Title: Socially guided individual learning mitigates the Double-Edge Sword of Pedagogy

Short title: Heuristics balance social learning and exploration

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Abstract

Social learning and innovation are fundamental processes in cultural evolution, yet their interaction remains poorly understood. Prior research suggests that inheriting social information reduces exploration. However, most studies have focused on the transmission of fully fledged solutions. Here, we investigate whether alternative types of information can facilitate cumulative cultural evolution without reducing exploration. Specifically, we conducted a preregistered experiment with 400 adult participants comparing the inheritance of solutions with that of heuristics – simple rules that guide problem solving. We found that social learners who inherited a heuristic explored more frequently and broadly than those who received a solution. Their productions were also less similar to those of their demonstrators, suggesting that heuristics foster more independent exploration. Despite these differences, both heuristics and solutions enabled learners to surpass their demonstrator's performance. These findings highlight that the type of social information transmitted plays a crucial role in the evolvability of culture.

Teaser: Guiding individual learning by transmitting heuristics mitigates the detrimental effect of social information on exploration.

1 Introduction

The capacity to build on the knowledge gathered by previous generations has been argued to be uniquely human [1–3], and is considered as a key factor in the ecological success of the human species [4]. The two key ingredients of cumulative cultural evolution (CCE) are social learning and innovation [5, 6]. While social learning is fundamental to ensure that the insights gathered by a given generation are transmitted to the next, innovation is just as crucial to allow cultural groups to refine their cultural repertoire over time and adapt to new environments.

Despite their importance, the interplay between these two processes remains poorly understood. Existing research suggests the existence of a trade-off between relying on social information and innovating. Indeed, knowledge about a previously discovered solution appears to constrain future exploration, ultimately preventing learners from discovering more efficient solutions. This phenomenon has been repeatedly observed both theoretically and empirically by researchers in diverse disciplines such as developmental psychology [7], design studies [8], and cultural evolution [9–11], in both adults and children. As a consequence, it has been argued that a "*challenge for educators may be how to foster learners capable of doing new things while simultaneously teaching what other generations have done.*" [7, p. 11].

However, all of these previous works have focused on a very specific way of transmitting social information: namely, communicating information about a previously discovered solution. This very narrow focus is in contrast with the wide diversity of pathways used by humans to transmit accumulated knowledge. Ethnographic research indicates that cultural demonstrators often provide learners with guiding principles rather than specific solutions. Finnish mushroom foragers, for instance, use such principles to guide their decisions, such as choosing between foraging locations ("*the older the forest the more mushrooms*") and identifying edible mushrooms ("*avoid white mushrooms altogether*") [12]. Similar heuristics are also used in the production of technological artifacts [13]. For instance, rules of thumb guide the dimensions of kayaks (e.g. "*the total length of the kayak should be approximately 3 times the height of the kayaker*" [14]), Marshallese canoes (e.g. "*the length of the canoe is equal to the length of the mast*" [15]), bows (e.g. "*a good bow was one whose string made a high musical note when tapped with an arrow or snapped with the fingers*" [16, p. 110]) and Viking ships [17].

Compared to solutions, heuristics do not provide learners with precise knowledge of the best-known solution. Instead, they specify constraints that, when followed, can lead to the creation of an efficient solution. These two types of cultural information are likely to have contrasting effects on innovation. While solutions provide learners with a specific point in the design space known to yield high payoffs, they reveal little about alternative solutions that may offer equally good or even superior results. In contrast, rules do not offer a fixed starting point for exploration but rather serve as guidelines for navigating the design space (Figure 1).

