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Social structure shapes consensus decision-making norms in small-scale societies

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Humans are uniquely capable of reaching consensus within large, hierarchically structured societies. Yet the pathways by which consensus emerges, especially under constraints imposed by social organization, remain poorly understood. We use an agent-based model to explore how marriage structure, social group nesting and decision-making norms can shape a group's ability to reach consensus. In our model, simulated agents are embedded in multi-level social networks and possess noisy information. Decisions are spread via three different cascades, each with different interaction norms. We find that grouping of individuals into families via marriages impedes consensus by slowing the rate of information diffusion and elevating informational entropy, especially when nested further into kin groups. By contrast, increasing the size of nested subgroups in a multi-level network reduces redundant social ties and promotes consensus. Finally, decision-making norms that rely on formation of coalitions or representative bodies lead to faster group decisions by bypassing early-stage clustering of information within families. These results offer insights into how consensus dynamics are shaped by social structure and provide a theoretical bridge between research on network topology, collective intelligence and human social evolution.

This article is part of the theme issue 'The evolution of collective intelligence'.

1. Introduction

Collective intelligence is the ability of a group to solve problems and make decisions more effectively than individuals alone [1]. Human collective intelligence relies on norms and institutions that facilitate cooperation between non-kin, helping to resolve conflicts and coordinate shared actions [2–4]. One of the institutions underpinning such coordination is marriage [5,6]. As both a reproductive and economic unit, marriage helps structure kinship systems, resource distribution and social alliances [5,7]. Marriage practices are highly variable across societies. However, throughout history and the ethnographic record, most marriages are monogamous, though the societies themselves many exhibit varying degrees of polygyny [8,9]. In societies where it occurs, polygyny often reflects underlying inequalities in resources and social status, influencing who can form multiple marriages and how kin networks are structured [10,11].

Marriage often underpins the formation of the smallest social unit within human multi-level societies: the immediate family, typically composed of a man, his spouse or spouses and their children [5,8]. These units rarely exist in isolation. Instead, they are nested within larger structures, such as extended families, residential groups and ethnolinguistic populations, which are hierarchically organized and often self-similar in form. Each level typically contains sub-units of the level below, forming a recursive pattern of kin-based clustering [12,13].

Residential groups, which are often referred to as 'bands', are especially flexible units in mobile hunter-gatherer societies [14]. Composed of extended families and sometimes unrelated individuals, these groups frequently undergo fission and fusion, with members joining or leaving depending on subsistence needs, social ties or seasonal cycles [15,16]. Within bands, individuals cooperate in food sharing, childcare and defence; however, as group size scales up from family to band to larger collective, the frequency of interactions drops, and so too does cohesion [17]. Smaller, nested units tend to show stronger ties and more frequent cooperation, while larger groupings often require additional coordination mechanisms to maintain collective action.

In some pastoralist societies, these multi-level networks exhibit what anthropologists describe as *segmentary lineage systems*—a social structure in which individuals belong to nested, patrilineal descent groups of increasing size and scale [18]. These groups may act autonomously in daily life but align strategically in response to external threats or opportunities. Among the Nuer and Dinka of south Sudan, for example, extended families may act independently in routine matters but unite at the clan or lineage level in times of conflict [18,19]. Among Somali pastoralists, segmentary logic also organizes grazing rights, political alliances, and collective punishment [20].

However, this pattern of nested kin-based male affiliation is observed even among many hunter-gatherer societies and smaller-scale pastoralists [12,13,21–23]. While these may look topologically similar to segmentary lineage systems, nested social groups are generalizable beyond that. What is perhaps more important to note is that many small-scale societies exhibit cooperation at multiple scales, depending on the context [24]. Within foragers, examples include Agta communities [21,25] or various Australian Aboriginal groups [23], where similar patterns of nested kin-based affiliation allow individuals to flexibly scale cooperation.

Maintaining group cohesion in these settings, where affiliation is multi-layered and residence is fluid, is a challenge. Not all decisions require the same degree of consensus. In some cases, such as where to camp or how to allocate labour, an internal family agreement may be sufficient. In others, such as collective movement, defence or large-scale ritual participation, consensus must scale up across multiple families or residential units. However, reaching consensus at larger scales is difficult. Individuals must weigh their preferences, coordinate with close kin, and often accept decisions that deviate from their optimal outcome to maintain group cohesion [24]. In such cases, cohesion may take priority over speed, accuracy or even participation. Conversely, when cohesion is less critical, faster decisions involving fewer people may suffice, even if they result in uneven outcomes.

