Social Learning and Collective Issue Prioritization

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June 30, 2025

Abstract

Societies often face competing challenges—such as economic growth versus climate change mitigation—yet frequently fail to prioritize the most pressing issues in a timely manner. This paper develops a dynamic model of collective issue prioritization that integrates differences in social learning across issues and political subgroups. We examine how individuals form concern levels based on independent judgment and socially transmitted cues, especially under political polarization. The model contrasts two types of issues: one grounded in personal experience (e.g., the economy) and another reliant on social learning (e.g., climate change). Our results show that (1) issues requiring higher social learning are more susceptible to polarization, (2) such issues are prone to systematic deprioritization when competing against more directly experienced issues, even when the former are objectively more urgent, and (3) increases in independent concern can fail to shift collective priority without changes in social dynamics. Introducing even modest levels of cross-group learning mitigates polarization and facilitates better alignment with independent judgments. These findings underscore the need to account for issue-specific social learning structures in models of public opinion formation and policy support.

1 Introduction

Human societies often face multiple, sometimes conflicting, challenges simultaneously. We seek economic growth while striving to mitigate climate change, or aim to curb the spread of an epidemic through social distancing while attempting to protect retail businesses. However, efforts to balance competing priorities frequently fall short. Despite scientific consensus on the threat of anthropogenic climate change and a slight majority of Americans expressing concern, no consistent federal-level mitigation policy has emerged. Similarly, during the COVID-19 pandemic, partisan divisions undermined the effectiveness of containment measures such as social distancing. A recurring pattern in these failures is that when issues differ in time scales and uncertainties, collective decision-making often falters, failing to prioritize the societal threats in a timely manner.

The formation of collective opinions has been widely studied through dynamical models across disciplines including physics, mathematics, psychology, and sociology [1–3]. Most models focus on how opinions about a single issue evolve as individuals influence each other and respond to external factors. Some of these models are generalized to a vector of issues [4–6]. A smaller but growing body of work examines the interaction of opinions across multiple issues, often emphasizing how associations between them are reinforced through social influence [7, 8]. However, when it comes to challenges that are present at the same time, the finite pool of worry theory [9, 10] suggests people have limited capacity for concern and different problems compete for attention, suggesting an inherent competitive dynamics between concerns. While trade-offs between competing priorities have been extensively studied on the individual level—particularly through measures like Willingness to Pay (WTP) in policy research [11] —there lacks the integration of the trade-off process in collective opinion dynamics. Developing models that integrate these dimensions could shed light on how societies form responses to complex, multifaceted problems.

Beliefs about societal issues are shaped by a mix of personal experience and social learning. Immediate, tangible issues—such as concern over ones' economic conditions—allow individuals to rely on first-hand experience. In contrast, abstract or uncertain issues like climate change or a novel pandemic rarely provide immediate personal evidence, making social learning from experts, media, and peers essential.

Climate change exemplifies a high social learning issue: its impacts unfold over long timeframes and distant locations, limiting direct experience and visceral response [12]. In such contexts, social cues—especially partisan ones—become primary sources of belief formation. In the U.S., climate change is among the most politically polarized issues [13]. Notably, personal encounters with climate-related events can narrow this partisan divide [14]. The COVID-19 pandemic similarly highlighted the importance of social learning, especially in its early stages. The virus was invisible and its consequences not immediately observable to many. As a result, public responses—such as mask-wearing and support for health policies—were heavily influenced by political and community cues. During 2020, partisan divisions in risk perception and behavior were stark, driven more by social narratives than by direct exposure to the disease [15]. Longitudinal data confirm that descriptive norms—what others are seen doing—strongly influenced future behavior, particularly in mask use [16]. As with climate change, personal experience can moderate partisan differences [15].

By contrast, economic conditions provide more immediate and personal feedback. People experience the economy daily through wages, prices, and employment, reducing reliance on social learning. A panel study around the 2016 U.S. election found that individuals' assessments of their household finances were largely unaffected by the political outcome [17]. The same study showed that while views of the national economy did show modest partisan influence, it is notably less than for issues like climate or COVID, and objective indicators such as unemployment and stock market trends shaped perceptions across party lines.

A general psychosocial pattern emerges: the more immediate and observable an issue, the less people depend on social learning; the more abstract and distant, the greater the role of social learning. This work focuses on understanding collective action in scenarios that require navigating trade-offs between these two types of issues—those grounded in personal experience (like the economy) versus those reliant on social learning (like climate change or COVID-19).

Beyond the extent of social learning, who individuals learn from is equally important. In a hyperpolarized society, people tend to learn from in-group partisans due to mechanisms like selective exposure—social networks dominated by co-partisans [18, 19], and motivated reasoning [20]—when exposed to information supporting the opposing view, one ignores this evidence and sticks with own party's opinion. Efforts to reduce polarization often aim to promote meaningful, cross-party collaboration [21], encouraging consideration of out-partisan perspectives.