Beyond influencing exploration at the individual level, solutions and heuristics may also shape exploration at the group level by affecting the similarity between demonstrators' and learners' solutions. Consider, for instance, the rule '*the length of the canoe should be equal to the length of the mast.*' Receiving such a rule would likely lead social learners to produce solutions resembling their demonstrators' in terms of canoe-to-mast length ratio, though not necessarily in the specific values of each dimension. We shall refer to this kind of similarity as *structural similarity*. In contrast, inheriting information about how to reproduce a specific design (e.g., a

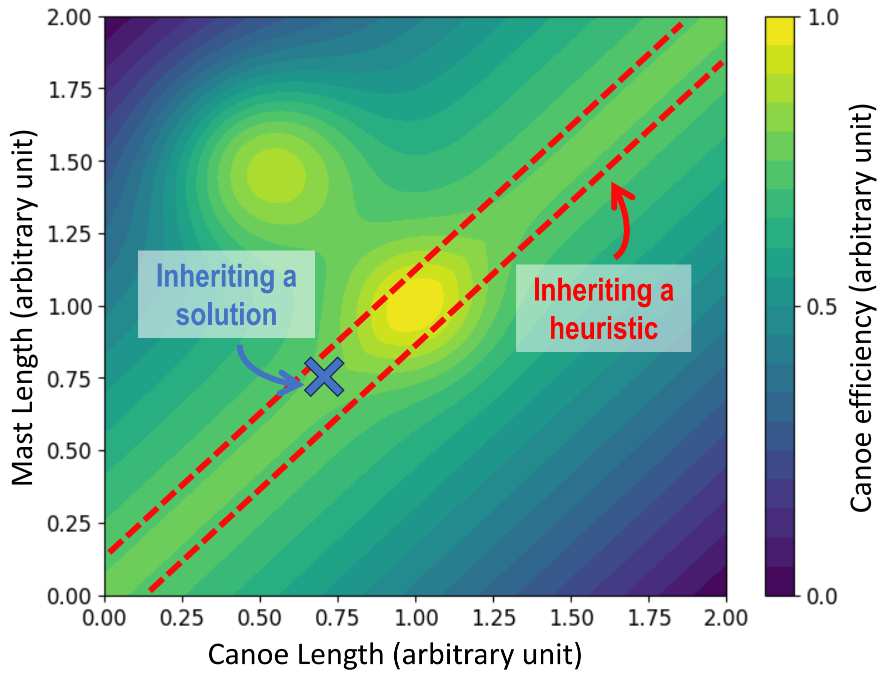

Figure 1: Hypothetical example of the effect of inheriting heuristics versus solutions Receiving a solution provides the social learner with a better-than-average starting point in the cultural fitness landscape (e.g. a specific canoe design illustrated by the blue cross). Receiving a heuristic provides the social learner with an area of the fitness landscape that should be preferentially explored (e.g. specific proportions between mast length and canoe length, represented by the area between the two dotted red lines). Notice that inheriting a rule can lead to a smoother fitness landscape. We expand on this observation in the Discussion.

particular canoe model) would promote closer similarity with the demonstrator's solution in both canoe length and mast length (Figure 1). We shall refer to this kind of similarity as *parametric similarity*.

These differences between solutions and heuristics suggest that restricted exploration may not inherently result from receiving social information in general but may specifically arise when social information is provided in the form of a solution. In this paper, we test this hypothesis by examining how the cultural transmission of heuristics influences the generation of variation, both at the individual and intergenerational levels, compared to the transmission of solutions.

To address this question, we asked participants in transmission chains to solve a task representative of complex problem-solving scenarios, characterized by a large solution space that could be navigated more effectively by identifying regularities among parameters. The task involved assigning guests to rooms to maximize total guest satisfaction across 10 trials [18, 19]. Guest satisfaction depended on two types of unknown preferences: room-based preferences (e.g., 'Guest A prefers room 1 over room 2') and neighbor preferences (e.g., 'Guests A and B should not be in adjacent rooms'; Figure 2.a). Participants took part in three-generation transmission chains, with the first generation receiving no social information. Participants in subsequent generations received either a configuration transmitted by the previous participant (Solution treatment) or a heuristic in the form of *'X and Y must be neighbors'* (Heuristic treatment).

