Young children build consensus in networks with local information *

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Abstract

How is consensus reached in groups and committees with limited access to information? To determine the fundamental attributes that support consensus building, we run a controlled laboratory experiment with very young children (5 to 8 years old). Two characteristics emerge as key for the success of a group. First, the endogenous adoption of complementary roles by different individuals: a leader who moves first and proposes a solution, a group of debaters who ponder over the alternatives, and a closer who patiently waits and locks the decision. Second, a degree of flexibility in the decision rule: consensus is achieved when participants follow the wisdom of the crowd with high probability but not with certainty. Comparing empirical choices with simple algorithms, we observe that while algorithms broadly capture behaviors, children's role heterogeneity and choice flexibility allows them to outperform simple computational models, particularly in the more complex conditions. From a developmental viewpoint, the study also reveals a sharp progression within our window of observation, with older children reaching near-perfect consensus rates. Overall, this work contributes to understanding developmental milestones in decision-making, providing a foundation for future investigations into how children navigate complex social environments.

Keywords: developmental decision-making, coordination, network experiments.

JEL Classification: C90, C92, D85.

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The ability to coordinate actions toward a shared goal is essential for success across economic and social activities. In the workplace, effective coordination boosts team efficiency, speeding project completion and improving outcomes. Large-scale scientific efforts rely on coordination among researchers to align methods, share data, and achieve breakthroughs. In healthcare, coordinated efforts among professionals enhance patient care, reducing errors and improving outcomes. Environmental resource management also depends on stakeholder coordination to sustainably manage resources and tackle challenges like climate change and biodiversity loss. Understanding *how* and *when* people develop these coordination abilities is therefore critical to fostering effective collaborations.

Experimental economics research indicates that mutually advantageous coordination is difficult to achieve in single-play games (Dal Bó et al., 2021), yet tends to emerge when two actors engage repeatedly (McKelvey and Palfrey, 2001). However, in many real-world situations, people lack the opportunity to build expertise through repeated interactions. More critically, these interactions are often complex, as individuals typically operate within large social networks where they directly interact with only a subset of nearby peers (Jackson, 2008; Goyal, 2012; Jackson et al., 2022). This networked structure adds layers of complexity to coordination, as individuals must navigate indirect influences and local information rather than relying on global knowledge or repetitive encounters.

In parallel, research in computer science has demonstrated that individuals in complex networks can still achieve coordination when allowed some form of communication before finalizing their choices. The work by Kearns and colleagues (Kearns et al. (2006); Judd et al. (2010); Kearns (2012), etc. collectively referred to as [$\mathcal{K}$]) shows that individuals with local information can effectively solve global problems, such as graph coloring and consensus-building, through an iterative "choose-observe-adjust" process. This tâtonnement-like approach resembles indirect communication: players choose a color, observe their neighbors' choices, and adjust their own choice accordingly. This method enables local interactions to support global coordination, highlighting the potential of structured observation and adaptation in complex social networks.

In this paper, we investigate the fundamental attributes that facilitate consensus-building in group decision-making. Specifically, we study a streamlined version of [$\mathcal{K}$]'s consensus problem within a population of very young children aged 5 to 8. Our experiment involves a six-person complete graph network, where each participant observes the choices of either two or three neighbors and has 30 seconds to achieve unanimous agreement on a single color. While the task is straightforward for adults, it poses a significant challenge for young children whose cognitive abilities, such as impulse control and attention, are still maturing. Our experiment has two advantages. First, the simplicity of the experimental setup provides a clear framework to identify the *fundamental* factors that promote consensus, which we hope can be extrapolated to more complex and socially relevant scenarios. Second, studying this age group helps assess whether the ability to coordinate actions is innate or develops very early in life. By pinpointing developmental milestones in group decision-making, we aim to better understand how children navigate and adapt to complex social dynamics.

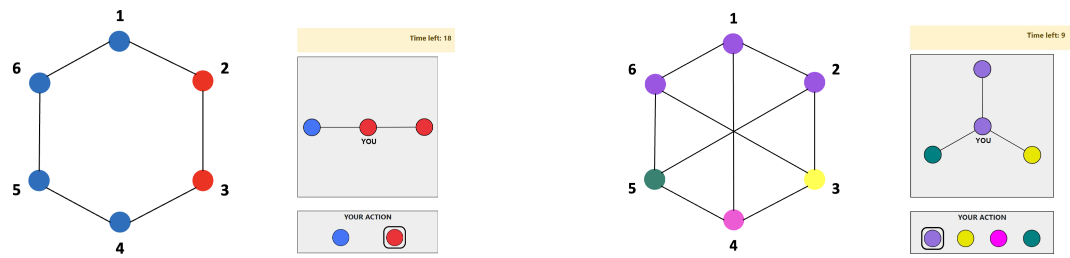
As a preview, the experiment yields two major findings. First, there is a marked discontinuity in coordination success between kindergarteners (ages 5-6) and first or second graders (ages 6-8): kindergarteners converge only 36% to 72% of the time, while their one- or two-years older peers almost always reach convergence, at rates of 81% to 100%. This suggests that while coordination ability is not entirely innate, it develops very early, with a noticeable shift around age 6. Second, simple imitation of neighbors' choices is insufficient for solving the task. Instead, the near-perfect convergence observed in first and second graders relies on two nuanced aspects of their decision-making process: (small) *choice frictions* and (large) *role heterogeneity.* Small choice frictions refer to the value of imitating the actions of the majority of the neighbors with high probability, but not with absolute certainty. Large role heterogeneity highlights the benefits of some players acting quickly to suggest an action and set a direction, others waiting for the debate to take shape, and a third group acting only to lock the consensus. To support our analysis, we develop several algorithms of increasing sophistication and compare simulated behavior to children's actual decisions. Although the algorithms effectively capture the general patterns in children's choices, they fall short of matching the performance of the oldest students. This underscores the advantages of children's flexibility and responsiveness to social cues, even at an early age. We conjecture that adopting flexible decision rules and heterogenous roles are also key features that facilitate coordination in more complex social activities.