Here, we aim to develop a model of collective issue prioritization that captures the competition between issues with differing degrees of social learning, accounting for varying degrees of political in-group social learning. Our model yields three main findings. First, issues requiring greater reliance on social learning tend to exhibit greater polarization in opinion outcomes. Second, when a high social learning issue competes with a lower social learning issue, the former is often deprioritized, even when it is objectively more urgent to address. Third, even as independent concern about a problem rises, shifts in collective priority toward the more pressing issue can remain slow or incomplete, depending on the intensity of social learning adopted by individuals in evaluating the issue. These findings underscore the importance of considering issue-specific differences in social learning intensity when analyzing public opinion formation and collective decision-making.

2 Model

We consider a collective consisting of two sub-groups of equal size (political parties or other salient group identities). They are confronted with two competing issues, one is more direct and observable, thus individuals are less likely to use social learning (*issue L*), the other is abstract and distant, where individuals are more likely to use social learning (*issue H*). The issues are inherently in conflict, such that actions to resolve one tend to exacerbate the other. Each issue is accompanied by its own political discourse, shaping how important it is perceived within each subgroup. The population-level concern for each issue is determined by averaging the concern levels of the two subgroups. The collective decision—whether to prioritize issue L or issue H—is then made by comparing these population-level concerns.

We first consider individuals forming opinions about the importance of each issue (a binary decision of whether they are worried about this issue or not). In line with classic models of belief dynamics, such as the DeGroot model [22], an individual's stance on each issue is shaped by both their independent judgment and the influence of relevant others. Optimistically, we assume that independent judgment reflects the objective severity of the issue, while social influence depends on the proportion of relevant others who are concerned about that issue.

We denote the actual proportion of individuals in group i (where $i = 1$ or 2) who are concerned about issue j (where $j = H$ or L) at time t, as $C_{ij}(t)$. Following a common formulation in dynamical modeling [23], we denote a target level for this proportion to be $C^*_{ij}(t)$, toward which the group adjusts over a belief adjustment time denoted by τ,

$$C_{ij}(t) = \frac{C^*_{ij}(t) - C_{ij}(t)}{\tau} \tag{1}$$

Following prior classic opinion dynamics models, we formulate the target proportion as a weighted sum of the independent judgment and the effect from social influence,

$$C^*_{ij}(t) = (1 - s_j)I_j + s_j f(X_{ij}(t); \alpha) \ , \tag{2}$$

where I_j reflects the average individuals' independent assessment of issue severity, from 0 (not concerning at all) to 1 (extremely concerning), if influence from others were not present. This can be informed by personal experience or scientific understanding of an issue. We assume there is no fundamental difference in the independent judgment between the two social groups about the same issue. The parameter s_j is the weight of social learning, ranging from 0 (fully independent) to 1 (fully social). $f(X_{ij}, \alpha)$ is a conformity function showing how the likelihood of adopting an opinion depends on the frequency of the opinion due to social learning, and takes an S-shape [24–26]. The functional form we chose for it is

$$f(x, \alpha) = \frac{x^\alpha}{x^\alpha + (1 - x)^\alpha} \tag{3}$$

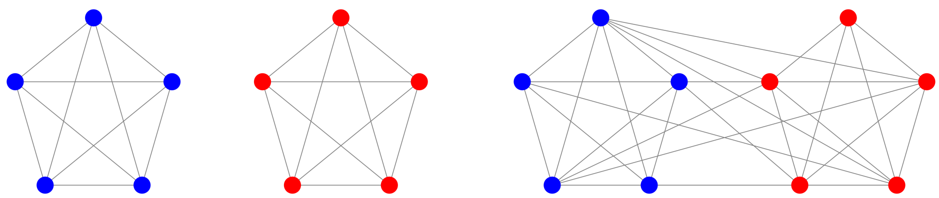
Here, $\alpha > 1$ is a shape parameter of the conformity function. Greater α gives more nonlinear response, and greater sensitivity to majority opinion.

The term X_{ij} is the proportion of relevant others concerned about issue j for an average individual in group i. The composition of these relevant others depends on the level of connectivity between the two subgroups. For simplicity, we consider individuals are connected to others within their own subgroup with a constant probability b, and to individuals in the other subgroup with probability ρb. The parameter ρ represents cross-group connectivity and ranges from 0 to 1 (see Figure 1 for an illustration). When $\rho = 0$, there are no cross-group connections, and individuals are not affected by out-group opinions at all. $\rho = 1$ indicates out-group members are as equally well-mixed as in-group ones. This parameter is especially relevant for capturing affective polarization, which tends to reduce cross-group connectivity. Thus the proportion of relevant others for group i concerned about issue j is, $X_{ij}(t) = \frac{1}{1+\rho} C_{ij}(t) + \frac{\rho}{1+\rho} C_{-ij}(t)$.