Here, *social structure* refers to the stable patterns of social relationships and interactions in a society or a group [26]. Social structuring can occur, for example, via kinship, mating or marriage, hierarchical nesting of social groups, overlapping group identities of individuals and social norms. Social structure is, therefore, a representation of the constraints within which people interact, exchange information and coordinate actions. These structural constraints, and not just individual traits or preferences, shape how decisions emerge, spread and resolve across a population [27].

Understanding how consensus emerges within structurally layered populations is central to understanding the evolution of human cooperation, however anthropologists rarely have access to the full population-level data needed to observe these processes in real time. The complexity of overlapping kinship, varying marriage practices and localized norms makes it nearly impossible to systematically test how group structure influences the capacity for consensus. For this reason, computational models, particularly agent-based models, offer a useful framework. These models allow us to simulate complex, structured populations and observe how information and decisions propagate across them under different conditions [28,29].

Here, we use agent-based modelling to explore how features of social structure, particularly marriage patterns and the recursive nesting of multi-level groups, shape the ability of human populations to reach consensus. Rather than modelling the fine-grained internal dynamics of households or co-wife relationships, we focus on how family units and nesting patterns constrain or facilitate consensus across the broader social structure. We simulate a population in which agents attempt to align on a shared decision, under one of three decision-sharing norms: (i) a *family-first single-connector cascade*, in which one designated family member communicates the household's initial consensus outward to non-family individuals; (ii) a *family-first multi-connector cascade*, in which all adult members propagate the household's decision simultaneously; and (iii) a *male-coalition cascade*, where males bypass building internal consensus with family members and coordinate directly with other men, using affinal ties to reach beyond their immediate family.

We examine how variation in key structural parameters—marriage prevalence, polygyny rates, average number of wives per male and branching ratios—affects two core metrics of decision dynamics. Branching ratio refers to the average number of sub-units within each level of a hierarchical structure (e.g. how many households form an extended family, how many extended families form a residential group) [13]. It shapes how deep and wide the nested social structure is, and therefore how far information must travel to reach group-level consensus.

The first outcome measure, $C_{\max}$, captures the highest proportion of the population that converges on a shared decision at any point in the simulation and functions as an indicator of how successful the group is at achieving consensus. The second, informational entropy (H), quantifies the level of uncertainty or fragmentation in the population's decision states [30]. Lower entropy reflects greater alignment and fewer competing informational states, while higher entropy signals ongoing disagreement or uncertainty. In human groups, lower entropy can be interpreted as a more coherent informational environment, which may or may not be accompanied by widespread consensus.

These outcomes reflect trade-offs between competing priorities: group cohesion, decision speed and participation. Rather than assuming a single optimal pathway, we ask how structural features of social organization produce different constraints and affordances, and what this reveals about the conditions under which consensus can emerge or fail across nested, modular social worlds.

2. Methods

(a) Overview

We used an agent-based modelling approach to simulate how different social structural variables influence a group's ability to reach consensus. In our model, autonomous computational entities ('agents' or 'individuals') are endowed with basic demographic traits and behavioural heuristics, allowing them to interact with each other and form social relationships. These local interactions give rise to emergent phenomena, i.e. group-level outcomes that cannot be predicted by summing up individual behaviours alone [28,29,31,32]. This modelling approach is particularly suited to questions of collective decision-making, where empirical data on the underlying interaction dynamics are often sparse or difficult to collect.

Our central aim was to quantify the independent effects of three key social structural variables on consensus formation at the level of ethnolinguistic groups: marriage patterns, branching ratios and decision-making norms. These social structural variables are not exogenous in real-world contexts; they emerge from ecological and demographic conditions such as resource inequality, adult sex ratios and the material cost of marriage. Accordingly, our model incorporates these empirically informed inputs to simulate how such conditions shape marriage markets and, in turn, multi-level social organization.