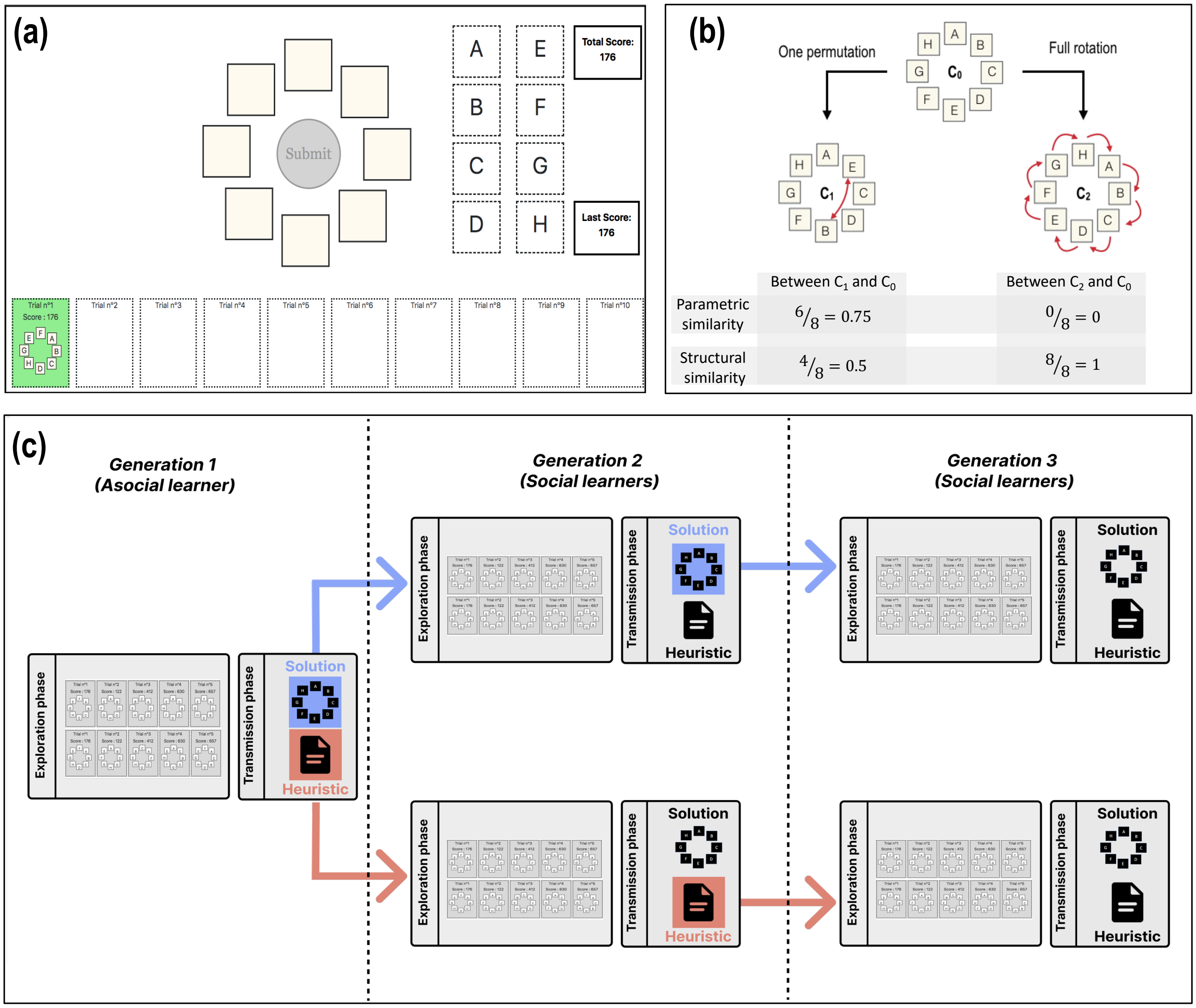

Figure 2: (a) The room assignment task. Screenshot of the task as presented to participants during the exploration phase. Guests (represented by the 8 letters on the right side of the screen) had to be placed in rooms (represented by the 8 empty squares in the middle of the screen). Participants could see their total score and their score at the last trial (right side of the screen), as well as the score of each previously submitted configuration (bottom of the screen). **(b) Examples of parametric and structural distances.** After a single permutation of guests B and E in configuration C0, the parametric similarity with C1 is $\frac{6}{8}$ (6 guests are assigned to identical rooms in C0 and C1) and the structural similarity is $\frac{4}{8}$ (4 couples of guests are neighbors in both C0 and C1). After a full rotation of guests in C0, the parametric similarity with C2 is $\frac{0}{8}$ (None of the guests are assigned to the same rooms in C0 and C2) and the structural distance is $\frac{8}{8}$ (all pairs of neighboring guests in C2 remain the same as in C0). **(c) Structure of the transmission chains.** The transmission chains we used involved one asocial learner producing two types of social information - a heuristic and a solution - each transmitted to a different social learner. Social learners in the *Heuristic* treatment received the heuristic, and then themselves transmitted a heuristic to the next participant in the chain. Social learners in the *Solution* treatment received the solution, and then themselves transmitted a solution to the next participant in the chain. Thus, all learners produced both types of information, but each social learner received and transmitted only one type.

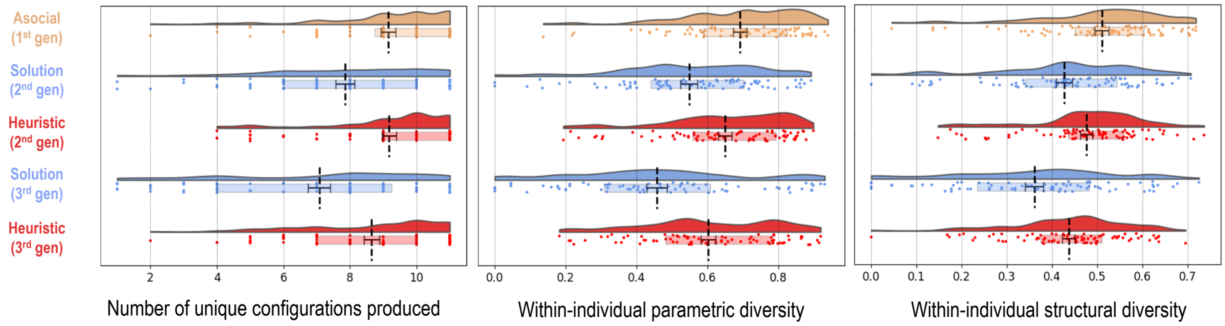