Thus, the full equation for the target level is,

$$C^*_{ij}(t) = (1 - s_j) \cdot I_j + s_j \cdot f\left(\frac{1}{1+\rho} C_{ij}(t) + \frac{\rho}{1+\rho} C_{-ij}(t);\ \alpha\right) \tag{4}$$

Note that $i \in \{1, 2\}$ denotes the group index (with $-i$ indicating the other group), and $j \in \{H, L\}$ indexes the issues, which differ in their levels of social learning.



(a) $\rho = 0$ (b) $\rho = 0.5$

Figure 1: assumed network structures with varying cross-group connectivity (ρ)

Notes. Nodes of the same color belong to the same group, and lines represent links formed between nodes. (a) When cross-group connectivity is 0, only nodes of the same color are connected, forming complete graphs within each group. (b) With cross-group connectivity of 0.5, there is a 50% probability of link formation between red and blue nodes in addition to forming complete graphs within each group.

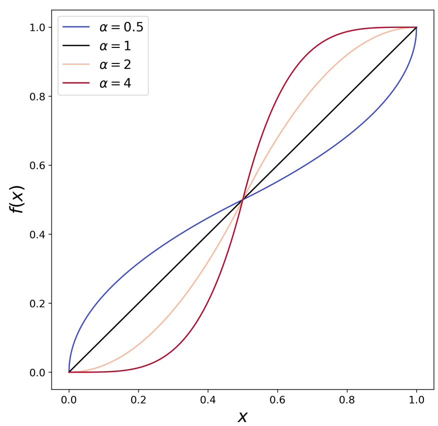


Figure 2: Conformity response $f(x, \alpha)$

The mechanism described in Equation 4 applies uniformly to the dynamics of all four types of concerns (C_{1H}, C_{1L}, C_{2H}, and C_{2L}).

Once group members form steady-state concerns, the model evaluates the population-level trade-off between *issue H* and *issue L*, which reflects support for mitigation efforts targeting *issue H*. This trade-off is modeled using a logistic function from the discrete choice literature [11, 27–29]:

$$P(t) = \frac{e^{C_H(t)/\sigma}}{\sum_{j \in \{H,L\}} e^{C_j(t)/\sigma}} \tag{5}$$

The smoothness parameter σ controls the sensitivity of prioritization (see Figure 3 for comparison of several values of σ). When $sigma = 0$, even small differences in concern lead to large differences in prioritization, with nearly all individuals favoring the more concerning issue. As σ increases, prioritization becomes more balanced, approaching a 50-50 split.

