once successful cultural knowledge may become irrelevant, and agents who rely solely on outdated cultural information are at a disadvantage.

Evolutionary models offer a population-level perspective, explaining how preferences for learning from peers may be selected for or against over the course of generations (e.g. Deffner et al., 2020), in the case where such preferences are relatively stable at the individual level (though also see Stamps & Bell, 2021; Walasek et al., 2025). However, population-level models do not generally address the decision-making problem faced by an individual learner capable of reasoning



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about the decision with knowledge of the process. In our day-to-day lives, we often face this problem and we often have at least some understanding of the key relevant factors: the stability of our environment, the reliability of our peers, and the cost and availability of these two sources of knowledge. Adolescents and adults are sensitive to these factors when consuming social information (Hofmans & van den Bos, 2025).

Cognitive models of learning from peers (see e.g. Ciranka & Bos, 2020; Hardy et al., 2023) have been used very widely to examine related questions about the normative structure of human social learning (see Liu & Xu, 2022, for a recent review). In the context of balancing inherited and peer knowledge in dynamically evolving environments, this approach allows us to specify the conditions under which cultural information remains valuable despite environmental change, when peer information becomes necessary, and how agents should adapt their information-gathering strategies based on the costs of doing so. Such a model is complementary to an evolutionary perspective, and may also provide a normative benchmark that can be directly compared to future behavioral data.

In this paper, we performed a resource rational analysis (Lieder & Griffiths, 2019) of a cognitive model that formalises how a learner should balance peer and cultural information in dynamically evolving environments under information acquisition costs. Specifically, we analysed how a rational agent should balance cultural and peer information as a function of (1) the age of cultural information, (2) the rate and extent to which the environment is changing, (3) the reliability of peer information, and (4) the costs associated with collecting peer and cultural information respectively. We also explore how limiting the cognitive capacities of agents or adjusting their assumptions about how information has been gathered may bias them toward cultural or peer data.

## Model: A resource-rational analysis of source integration in dynamic environments

In this section, we describe the model and its predictions in detail. It is important to mention that our model is *highly* simplified relative to some of the real world examples we have used to motivate this paper. We describe how this model could be extended to more complex scenarios in the discussion.

### A Changing Environment

We make the simplifying assumption that the environment can be captured by a state variable $x_t$ that either changes at some time point, or remains the same, depending upon some volatility rate $v \in (0, 1)$. That is, the state can change by some increment $\epsilon_x \sim \mathcal{N}(0, \sigma_x^2)$ depending upon on the outcome of a sample from a change point variable $c_t \sim Bernoulli(v)$. In other words, if the state changes from $t$ to $t+1$, it changes in increments with variance $\sigma_x^2$, and depending upon the outcome of a probabilistic event with weight $v$.

$$x_t = x_{t-1} + c_t \epsilon_x \tag{1}$$

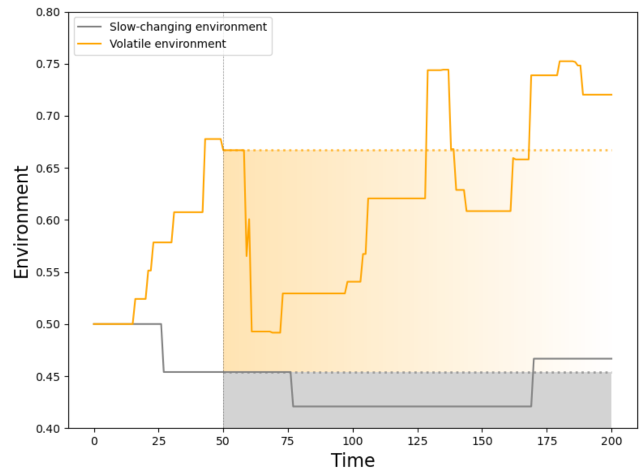



Figure 1: The x-axis shows time and the y-axis shows the environmental state $x_t$. Two environments start from the same initial condition at $t = 50$ and evolve with different change frequencies (orange: higher volatility $v$, larger $\sigma_x$). At $t = 150$, a cultural template is written. Its accuracy degrades over time, indicated by a decreasing reliability parameter illustrated by the transparency, with slower degradation for the gray one