1 Results

1.1 Research design

We conducted the experiment with 150 students from LILA, a K-12 private school in Los Angeles, comprising 54 kindergartners (33f, 21m, aged 5-6), 48 first graders (26f, 22m, aged 6-7) and 48 second graders (24f, 24m, aged 7-8). We refer to these groups as **K**, **1** and **2**. In the experiment, groups of six children from the same grade participated in the "consensus task" described in Figure 1, where they chose between either 2 or 4 colors (C2 or C4) while observing the decisions of either 2 or 3 neighbors (N2 or N3). We employed a 2×2 within-subject design. Participants played 4 rounds in each condition (C2N2, C2N3, C4N2, C4N3) in counterbalanced blocks of two rounds with the same five partners, totalling 16 rounds. We anticipated consensus building to be more difficult with more color choices and fewer peers to observe.

Each round began with a 30 second countdown, during which participants started without an initial color. Within this timeframe, they could select and change their color choice as often as desired. A round was a "success" if all players converged on the same color within the 30 seconds, and it was a "failure" if the timer expired without convergence. At the end of each round, participants received feedback on the outcome (success or failure) and the distribution of participants across each color choice.



(a) (b) (c) (d)

Figure 1: Consensus Task. Panels (a) and (c) show the full network structure–visible only to the experimenter–for C2N2 and C4N3, respectively. Each node corresponds to a player's current color choice, with lines representing the direct connections (observed neighbors) and the number next to the node capturing the player's ID. Panels (b) and (d) show screenshots of the graphical user interface from the perspective of player ID #2. The player is marked as "you" in the center, with neighbors arranged equidistantly to prevent framing effects. Players can change their color choice simply by tapping on an option under "your action", with a minimum interval of one second between changes. As soon as all players end up on the same color, the timer stops, marking the round as a success.

Participants were incentivized with points, which they could exchange for toys of their choice in our toy shop at the end of the session. They were explicitly instructed that earning more points meant receiving more toys. Each session lasted around 30 minutes, with all participants earning between 4 and 8 toys. The full set of instructions, read aloud to participants, are available in SI1.

1.2 Network outcomes

The primary question is to assess the network's performance. Given the uncertain level of difficulty in reaching consensus, we introduce a comparison benchmark using a *simple* wisdom of the crowd algorithm, referred to as **AL**: "Each player initially chooses a color at random. Next, a player is randomly selected and adopts the color of the majority within their neighborhood, counting their own choice when the number of neighbors is even (N2) and excluding it when the number of neighbors is odd (N3). Afterward, another player is randomly chosen from the remaining five and follows the same rule. This process continues for a maximum of 30 moves after the initial selection" (we used a different algorithm in N2 and N3 only to prevent ties). While we could consider many other algorithms, this one serves as a simple yet reasonable reference benchmark.

Likelihood of convergence

In Figure 2, we begin by calculating the probability of convergence within the allotted 30 seconds and comparing it to our algorithm's performance.

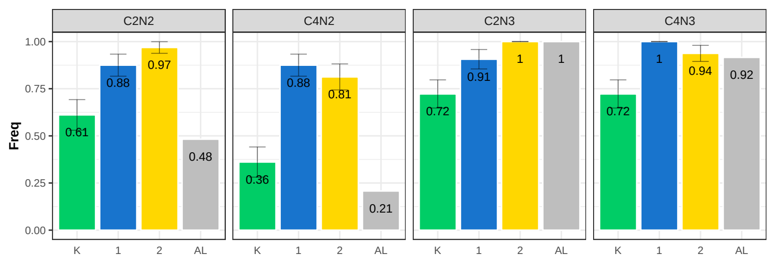


Figure 2: Percentage of network convergence for grades **K**, **1** and **2**, and comparison with 10,000 simulations of our behavioral algorithm, **AL**, computed separately for each condition (C2N2, C4N2, C2N3, C4N3). Error bars represent confidence intervals.

The results demonstrate a very significant age-related improvement within our window of observation. First and second graders exhibit an impressive ability to reach consensus across all conditions, with network success rates ranging from 26 to 32 out of 32. There are no statistically significant differences between **1** and **2** (pairwise two-sided test of comparison of proportion with Holm adjustment, all p-values > 0.30). By contrast, kindergartners face greater difficulty, with consensus achieved in only 13 to 26 out of 36 rounds, with all proportions significantly different from the older grades (pairwise two-sided test of comparison of proportion with Holm adjustment, all p-values < 0.05) except for **K** v. **1** in C2N3 (p=0.159). The algorithm performs (surprisingly) poorly with two neighbors (even below **K**'s performance) but excels with three neighbors, underscoring the role of increased connections in facilitating consensus. More generally, **K**'s behavior is consistent with the hypothesis that consensus is hardest with more colors and fewer neighbors (C4N2). These findings are further supported by a Probit regression analysis of network convergence probability (see SI2 for details).

Speed of convergence

Next, we examine the speed of convergence as an additional performance metric. When examining the empirical number of choices needed to reach consensus (conditional on successful convergence), there are no statistically significant differences across grades, except between **2** v. **K** and **2** v. **1** in condition C4N2 (pairwise two-sided t-test for mean comparison using pooled standard deviation and Holm adjustment, p-value = 0.003 and p-value = 0.009, respectively). To enhance statistical power, Figure 3 presents the distribution of choices until consensus, pooled across all grades but separated by condition. This distribution is also compared to the algorithm's performance **AL**.

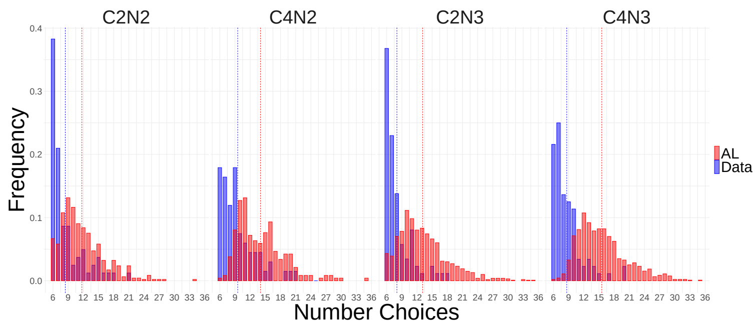


Figure 3: Distribution of the total number of choices in the network, conditional on successful convergence, for our combined population (all grades grouped) and for the algorithm, calculated separately for each condition (C2N2, C4N2, C2N3, C4N3) [vertical lines indicate the average values in the graph].