Figure 3: Participants who inherited a heuristic explore more often and less locally than participants who inherited a solution. Exploration measures for participants in the *Asocial* (beige), *Solution* (blue) *Heuristic* (red) treatments. Dashed black lines represent the mean for each treatment. The error bars represent the standard error of the mean. Rectangles represent the range from the first to the third quartile. **(a)** Number of identical configurations produced by each participant. Each participant is represented by a dot. **(b)** Average pair-wise parametric distance between solutions produced by a given participant. Each pair of solution is represented by a dot. **(c)** Average pair-wise structural distance between solutions produced by a given participant. Each pair of solutions is represented by a dot.

To evaluate how the type of social information affects exploration of the design space, we defined two metrics capturing how similar two configurations are. We defined one measure of *parametric similarity*, and one measure of *structural similarity* (Figure 2.b). The *parametric similarity* between two configurations is defined as the fraction of guests that are assigned to identical rooms in both configurations. The *structural similarity* between two configurations is defined as the fraction of pairs of guests that are neighbours in both configurations. These measures allowed us to quantify how broadly participants explored the design space, as well as how much they deviate from the previous generation.

2 Results

2.1 Exploration

How often do participants explore? Participants who received a solution generate a significantly lower number of unique configurations than those who received a heuristic (*Solution* - *Heuristic* contrast 89% CI : [-1.868; -0.746]) and those who received no social information (*Solution* - *Asocial* contrast 89% CI : [-1.844; -0.747]; Figure 3.a). On the other hand, we did not detect any significant difference between participants who received a heuristic and those who did not receive any social information (*Heuristic* - *Asocial* contrast 89% CI : [-0.531; 0.595]).

