Social and general intelligence improves collective action in a common pool resource system

Jacob Freeman[a,b,1,2], Jacopo A. Baggio[c,d,e,1], and Thomas R. Coyle[f,1]

[a]Anthropology Program, Utah State University, Logan, UT 84321; [b]Ecology Center, Utah State University, Logan, UT 84321; [c]School of Politics, Security, and International Affairs, University of Central Florida, Orlando, FL 32816; [d]Sustainable Coastal Systems Cluster, University of Central Florida, Orlando, FL 32816; [e]National Center for Integrated Coastal Research, University of Central Florida, Orlando, FL 32816; and [f]Department of Psychology, University of Texas at San Antonio, San Antonio, TX 78249

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On a planet experiencing global environmental change, the governance of natural resources depends on sustained collective action by diverse populations. Engaging in such collective action can only build upon the foundation of human cognition in social–ecological settings. To help understand this foundation, we assess the effect of cognitive abilities on the management of a common pool resource. We present evidence that two functionally distinct cognitive abilities, general and social intelligence, improve the ability of groups to manage a common pool resource. Groups high in both forms of intelligence engage in more effective collective action that is also more consistent, despite social or ecological change. This result provides a foundation for integrating the effects of cognitive abilities with other dimensions of cognitive diversity to explain when groups will and will not sustainably govern natural resources.

collective action | cognition | common pool resources | theory of mind

The evolution of collective action beyond close kin is a hallmark of human society (1). Yet, although collective action to manage natural resources can persist for centuries (2), collective action also sometimes fails, spectacularly (3). Understanding why is critical on a planet where people from different backgrounds must cooperate to adapt to global environmental change (4). For example, reducing CO_2 emissions requires many individuals from diverse backgrounds to reduce, at a short-term personal cost, their use of fossil fuels to maintain a more suitable climate, a societal benefit, for future generations. Engaging in collective action at such a large scale can only build upon the foundation of human cognition in social–ecological settings. To help understand this foundation, we investigate the effects of general and social intelligence on the ability of groups to act collectively to solve a sustainability challenge.

Sustainability challenges often require collective action by groups with different background experiences (e.g., Swedish vs. American culture), modes of inquiry (e.g., visual–spatial vs. verbal representations of the world), and preferences (e.g., maximize income vs. minimize suffering) to solve problems. Differences in experiences, modes of inquiry, and preferences are all dimensions of a social group's cognitive diversity (5). Cognitive diversity, in this sense, describes the configuration of social groups along one or more of the above dimensions. Studies of cognitive diversity, across disciplines, converge on a key insight. Diverse experiences and modes of inquiry (but not necessarily preferences) have positive net benefits for cooperation, learning, and problem solving among social groups (e.g., refs. 5–9). This insight, however, is incomplete. The issue is that experiences and modes of inquiry are framed as factors that explain group performance better than cognitive abilities (5). A particularly pithy result indicates the following: Groups with diverse predictive models make better predictions than smart (high-IQ) groups (9). This framing obscures the fact that groups need multiple types of cognitive abilities—an underexplored dimension of cognitive diversity—to solve complex problems and, importantly, that levels of cognitive abilities should affect the capability of groups to understand any given social–ecological setting. Thus, in this paper, we fill an important knowledge gap by studying the effects of general and social intelligence—two distinct types of cognitive ability—on the capability of groups to solve a sustainability challenge, and we use these results to hypothesize how diverse experiences, modes of inquiry, and cognitive abilities interact to affect the capability of social groups to solve sustainability challenges.

All sustainability challenges require groups to model ecological and social components of a system. For instance, in an open access fishery, stakeholders must model how fish populations respond to external drivers, such as climate variation, to make effective harvest decisions in terms of catch levels. Similarly, stakeholders must model how other stakeholders will act and their intentions to form a joint harvest goal that avoids overfishing. Our basic proposition is that effective cooperation to sustainably manage natural resources improves when groups are configured with high levels of two distinct cognitive abilities: general intelligence and social intelligence, theory of mind in particular (10, 11). These cognitive abilities fundamentally affect the ability of groups to understand the ecological and the social dimensions of sustainability challenges and should, thus, affect the performance of groups in solving such challenges.

Significance

Initiating large-scale collective action to sustain natural resources is a key challenge in a world of global environmental change. Research relevant to meeting this challenge must assess the effects of human cognitive abilities on collective action under multiple scenarios of social and ecological change. This paper illustrates the importance of social and general intelligence for solving a collective action problem. Groups high in general intelligence—useful for modeling natural resources—and social intelligence—useful for modeling social relationships—more effectively and consistently learn to sustain natural resources in an experiment. Our results shed light on the ability of groups/teams to solve collective action problems under changing social–ecological conditions.

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[1]J.F., J.A.B., and T.R.C. contributed equally to this work.

[2]To whom correspondence may be addressed. Email: jacob.freeman@usu.edu.

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The specific abilities of spatial memory, valuation of rewards, and executive control are critical to model the complex rules of an ecological system, and one single factor explains a significant amount of the variation in these abilities (general intelligence, g) (12). Thus, g affects the ability to understand the rules of a complex system, and groups higher in overall g should better understand how to implement strategies that sustain natural resources. Similarly, social–cognitive theory of mind (ToM) is a dimension of social intelligence that refers to the ability to model what other individuals within a social group attend to (i.e., beliefs about others' locus of attention) (13, 14). In this regard, ToM serves a distinct function: ToM allows one to predict how others will act in a given situation and develop shared intentions.