Participants reach consensus significantly faster than the algorithm predicts (Kolmogorov-Smirnov test, p-values < 0.001 for all four conditions). Indeed, 72% to 84% of participants converge within 10 choices, compared to only 9% to 49% in the algorithm. Convergence is rare after 30 choices (or even earlier) validating the experimental time limit and the theoretical choice cap in the algorithm.

Overall, **AL** accurately captures the likelihood of convergence for **K** in N2 and for **1** and **2** in N3, though it fails to capture the speed of convergence in any condition.

1.3 Individual behavior

Next, we analyze individual behavior to gain insight into the strategies employed by our participants. Our methodology is as follows: first, we identify the empirical features of participants' choices, and then we incorporate these features into **AL** to determine if the modified algorithm better aligns with the observed behaviors.

Dynamic imitation

For each participant, we calculate how frequently they follow the strategy prescribed by the algorithm. Specifically, we observe the network from the perspective of individual i at a given moment and check if their choice aligns with **AL**. We then examine the network after one neighbor has changed their action, repeating this analysis iteratively until no further changes occur. From this, we compute p_i, the fraction of i's choices consistent with the algorithm and designate $1 - p_i$ as the level of non-compliance with the algorithm, "degree of flexibility", or "choice frictions". This procedure is repeated for all participants, in all configurations where at least one neighbor has already made a choice. Figure 4 presents a histogram of the empirical distribution of p_i across **K**, **1** and **2**.

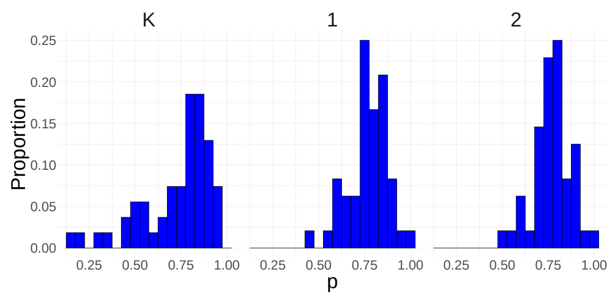


Figure 4: Empirical fraction of p_i, representing the choices consistent with **AL**, presented by grade.

The average empirical fraction of choices consistent with **AL** by grade is $\hat{p}_{\mathbf{K}} = 0.73$, $\hat{p}_{\mathbf{1}} = 0.77$ and $\hat{p}_{\mathbf{2}} = 0.77$, yielding a population average of $\hat{p} = 0.75$. Friction disparities are higher in **K**, supporting the idea that confusion or inattention ($p_i < 0.50$)—though rare—occurs primarily among the youngest participants. This, in turn, might explain their lower success rate in reaching consensus. In general, choice frictions are low ($p_i \in [0.7, 0.9]$ for two-thirds of participants), but no frictions are uncommon.

To assess whether frictions are, in theory, beneficial or detrimental to performance, we extend our algorithm to incorporate the possibility of deviations. Figure 5 displays the convergence of **AL** as we vary p ($\in [1/2, 1]$), which we call $\mathbf{AL_p}$ (where, naturally, $\mathbf{AL_1} \equiv$ **AL**). In this extended algorithm, each individual follows the majority with probability p ($\in [1/2, 1]$) and deviates with probability $1 - p$. Deviations involve either keeping their current choice when the strategy requires switching or randomly changing to one of the minority colors when the strategy requires maintaining their choice.

From a theoretical perspective, *some* departures from full compliance with **AL** are highly beneficial in N2. They can be either beneficial or detrimental in N3. The reason is simple: while deviations generally delay convergence, they also prevent scenarios where two subgroups lock into different colors with no incentives to switch—a configuration much more common in N2. In such cases, deviations help overcome impasses, facilitating consensus that might otherwise be unreachable.

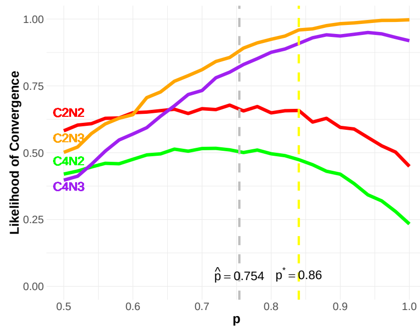


Figure 5: $\mathbf{AL_p}$: convergence of the algorithm by condition as a function of choice frictions (we run 3,000 simulations for $p \in [0.5, 1]$ in 0.02 intervals). We also report the empirical average ($\hat{p}$) and the optimal average level of choice frictions (p^*).

The level of frictions that maximizes convergence across all conditions is $p^* = 0.86$, lower but close to the observed empirical level ($\hat{p} = 0.75$). Notably, convergence under the empirical friction level ($\hat{p}$) surpasses convergence under no frictions ($p = 1$) when averaged across all conditions. It suggests that some flexibility in choice can enhance performance. At the same time, choice frictions notably decrease the speed of convergence (see SI3 for details).

Initial choice

Another feature of our basic algorithm is that all six participants make their initial choice randomly. However, several indicators suggest this assumption does not hold empirically. Firstly, the probability of achieving convergence in exactly six moves (one per participant) is 30% in C2 and 19% in C4—much higher than the expected 3.1% and 0.03% if initial choices were entirely random (two-sided tests of comparison of proportions with theoretical proportions, both p-values < 0.001). Additionally, conditional on achieving convergence, the likelihood that the first color selected by the first player to choose aligns with the final consensus color is 73% in C2 and 67% in C4, compared to 50% and 25% respectively if initial choices were random (two-sided tests of comparison of proportions with theoretical proportions, both p-values < 0.001). Finally, for rounds converging in more than six moves, there is a 43% likelihood in C2 and 37% in C4 that consensus is reached immediately after the first move of one of the players. The first two observations suggest that neighbor imitation occurs even within the first choices of the players (hence, not random). The third observation suggests a "sniping" behavior, where one participant, the closer, delays their choice, waiting for the opportune moment to make the decisive, consensus-reaching final move.