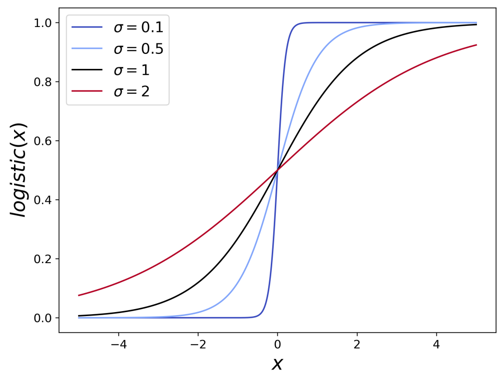


Figure 3: Logistic function $logistic(x, \sigma)$

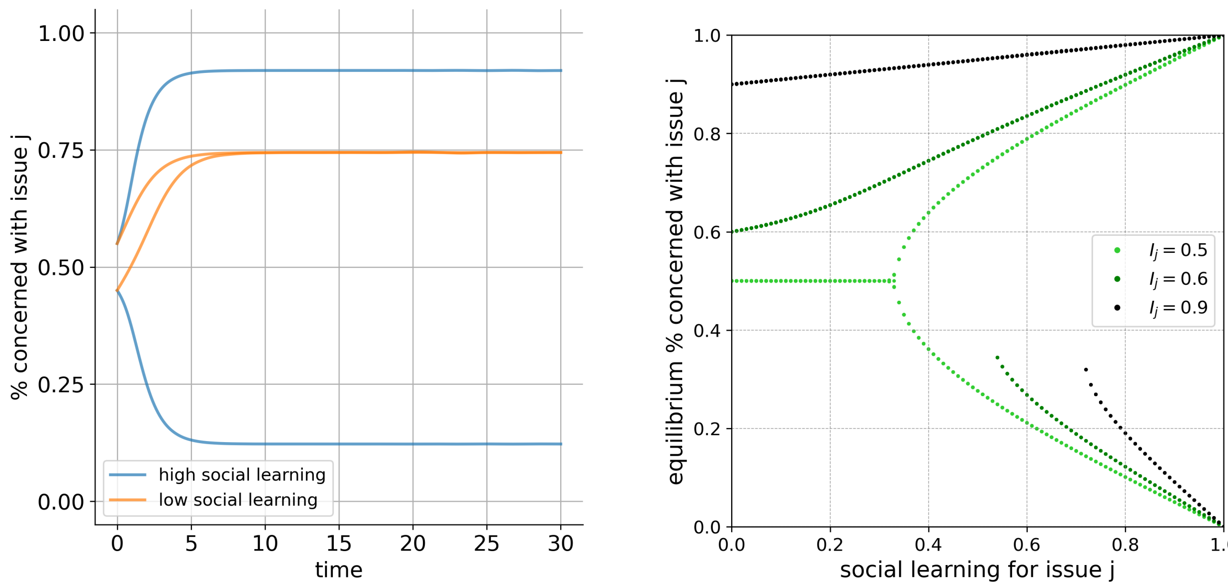
3 Results

Without inter-group learning

For simplicity in illustrating model predictions, we consider groups have reached equilibrium in their concerns. Additionally, the two groups begin on opposite sides of the neutral point ($C_{ij}(t) = 0.5$), with one group slightly more concerned and the other slightly less (e.g., $C_{1j}(0) = 0.55$, $C_{2j}(0) = 0.45$). We first examine the case without any cross-group connection, reflecting highly affectively polarized subgroups.

The most important parameter in the model is the issue-specific level of social learning (s_j). When social learning is low to moderate, two groups arrive at the same level of concern for the same issue. However, when social learning is high, two groups may reach very different conclusions—one highly concerned about the issue, while the other is not concerned at all. As shown in Figure 4a, while other parameters and initial conditions stay the same, increasing s_j from 0.4 to 0.8 leads to divergence between groups. Figure 4b provides a more general view of how the set of possible equilibria changes as s_j increases. Line colors represent levels of independent concern: at low s_j, concern levels tend to align with, but are inflated compared to, independent judgment. At high s_j, however, an additional equilibrium can emerge in the opposite direction—for example, an unconcerned state may arise even under high independent concern, becoming further amplified as social learning increases.

Figure 4: Social learning alters equilibrium outcomes



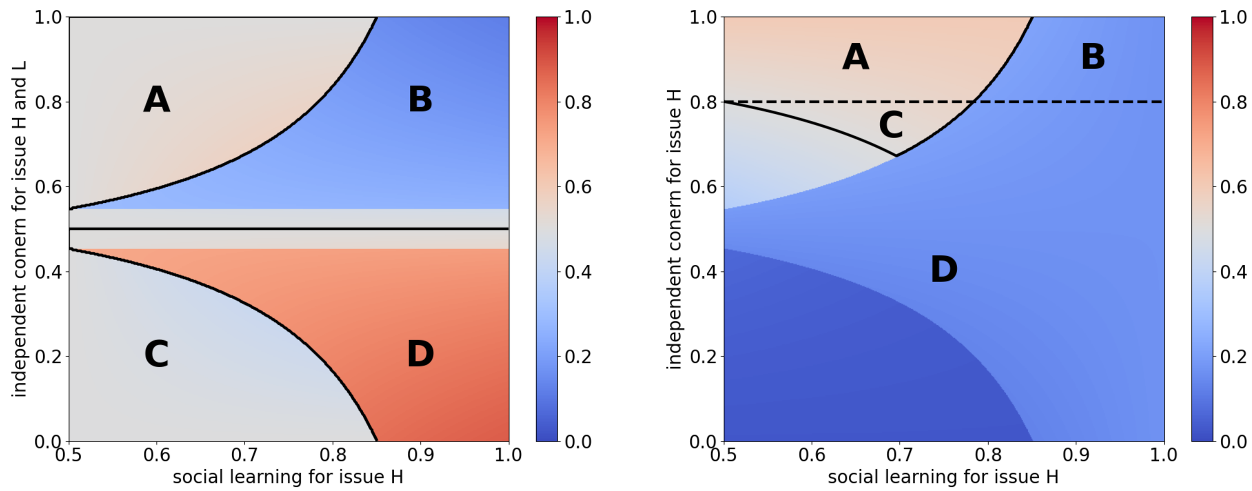
(a) Concern dynamics under low vs. high social learning

(b) Bifurcation of concern equilibria with social learning

Notes. (a) Time evolution of the percentage concerned with issue j for two parties. Parameters used: $(C_{1j}(0), C_{2j}(0)) = (0.55, 0.45)$, $\alpha = 3$, $\rho = 0$, and $I_j = 0.6$. High social learning ($s_j = 0.8$) is shown in blue; low social learning ($s_j = 0.4$) in orange.(b) Bifurcation diagram showing the equilibrium percentage concerned with issue j as a function of the degree of social learning s_j. Parameters: $\alpha = 3$; color gradient from light green to black represents increasing I_j from 0.5 to 0.9.