Exploratory analyses revealed that by the third generation, there was still no significant difference between the *Heuristic* and the *Asocial* treatment (*Heuristic-3rdGeneration* - *Asocial* contrast 89% CI : [-1.056; 0.081]). In contrast, exploration continued to decrease for participants in the *Solution* treatment (*Solution-3rdGeneration* - *Solution-2ndGeneration* contrast 89% CI : [-1.317; -0.198]).

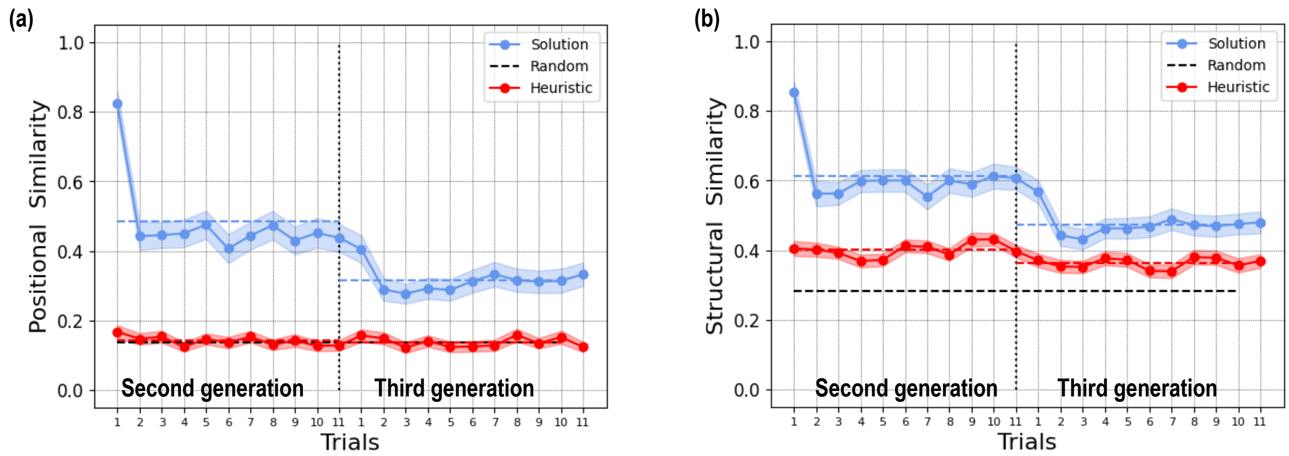

Figure 4: Social learners who inherited a heuristic produce solutions that are less similar to that of their demonstrator. Inter-generational similarity for participants in the *Solution* (blue) and *Heuristic* (red) treatments, in both second and third generations. Colored dots represent the mean over all participants of a given treatment at the corresponding trial. Dashed colored lines represent the mean for the corresponding treatment over all participants and all trials. The black dashed line represent the expected similarity between random configurations. The filled areas represent the standard error of the mean. **(a)** parametric similarity between a configuration and the configuration transmitted by the *Asocial* learner. **(b)** Structural similarity between a configuration and the configuration transmitted by the *Asocial* learner.

How broadly do participants explore? We quantified how social information influenced exploration by computing the pairwise parametric and structural similarities between configurations submitted by a participant, and averaged it over all pairs (Figures 3.b and 3.c). We then report the *within-individual diversity* values, defined as *1-average similarity*. Compared to participants in the *Asocial* treatment, participants in both *Solution* and *Heuristic* treatments explored more locally, displaying lower parametric diversity (*Solution* - *Asocial* contrast 89% CI : [-0.166; -0.112]; *Heuristic* - *Asocial* contrast 89% CI : [-0.067; -0.015]) and lower structural diversity (*Solution* - *Asocial* contrast 89% CI : [-0.104; -0.06]; *Heuristic* - *Asocial* contrast 89% CI : [-0.056; -0.012]).

Participants in the *Heuristic* treatment displayed higher diversity in their exploration than participants in the *Solution* treatment, both in therm of parametric diversity (*Heuristic* - *Solution* contrast 89% CI : [0.072; 0.126]) and structural diversity (*Heuristic* - *Solution* contrast 89% CI : [0.025; 0.071]).