To evaluate the degree of sequentiality in participants' initial choices, we construct a ranking measure. For each participant, we determine the ranking of their initial choice within their network in each round (first to sixth) and calculate the average ranking of the participant across all 16 rounds. Figure 6 shows the empirical distribution of these average rankings across **K**, **1** and **2**.

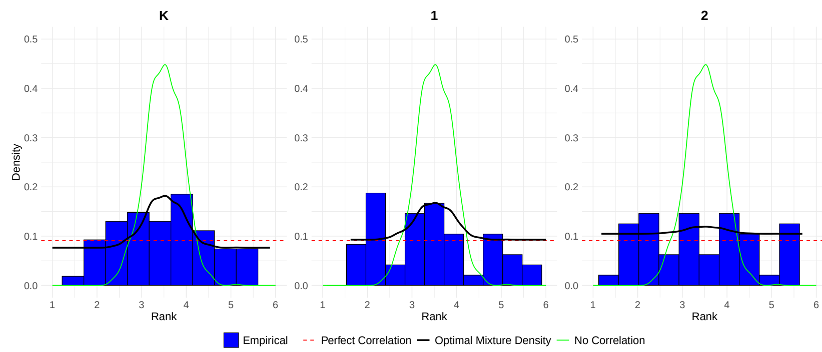


Figure 6: Distribution of average rankings in the population (blue histogram), presented by grade. For comparison, we include the two polar cases, where the 16 rankings are random across rounds (solid green line) and perfectly correlated across rounds (dashed red line).

The distribution of initial choice rankings reveals large heterogeneity across individuals (blue histogram). Some participants, the leaders, consistently make their initial decisions quickly, aiming to guide the group. Others, the debaters, observe the initial behavior and react accordingly. Finally, there is a group of closers, who systematically wait, observe their peers, and aim to make the final, consensus reaching move. This pattern aligns more closely with a perfectly correlated ranking across rounds (dashed red line) than with a random ranking across rounds (solid green line). The dispersion is also higher in older children. Overall, $\mathbf{AL}_{\hat{\mathbf{p}}}$'s assumption of random initial choice does not accurately capture the behavior of our participants.

To evaluate the level of endogenous role heterogeneity in our population, we estimate the average degree of sequentiality in participants' initial choices. It involves creating a weighted combination of simulated densities with no rank correlation (participants make their initial choice simultaneously, $q = 1$) and perfect rank correlation (participants make their initial choice sequentially, $q = 0$). Using maximum likelihood estimation techniques, we find that the mix that best matches the data's histogram in each grade (represented by a thick black solid line in Figure 6) are $\hat{q}_{\mathbf{K}} = 0.24$, $\hat{q}_{\mathbf{1}} = 0.17$ and $\hat{q}_{\mathbf{2}} = 0.03$, for a population average of $\hat{q} = 0.19$. The result also points to a higher degree of sequentiality in **2** than in **1** or **K**.

Are these endogenously heterogeneous roles, which we empirically found to be adopted by our participants in their initial decisions, associated with improved performance? To explore this, we further extend our algorithm by assuming that each player's initial choice is simultaneous with the preceding player with probability q and sequential with probability $1-q$. Here, $q=1$ represents minimal role heterogeneity, while $q=0$ represents maximal role heterogeneity.[1]

Figure 7 depicts $\mathbf{AL_{\hat{p},q}}$, the theoretical likelihood convergence as we vary role heterogeneity q ($\in [0,1]$) and given the empirically observed level of choice frictions $\hat{p}$ (naturally, $\mathbf{AL_{\hat{p},1}} \equiv \mathbf{AL_{\hat{p}}}$).

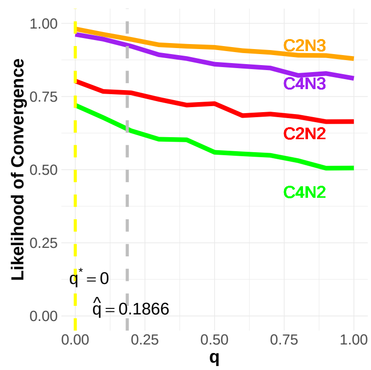


Figure 7: $\mathbf{AL_{\hat{p},q}}$: convergence of algorithm given $\hat{p}$ choice frictions as a function of q. We also report the empirical average ($\hat{q}$) and the optimal average role heterogeneity (q^*).

Convergence is monotonically decreasing in q. Sequentiality in initial choices significantly enhances imitation and, consequently, convergence, as it allows participants to follow the initial choices of others. Given the absence of a pre-specified order of moves, this requires a high level of coordination regarding who acts and who waits. The effect is roughly linear and slightly more pronounced in N2, where achieving consensus is inherently more challenging. Furthermore, sequentiality impacts the distribution of choices until convergence even more than the likelihood of convergence itself. Indeed, the updated algorithm $\mathbf{AL_{\hat{p},\hat{q}}}$ aligns much more closely with the observed speed of convergence among participants than the initial **AL** (see SI3 for details).

To summarize our findings, Table 1 compares the likelihood of convergence across our three participant groups and the three algorithmic models.