The effect of social learning on prioritization outcomes is more nuanced. Since prioritization involves comparing issues with differing levels of social learning, we first fix independent concern for both issues at the same level to isolate the impact of social learning differences, and then we relax this assumption by fixing the independent concern for *issue L* while allowing that for *issue H* to vary freely. Each heatmap in Figure 5 shows the prioritization of *issue H* as a function of independent judgment and social learning for *issue H*. The plots are divided into four regions by a contour line representing the threshold where prioritization of *issue H* is exactly 0.5. Red regions indicate a majority prioritizing *issue H*, while blue regions indicate a minority, with color intensity reflecting the strength of the majority or minority.

Figure 5: Social learning affects the priority of *issue H*



(a) independent concern is set at equal level for both issues

(b) independent concern for *issue L* is fixed at high level

Notes. Heatmaps of the percentage of the population prioritizing *issue H* over *L*. Gray indicates 50%; blue indicates a minority, and red a majority prioritizing *issue H*. (a) Priority as a function of s_H, I_H, and I_L. Here, s_L is fixed at 0.5, and $I_H = I_L$ to isolate the effect of social learning. Regions A to D are delineated by black contour lines marking the 50% threshold. Parameters: $(C_{1H}(0), C_{2H}(0), C_{1L}(0), C_{2L}(0)) = (0.55, 0.45, 0.45, 0.55)$, $\alpha = 3$, $\rho = 0$, $s_L = 0.5$, and $\sigma = 0.25$. (b) Priority as a function of s_H and I_H. Here, $s_L = 0.5$ and $I_L = 0.8$, representing a population independently concerned about *issue L*. The dotted black line indicates $I_L = 0.8$, and solid black contours mark the 50% threshold, together delineating regions A to D. Below the dotted line, individuals are more concerned about *issue L* in the absence of social learning; above, they are more concerned about *issue H*. Parameters: $(C_{1H}(0), C_{2H}(0), C_{1L}(0), C_{2L}(0)) = (0.55, 0.45, 0.45, 0.55)$, $\alpha = 3$, $\rho = 0$, $I_L = 0.8$, $s_L = 0.5$, and $\sigma = 0.25$.

In Figure 5a, we vary the independent concern for both issues simultaneously, keeping them equal, to focus solely on the role of social learning in shaping prioritization. We fix the level of social learning for *issue L* at 0.5 and increase it for *issue H* from 0.5 to 1, allowing us to examine how increasing asymmetry in social learning influences outcomes.

Region A represents scenarios where social learning for *issue H* is relatively low, and independent concern is high. In this case, social learning amplifies concern without fundamentally shifting opinions, leading to a weak majority prioritizing *issue H*. In Region B, social learning becomes strong enough to push one group into an unconcerned equilibrium, while the other group remains concerned with elevated values due to conformity dynamics. As a result, the overall concern for *issue H* is only slightly higher than neutral, whereas concern for *issue L* remains strongly elevated, resulting in a population-level minority prioritization of *issue H*. Notably, once social learning for *issue H* exceeds approximately 0.85, this underprioritization persists regardless of how strong the independent concern is—highlighting a systematic bias against highly socially learned issues when compared to less socially learned ones.

Regions C and D mirror Regions A and B, but in this case the more socially learned issue becomes overprioritized relative to the less socially learned one. In Region C, both issues are independently considered unconcerning, and social learning is not strong enough to push either group toward a concerned state. As a result, prioritization of *issue H* remains a slight minority. In contrast, Region D reflects a scenario where the high level of social learning for *issue H* is sufficient to drive one group into a concerned equilibrium, making the overall population more concerned about *issue H* than *issue L* and leading to majority prioritization of the more socially learned issue.

In Figure 5b, we relax the previous restriction on independent concern by fixing the independent judgment for *issue L* at a high level ($I_L = 0.8$) while varying the independent judgment for *issue H*. The horizontal dashed line separates the region where independent concern for *issue H* exceeds that for *issue L*, and vice versa. For example, Regions A and B represent cases where individuals exhibit greater independent concern for *issue H* than for *issue L*, in the absence of social learning. In Region A, social learning is not strong enough to destabilize this concern, so both groups remain concerned about *issue H*, resulting in a slight majority prioritizing it. In contrast, in Region B, social learning is strong enough to push one group into an unconcerned equilibrium, despite high independent concern. This leads to a minority prioritizing *issue H*, producing a prioritization outcome that misaligns with the underlying independent judgment.