In sum, we can conceive of the configuration of social groups along two axes: a g and a ToM axis (Fig. 1*A*). Groups with high g and high ToM should share better models of the ecological and social components of a system and, thus, should make decisions that more consistently favor higher levels of collective action to govern resources at risk for overexploitation. Groups lower in one cognitive ability or the other will display lower and less consistent performance due to misunderstanding either the ecological patterns or social situations that arise in a system. Elsewhere, we have called this hypothesis the functional intelligences proposition (FIP) (10, 11).

Several lines of evidence support the FIP. First, evidence suggests that g and ToM measure distinct processes. For instance, measures of g and ToM share very little variance among research participants tested for both abilities (10, 15–17). Similarly, autistic individuals with high g show a deficit in ToM (18), and when such individuals attempt to model others' attention, brain regions associated with ToM remain inactive (18). Second, proxy data for g and ToM strongly predict the performance of US state governments at providing public goods, which requires sustained collective action (11). Finally, in a limited set of common pool resource experiments, groups high in both g and ToM display the most effective collective action to sustain resources despite unexpected negative changes to an ecological system (10). While these studies hint that levels of g and ToM are partly independent abilities important for groups to solve collective action problems, the above studies ignore critical dimensions of social change, including learning by doing and changes in group size. Here, we provide a synthesis of the effects of g and ToM across multiple contexts of social and ecological change in an experimental setting. This synthesis provides a foundation to integrate multiple cognitive abilities with more traditional studies of group cognitive diversity.

To evaluate the effects of g and ToM across multiple contexts, we conducted four treatments of a controlled common pool resource experiment. In each treatment, participants played an anonymous multiplayer foraging game for six rounds (19) and experienced an unexpected perturbation in round four of the game. Two treatments simulate a negative perturbation to the system that makes collective action more difficult (a reduction in resource growth rate or an increase in group size), and two treatments simulate a positive perturbation (an increase in resource growth rate or a reduction in group size; *SI Appendix*, section 1). In the experiment, the optimal strategy for a group to harvest tokens, regardless of treatment, is to let the tokens grow, without harvest, until very near the end of a round and then harvest every last token just as time expires. While sustaining the resource is necessary to maximize the collection of tokens, sustaining the resource is not sufficient for maximizing the harvest of tokens (i.e., groups may leave tokens in the commons even though they do not carry over from round to round). Measuring both types of performance allows us to understand whether groups with different levels of g and ToM prefer sustaining over maximizing resources or vice versa.

To assess the governance of the resource we use four metrics. First, to estimate the sustainable governance of resources we measure the proportion of time a group leaves tokens in the commons during a round ($Time$). Second, to assess the consistency of resource governance despite social–ecological changes we measure the coefficient of variation of $Time$ over rounds two through six ($CV\ \ Time$). The greater the proportion of time a group leaves tokens in the commons in a given round or on average over all rounds ($Mtime$), the more effectively they work together to sustain the resource. The less consistently groups sustain tokens over rounds, the more sensitive they are to social–ecological change. Third, we assess the ability of groups to maximize token harvest ($Tokens$) and finally, we assess the consistency of token maximization by measuring the coefficient of variation of $Tokens$ over rounds two through six ($CV\ \ Tokens$). We estimate both the effectiveness of performance and the consistency of performance (coefficient of variation) because the FIP (11) suggests that groups high in both g and ToM should