Agents first formed marriages using a polygyny threshold model (PTM), which operationalizes female mate choice in contexts of male resource inequality [33]. Parameters such as adult sex ratio, Gini coefficient of male wealth and bridewealth requirement jointly determine which agents marry, how many spouses they have and ultimately how households are formed [11,33]. These household units are then nested hierarchically into extended families and residential bands, following ethnographic patterns observed in many small-scale decentralized societies [12,13,18,19,21,23]. It is worth noting that while we provide specific empirical examples in our introduction, we are not rigidly adhering to such societies for interpretation. What we are ultimately interested in is how individuals in nested social networks and varying degrees of polygyny balance decision-making at different scales, given that all other internal conflicts of interest are not significant.

By simulating 45 unique combinations of sex ratio, resource inequality and bridewealth cost, we generated a wide range of marriage patterns and associated social networks. For each parameter set, 100 distinct networks were generated. Each of these networks underwent 200 independent decision-making cycles under a specified norm. Thus, each data point in our final analysis represents an average across 200 000 simulations. Although many ecological and demographic parameters are not directly analysed in the final models, their inclusion enables a more realistic simulation of the endogenous relationship between social structure and decision-making.

Further methodological details, such as the precise structure of the marriage formation algorithm, the hierarchical organization of social units and the consensus decision-making rules, are described in the following subsections.

(b) Self-organisation into marriages

Each simulation began with 1200 agents. Cross-cultural data show that hunter-gatherer group sizes average around 1700 individuals, with a median of 876, making our simulated group size well within empirically observed ranges [12].

Agents were assigned male or female sex based on predefined sex ratios. To reflect realistic variation, one-third of simulations used each of the following sex ratios: 0.8, 1.0 and 1.2 (males per female) [34]. These values approximate the median ± 1 standard deviation from cross-cultural samples.

Next, we assigned each male agent a level of wealth, drawn from a range of 1 to 10 units. Wealth was distributed such that the group-level Gini coefficient matched one of five target values: 0.05, 0.2, 0.35, 0.5 or 0.6. These values are well within the range observed in small-scale societies [11]. Female agents did not possess wealth in this model. However, to marry, a male was required to pay a fixed amount of bridewealth to the female's family. We tested three bridewealth costs: 0.5, 5 and 10 units.

These three ecological parameters (sex ratio, wealth inequality (Gini coefficient) and bridewealth) were combined in a fully crossed factorial design, producing 45 unique combinations. Each combination generated a different marriage structure, leading to variation in the proportion of males who married, the proportion of those married polygynously and the average number of wives per married male.

While the sex ratio, wealth inequality and bridewealth were not directly analysed as predictors in our consensus models, they served as generative parameters that produced a broad range of plausible marriage structures.

To form marriages, agents followed local decision rules based on a standard PTM [11,33]. In each round, an unmarried female selected the wealthiest available male who could afford to pay the required bridewealth. Upon marriage, the male transferred the bridewealth to the female's family, which was then deducted from his remaining wealth. This updated wealth distribution could shift the male rankings, making a different male the new wealthiest. The next unmarried female would then choose from the updated pool of eligible males. This process continued iteratively until no males could afford the set bridewealth and at least one female remained unmarried.

When no males could afford the bridewealth of the remaining unmarried females, we implemented a 'tolerance margin' that progressively lowered their bridewealth requirements until a match became possible. This ensured that all females eventually found a spouse.

Males were permitted to take multiple wives as long as they remained wealthier than other males and could continue to afford bridewealth payments. We did not impose a cap on the number of wives a male could have; instead, polygyny emerged naturally from the interaction between wealth inequality, bridewealth cost and sex ratio. The proportion of males with multiple wives and the number of wives per polygynous male varied across simulations depending on these parameters.

Notably, while our implementation aligns with the basic principles of the PTM, it differs from Ross *et al*. [11], who incorporated more nuanced female choice metrics and tracked lifetime polygyny, including serial monogamy [11]. By contrast, we model marriage patterns at shorter time spans to simplify interpretation and keep the network-generating process tractable.

(c) Hierarchical structuring

Once self-organization into marriages was complete, every male, regardless of marital status, was first given a unique identifier for the family to represent his immediate family unit. Wives adopted the family grouping of their husbands upon marriage, ensuring that all members of a household shared the same identifier.