In Figure 5b, Regions C and D correspond to cases where independent concern for *issue H* is lower than that for *issue L*. In the absence of social learning, we would expect *issue H* to be consistently deprioritized, as seen in Region D, where only a minority prioritize it. However, in Region C, a slight majority prioritize *issue H*, despite its lower independent concern. This outcome reflects two interacting effects of social learning. Initially, as social learning increases, concern for *issue H* is amplified across both groups, raising its perceived severity. However, once social learning becomes too strong, one group shifts to an unconcerned equilibrium, marking the transition into Region D.

So far, we have examined model behavior under the assumption that independent judgment remains fixed over time. However, introducing a simple time-varying dynamic can provide additional insights without adding significant complexity to the model. Table 1 outlines three simulation scenarios. In Scenario 1, independent concern for *issue H* is static and extremely high, social learning for *issue H* is set to be twice that of *issue L*, and independent judgment for *issue L* is fixed at a neutral level. Scenario 2 builds on Scenario 1 by allowing independent concern for *issue H* to start at a neutral level and gradually increase to an extremely concerned state. Scenario 3 modifies Scenario 2 by slightly reducing the level of social learning for *issue H*.

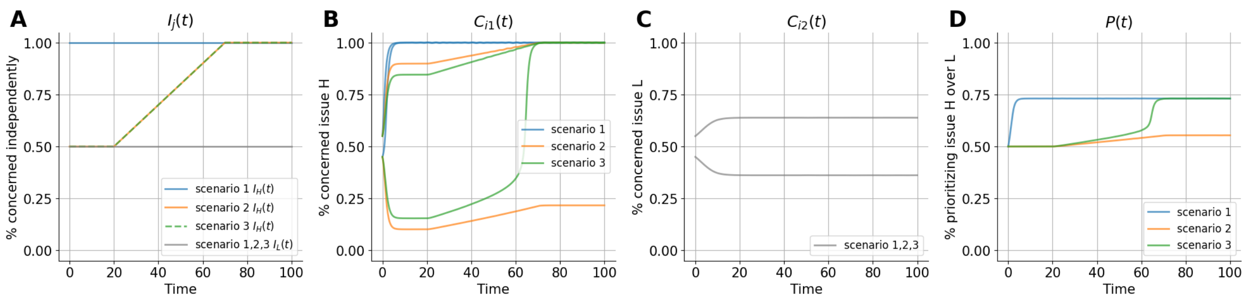
Table 1: Parameters used in each scenario

Scenario	$I_H(t)$	s_H	$I_L(t)$	s_L
1	fixed at 1	0.8	0.5	0.4
2	increase from 0.5 to 1	0.8	0.5	0.4
3	increase from 0.5 to 1	0.7	0.5	0.4

Notes. Dynamic version of independent judgment for *issue H* in scenarios 2 and 3 is given by: $I_H(t) = \min(1, \max(0.5,\ 0.5 + 0.01(t - 20)))$, i.e., I_H starts at an ambiguous level of 0.5 and begins increasing at time $t = 20$ by 0.01 per unit time, reaching 1 at $t = 70$ and remaining at 1 thereafter.

Figure 6A shows the evolution of independent judgment over time for each issue across the three scenarios, while panel B displays the color-coded concern dynamics. Since all three scenarios share the same independent judgment for *issue L*, the development of concern for *issue L* is identical across scenarios (panel C). In Scenario 1, where the public maintains a consistently high level of independent concern for *issue H*, both groups converge to an extremely concerned state. In Scenario 2, the public begins with a neutral level of concern that gradually increases to an extremely high level. Despite this, the two groups diverge in their steady-state concern levels, with one group remaining significantly unconcerned about *issue H*. In Scenario 3, where the degree of social learning for *issue H* is slightly reduced, this divergence disappears—both groups ultimately converge to a concerned state. Notably, convergence occurs only once independent concern becomes extremely high, triggering a rapid shift in the previously under-concerned group. Until that tipping point, concern in the under-concerned group remains low but steadily rises. As a result, in Figure 6D, the prioritization of *issue H* reaches a strong majority in Scenarios 1 and 3, but remains only a slight majority in Scenario 2 due to the persistent divergence in concern levels.