Exploratory analyses revealed that this difference was maintained at the third generation, with participants in the *Heuristic* treatment displaying broader exploration than participants in the *Solution* treatment, both in terms of structural diversity (*Heuristic-3rdGeneration* - *Solution-3rdGeneration* contrast 89% CI : [0.109; 0.17]) and parametric diversity (*Heuristic-3rdGeneration* - *Solution-3rdGeneration* contrast 89% CI : [0.051; 0.099]).

2.2 Inter-generational variation

How similar are the solutions produced by social learners to those of their demonstrators? Receiving a solution led social learners to produce solutions more similar to that of their demonstrator compared to receiving a heuristic, both in terms of parametric similarity (*Heuristic* - *Solution* contrast 89% CI :[-0.489; -0.37]) and structural similarity (*Heuristic* - *Solution* contrast 89% CI :[-0.331;-0.233]). When receiving a heuristic, the parametric similarity between social learners and asocial learners was at chance level (Chance 89% CI : [0.12,0.14] included in Heursitic 89% CI: [0.112; 0.192]), but not the structural similarity (Chance 89% CI : [0.256; 0.282] not overlapping with Heursitic 89% CI: [0.351; 0.42]).

There was also a significant interaction between the effect of treatment and that of trial : both parametric and structural similarities with the demonstrator decreased faster for participants in the *Solution* treatment than for participants in the *Heuristic* treatment (effect of trial on parametric similarity : *Heuristic* - *Solution* contrast 89% CI :[0.009; 0.02]; effect of trial on structural similarity : *Heuristic* - *Solution* contrast 89% CI :[0.007; 0.17]). As can be seen on Figure 4, this effect appears to be mainly driven by trial 1, after which similarity remains stable. This pattern likely stems from participants' tendency to initially replicate the received solution before exploring alternative configurations (Figures S1 and S2).

Exploratory analyses revealed that for participants in the *Solution* treatment, the similarity with the original demonstrator kept on decreasing at the third generation, with respect to both parametric similarity (*Solution-3rdGeneration* - *Solution-2ndGeneration* contrast 89% CI :[-0.216;-0.118]) and structural similarity (*Solution-3rdGeneration* - *Solution-2ndGeneration* contrast 89% CI :[-0.183;-0.096]). For participants in the *Heuristic* treatment, the average similarity to the original demonstrator did not differ between the second and third generations, neither in terms of parametric similarity (*Heuristic-3rdGeneration* - *Heuristic-2ndGeneration* contrast 89% CI :[-0.053;0.045]) nor structural similarity (*Heuristic-3rdGeneration* - *Heuristic-2ndGeneration* contrast 89% CI :[-0.08;0.003]).

2.3 Cumulative improvement

Do social learners outperform their demonstrator? Whether they inherited a configuration or a heuristic, second-generation participants outperformed first-generation participants, with respect to both the total score obtained over all trials (*Solution* - *Asocial* contrast 89% CI :[830.223, 1018.823]; *Heuristic* - *Asocial* contrast 89% CI :[705.473, 894.746]) and the score obtained at the last trial (*Solution* - *Asocial* contrast 89% CI :[23.667, 65.441]; *Heuristic* - *Asocial* contrast 89% CI :[5.305, 46.246]). Participants who received a solution obtained a slightly higher total score than participants who received a heuristic (*Heuristic* - *Solution* contrast 89% CI :[- 218.053, -31.348]), but we found no significant difference when looking at the score obtained at the last trial (*Heuristic* - *Solution* contrast 89% CI :[- 40.131, 1.852]). This is consistent with participants from the *Solution* treatment being more exploitative: compared to participants from the *Heuristic* treatment, they don't have a superior solution, but they exploit it more extensively.