These immediate families were then grouped into progressively larger social units using a specified branching ratio. Branching ratios refer to the number of smaller sub-units that are nested, on average, within each higher-level unit. For each set of 45 social networks, we implemented one of five empirically grounded branching ratios (2, 3, 4, 5 or 6), which have been documented across various hunter-gatherer societies [12,13].

For example, under a branching ratio of 4, approximately four immediate families were randomly grouped and assigned to the same unique extended family group. Then, four extended families were grouped to form a unique residential group, and so on. While the goal was to achieve a mean grouping size equal to the branching ratio, occasional variation occurred because of rounding, and some groups contained three or five sub-units. Nonetheless, the average number of sub-units per grouping reliably matched the specified ratio.

As a result, each individual carried a structured set of unique hierarchical identifiers for family, extended family, residential group, larger residential group aggregations, and lastly, the ethnolinguistic group.

(d) Interaction matrix

To create more realistic social networks within the hierarchical structure, we assigned ties between individuals based on the level of shared group membership. The likelihood of a tie between any two individuals depended on whether, and at what hierarchical level, they belonged to the same social unit, with tie densities set to reflect empirically observed interaction rates in small-scale societies [35,36].

All individuals within the same extended family were fully connected: every possible tie was present, resulting in a network density of 1. These ties were labelled as 2 in our interaction matrix. Spousal ties were separately coded as 1 and were established during the marriage formation phase.

Within each residential group, we imposed a tie probability of 0.78. This included all existing ties from family and extended family membership, as well as additional ties among unrelated individuals within the same residential group. These were labelled as 3. Occasionally, during periods of low mobility, residential bands can also aggregate further [12,13]. Such ties between individuals belonging to different residential groups were added with a probability of 0.48 and labelled as 4. These reflected occasional inter-group interactions such as trade, visits or ritual cooperation.

Finally, to account for rare but meaningful interactions across the entire ethnolinguistic community, we added a small number of random long-range ties between individuals who were not otherwise connected. These ties were labelled as 5 and were assigned a probability, such that the total network density reached approximately 0.005. This reflects ethnographic observations that even in fission–fusion societies, individuals often maintain sparse ties beyond their immediate social units, for example, through trade, political alliances or regional gatherings. Such low-frequency interactions have been estimated to occur at rates exceeding 0.01 [35].

Additionally, to model the frequency of interactions during the decision-making process, we transformed the categorical relationship matrix into a probabilistic interaction matrix. In the relationship matrix, each edge between individual i and individual j had an edge weight $w_{ij} \in \{1,2,3,4,5\}$, where lower values indicate stronger or closer relationships. To reflect the assumption that individuals are more likely to interact with those they are more closely connected to, we made the probability of interaction between individuals i and j, denoted p_{ij}, inversely proportional to the relationship weight:

$$p_{ij} = \frac{1}{w_{ij}}.$$

This means that closer ties (e.g. extended family) are more likely to be sampled for interaction than distant or randomly connected individuals. All interaction probabilities were normalized for each individual such that the sum of their probabilities across all possible partners equalled 1. This resulted in a row-stochastic matrix, where each row defines an individual's probability distribution over their potential interaction partners.

During consensus decision-making, described in §2e(ii) below, individuals select others to interact with by sampling from this probability distribution. This approach ensures that while interaction is biased towards close and structurally proximate ties, individuals still occasionally interact with more distant or weakly connected members of the population.