Figure [1] shows how a single-dimensional state of an environment changes over time. The more rapidly evolving environment is coloured in orange, and the slower one in gray. As shown by the transparency of the strips, a cultural signal produced in the orange-environment is worse at $t = 200$ than the one in gray written at the same time. Therefore, in order to tell if a cultural signal is useful, it is important to have an estimate of how rapidly the environment is changing.

### A rational agent

In this work, the agent's objective is to predict the current state of the environment as accurately as possible based on information obtained from a cultural signal or $n$ peers. However, this objective incurs two costs: (1) effort spent on collecting information about how volatile the environment is (to weigh culture versus peers), and (2) effort spent on collecting peer data. The agent begins with a prior over environmental volatility (here given by a beta prior with $(\alpha_0, \beta_0)$). The decision process is as follows: At each step in time, the agent estimates the cost of taking one more sample from the environment (per-sample-cost of $\lambda_A$) against the benefit of future predictive accuracy, minus the future costs. Upon reaching the stopping point, the agent obtains $n$ independent samples from their peers (each sample costs $\lambda_n$), and combines that information with a cultural signal to predict the current state of the environment. The objective function implied is given by:

$$J(w, n, A) = MSE(w, n, A) + \lambda_n n + \lambda_A A \tag{2}$$

Where $MSE(w, n, A)$ is the mean squared error on the prediction of the agent based on $n$ peer samples, and $A$ samples used to estimate the volatility rate in the environment. $w$ is the weight used to combine the peer and cultural signal. We will present these components in reverse order, by first describing the dynamics of the agent once the stopping criterion has been reached. In later sections, we describe a simple strategy to estimate the stopping point itself.

**Peer signal** Each peer signal $y^i$ consists of a noisy estimate of the current state of the environment i.e. $y^i_t = x_t + \epsilon^i$, where $\epsilon^i \sim \mathcal{N}(0, \sigma_p^2)$. Using the mean of $n$ such samples, we obtain the peer estimate:

$$y^p_t = x_t + \epsilon^p, \quad \epsilon^p \sim \mathcal{N}\left(0, \frac{\sigma_p^2}{n}\right) \tag{3}$$

Therefore, as $n$ increases, the variance on the peer estimate reduces. Note that this is only one simple way to integrate peer testimony. See the Discussion for how our model could be extended to to account for other ways people may evaluate the reliability of our peers.

**The cultural signal** The cultural signal represents the exact state of the environment from $L$ time-steps ago. Therefore, we can approximate the current state of the environment as a noisy variant of the cultural signal, giving us:

$$x_t \approx x_{t-L} + \epsilon^c, \quad \epsilon^c \sim \mathcal{N}(0, Lv\sigma_x^2) \tag{4}$$

Eqn.(4) shows that the noise variance is given by $Lv\sigma_x^2$, where $L$ is the age of the cultural signal, $v$ is its volatility rate, $\sigma_x^2$ is the expected value on the change it undergoes at those changepoints.

**The agent's prediction: Weighing cultural and peer estimates** A benefit of our model is that we can not only quantify how uncertain an agent should be about peer versus cultural information, but that the agent can also use these estimates to form their own prediction about the true state of the environment without ever having observed it directly. The agent's prediction about the true state of the environment at time-step $t$ is given by a weighted combination of the peer and cultural signals:

$$y_t = wy^p_t + (1-w)x_{t-L}$$

where $w$ is a weighting parameter, described below. The expected value of the mean squared error based upon this prediction is given by:

$$MSE(w; n, A) = w^2\frac{\sigma_p^2}{n} + (1-w)^2 Lv\sigma_x^2 \tag{5}$$

Intuitively, due to the different reliabilities of the sources, weighing them appropriately is critical to making a good prediction about the environment.