Figure 6: Equilibria are path dependent on independent judgment



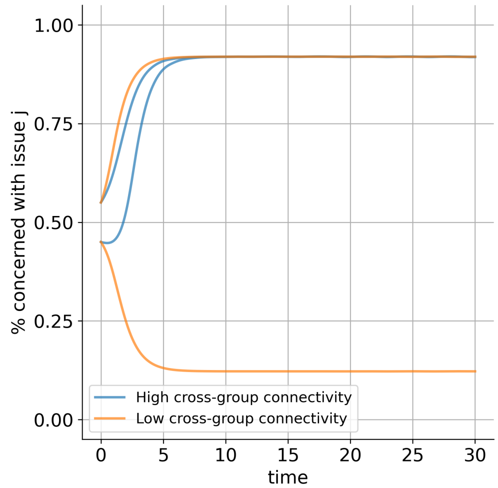
Notes. (A) Time evolution of independent judgment for *issue H* and *L* across different scenarios. (B) Time evolution of the percentage concerned with *issue H* for both parties across different scenarios. (C) Time evolution of the percentage concerned with *issue L* for both parties across different scenarios. (D) Time evolution of the percentage of the population prioritizing *issue H* across different scenarios. Parameters used: $(C_{1H}(0), C_{2H}(0), C_{1L}(0), C_{2L}(0)) = (0.55, 0.45, 0.45, 0.55)$, $\alpha = 3$, $\rho = 0$, and $\sigma = 0.5$. Other scenario-specific parameters are as listed in Table 1.

With inter-group learning

Next, we introduce cross-group learning, particularly in cases where the two groups begin on opposite sides of the neutral point—due, for example, to group elite messaging or inherent differences in values and attitudes toward the issues. Cross-group learning operates by reducing the divergence in concern levels between the groups. As inter-group connectivity increases, the magnitude of divergence decreases, and beyond a critical threshold, only convergent outcomes remain—either both groups are concerned or both are unconcerned. Figure 7 illustrates how increasing cross-group connectivity leads to convergence in steady-state concern. As connectivity increases from 0 to 0.2, the equilibrium shifts from divergent group concerns to a shared, convergent outcome.

Figure 8 mirrors Figure 5, with the key difference being the level of cross-group learning: the former uses a moderately low value ($\rho = 0.2$), while the latter assumes no cross-group learning

Figure 7: Concern dynamics under low vs. high cross-group learning

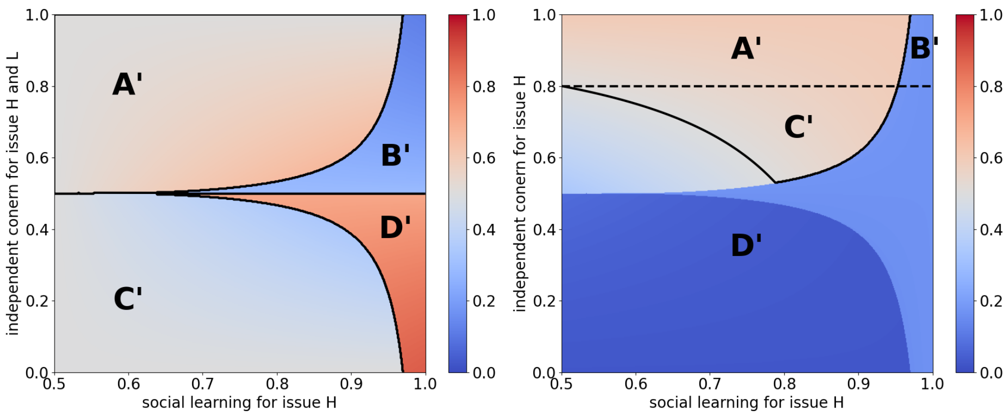


Notes. Time evolution of the percentage concerned with issue j for two parties. Parameters used: $(C_{1j}(0), C_{2j}(0)) = (0.55, 0.45)$, $\alpha = 3$, $s_j = 0.8$, and $I_j = 0.6$. High cross-group connectivity ($\rho = 0.2$) is shown in blue; low cross-group connectivity ($\rho = 0$) in orange.

($\rho = 0$). In both subplots, we observe that Regions A′ and C′ have expanded relative to their counterparts (A and C) in Figure 5. This expansion is driven by the presence of cross-group learning, which enables both groups to converge more easily at higher levels of social learning. In Figure 8a, Region A′ corresponds to cases where both groups converge to a higher level of concern for *issue H* than for *issue L*, while Region C′ reflects convergence to a lower level of concern for *issue H*. In both cases, higher social learning for *issue H* amplifies concern or lack thereof, reinforcing whichever direction the independent judgment favors. Consequently, Regions B′ and D′, where only one group diverges to a concern or unconcerned state, become smaller, as cross-group learning makes these asymmetric outcomes less likely.

In Figure 8b, we observe a similar pattern. Region A′, where the ranking of independent concern aligns with the prioritization outcome, becomes larger compared to Region A in Figure 5b, with a corresponding decrease in Region B′. Similarly, Region C′ grows substantially relative to Region C. This expansion occurs because cross-group learning raises the threshold of social learning required for one group to diverge into an unconcerned state. Instead, the group is nudged toward the concern level of the other group, aligning more closely with the direction of independent judgment for *issue H*. As a result, Region D′—where concern and priority are misaligned—shrinks compared to Region D in Figure 5b.