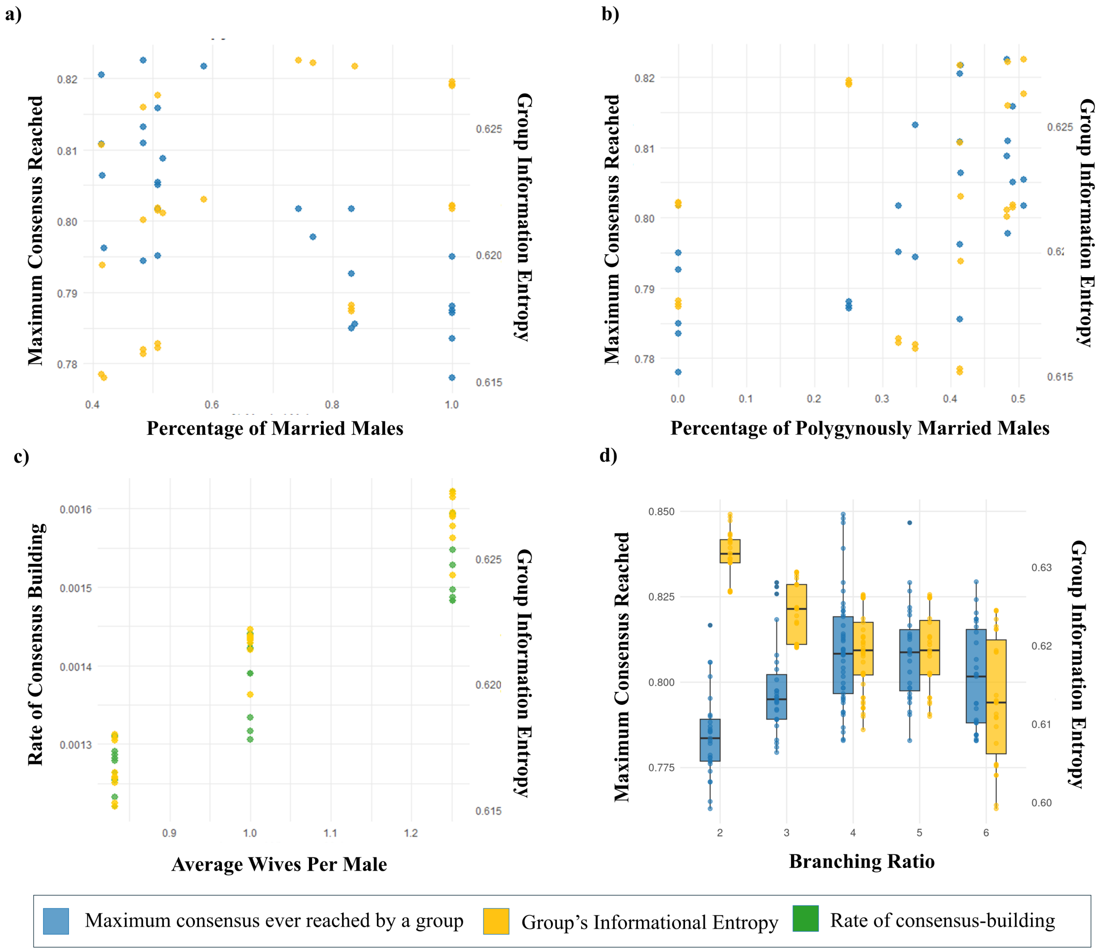

Figure 1. Effects of marriage structure and branching ratio on group consensus, entropy and consensus-building rate. (a–c) The relationship between three marriage-related variables: (a) percentage of married males, (b) percentage of polygynously married males, and (c) average number of wives per male; and group-level outcomes: maximum consensus reached (blue), informational entropy (yellow) and consensus-building rate (green). (d) Boxplots of the same three metrics across branching ratio values from 2 to 6.

(e) Decision-making

(i) Information priors

In our model, agents make a binary decision between two options, *A* and *B*. These could represent any collective choice faced by a group, whether to go to war or negotiate peace, adopt or reject a norm, allow outside researchers into a community, or not. For the simulation, we assume that there is no fundamental conflict of interest across individuals: one of the two options is objectively better for everyone. While this rarely holds in real-world scenarios, it allows us to isolate the effects of social structure on consensus formation without introducing additional complexity from strategic disagreement.

In most simulations, we set the 'goodness' of option *A* to 0.8 and of *B* to 0.2. However, agents are not aware of these values. Instead, each agent's priors are sampled from logistic distributions centred on the true goodness values (mean 0.8 for *A*, 0.2 for *B*), and a standard deviation of 2. This introduces substantial uncertainty, simulating decision-making in a noisy and complex informational environment.

As the simulation proceeds, agents interact with others in their network and update their priors through Bayesian inference, incorporating the beliefs of their interaction partners. The mechanics of this interaction and belief updating process are described in §§2e(i) and 2e(ii). To make a decision, each agent compares its current estimates for the goodness of *A* and *B*. If the estimated goodness of *A* exceeds that of *B*, the agent chooses *A*; otherwise, it chooses *B*.