## Results

**Optimally weighing sources of information** We break down the objective function in Eqn. 2 by first fixing the information-gathering decisions $(n, A)$. The optimal agent must now only optimally mix together $n$ peer signals and a cultural signal down-weighted by how old it is. We do this by differentiating Eqn. 2 with respect to $w$ and setting the derivative to zero, yielding the optimal weight on peer information:

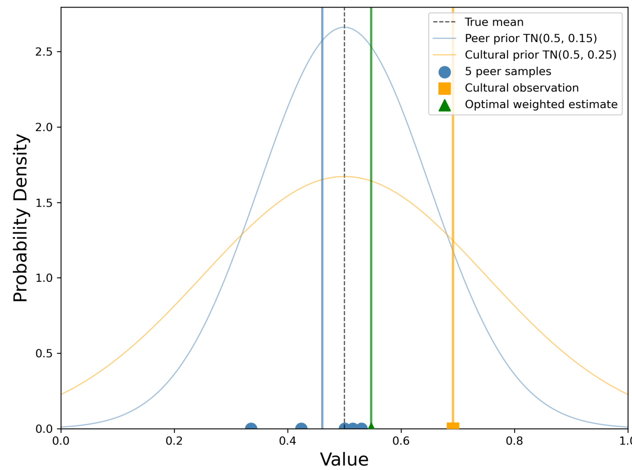



Figure 2: The x axis shows the possible states of the environment. The priors are chosen for illustrative convenience. The blue dots show peer predictions about the environment, and the orange dot shows a degraded cultural signal. The agent's prediction of the current environmental state (green) is formed by a weighted combination of peer estimates and cultural information.

$$w^*(n, A) = \frac{b(A)}{b(A) + a(n)}, \text{ with } b(A) = L\sigma_x^2 v, \; a(n) = \sigma_p^2/n \tag{6}$$

Intuitively, $b(A)$ represents the amount of cultural degradation, and $a(n)$ measures peer-variance. Therefore, the optimal weight is a tradeoff based on reliability of these sources: cultural information should be prioritised it remains informative ($b(A) < a(n) \implies w^* < 0.5$), and peers are valuable when they are plenty and reliable ($b(A) > a(n) \implies w^* > 0.5$). Figure [2] shows how these two information sources are combined to make a prediction. Here, the optimal weight depends on the relative uncertainty of each source, with peer information becoming more influential as cultural information degrades. Substituting this optimal weight back into the objective function reduces the objective function in Eqn.2 to a function over $(n, A)$, giving us:

$$J^*(n, A) = \frac{\sigma_p^2 b(A)}{\sigma_p^2 + b(A)n} + \lambda_n n + \lambda_A A \tag{7}$$

This reduced objective makes explicit that increasing $n$ or $A$ improves accuracy (increasing $n$ reduces the effect of noise, increasing $A$ makes the estimation of $v$ more reliable), but also incurs greater cost. The agent's problem now is to find a balance between the benefits of sampling and its associated costs.

**Choosing the optimal number of peers** Next, fixing the number of volatility estimation samples and differentiating

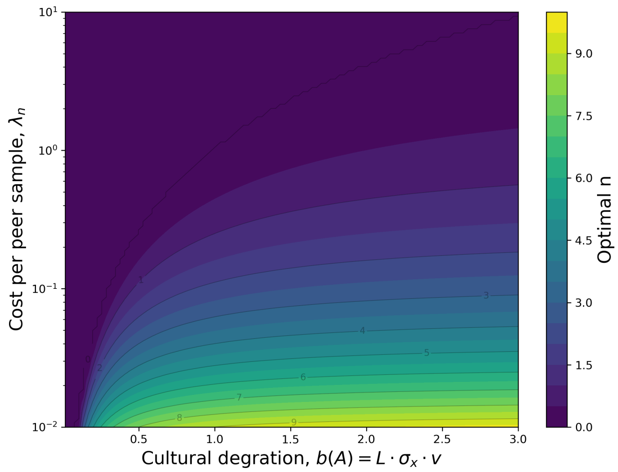



Figure 3: The x axis shows the degradation of the cultural signal, and the y axis is the unit cost per additional peer sample. Depending on the degradation of cultural information, the optimal solution may involve consulting no peers or an interior optimum with $n^* > 0$