Figure 8: Social learning affects the priority of *issue H* with cross-group learning



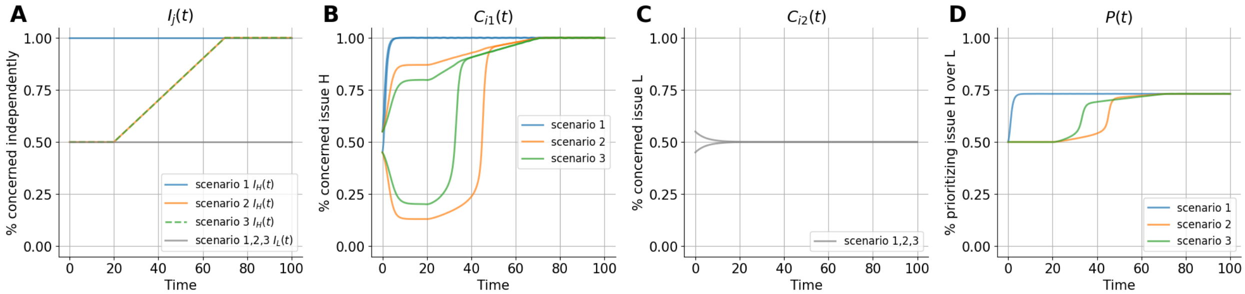
(a) independent concern is set at equal level for both issues

(b) independent concern for *issue L* is fixed at high level

Notes. Heatmaps of the percentage of the population prioritizing *issue H* over *L*. Gray indicates 50%; blue indicates a minority, and red a majority prioritizing *issue H*. (a) Priority as a function of s_H, I_H, and I_L. Here, s_L is fixed at 0.5, and $I_H = I_L$ to isolate the effect of social learning. Regions A′ to D′ are delineated by black contour lines marking the 50% threshold. Parameters: $(C_{1H}(0), C_{2H}(0), C_{1L}(0), C_{2L}(0)) = (0.55, 0.45, 0.45, 0.55)$, $\alpha = 3$, $\rho = 0.2$, $s_L = 0.5$, and $\sigma = 0.25$. (b) Priority as a function of s_H and I_H. Here, $s_L = 0.5$ and $I_L = 0.8$, representing a population independently concerned about *issue L*. The dotted black line indicates $I_L = 0.8$, and solid black contours mark the 50% threshold, together delineating regions A′ to D′. Below the dotted line, individuals are more concerned about *issue L* in the absence of social learning; above, they are more concerned about *issue H*. Parameters: $(C_{1H}(0), C_{2H}(0), C_{1L}(0), C_{2L}(0)) = (0.55, 0.45, 0.45, 0.55)$, $\alpha = 3$, $\rho = 0.2$, $I_L = 0.8$, $s_L = 0.5$, and $\sigma = 0.25$.

We can observe how inter-group connectivity influences the path dependence of concern levels with respect to independent judgment. Figure 9 replicates the setup of Figure 6, but with a moderately low level of cross-group learning instead of none. Unlike in Figure 6B, where the scenarios diverged in their long-term concern levels, all three scenarios in Figure 9B converge to the same extremely high level of concern, reflecting the final state of independent judgment. Comparing Scenarios 2 and 3, we observe that decreasing the strength of social learning leads to earlier convergence between groups, while higher social learning (as in Scenario 2) causes a more delayed alignment. As a result, in panel D, all three scenarios ultimately reach strong majority prioritization of *issue H*, but Scenario 3—having lower social learning—achieves this strong majority earlier than Scenario 2.

Figure 9: Equilibria are path dependent on independent judgment with cross-group learning



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4 Conclusion

This study presents a dynamic model of collective issue prioritization that examines how inherent heterogeneity in social learning across issues, along with political group structures, shapes the formation of public concern. By distinguishing between issues more grounded in direct personal experience or scientific information and those reliant on socially transmitted cues such as the observed frequency of belief, the model captures how polarization can emerge and persist—even when independent concern for an issue is high. The analysis shows that strong social learning can generate path-dependent dynamics and sustained divergence in concern across groups, leading to the systematic deprioritization of high-salience issues such as climate change and pandemic response. Notably, the results indicate that even modest levels of cross-group learning are sufficient to reduce polarization and produce prioritization outcomes more closely aligned with independent judgments. These findings highlight the importance of incorporating issue-specific social learning structures—rooted in characteristics such as complexity and psychological distance—into models of public opinion formation, and they offer theoretical guidance for designing interventions aimed at better aligning public priorities with societal needs.

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