(ii) Decision-making process

All decision-making cascades begin with a randomly selected male individual. Although the specific propagation mechanisms vary depending on the decision-making norm adopted, several procedures are common across all conditions. Initially, all individuals have a decision status of 0 (undecided). Once an individual has made a decision, their status is updated to 1 (decided). During propagation, connectors probabilistically sample individuals from their row in the interaction matrix, but only among those who are still undecided (status = 0). This sequential process ensures that once a connector has initiated a decision cascade, only the new focal individual may update their priors; the connector does not update again. This prevents recursive loops and ensures directional information flow.

Under the family-first single-connector cascade, a focal male first pools information from his wives. The family's priors are updated through a Bayesian mechanism, and the entire family must reach consensus before proceeding. Once consensus

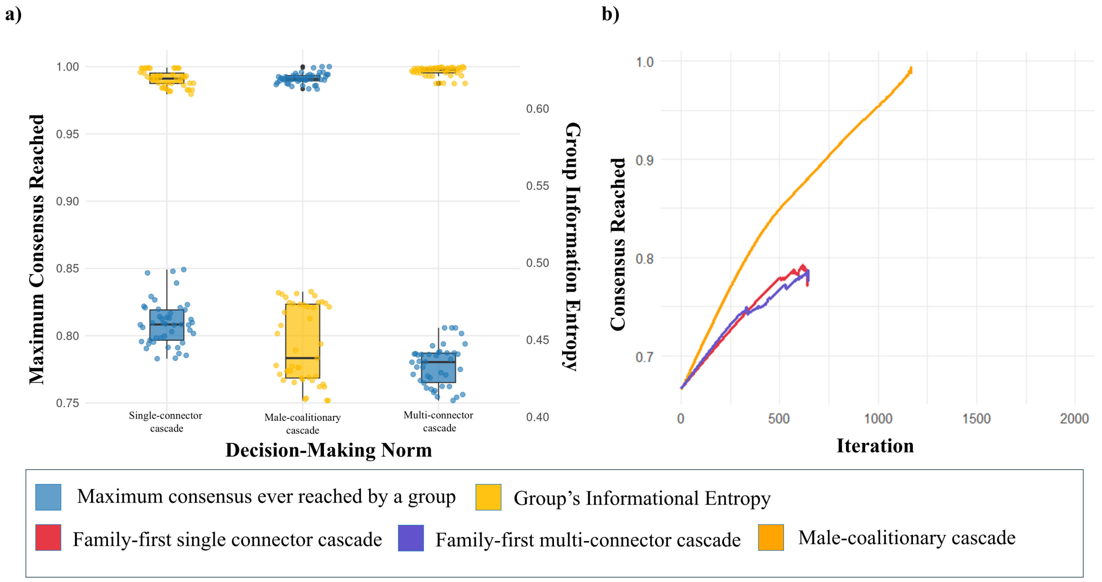

Figure 2. Effects of decision-making norms on group consensus, entropy and diffusion dynamics. (a) Maximum consensus (blue) and group informational entropy (yellow) achieved under each norm. Family-first norms (single-connector and multi-connector cascades) result in lower consensus and higher entropy compared to male-coalitionary norms, which show the highest consensus and lowest entropy. (b) Mean consensus trajectories over time for each decision-making norm at branching ratio 4.

is reached, a single connector is randomly selected from the family to propagate the decision. This connector samples from his social ties to identify a new focal individual. If the new focal individual is married, the process repeats with his family; otherwise, he makes a decision independently, and the cascade continues.

In the multi-connector cascade model, all family members who have reached consensus participate in propagating the decision. Each may sample from their ties independently, potentially initiating parallel cascades. This norm emphasizes broader diffusion at the cost of coordinated signal coherence.

In the male-coalitionary model, consensus formation occurs exclusively among males. Family-level deliberation is skipped, although males may include their wives' ties when sampling from the network. However, only male-to-male interactions contribute to decision formation and propagation. Wives simply adopt the decision made by their husbands, without engaging in their deliberation.

Across all models, the simulation runs over 200 000 iterations. From each run, we extract the maximum proportion of individuals who converge on the correct decision. This value, C_{max}, represents the group's ability to achieve collective consensus. We also calculate group entropy as a measure of informational disorder using Shannon's entropy formula: $H = -(p_A \log_2 p_A + p_B \log_2 p_B)$, where p_A and p_B represent the final proportions of individuals choosing option A or B, respectively.