Eqn. 7 with respect to $n$ and setting it to 0 gives us the number of peers the agent needs to consult:

$$n^*(A) = \max\left\{0, \sqrt{\frac{\sigma_P^2}{\lambda_n}} - \frac{\sigma_P^2}{b(A)}\right\} \tag{8}$$

Figure [3] shows that the agent should consult more peers when they have accumulated evidence that the environment is changing (when $b(A)$ is large). A more degraded culture can be the result of an older cultural signal (large $L$), larger step changes $\sigma_x$, or a more volatile environment $v$. When this degradation is severe, peers become more valuable despite the noise in their estimates. Importantly, there exists a threshold above which the agent will always have to consult peers: $n^* > 0$ when $b(A) > \sqrt{\lambda_n \sigma_P^2}$.

**Choosing the optimal number of volatility rate samples** The amount of time an agent should spend collecting information about the volatility depends upon two factors: the potential benefit of an additional sample (which improves the quality of $w^*$) weighed against the cost of spending that energy. This number can be calculated based on a myopic, value of information strategy, in which the agent continues to sample only when the expected one-step reduction in downstream optimal loss exceeds $\lambda_A$ (sketched in Table 1).

Figure [4a] shows how agents with different priors choose stopping points based on this strategy: if the prior mean is low, then the agent stops sooner, and relies on culture to make a prediction. Figure [4b] shows how this changes when a single agent is in a situation with greater costs on sampling from peers. Higher costs (in red) lead to early stops, while more relaxed cost parameters result in late stopping. The lower panels in Figure [4] shows that when the expected benefit falls below the cost of taking one more sample, the agent stops.

Additionally, we derived the optimal value of $A$ in expectation, and obtained the following terms under two regimes (given that $\frac{\alpha_0}{\gamma_0} > v$, where rewrite $\alpha_0 + \beta_0 = \gamma_0$, the pseudocounts):

$$A^* = \begin{cases} \sqrt{\frac{C(\alpha_0 - v\gamma_0)}{\lambda_A}} - \gamma_0 & b(A) \le \sqrt{\lambda_n \sigma_P^2} \\ \frac{1}{v}\left(\sqrt{\frac{(\lambda_n \sigma_P^2/C)(\alpha_0 - v\gamma_0)}{\lambda_A}} - \alpha_0\right) & b(A) > \sqrt{\lambda_n \sigma_P^2} \end{cases} \tag{9}$$

Under this expectation-based analysis of the baseline model, $A > 0$ arises only when the prior mean overestimates the true volatility, i.e., $\frac{\alpha_0}{\gamma_0} > v$. In this regime, volatility sampling is potentially beneficial because it reduces the agent's expected estimate of environmental volatility, increasing the relative usefulness of cultural information and reducing reliance on costly peer sampling. Here, the agent may optimally choose to sample fewer peers and combine them with culture, as captured by Eqn. 9.

The contrasting situation of *underestimating* volatility may be best illustrated by analogy: when deciding to follow established medical guidelines or seek multiple second opinions, we may take into account the rapidity with which medical solutions have changed in the recent past. Second opinions may be less worthwhile in a stable situation, because they only increase uncertainty while incurring additional costs. In the model, under a prior assessment of stability ($\frac{\alpha_0}{\gamma_0} < v$), the optimal choice is to refrain from estimating volatility rate.