[1] Specifically, one player is randomly chosen to make the first initial action, which they select randomly. A second player is then chosen at random. If this second player is not a neighbor of the first, they make a random choice. However, if the first player is a neighbor, then with probability q, the second player's choice is "simultaneous" (i.e., made without observing the first player's action, thus remaining random). With probability $1-q$, the choice is "sequential" (i.e., made after observing the first player's action) and follows the prescriptions of **AL**. This process repeats until all six players have made their initial choice, at

	empirical			algorithm *		
	K	**1**	**2**	**AL**	$\mathbf{AL}_{\hat{\mathbf{p}}}$	$\mathbf{AL}_{\hat{\mathbf{p}},\hat{\mathbf{q}}}$
% convergence						
C2N2	0.61	0.88	0.97	0.48	0.67	0.77
C4N2	0.36	0.88	0.81	0.21	0.50	0.64
C2N3	0.72	0.91	1.00	1.00	0.89	0.95
C4N3	0.72	1.00	0.94	0.92	0.82	0.92

* $\hat{\mathbf{p}} = 0.75$ and $\hat{\mathbf{q}} = 0.19$

Table 1: Summary comparison of performance between participants and algorithms

The algorithm incorporating small choice frictions and large role heterogeneity, $\mathbf{AL}_{\hat{\mathbf{p}},\hat{\mathbf{q}}}$, underestimates convergence in N2 but otherwise captures reasonably well the probability of consensus-building in grades **1** and **2**.

We also perform an OLS regression and show that individuals who move earlier (the leaders, with ranks closest to 1 in Figure 6) are more likely to follow the prescriptions of the algorithm in their subsequent moves. Conversely, impulsive participants (who repeatedly click on the same action even though it has no practical effect in the game) are less likely to adhere to it (see SI4 for details).

Finally, we explore the prevalence and underlying factors of sniping behavior, the closers, and show that younger players are less likely to converge in C4 but more likely to do so through sniping (see SI5 for details). Then, we show that convergence increases when the first player to move does so faster, and when the individuals in the network are more efficient at (endogenously) adopting different roles, leader v. closer (see SI6 for details).

2 Discussion

This experiment uncovers a sharp developmental progression in children's ability to coordinate actions in groups. Kindergarteners (ages 5-6) show lower consensus-building proficiency compared to first and second graders (ages 6-8), indicating that cognitive mechanisms crucial to coordination—such as impulse control, sustained attention, and processing social information—sharpen notably between these ages. This likely stems from improvements in executive functions, working memory, and abstract thinking (Diamond, 2013). The task also demonstrate a fine sensitivity to developmental nuances within this narrow age range, as our previous research in strategic behavior among young children has shown (Brocas and Carrillo, 2020, 2021).

which point the algorithm proceeds as before.

An interesting empirical aspect is the endogenous role heterogeneity—variability in speed of the initial decision. Groups with both fast and slow decision-makers reach consensus more effectively, with quick responses providing direction and slower responses locking consensus. This balance of speeds may enhance decision-making in real-world group scenarios, where the presence of leaders and closers allows adaptation to changing information. Role heterogeneity aligns with evolutionary theory, which holds that diversity in traits, like decision-making speed, can benefit group survival by fostering adaptability (Simons, 2011). In social contexts, variation prevents premature convergence on suboptimal choices and supports resilience. This diversity reflects the idea from evolutionary game theory that variation in behavior benefits groups in cooperative settings (McNamara et al., 2004).

The study also shows that pure imitation does not guarantee coordination success. Children who adjust choices based on social cues, which we label as choice frictions, coordinate better and faster, indicating that they use more complex mechanisms than previously assumed. This aligns with theories of social cognition, which argue that children are not passive imitators but active participants in social learning (Tomasello, 2009). They employ adaptive strategies based on peers' behaviors, reflecting early-developed skills like shared intentionality and theory of mind (Wellman et al., 2001), and problem-solving skills that are fine-tuned in social contexts (Gopnik and Wellman, 2012). These traits are also likely to be beneficial in complex workplace environments, where a few divergent perspectives can foster collaboration and help prevent scenarios where clusters of individuals coordinate on conflicting strategies.

Network complexity, in the form of fewer neighbors or more options, makes consensus significantly more challenging. This finding aligns with research suggesting that network structure and visibility critically influence collective decision-making. For instance, Kearns et al. (2006) demonstrates that consensus is challenging in networks with limited connectivity, and that increasing visibility of others' choices or reducing options can simplify coordination by clarifying social cues. At the same time, our participants exhibit an impressive collective ability to reduce complexity, even when full coordination is not achieved. In fact, when we consider networks with four choices where consensus is not reached, participants manage to eliminate two choices in 83% of cases. Also, five out of six participants successfully coordinate at some stage in 35% of cases. Non-convergence is often due to a single stubborn player who blocks progress towards a complete alignment.

Simple behavioral algorithms predict children's choices in broad strokes but miss critical nuances, particularly regarding decision speed and friction, underscoring the flexibility of children's heuristic strategies shaped by social cues. This aligns with theories of heuristic decision-making, where children make good enough choices suited to their cognitive limits and environmental constraints (Simon, 1955; Todd and Gigerenzer, 2000; Kahneman, 2011). Ecological rationality further asserts that these strategies are adapted to specific contexts, allowing humans, including young children, to outperform rigid models in real-life settings by relying on simple, context-sensitive strategies (Gopnik, 2012).

More broadly, our findings suggest that integrating structured group tasks that promote coordination and peer adaptation into early education may enhance the cooperative skills, social cognition, and iterative problem-solving ability of children, competencies that are highly useful in their future adult lives. Practical applications include designing collaborative team-building activities, early interventions for impulsive children, and educational tools that align with developmental stages in social cognition. Future research could build on these findings by exploring diverse socio-economic groups and cultural differences or incorporating more complex tasks, such as fairness and resource allocation, to deepen our understanding of developmental coordination skills.

It is important to consider the limitations of our study. First, participants are drawn from a single private school in Los Angeles, which may have limited socio-economic and cultural diversity, potentially affecting decision-making styles and coordination abilities. Additionally, experimental tasks such as color-matching in small networks, do not fully reflect the complexities of real-world coordination scenarios or the challenges of decision-making in more intricate social networks. Also, while the study successfully identifies key characteristics that promote consensus-building, it does not explore the other side of the coin, namely the features that prevent consensus. Designing experiments that create more room for miscoordination would help filling this gap. Finally, the controlled laboratory setting, while beneficial for isolating specific variables, may not entirely replicate the dynamics of more natural, ecological environments, where external pressures and unobservable factors often play a significant role in coordination.