3. Results

(a) Marriage patterns as predictors

As expected, given the emergent nature of marriages in our model, the three marriage-related variables—per cent of married males, per cent of polygynously married males and average number of wives per male—exhibited multicollinearity. We assessed this using both pairwise Pearson correlations and variance inflation factors (VIF), the results of which are included in the electronic supplementary material. Notably, *per cent of married males* and *per cent of polygynous* males were negatively correlated (r = −0.67), reflecting the underlying trade-off between the prevalence of marriage and its concentration among fewer individuals. By contrast, average wives per male appeared more weakly correlated with either variable and showed an acceptable VIF, suggesting that it could be treated as a more independent predictor.

These inter-relationships are reflected in our simulation results for C_{max}, the highest level of consensus achieved by a group. Across family-first simulations, we observed that higher percentages of married males were associated with lower C_{max}, while higher percentages of polygynously married males predicted higher C_{max}; see figure 1a,b. Although the effect of average wives per male on C_{max} was weakly positive, this variable showed a stronger association with consensus rate C_{max}, suggesting that more skewed marriage structures, characterized by a small number of men marrying multiple wives, may expedite decision-making dynamics even if they do not improve the maximum consensus achieved. While figure 1c shows the plot between consensus rate, entropy and average wives per male, the electronic supplementary material, figure S2 shows the plot for C_{max} versus average wives.

We also examined how these structural features influenced informational entropy at the group level following consensus. Entropy showed no clear association with per cent married males but increased with both per cent polygynous males and average wives per male. This suggests that even as skewed marriage structures promote faster consensus, they may also increase informational diversity or disagreement within the group. In this context, the model shows a subtle trade-off: marriage inequality can both accelerate consensus and increase informational noise, reflecting the complex and sometimes paradoxical effects of social structure on collective behaviour.

(b) Branching ratios as predictors

Figure 1d reveals a clear pattern: increases in branching ratio are associated with higher maximum consensus (C_{max}) and lower group entropy. Notably, branching ratio 4 appears to be a critical inflection point where both consensus and informational clarity are optimized. While this trend is also evident at branching ratios 5 and 6, there is a slight decline in C_{max} at ratio 6. It remains uncertain whether the plateau across branching ratios 4–6 is driven by similar entropy dynamics as in lower ratios (2 and 3), or whether it reflects a limitation in model design, namely, the fixed group size of 1200, which may render higher branching increasingly redundant.

What is clear, however, is that unlike the marriage-related variables, the branching ratio has a systematic and interpretable relationship with informational entropy. Lower branching ratios yield denser and more overlapping social categories (e.g. family, residence), creating redundant or conflicting signals that increase entropy and impede group coordination. By contrast, higher branching ratios reduce this categorical overlap, enabling information to flow more efficiently through the network. This diffusion mechanism lowers entropy and facilitates more consistent group-level consensus.

(c) Decision norms as predictors

Figure 2a shows clear differences in maximum consensus (C_{max}) and group entropy across the three decision-making norms. Male-coalitionary networks achieved the highest levels of consensus and the lowest group entropy. By contrast, multi-connector cascade networks reached the lowest consensus and exhibited the highest informational entropy. Family-first single-connector networks occupied an intermediate position, with moderate levels of both consensus and entropy. These findings demonstrate that the structure of decision-making norms strongly shapes both the quality of group agreement and the coherence of the information environment.

Figure 2b provides mechanistic insight into these differences by showing how consensus evolves over time under each norm. The male-coalitionary norm displays a steady, uninterrupted increase in mean consensus, rapidly approaching near-total agreement. This pattern suggests that concentrating decision-making influence within a connected subset of males facilitates efficient and coordinated information transmission. The hierarchical structure channels signals cleanly, minimizing contradictions and accelerating convergence.

By contrast, both family-first single-connector and multi-connector cascade networks show early gains in consensus but quickly plateau, never reaching the levels achieved by the male-coalitionary condition. The family-first single-connector model requires decisions to emerge within nuclear family units before spreading outwards via a single connector. While this promotes strong internal alignment, it limits inter-family communication and creates delays and inconsistencies in how signals propagate through the network. The result is slower, more fragmented consensus-building.