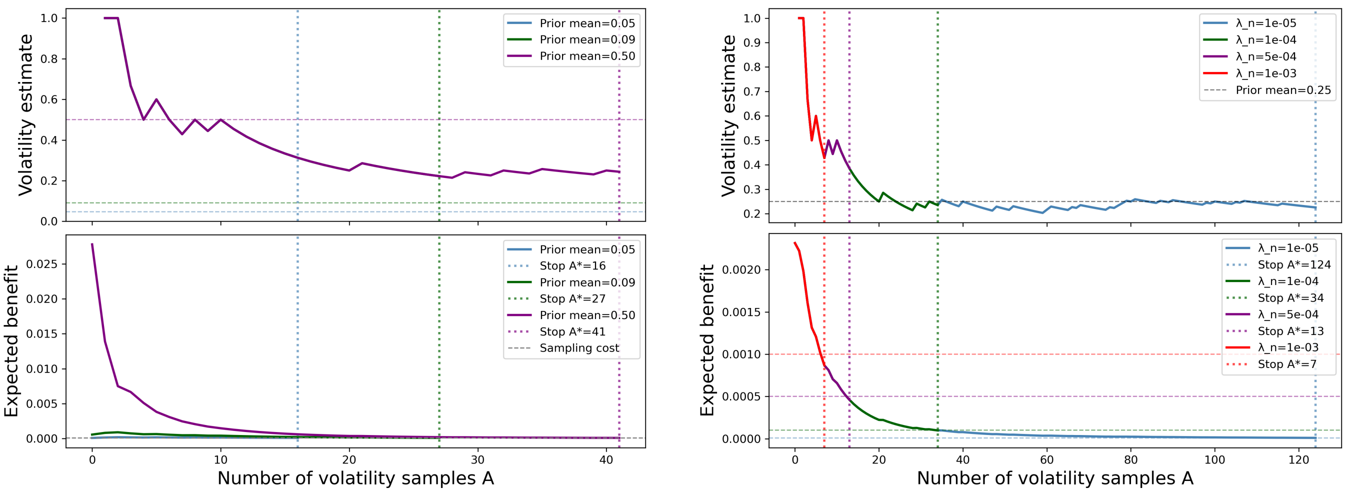
## Biasing agent capacities

So far we have used our model to describe the optimal trade offs between peer and cultural information in different contexts. However, we can also use our model to explore how different kinds of cognitive limitations or biases can produce different behaviors.

**Bias in sampling environmental change** One way people may be suboptimal is through biases in the process of estimating environmental change. For example, some people might be systematically more likely to remember instances of *change* in the environment versus instances of no change, or vice versa. Such behavior would be consistent with a number of cognitive biases, such as availability bias, whereby people could overestimate whichever type of event (change or stability) is easier to recall, for example if it occurred more recently or was especially memorable (Tversky & Kahneman, 1973).

We encode this assumption into the model by adding a "change bias" parameter, $\kappa$, into the calculation of the rate of change: $\tilde{r} = \min(1, r \cdot \kappa_r)$. That is, whenever the agent computes the volatility rate $v$, they scale it by $\kappa_r$. When $\kappa_r < 1$ the agent underestimates volatility, and as a result seeks out fewer peers testimonies. Although such agents incur fewer costs, their predictions also become worse.

In Figure 5(left) we show how varying $\kappa_r$ affects prediction error and total cost. This pattern of results immediately suggests a Pareto frontier of solutions: The intuition here is




(a) Volatility/benefit estimate over samples, controlled by prior

(b) Volatility/benefit estimate over samples, controlled by cost

Figure 4: The relationship between volatility samples (x-axis) and benefit/estimates on the y-axis. The vertical lines mark the stopping point for various parameterizations. (a) shows how the prior mean affects stopping point: more conservative estimates lead to earlier stopping, volatile initial estimates lead to later stopping. (b) shows how peer sample cost affects stopping point: greater costs drive earlier stops.