In exploratory analyses, we observed the same results at the third generation: participants who received a solution were slightly better with respect to their total score (*Heuristic-3rdGeneration* - *Solution-3rdGeneration* contrast 89% CI :[-227.317; -6.597]), but there was no significant difference for the score at the last trial (*Heuristic-*

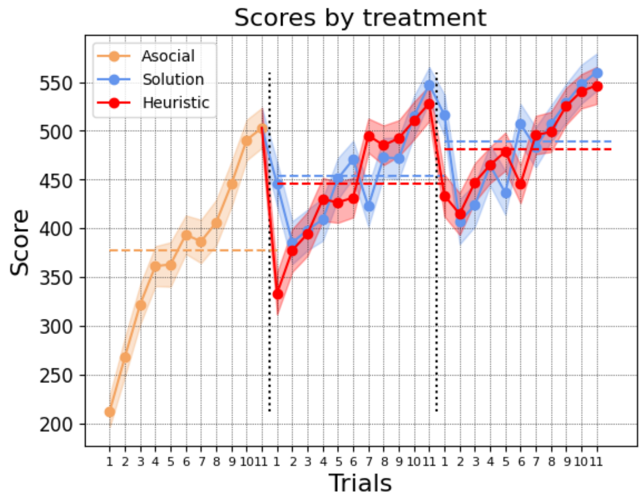

Figure 5: Both receiving a heuristic and a solution allows social learners to outperform their demonstrator. Score at each trail of participants in *Asocial* (beige), *Solution* (blue) and *Heuristic* (red) treatment. Colored dots represent the mean over all participants of a given treatment at the corresponding trial. Dashed colored lines represent the mean for the corresponding each treatment over all participants and all trials. The filled areas represent the standard error of the mean.

3rdGeneration - *Solution-3rdGeneration* contrast 89% CI :[-37.171; 9.784]).

In both treatments, participants' total score kept on increasing at the third generation (*Solution-3rdGeneration* - *Solution-2ndGeneration* contrast 89% CI :[308.48; 526.231] - *Heuristic-3rdGeneration* - *Heuristic-2ndGeneration* contrast 89% CI :[302.843; 526.831]), but not their score at the last trial (*Solution-3rdGeneration* - *Solution-2ndGeneration* contrast 89% CI :[-12.584; 35.016] - *Heuristic-3rdGeneration* - *Heuristic-2ndGeneration* contrast 89% CI :[-4.904; 40.515]).

3 Discussion

Social information is typically viewed as limiting exploration, yet prior research has primarily focused on the transmission of fully fledged solutions, overlooking other prevalent forms of information transfer. Here, we have addressed this gap by examining the relative effects of transmitting a solution versus a heuristic on the cultural variation generated by social learners. Our findings indicate that social learners who receive a heuristic produce greater cultural variation than those receiving a solution, demonstrating that the reduced exploration identified in previous works [7, 9–11] does not extend to all forms of social information.

These results highlight a largely overlooked aspect of cultural transmission: different transmission mechanisms vary in their impact on learners' exploration patterns. Culturally evolved solutions often provide naïve learners with a better-than-average starting point in the parameter space. However, they offer little guidance for further exploration. Yet, during the process of developing those solutions, demonstrators may have uncovered useful regularities and structural properties of the search space. Transmitting only the final solution discards this acquired knowledge. Heuristics, by contrast, can preserve and transmit such insights, serving as guides that support exploration and facilitate continued cultural innovation. For instance, the heuristic "avoid white mushrooms altogether " [12] creates a new, more navigable search space by effectively removing particularly detrimental areas from the set of potential options. These considerations shed a new light on the importance of verbal teaching for cultural evolution. Indeed, teaching is generally thought to be central because it allows to faithfully replicate existing solutions – that is, it contributes to cultural stability [20, 21]. Our results suggest that verbal teaching may also crucially contribute to cultural evolvability: while social learning mechanisms such as emulation or imitation only enable the transmission of the outcome of previous exploration, verbal teaching allows to provide information about the properties of the search space – for instance, by transmitting heuristics.