3 Methods

The study was conducted with approval from the University of Southern California Institutional Review Board (IRB) under protocol UP-12-00528. Consent forms were distributed to parents via the school administration, offering an opt-out option. An information session was organized by the school for parents to ask questions to researchers a few weeks before the experiment. On the day of the experiment, children were read an assent form and asked if they wished to participate. No student or parent declined participation. Participant data were anonymized to maintain confidentiality and stored securely in accordance with our approved protocol.

We conducted 10 sessions at LILA with 12 or 18 participants each (2 or 3 networks).

We brought a portable lab to each classroom, gave PC tablets to every student, and connected the tablets to each other and to the portable server in a closed circuit with a wireless router. The experiment was programmed in oTree (Chen et al., 2016). Since we needed groups of six players, we sometimes mixed students from two different classes but always from the same grade. When multiples of six were not possible, the extra student(s) were randomly occupied on a different task. We used cardboard separations to preserve anonymity and made sure that students seated next to each other always belonged to different networks.

The timing of the experiment was as follows. First, in order to elicit their interest, we showed a sample of the toys the students would be playing for. These include 20 to 25 pre-screened, currently fashionable small toys such as bouncy balls, pop-up bracelets, scented pens, slime, emoji keychains, etc. We then read the instructions aloud with the support of a powerpoint presentation (as described in SI1). After, students played one practice round, where they could raise their hand and privately ask clarification questions. We then conducted the 16 rounds of the "network" task with 2 and 4 colors (C2 and C4) and with 2 and 3 neighbors (N2 and N3), in the following counterbalanced blocks of two: C2N3 C2N3 C2N2 C2N2 C4N3 C4N3 C4N2 C4N2 C2N2 C2N2 C2N3 C2N3 C4N2 C4N2 C4N3 C4N3, with a brief stretching pause halfway through the experiment. Finally, they learned the number of toys they had won. We accompanied them to another classroom where we had setup the "toy shop" and they selected their favorite items.

For payments, participants obtained 2 points for each network convergence and 1 point for non-convergence. The conversion rate was one toy for each 10 points, rounded to the next ten (for example, 12 points = 2 toys). The procedure entailed incentives for performance but, at the same time, relatively small variance, which ensured that every participant was happy with their rewards. Among our participants, 84% obtained between 6 and 8 toys.

Finally, we employed 16 different colors so that no four consecutive rounds were played with the same colors. This ensured that choices were unlikely to be driven by a "favorite" color. More importantly, it also prevented the possibility that participants who converged in a round decided all to start the next round on the same color.

Data availability statement: The datasets generated and analyzed in this study are available at `https://github.com/labelinstitute/Networks-consensus`.

Code availability statement: The custom code used for simulating our algorithms is available at `https://github.com/labelinstitute/Networks-consensus`.

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Supplementary Information

SI1. Instructions

Hi everyone. My name is Juan. Today, we are going to play several games and you are going to win points. At the end, you are going to exchange the points for toys in our toy shop. You will all get many toys, but the better you do, the more points you earn, and the more points you earn the more toys you get.

NETWORK GAME

The computer is going to form several groups of six, but you will not know who is in your group and it is not the point to find out [**SLIDE 2**].

Each of you will be connected to some people in your group but not to others. When you are connected to someone, it means that you can see their choices. For example, here Bob sees the choices of John and James but not the other kids in his group. John sees the choices of Bob and Ann but not James or the others, and so on [**SLIDES 3 and 4**].

In some games, each of you will see the choices of two other people in your group. In some other games, you will see the choices of 3 other people [**SLIDES 5 and 6**]. This is an example of what the people in a group will see [**SLIDE 7**].

What you have to do in this game is very simple! You have to choose a color. That's it. If you all choose the same color at the same time, you all win two points! Otherwise, you will only win one point. So, it's not about choosing your favorite color but about choosing the same color as others. The good news is that you can change the color as many times as you want. There is only one rule: you cannot talk.

Let me give you an example. This is what you will see in your screen [**SLIDE 8**]. This is you (point), and these are the people around you (point). You are always at the center of your own group. In this case how many other people can you see? Two. Very good. Remember there are other people in your group. It's just that you can't see them. This is the screen when there are three other people in your group [**SLIDE 9**].

Let's go back to the case where you see two people. Now, this is where you choose a color [**SLIDE 10**]. In this case, everyone chooses between two colors, BLUE and RED, but in different rounds you will see different colors. As soon as you choose a color, it will appear here. And the people connected to you will be able to see it.

In this example, you chose red [**SLIDE 11**]. Here you see that one person chose blue and the other red [**SLIDE 12**]. Then, you can change your color as many times as you want. It is totally up to you. Remember the goal is to have everyone in your group of six choose the same color. This means not only the people you can see but also the others you do not see.

So, for example, imagine you are Bob. In this case, [**SLIDE 13**] everyone you see is choosing blue (including yourself), but you are still not winning two points because these guys are choosing red. While here [**SLIDE 14**], everyone in your group is choosing blue, so you all get two points. Does that make sense to everyone?

Now two more things. Every time you play, you will see a clock at the top of the screen [**SLIDE 15**]. This tells you the amount of time left to play. You start with 30 seconds and the clock runs backwards (29, 28, 27). Everyone can change their action as many times as they want. When everyone is in the same color, the clock stops, and you get two points. As long as everyone is not in the same color, the clock keeps running. If it hits 0 and not everyone is in the same color, you will only get one point.

You are going to play many rounds. Sometimes, you will see the choices of two people and sometimes you will see the choices of three people. Also, sometimes you will choose between two colors as in this example, and sometimes you will choose between four colors as in this example [**SLIDE 16**]. However, the rules are always the same: everyone has to be in the same color, it does not matter which one.

At the end of each round, you will know how many people chose each color. You will see a screen like this [**SLIDE 17**]. In this example, did you get two points? Why? How about this one? [**SLIDE 18**]. After you see if you won that round, you press the green button and move to the next round to win more points. Are you ready to play?

You are going to play many times, so you are going to have many chances to win points. Before we start, we are going to play a pretend round. This is only to make sure you understand the game. This round does not count for real so feel free to try different things. If you don't understand what's going on, raise your hand and we'll be happy to come and help you. Any questions?