Table 1: Simplified Model Procedure.

| **Conceptual description** | **Mathematical description** |
|---|---|
| **1.** Use a myopic, value-of-information rule to determine stopping point $A$ | $\Delta_A = J^*(A) - \mathbb{E}[J^*(A+1)]$, if $\Delta_A > \lambda_A$, stop sampling |
| **2.** Compute how degraded the cultural information is as a function of environmental change and time. | $b(A) = L\sigma_x^2 \frac{\alpha + rA}{\alpha+\beta+A}$ |
| **3.** Determine the optimal number of peer samples given cultural degradation and sampling costs. | $n^* = \max\left\{0, \sqrt{\frac{\sigma_p^2}{\lambda_n}} - \frac{\sigma_p^2}{b(A^*)}\right\}.$ |
| **4.** Compute the optimal weighting of peer information relative to cultural information. | $w^* = \frac{b(A^*)}{b(A^*)+\frac{\sigma_p^2}{n^*}}.$ |

that decision making is still governed by the same optimality considerations, but biased in some way. These decisions then result in a space of solutions—with costs and benefits—that were not explored by the unbiased agent. Here, we find that as $\kappa_r$ decreases, the agent explores cheaper solutions because it underestimates volatility, and relies more heavily on culture.

**Bias in assessing the reliability of peers** Another way that people could be biased is by assuming that peers are more or less reliable than they really are. In other words, bias in estimating $\sigma_p^2$. Such a bias could be linked to, for example, individual differences in wanting to conform to social identity (MacDonald et al., 2013), trusting friends or family members more than their expertise warrants (Cui et al., 2020), or assuming that peer observations are non-independent (Alister et al., 2025). One simple way to formalise this is by adding a "reliability bias" parameter, $\kappa_p$ into the original calculation of peer reliability: $\tilde{\sigma}_p = \kappa_p \cdot \sigma_p$. Therefore, when $\kappa_p > 1$, the agent believes peers are less reliable.

Figure [5](right) shows that when $\kappa_p < 1$, agents believe that peers are more consistent, and as a result—under that incorrect assumption—require fewer peers to predict the environment. This is why the darker colored dots appear to the left of the ones with greater values of $\kappa_p$. On the other hand, integrating unreliable peer information is viable only until a point, beyond which the agent decides to rely on culture again. This is because under a sufficiently low peer-reliability regime, it is least expensive to consult cultural information alone rather than relying on a possibly noisy peer group. This leads to a closed space of possible solutions, where agents who are extremely mistrustful *and* agents who are extremely trusting show very little peer influence.

## Discussion

A fundamental challenge in human social learning is deciding how to integrate "cultural" information inherited from previous generations with contemporary information available from our "peers". We examined a model of this decision process that accounts for a learner capable of reasoning about the