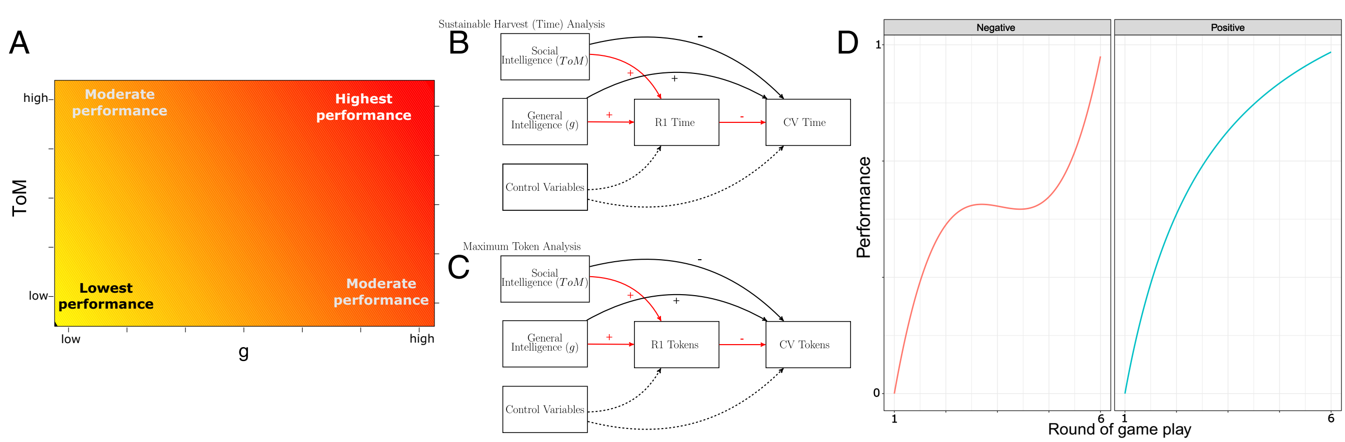

Fig. 1. (*A*) Heat map of the predicted effects of *g* and *ToM* on the mean performance of groups. Yellow indicates poor performance and red indicates high performance (measured as either *Mtime* or *Mtokens*). (*B*) Path model of the effects of *g* and *ToM* on the sustainability of resource harvest in round one (R1) and the consistency of sustainable harvest in rounds two to six. (*C*) Path model of the effects of *g* and *ToM* on the level of optimal harvest in round one and the consistency of optimal harvest in rounds two to six. See *SI Appendix*, section 3 for analysis of the "control variables." (*D*) Predicted learning curves in the negative perturbation and positive perturbation treatments.

not only more effectively engage in collective action but also do so more consistently.

Six predictions guide our analysis. Prediction 1: g, on average, improves the ability of groups to engage in collective action to sustain a common pool resource ($Mtime$) and maximize the production of the resource ($Mtokens$). Higher average g means better models of a resource's dynamics (12). Understanding the resource's ecology is a cumulative task for a group: "I understand X, and you understand Y"; together we understand X + Y > X and X + Y > Y (20). Thus, groups that have better average models of the resource should understand that to maximize their harvest, they must first sustain the resource (increasing $Mtime$) and should also know to collapse the resource prior to the end of a round to harvest more tokens (increasing $Mtokens$). Prediction 2: Groups with all individuals high in ToM should better model the intentions of other actors and better form the joint goal of sustaining the resource. ToM affects social interactions more critically than g, and this modeling ability is a conjunctive task where the minimum level of ToM determines the nature of the interaction within a group (20, 21). The collective management of a common pool resource is a conjunctive task because all members of a group must attend to the goal of sustaining the resource. Thus, we expect that higher minimum levels of ToM lead to groups better at forming a joint goal to sustain the resource (increasing $Mtime$). Further, to maximize the resource, groups must first sustain it. Thus, we expect ToM to improve, on average, how well groups maximize the harvest of resources (increasing $Mtokens$). Fig. 1*A* summarizes these two predictions.

Prediction 3: G and ToM have positive effects on sustaining and maximizing the resource in round one. Round one is a novel environment in which individuals who have trained separately learn how to play the game jointly through trial and error. Following the FIP, groups with high g and ToM should have better models of the resource and social situation entering the game and thus perform more effectively. As illustrated in Fig. 1 *B* and *C*, this means that g and ToM should have positive direct effects on the performance of groups in round one of the game. Prediction 4: We expect g and ToM to impact the consistency of performance through the effects of these abilities on the performance of groups in round one and round one's effect on the consistency of performance (red path arrows in Fig. 1 *B* and *C*). Previous studies of repeated games indicate that performance in round one has a reputation effect on future rounds (22, 23). Given the strong ceiling effect in the ability of groups to sustain or maximize a resource (e.g., they can sustain it only for the length of a round), the success of game play in round one should impact how consistently groups perform over subsequent rounds. Groups who perform well from the start should perform more consistently because they have less room to improve and because they establish a stronger rapport with group mates. Groups who begin poorly should perform less consistently as learning between rounds and perturbations lead to larger gains and losses due to trial and error on the part of groups who have less rapport. Prediction 5: In contrast to the indirect effects of g and ToM, we expect g and ToM to have opposite direct effects on the ability of groups to consistently sustain and maximize the harvest of the resource. Previous research indicates that high-g individuals tolerate more risk than others (24, 25) and should understand that reputation may carry over from round to round but not the collapsed resource. Thus, groups high in g should be more willing to harvest as much as possible and make sure that they get "theirs" in any given round. Conversely, previous research indicates that ToM associates with more other-regarding preferences (26) which should lead to more investment in the joint goal of sustaining the resource. In this context, we expect groups high in minimum ToM to be more other regarding and less sensitive to changes in the experimental environment because they harvest more cautiously, favoring hitting a consistent target rather than maximizing returns in any given round per se.

Prediction 6: Fig. 1*D* summarizes the form of two learning curves that we expect groups to display as they learn how to sustain the resource ($Time$). The panel labeled negative in Fig. 1*D* illustrates how we expect collective action to sustain the resource to change over six rounds of game play when groups face an unexpected negative perturbation. In this case, we expect an increase in $Time$, followed by a decrease immediately after the perturbation itself, followed by an increase in $Time$. Conversely, in the positive perturbation treatments, we expect an increase in $Time$ over all six rounds with negative marginal returns as groups approach the maximum ability to cooperate. In both types of treatments, groups high in g and ToM should display learning curves consistently above the mean curve of all groups, whereas groups low in both abilities should display curves consistently below the mean. Groups specialized in g or ToM could result in curves sometimes above or below the mean.

Results

We first summarize our results and then discuss them in detail. In general, we find that g and ToM increase the ability of groups to engage in collective action to sustain resources; however, only g improves the ability of groups to maximize harvest (Fig. 2 *A* and *B*). In addition, g and ToM improve the ability of groups to sustain resources in round one (Fig. 2*C*) but have little effect on the ability of groups to maximize tokens in round one (Fig. 2*D*). The performance of groups in round one has a positive and significant effect on their ability to consistently sustain the resource in subsequent rounds (Fig. 2*C*) but a negative effect on their ability to consistently maximize harvest (Fig. 2*D*). Finally, groups faced with a negative perturbation display a cubic learning curve while groups faced with a positive perturbation experience a continuously increasing curve with declining marginal returns (Fig. 3). In short, the FIP helps us understand when groups will act collectively to sustain resources but not to maximize production.