The multi-connector cascade model, while designed to increase the spread of information by allowing individuals to receive input from multiple peers simultaneously, suffers from too much signal overlap. Individuals are bombarded by inputs from different parts of the network, many of which are uncoordinated or contradictory. This overwhelms decision-making and elevates group-level entropy, stalling consensus at relatively low levels. The trajectory in figure 2b reflects this: after an initial burst of agreement, the network saturates with conflicting signals, flattening the consensus curve.

4. Discussion

Our results show that different decision-making norms produce markedly different outcomes in both group consensus and information entropy. Family-first single-connector cascades produced the lowest consensus levels, followed by multi-connector cascades, while male-coalitionary networks consistently achieved the highest group consensus. These results held even in robustness checks where prior accuracy was lower (e.g. when goodness $A = 0.6$), suggesting that the effect is not contingent on high signal quality. Details regarding the robustness test can be found in the electronic supplementary material. Importantly, as shown in figure 2a, both male-coalitionary and rapid-spread networks reached higher consensus than family-first, but with different trajectories: male-coalitionary cascades were slower yet more complete, whereas rapid-spread cascades quickly plateaued. This distinction is key. The sequencing of decisions, as well as who propagates them, shapes outcomes. While multi-connector cascades have speed, they lack the focused consolidation achieved by coordinated male–male propagation in coalitionary structures.

These trajectories reveal how the internal logic of each norm influences the percolation of information. In both family-first conditions, families must reach an internal consensus before interacting with others. This initial bottleneck, especially when families are embedded in clustered networks, creates pockets of agreement that diverge early. Because these subgroups begin updating beliefs before connecting to the broader network, they foster transient diversity: early differentiation of ideas that persists long enough to shape population-level outcomes [37]. In most models, transient diversity boosts problem-solving. However, here, it competes with the need to converge, reducing overall consensus. By contrast, coalitionary and cascade models facilitate earlier cross-cutting information flow across families, shortening the window of differentiation and increasing the chances of convergence.

This aligns with broader insights from the network science of collective intelligence [38,39]. Dense, overlapping group structures (as seen in low branching ratios or tight family clusters) tend to reinforce local agreement at the expense of global consensus. Our results show that while such structures may promote cohesion within units, they hinder alignment across them. Increasing the branching ratio improves consensus by reducing these overlaps and enabling diffusion through more modular, less redundant ties. This explains why even random networks, which preserve density but eliminate structural clustering, perform better than family-first conditions in our robustness tests.

While we frame our results as a function of the 'male-coalitionary' norm here, specifically, the use of patrilocal and affinal ties, we do not treat this as prescriptive or exclusive. In many societies, particularly those with elders' councils, ritual authorities or designated political subgroups, collective decisions are made by representatives rather than by all members equally [40]. Our model suggests that such representative bodies, regardless of whether they are based on gender, age or institutional role, can enhance group consensus without requiring specialization or privileged access to information. In these cases, leadership does not emerge from superior competence or formal authority, but from network position and propagation efficiency. This is consistent with ethnographic observations in egalitarian and semi-egalitarian contexts, where leadership is less about control or decision accuracy and more about enabling cohesion.

Among the Nyangatom, consensus decisions often emerge from tightly bonded male coalitions [41]. Tsimane leaders facilitate discussion without exerting authority [42]. Even councils of elders in East African agropastoralist societies, including women, serve as bottlenecks through which decisions are coordinated and propagated [43,44]. These patterns suggest that decision-making norms can evolve to address structural constraints when group-level agreement is critical for coordination, movement or resource use. Clay *et al.* also explore further feedback loops between social cohesion and collective intelligence from a cognition and psychology perspective [45].

Ethics. This work did not require ethical approval from a human subject or animal welfare committee.

Data accessibility. The complete code for our agent-based model and statistical analysis can be found here [46].

Supplementary material is available online [47].

Declaration of AI use. We have not used AI-assisted technologies in creating this article.

Authors' contributions. B.D.V.: conceptualization, formal analysis, investigation, methodology, project administration, writing—original draft, writing—review and editing; Z.H.G.: supervision, validation, writing—review and editing; L.G.: conceptualization, investigation, project administration, supervision, writing—review and editing.

All authors gave final approval for publication and agreed to be held accountable for the work performed therein.

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