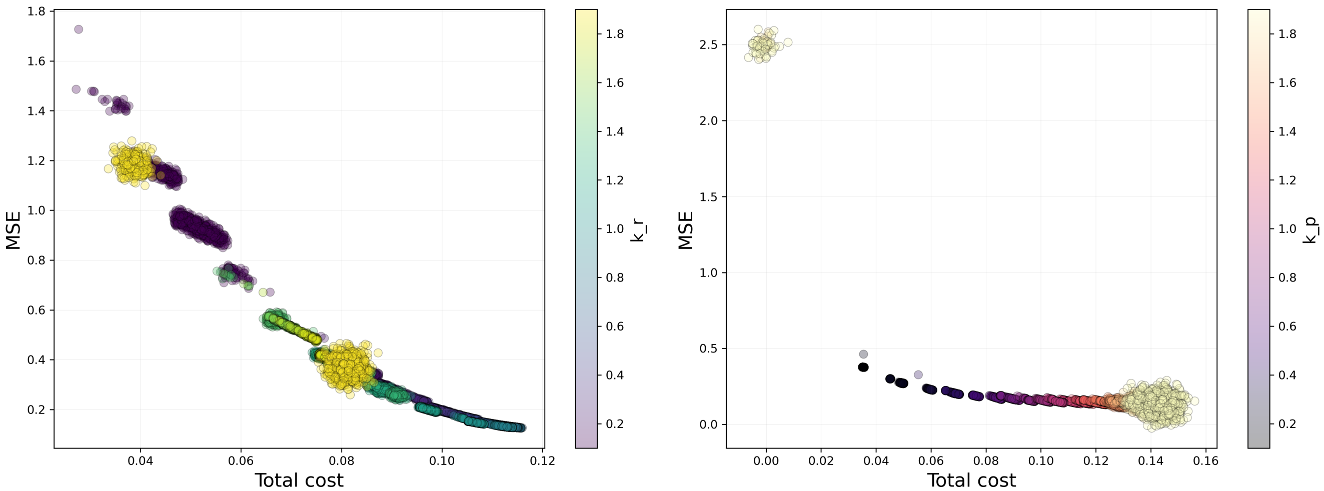



Figure 5: Cost versus Accuracy for agents with different cognitive biases in the same environment. Simulations use Table 1 to derive stopping points and select number of peers under the same environment parameters (Left) shows how the cost/accuracy location changes under biased rate estimates (Right) shows the same in peer reliability biased agents.

reliability of the sources of their data and the rate at which their environment is changing. Our analysis model focused on two factors. First, the amount the environment has changed since the cultural information was generated: as the cultural information ages and under sufficient rate of environmental change, cultural information loses it's value. Second, the reliability of peers: if peer observations are unreliable, and/or there are insufficient peer observations, peer information becomes less valuable.

We are not the first to highlight that peer knowledge becomes more important in dynamic environments (for empirical work, see Knafo & Schwartz, 2001). For example, models of cultural evolution suggest that agents with at least some propensity to trust peers are more likely to pass on their traits to the next generation, since those who rely entirely on cultural information will struggle to survive if the environment has changed (Acerbi & Parisi, 2006; Deffner & McElreath, 2022). However, our model analysed this question from a different perspective. Rather than asking how, on the population level, preferences for peer learning may be evolutionarily desirable, we instead examined how rational individual reasoning can generate such preferences.

One benefit of this approach is that we could not only analyse how people may weigh different information sources, but also investigate a possible mechanism for how people acquire relevant evidence (i.e., by sampling peers and information about environmental change), broadly aligning it with existing process models of decision making (Busemeyer & Townsend, 1993; Evans & Wagenmakers, 2020; Krafft et al., 2021). This approach also allowed us to investigate a fundamental aspect of this process that has not typically been included in cognitive models of social learning – how people might weigh cognitive costs associated with peer and cultural learning in dynamic environments, offering a resource rational perspective (Lieder & Griffiths, 2020) on strategic use of social information in contexts where it's acquisition involves costs.

We also reiterate that our analyses here examined a highly simplified scenario. Our model could be extended in many ways. A natural next step will be to compare this model's predictions with how people actually weigh cultural and peer information. One extension could be to examine different kinds of environmental change. Our analysis assumes that the environment changes in an unpredictable way (see also Acerbi & Parisi, 2006; Deffner & McElreath, 2022). In reality, environments often change systematically. For example, the cost of most goods usually increases by a consistent amount each year (inflation) and many cultural phenomena, such as fashion trends, are often cyclical. Another way our model could be improved is through a more sophisticated mechanism of evaluating the reliability of peers (Alister & Perfors, 2025); independence among multiple peers could also influence reliability (e.g., Whalen et al., 2018). Finally, our model also makes the particularly unnatural assumption that agents cannot sample the state of the environment directly, despite estimating its stability. These and other assumptions could be relaxed in future analyses.

With these limitations acknowledged, our model offers insight into a fundamental trade-off faced by all social learners in the context of culturally evolving knowledge. According to the model, trusting our elders is probably a good idea when (1) they're not too old; (2) our peers are poorly-informed; and (3) it is difficult to determine how quickly things are changing.

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