For example, Fig. 2 illustrates the marginal effects of g and general least squares (GLS) ToM on the average performance of groups from two GLS regressions. In Fig. 2*A*, as g and ToM increase, groups more effectively sustain the resource on average (shading becomes redder on the diagonal from left to right). However, groups become more effective at maximizing their harvest, on average, only as g increases in Fig. 2*B* (shading becomes redder horizontally). Fig. 2 *C* and *D* illustrates a similar result. G and ToM have positive and significant effects on the ability of groups to sustain the resource in round one ($Time$), but only weak and insignificant direct effects on the ability of groups to maximize production in round one ($Tokens$). Rather, treatment type (positive or negative perturbation) most strongly and significantly impacts the ability to maximize production in round one. Groups who begin harvesting in a challenging environment do a poorer job of maximizing production (*SI Appendix*, Tables S3–S8).

With respect to the consistency of performance, g and ToM have negative and significant indirect effects on CV Time through their effect on group performance in round one (Fig. 2*C*, $Ind\ g = -0.078$, $P = 0.03$; $Ind\ ToM = -0.063$, $P = 0.06$); however, g and ToM have positive and insignificant indirect effects on CV Tokens through their effect on group performance in round one (Fig. 2*D*, $Ind\ g = 0.009$, $P = 0.65$; $Ind\ ToM = 0.01$, $P = 0.54$). The above result contrasts with the direct effects of g and ToM on the consistency of performance. G and ToM have weak, positive, and insignificant direct effects on $CV\ Time$. Conversely, g has a positive and significant direct effect on $CV\ Tokens$, and ToM has a negative and significant direct effect on $CV\ Tokens$. This suggests that g and ToM may underlie different preferences for maximizing returns.

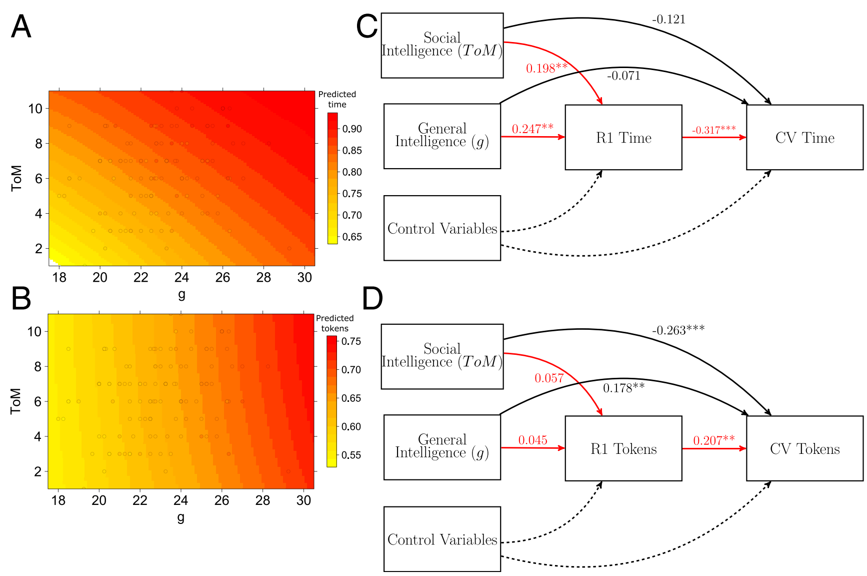

Fig. 2. (*A*) Heat map of the marginal effects of *g* and *ToM* on *Mtime*. (*B*) Heat map of the marginal effects of *g* and *ToM* on *Mtokens*. (*C* and *D*) Path model that describes the effects of *g* and *ToM* on the effectiveness of collective action in round one (*Time* and *Mtokens*) and the effects of *g*, *ToM*, and performance on the coefficient of variation in performance in rounds two to six. R1 stands for round one. Standardized coefficients; significance is indicated at $^{***}P < 0.01$ and $^{**}P < 0.05$.

Finally, a cubic learning curve best fits the data in the negative perturbation treatments (Fig. 3 *A* and *B*). In addition, in both the "four-to-eight" group size and "high-to-low" resource treatments, g and ToM have positive and significant independent effects on the sustainability of the resource. This is consistent with the results presented above (Fig. 2 *A* and *C*). Similarly, the first term of the polynomial on $Round$ significantly interacts with g and ToM. Groups low in g and ToM actually experience faster increases in performance between rounds one and three than groups high in g and ToM (the red curve is steeper than the blue curve over the first three rounds). These results are consistent with our path model results above; groups with higher g and ToM perform better in round one and have less room to improve than groups low in these factors.