[After the practice round] We are going to start the real game

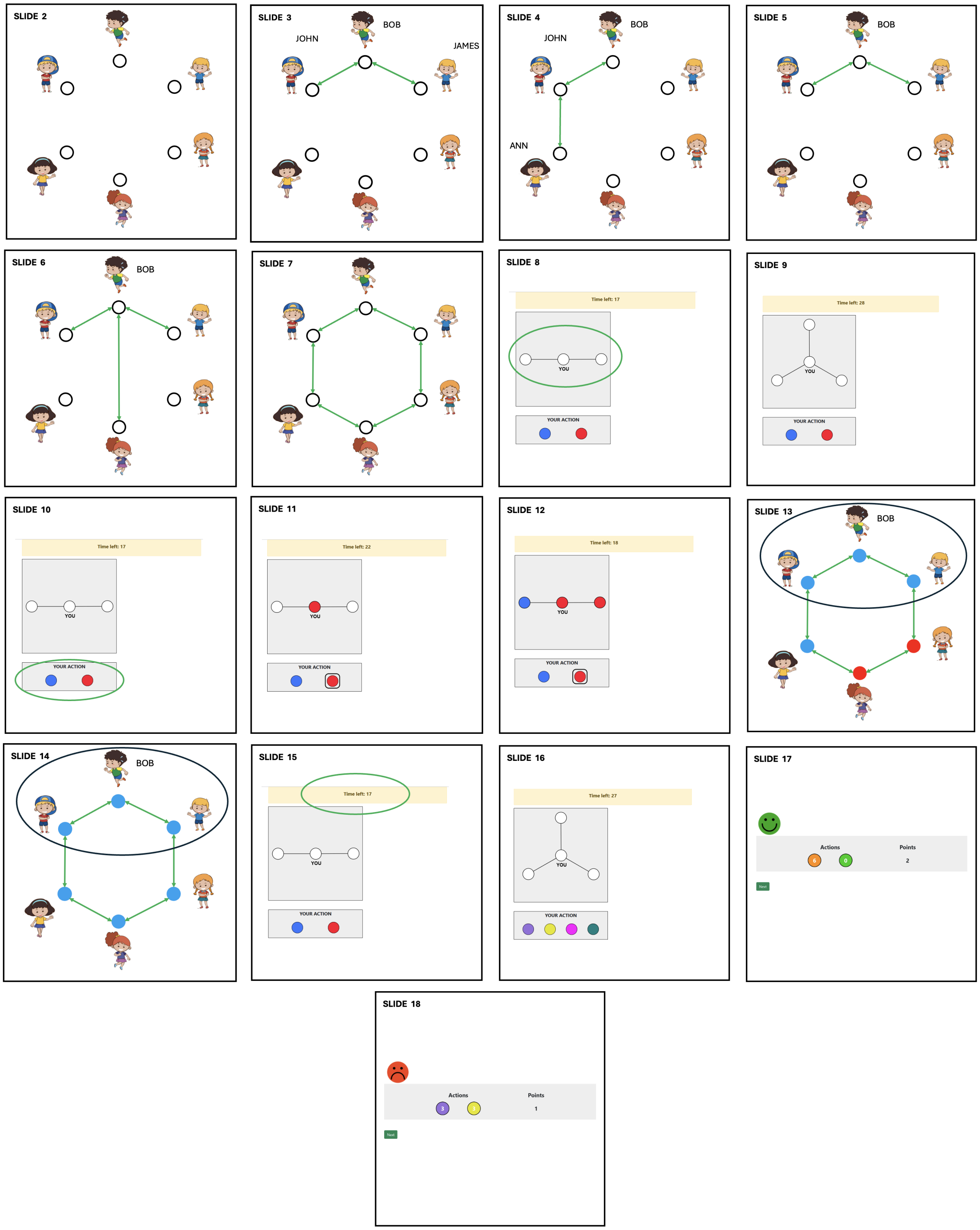

Figure SI1: Slides projected on screen for instructions

SI2. Probit regression of likelihood of network convergence

Table SI1 presents a Probit regression of network convergence probability with dummy variables for grade, number of males in the network, number of links, number of colors, and first v. second half of the experiment.

	Prob. Conv.
(Intercept)	1.840^{***}
	(0.455)
Grade **K**	-1.190^{***}
	(0.261)
Grade **2**	0.129
	(0.246)
# males	-0.040
	(0.126)
Second-Half	0.378°
	(0.203)
C4	-0.297^{*}
	(0.148)
N2	-0.621^{***}
	(0.150)
AIC	324.5
Num. obs.	400

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Table SI1: Probit regression of probability of network convergence (standard errors are clustered at the session level). Convergence is significantly less frequent with more colors (C4), with fewer neighbors (N2), and in **K** (compared to **1** and **2**). Convergence is also marginally more frequent towards the end of the experiment. Sex composition of the network has no effect.

SI3. Choices conditional on convergence under frictions

Figure SI2 compares the empirical distribution of number of choices conditional on convergence with the distribution under 10,000 simulations of algorithms $\mathbf{AL}_{\hat{\mathbf{p}}}$ (left) and $\mathbf{AL}_{\hat{\mathbf{p}},\hat{\mathbf{q}}}$ (right), that is, the algorithm with frictions or with frictions and heterogenous roles.

Convergence is much slower under $\mathbf{AL}_{\hat{\mathbf{p}}}$ than under **AL** (see Figure 3) and therefore also much slower than that of our participants. The introduction of choice frictions decreases the number of instances where the network gets stuck in configurations where two subset of players coordinate in two different colors. However, these small "mistakes" increase the expected number of choices it takes to achieve consensus.