An important difference exists between the four-to-eight and high-to-low treatments. The interaction effect between the second term of the $Round$ polynomial, g and ToM indicates a negative and significant interaction in the four-to-eight treatment. Groups high in ToM experience a larger decline in performance than groups low in ToM following an increase in group size. The impact of this decline in performance is moderated by increases in g. As one moves from *Left* to *Right* across the panels in Fig. 3*A*, the post–round-three dip in performance increases in its minimum value. Low-ToM, high-g groups are predicted to perform the best following the increase in group size, although predicted performance subsequently converges in rounds five and six. This is an indication of a subtle trade-off. Groups high in ToM may be good at establishing a joint goal, and high-g, high-ToM groups perform better until the group size perturbation hits. Postperturbation, high-g, low-ToM groups best maintain collective action when group size increases. In this circumstance, specializing in g may be useful, but it will entail worse performance early on in the game. Conversely, high-g, high-ToM groups sacrifice a little performance postperturbation, but sustain the resource more consistently at a high level across all six rounds.

Fig. 3 *C* and *D* illustrates the marginal effects of $Round$, g, and ToM in the positive perturbation treatments. Consistent with Fig. 1*D*, the "low-to-high" resource condition is best fitted by a quadratic function. Conversely, the "eight-to-four" treatment is best fitted by a cubic function. This indicates that when group size changes from eight to four, most groups perform worse, but then collective action begins to stabilize/recover. In both of these treatments, the only variable that has a significant independent effect (other than $Round$) is g. Groups with higher mean g scores sustain the resource more effectively than groups with lower g. In both of these treatments, there are no statistically significant interactions. G and learning by doing impact the ability to sustain the resource over time.

Discussion: Cognitive Ability–Diversity Interaction

On a planet undergoing global environmental change, the sustainable governance of natural resources depends on sustained collective action by diverse populations. Sustained collective action to govern resources must build upon the foundations of human cognition in social–ecological settings. In this paper, we study the effects of two fundamental human cognitive abilities: g and ToM. Partly consistent with the FIP, g and ToM both have positive effects on the ability of groups to effectively and consistently sustain a common pool resource. However, only g has a positive and significant effect on the ability of groups to maximize the production of the resource. Over sequential rounds of resource management, groups consistently learn to better govern the resource; however, especially in the negative perturbation treatments, groups high in g and ToM sustain the resource better than groups high in only one cognitive ability. High levels of two separate, well-defined cognitive abilities (g and ToM) improve the ability of groups to solve a complex collective action problem. This has at least two important implications.

First, the benefits of learning by doing have been known for production processes for a long time (27). Learning by doing also helps groups understand how to solve sustainability challenges; however, learning by doing creates a fit between behavior and a current sustainability challenge that may change over time. Our results suggest that the configuration of a group in terms of g and ToM significantly affects the adaptive capacity of a group to not only learn to more effectively manage a current challenge but also respond to changing environmental conditions. To sustain a resource, despite perturbations, groups need to both understand the resource (activate g) and form an effective joint goal (activate ToM). However, to maximize production, groups just

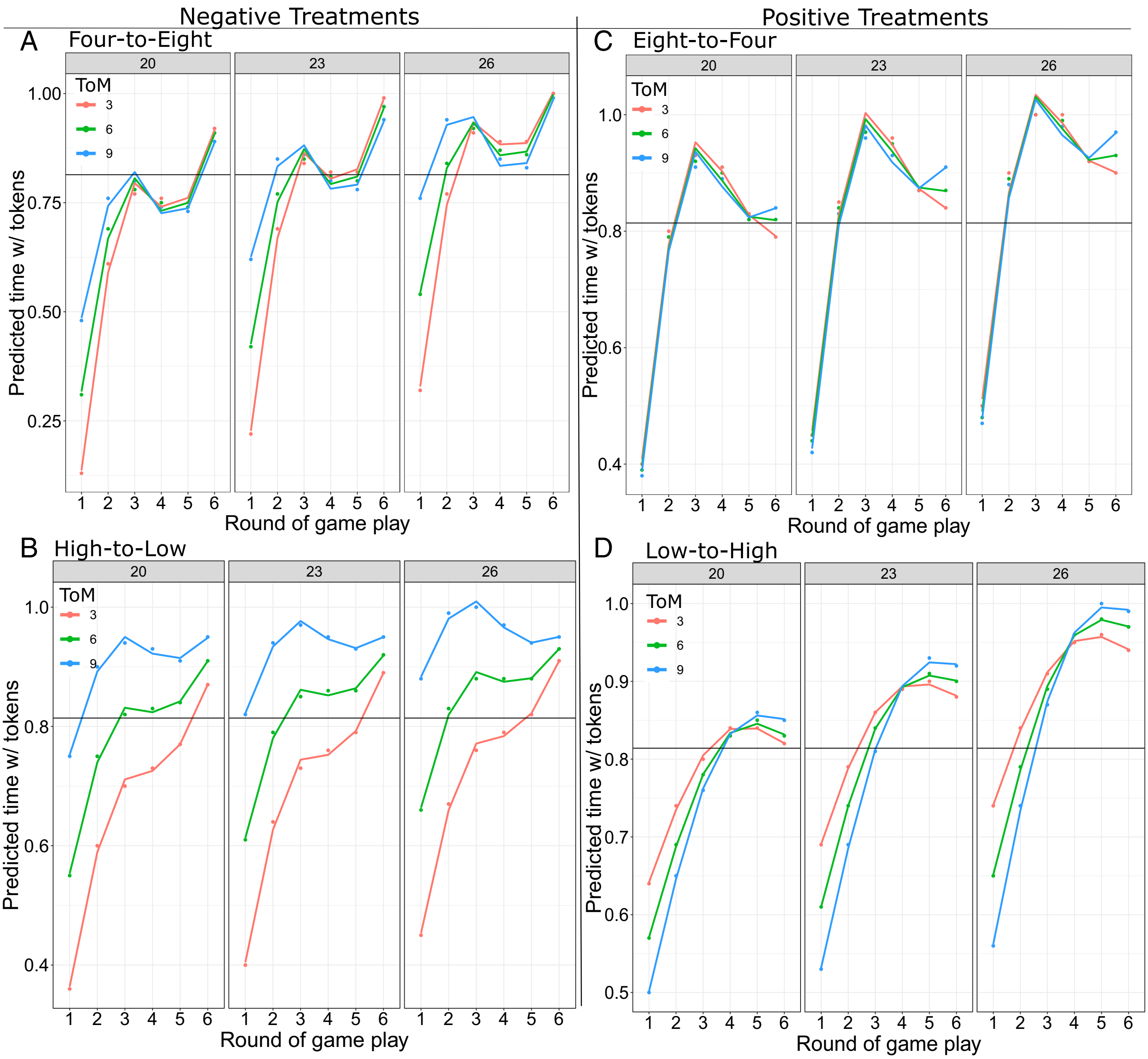

Fig. 3. Three-way marginal effect plots. Green curves illustrate groups with mean *ToM* scores, blue curves one SD above mean *ToM*, and red curves one SD below. In each set of three graphs, panels move from one SD below the mean group *g* score (estimated by ACT) to the mean to one SD above. (*A*) Four-to-eight group size (negative) perturbation treatment. (*B*) High-to-low growth rate (negative) perturbation treatment. (*C*) Eight-to-four group size (positive) perturbation treatment. (*D*) Low-to-high growth rate (positive) perturbation treatment.

need to understand how the resource works (activate g), which implies little attention paid to the joint consequences of actions on others. Higher g and ToM are necessary for groups to most effectively take advantage of the benefits of learning by doing and still respond to changing circumstances to achieve sustainability goals.

Second, our results provide a foundation to model the joint rather than alternative effects of cognitive abilities and other dimensions of cognitive diversity on the capability of groups to sustain natural resources. This framing is important to scale the cognitive foundations of collective action up to promote large-scale collective action among diverse populations. For instance, Fig. 4 captures two basic postulates: 1) All else equal, the capability of groups to find solutions to sustainability challenges increases with more diverse experiences and modes of inquiry, which we call representational diversity, and then decreases due to the increasing costs of representational gaps (7, 28, 29). Representational gaps refer to how much energy it takes to get everyone focusing on the same goal such that group effort does not degrade into everyone working at cross-purposes (29). For example, Aggarwal and coworkers (7) illustrate that collective intelligence, a measure of the ability of teams to perform well on a battery of tasks (30), first increases and then decreases with increasing diversity in how teams represent problems (visual–spatial vs. verbal). In short, an optimal representational diversity exists to solve a given sustainability challenge.

2) The diversity and nonlinearity of the ecological environment (ecological complexity) and the diversity of goals and distribution of knowledge in a system (social complexity) determine the benefits of cognitive abilities, which affects the costs and benefits of diverse experiences and modes of inquiry. The dashed horizontal lines in Fig. 4 that intersect the red and blue

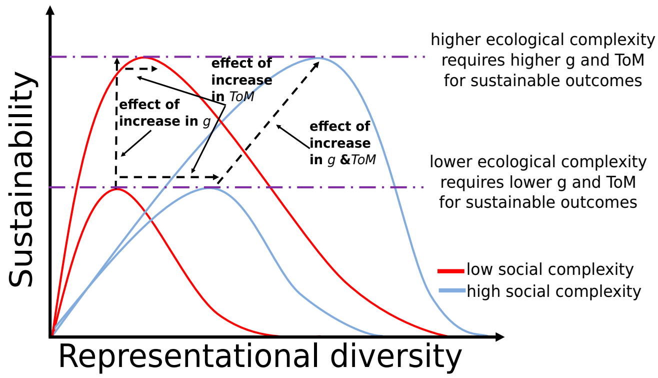

Fig. 4. Hypothesized relationships among representational diversity, sustainable collective action, and functionally distinct cognitive abilities.

"representational diversity–sustainability curves" illustrate this postulate. Moving from the simpler ecological challenge (lower purple horizontal line) to the harder challenge (upper purple horizontal line), groups need higher g and more representational diversity to understand the dynamics of the system and engage in effective collective action. They need higher g to better reduce uncertainty about the ecological components of the system and more diverse experiences and modes of inquiry to explore a greater range of solutions, a key benefit of diverse experiences and modes of inquiry (5). Similarly, when problems become more complex socially, which is partly a consequence of increasing cognitive diversity along several dimensions, even simple ecological problems require higher ToM to achieve a sustainable outcome (compare the lower red and blue curves in Fig. 4). An increase in social complexity means an increase in representational gaps as the knowledge needed to solve a sustainability challenge becomes more fragmented, and we propose that increases in ToM reduce these representational gaps, leading to a better-defined joint goal/preference (30, 31).