By contrast, sequentiality has a very large positive effect on speed of convergence. $\mathbf{AL}_{\hat{\mathbf{p}},\hat{\mathbf{q}}}$ matches the empirical behavior of our participants much better than the other algorithms. However, it is still not perfect. Indeed, the fraction of both 'immediate' convergence (6 choices) and

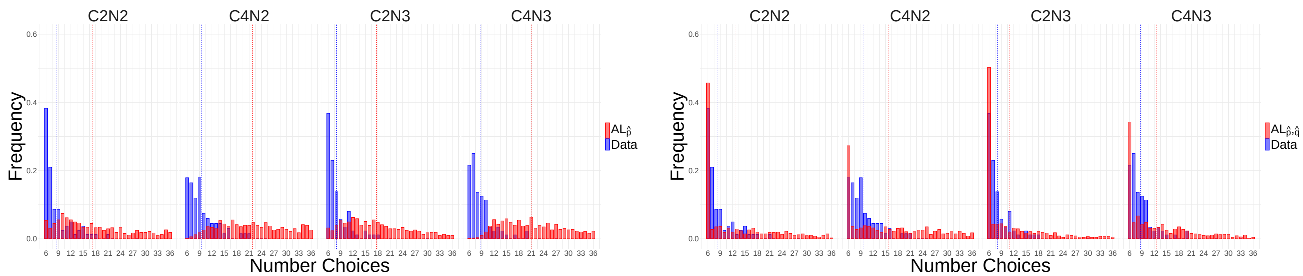

Figure SI2: Distribution of choices in the population and in the algorithms $\mathbf{AL}_{\hat{\mathbf{p}}}$ (left) and $\mathbf{AL}_{\hat{\mathbf{p}},\hat{\mathbf{q}}}$ (right) [averages are reported with vertical lines].

'delayed' convergence (12 choices or more) is larger than in the data while the fraction of 'intermediate' convergence (between 7 and 11 approximately) is smaller.

SI4. OLS regression of dynamic imitation

We investigate in Table SI2 the determinants of playing according to **AL**, p_i, as a function of the participant's age (in months), sex, and average rank of their first choice (q_i) which captures their leadership skills and ability to move outcomes in their direction. We also include extra clicks, which captures the impulsivity of the individual. Formally, it is the number of instances where the participant clicks in the same color twice or more. Those decisions have no effect on outcomes (they are not even observed by others) and only denote willingness to impose their choices.

	p_i
(Intercept)	0.914***
	(0.071)
Age	-0.001
	(0.001)
Male	-0.014
	(0.016)
Rank	-0.0174*
	(0.007)
ExtraClicks	-0.211***
	(0.017)
Adj. R^2	0.539
Num. obs.	148

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Table SI2: OLS regression of p_i.

Leaders (early movers) are more likely to follow the algorithm, thus showing a better understanding of the game. Conversely, impulsive participants are less likely to follow the algorithm, as they want to impose their choices on others. Interestingly, age has no effect on p_i, mostly because kindergartners—who are more likely to deviate from the algorithm—are also the more impulsive players.

SI5. Sniping behavior

We have previously noted some differences across grades in the sequentiality of initial choices (Figure 6). Nevertheless, conditional on convergence, the percentage of rounds where it is achieved in exactly 6 moves is similar across grades: 29% in **K**, 29% in **1** and 26% in **2**. Perhaps more interestingly, the percentage of rounds where convergence is reached in more than 6 moves but immediately after the first move of one participant–what we call sniping–is high and also similar across grades: 30% in **K**, 28% in **1** and 27% in **2**.

Table SI3 reports the proportion of sniped networks among networks that converged in more than 6 moves, separated by grade and number colors to choose from.

	C2	C4
K	0.37	0.52
1	0.43	0.38
2	0.48	0.27

Table SI3: Sniping by grade and complexity

Differences in sniping across grades is mostly related to the complexity of the situation. Indeed, conditional on convergence, children in **K** show a higher tendency than children in **2** to snipe in the more complex case with 4 colors (C4, two-sided test of comparison of proportions, p-value = 0.053), even if they are less likely to reach overall convergence. This suggests that older children are better able to think and dynamically adapt to complex situations.

Finally, Figure SI3 illustrates for each of the 25 networks in the experiment, the number of rounds (out of 16) where convergence was achieved through sniping behavior. On average, sniping occurred in 22.8% of rounds but we notice very different behavior across networks, with a minimum of 0 and a maximum of 9 sniping in a given network.

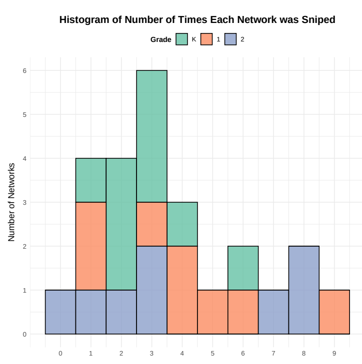

Figure SI3: Rounds of convergence through sniping behavior

SI6. Timing of the first choice

For each round, we calculate a measure called "Delay" which represents the time elapsed between the beginning of the game and the first move of the participant who moves first. We then include this measure in the original Probit regression model of probability of convergence (Table SI1), and present the results in Table SI4. As the regression shows, having one player in the network who moves fast (lower value of "Delay") helps convergence.

	Prob. Conv.
(Intercept)	2.790^{***}
	(0.472)
Grade **K**	-1.213^{***}
	(0.206)
Grade **2**	0.086
	(0.242)
# males	-0.060
	(0.080)
Second-Half	0.314°
	(0.16673)
Delay	-0.303^{**}
	(0.106)
C4	-0.303°
	(0.164)
N2	-0.689^{***}
	(0.17112)
AIC	318.0
Num. obs.	400

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\circ}p < 0.1$

Table SI4: Probit regression of probability of network convergence, including 'Delay' as a predictor.

We also calculate the variance of the rank for each individual and then average these variances to obtain a measure of "spread" for each network. The spread differs significantly between networks in **K** and networks in **2** (two-sided t-test 1.77 v. 1.29, df = 14.744, t = 2.2327, p = 0.041; Cohen's d=1.07, Confidence Interval $[-0.039, 2.17]$) and it is marginally correlated with the probability of convergence of the network (Pearson Correlation Coefficient PCC = -0.38, p = 0.063). This finding suggests that better self-sorting of players within the network which results in less ambiguity in roles (and thus, a smaller variance) enhances the likelihood of consensus, and is a skill that develops over time.