This graphic model makes testable predictions. Most relevant here, when groups face more difficult ecological problems that require collective action, they need higher g to solve such challenges, but g is not sufficient. Such groups also need more representational diversity to improve the ability of the group to search for and discover appropriate solutions. Higher ToM maximizes the benefits of such representational diversity. For example, consider the foraging game studied in this paper. Holding treatment and the g of groups equal, we would expect increases in representational diversity to first increase and then decrease the ability of groups to sustain the resource, on average. The inflection point at which the performance curve peaks is key. We expect that higher ToM moves the peak of the curve to a higher level of representational diversity (e.g., sustainability peaks at a representational diversity value of four as opposed to three). One could make similar predictions across types of behavioral games, holding representational diversity equal, based on variation in the social–ecological complexity of the games.

In the end, groups with high levels of multiple intelligence capacities (high g and ToM) engage in more effective collective action to sustain resources than groups with lower levels. We propose that these functional cognitive abilities moderate the effects of cognitive diversity on the ability of groups to act collectively to solve problems. Understanding such interactions is key to integrating diverse populations at large scales to solve sustainability challenges.

Data and Methods

The experimental common pool resource system consists of a spatially dispersed resource (tokens) that grows according to a density-dependent function (*SI Appendix*, section 1). Each participant received \$0.02 per token harvested. Thus, individuals constantly faced the temptation to harvest tokens quickly to maximize their revenue in the short run. However, this strategy has a community cost: The tokens deplete and collapse. In each treatment, groups of four or eight anonymous individuals harvest tokens for six rounds (180 s each) on a 20 × 20 grid (SI Appendix, section 1). In the negative treatments, we evaluated the effects of a negative change in the growth rate or an increase in group size on the ability of groups to collectively harvest tokens. In the positive treatments, we evaluated the effect of a positive change in the growth rate of the resource or a decrease in group size on collective action. In all treatments individuals had the option to communicate before each round of the game. This study complied with all relevant ethical regulations for work with human participants, informed consent was obtained by each participant, and the research was approved by the Institutional Review Boards (IRBs) at Utah State University (protocol 7664) and at the University of Texas at San Antonio (document HRP-522, IRB no. 16-256).

We measured the proportion of $Time$ per round that a group leaves tokens in the commons to estimate how well groups sustain the resource, and we measured how closely groups approximated the maximum possible per person harvest of tokens if they follow the optimal strategy (*SI Appendix*, section 2). We use the coefficient of variation of $Time$ and $Tokens$ in rounds two through six to measure the consistency of performance. We calculated this for rounds two through six, excluding round one, because we expect the performance of groups in round one to set a baseline expectation for performance in the following rounds. To measure g, participants were asked to release their official ACT/SAT scores. ACT/SAT scores correlate highly with IQ scores and other measures of g (corrected $r = 0.86$, refs. 32 and 33), which drives the predictive validity of cognitive tests (ref. 12, pp. 270 to 301). We used equivalence tables from the College Board 2016 to transform SAT scores into ACT scores (34). To estimate group g we averaged such scores at the group level. To measure ToM, each participant completed a short story test (SST) designed to measure social reasoning (35). The SST requires reasoning about the mental states of characters in a short story (35) and estimates social–cognitive theory of mind (13). To estimate group ToM, we used the minimum ToM score within a group, following the saying that one "low ToM" can have detrimental effects on the overall group by increasing conflict and reducing the effectiveness of joint attention (*SI Appendix*, section 2). All data reported in this paper are available at https://doi.org/10.3886/E110601V2 (36).

To assess the effect of g and ToM on $Mtime$ and $Mtokens$ we used GLS regression fitted by maximum likelihood. To estimate the effects of g and ToM on round one and the coefficient of variation of performance in rounds two to six, we used simultaneous equations with bootstrapped standard errors (*SI Appendix*, section 3). To evaluate the functional forms of the collective action learning curves in each specific treatment over six rounds, we first ran GLS regressions to identify the form of the curve that best fitted the data in each treatment (i.e., we compared the fit of the linear, quadratic, and cubic functions). We then built specific statistical models that interacted $Round$, g, and ToM to evaluate whether these variables modified the learning curves as expected. We used linear mixed-effects models to model the effects of groups of eight in the group size treatments (see *SI Appendix*, section 4 for step-by-step details).

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1. K. R. Hill, B. M. Wood, J. Baggio, A. Magdalena Hurtado, R. T. Boyd, Hunter-gatherer inter-band interaction rates: Implications for cumulative culture. *PLoS One* **9**, e102806 (2014).
2. E. Ostrom, *Governing the Commons: The Evolution of Institutions for Collective Action* (Cambridge University Press, 1990).
3. C. Ford Runge. Common property and collective action in economic development. *World Dev.* **14**, 623–635 (1986).
4. S. A. Levin, Public goods in relation to competition, cooperation, and spite. *Proc. Natl. Acad. Sci. U.S.A.* **111**, 10838–10845 (2014).
5. S. E. Page, *The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies* (Princeton University Press, 2008).
6. P. Aminpour *et al.*, Wisdom of stakeholder crowds in complex social–ecological systems. *Nat. Sustain*. **3**, 191–199, (2020).
7. I. Aggarwal, A. W. Woolley, C. F. Chabris, T. W. Malone, The impact of cognitive style diversity on implicit learning in teams. *Front. Psychol.* **10**, 112 (2019).
8. R. Arlinghaus, J. Krause, Wisdom of the crowd and natural resource management. *Trends Ecol. Evol.* **28**, 8–11 (2013).
9. L. Hong, S. E. Page, Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proc. Natl. Acad. Sci. U.S.A.* **101**, 16385–16389 (2004).
10. J. A. Baggio *et al.*, The importance of cognitive diversity for sustaining the commons. *Nat. Commun.* **10**, 875 (2019).
11. J. Freeman, T. R. Coyle, J. A. Baggio, The functional intelligences proposition. *Pers. Indiv. Differ.* **99**, 46–55 (2016).
12. A. R. Jensen, *The g Factor: The Science of Mental Ability* (Praeger, Westport, CT, 1998).
13. D. Nettle, B. Liddle, Agreeableness is related to social-cognitive, but not social-perceptual, theory of mind. *Eur. J. Pers.* **22**, 323–335 (2008).
14. R. I. M. Dunbar, The social brain: Mind, language, and society in evolutionary perspective. *Annu. Rev. Anthropol.* **32**, 163–181 (2003).
15. H. A. Marlowe, Social intelligence: Evidence for multidimensionality and construct independence. *J. Educ. Psychol.* **78**, 52–58 (1986).
16. T. R. Coyle, K. E. Elpers, M. C. Gonzalez, J. Freeman, J. A. Baggio, General intelligence (g), ACT scores, and theory of mind: (ACT)g predicts limited variance among theory of mind tests. *Intelligence* **71**, 85–91 (2018).
17. F. J. Ferguson, E. J. Austin, Associations of trait and ability emotional intelligence with performance on theory of mind tasks in an adult sample. *Pers. Indiv. Differ.* **49**, 414–418 (2010).
18. S. Baron-Cohen *et al.*, Social intelligence in the normal and autistic brain: An fMRI study. *Eur. J. Neurosci.* **11**, 1891–1898 (1999).
19. M. A. Janssen, R. Holahan, A. Lee, E. Ostrom, Lab experiments for the study of social-ecological systems. *Science* **328**, 613–617 (2010).
20. M. R. Barrick, G. L. Stewart, M. J. Neubert, M. K. Mount, Relating member ability and personality to work-team processes and team effectiveness. *J. Appl. Psychol.* **83**, 377–391 (1998).
21. N. Meslec, I. Aggarwal, P. L. Curseu, The insensitive ruins it all: Compositional and compilational influences of social sensitivity on collective intelligence in groups. *Front. Psychol.* **7**, 676 (2016).
22. J. A. Baggio, N. D. Rollins, I. Pérez, M. A. Janssen, Irrigation experiments in the lab: Trust, environmental variability, and collective action. *Ecol. Soc.* **20**, 12 (2015).
23. C. Schill, T. Lindahl, A.-S. Crépin, Collective action and the risk of ecosystem regime shifts: Insights from a laboratory experiment. *Ecol. Soc.* **20**, 48 (2015).
24. A. Dragicevic, A. Lobianco, A. Leblois, Forest planning and productivity-risk trade-off through the Markowitz mean-variance model. *For. Pol. Econ.* **64**, 25–34 (2016).
25. T. Dohmen, A. Falk, D. Huffman, U. Sunde, Are risk aversion and impatience related to cognitive ability? *Am. Econ. Rev.* **100**, 1238–1260 (2010).
26. T. Yamagishi, M. Kikuchi, M. Kosugi, Trust, gullibility, and social intelligence. *Asian J. Soc. Psychol.* **2**, 145–161 (1999).
27. K. J. Arrow, The economic implications of learning by doing. *Rev. Econ. Stud.* **29**, 155–173 (1962).
28. M. A. Cronin, L. R. Weingart, Conflict across representational gaps: Threats to and opportunities for improved communication. *Proc. Natl. Acad. Sci. U.S.A.* **116**, 7642–7649 (2019).
29. M. A. Cronin, L. R. Weingart, Representational gaps, information processing, and conflict in functionally diverse teams. *Acad. Manag. Rev.* **32**, 761–773 (2007).
30. A. W. Woolley, C. F. Chabris, A. Pentland, N. Hashmi, T. W. Malone, Evidence for a collective intelligence factor in the performance of human groups. *Science* **330**, 686–688 (2010).
31. D. Engel, A. Williams Woolley, L. X. Jing, C. F. Chabris, T. W. Malone, Reading the mind in the eyes or reading between the lines? Theory of mind predicts collective intelligence equally well online and face-to-face. *PloS One* **9**, e115212 (2014).
32. K. A. Koenig, M. C. Frey, D. K. Detterman, ACT and general cognitive ability. *Intelligence* **36**, 153–160 (2008).
33. T. R. Coyle, D. R. Pillow, SAT and ACT predict college GPA after removing g. *Intelligence* **36**, 719–729 (2008).
34. College Board, Concordance tables. https://collegereadiness.collegeboard.org/pdf/higher-ed-brief-sat-concordance.pdf. Accessed 9 March 2020.
35. D. Dodell-Feder, S. H. Lincoln, J. P. Coulson, C. I. Hooker, Using fiction to assess mental state understanding: A new task for assessing theory of mind in adults. *PLoS One* **8**, e81279 (2013).
36. J. Freeman, T. Coyle, J. Baggio, Cognitive styles and collective action. openICPSR. https://doi.org/10.3886/E110601V2. Deposited 11 March 2020.