The transmission of heuristics creates an interesting complementarity between social learning and individual learning. When solutions are transmitted, the two processes operate largely independently: having access to an efficient, previously discovered solution is beneficial regardless of the learner's subsequent exploration. In contrast, the transmission of heuristics is only effective when combined with the social learner's capacity for trial-and-error learning. This is clearly illustrated in our results: participants who inherited a heuristic began with lower performance but, through individual learning, gradually caught up to the performance of those who had received a solution. This view aligns closely with two recent models of cultural evolution. In the first [22], the authors address the challenge of transmitting tacit knowledge, demonstrating that expert knowledge can be used to reorganize the problem space so that trial-and-error learning reliably converges on a correct solution. In the second [23], the authors model the transmission of analogies and suggest that *"teachers guide learners to the solution to a novel problem by invoking similarities to known problems and their known solutions"* [23]. In both models, as in our experiment, cultural transmission allows learners to engage in socially-guided, efficient exploration, rather than enabling them to faithfully replicate their demonstrator's solution.

That faithful replication is not crucial to the efficiency of social learning is further supported by our results on inter-generational variation. While social learners who received a solution produced outputs closely resembling those of their demonstrator, participants who received a heuristic exhibited only limited structural similarity, and no parametric similarity, with their demonstrator's solution. Despite this low inter-generational similarity, our analysis of the scores revealed that transmitting heuristics, just like transmitting solutions, was sufficient to observe cumulative improvement. Moreover, we found no significant difference between those two treatments with respect to the efficiency of the last solution produced by social learners. These findings suggest that high fidelity between teacher and learner outputs is not a necessary condition for cumulative improvement. Instead, they highlight the equally important role of cultural transmission in fostering socially-guided, efficient exploration.

It appears important to make one clarification here. Although our results suggest that faithful replication of cultural *products* is not necessary for cumulative culture, this does not imply that high-fidelity transmission of cultural *information* is not important. Actually, our experimental design assumes perfect transmission of cultural information: solutions and heuristics are both transmitted to the social learner without errors. It is therefore crucial to make the distinction between cultural information and cultural products: a low similarity between two cultural products does not necessarily correspond to a large difference between the cultural information that led to their productions. In our case, two individuals employing the same heuristic ("cultural information") may produce very different configurations ("cultural product"). The issue here arises from what has been described as the *relevance problem* [24], which describes the difficulty in determining which are the relevant dimensions along which to compute similarity. In our case, parametric similarity is irrelevant for inferring transmission of heuristics, while it is relevant for identifying the transmission of solutions. The relevance problem, which is clearly illustrated in our study, might be especially important for researchers aiming to infer cultural dynamics from the archaeological record [25, 26].

While our study focused on the capacity of heuristics to sustain exploration, it opens several avenues for future research. First, a natural extension of the current work would be to evaluate the advantage of heuristics relative to solutions in changing environments. Indeed, a key feature of heuristics is their flexibility [13, 27]. When a social learner inherits a solution that becomes ineffective or obsolete due to environmental change, they are left with little guidance for generating a new one. For example, a learner taught exactly where to forage for mushrooms may struggle to adjust if that specific patch becomes unavailable. By contrast, a heuristic such as "the older the forest the more mushrooms" [13] offers a transferable principle that can be applied flexibly to novel situations. Our results support the view that the transmission of heuristics may be more beneficial than the transmission of solutions in variable environments: social learners who received a solution tended to explore locally around the inherited configuration, which may hinder adaptation if a previously optimal solution becomes maladaptive. In contrast, the broader exploratory behavior observed among participants who received a heuristic may offer a better foundation for responding to environmental change. This prediction is also supported by [23], who show that the evolution of socially-guided individual learning is favored in variable environments. This links with a second fruitful avenue for future research, namely the cultural evolution of heuristics themselves. In our experimental design, participants were explicitly asked to provide a heuristic in a specific format. Those heuristics targeted structural properties of the search space, and were simple to understand and to apply, in line with most reported examples of heuristics. It would however be very informative to study how heuristics come to acquire such features, and how their evolution is jointly determined by selection for function – targeting relevant variables – and selection for fidelity – being easy to remember and apply [28]. This line of research could also help clarify the conditions under which heuristics become the preferred pathway of cultural inheritance.

Overall, although most empirical studies have focused on the transmission of solution, our study suggests that guiding the exploratory behavior of the social learner by transmitting heuristics may be sufficient to observe cumulative improvements of the cultural products. We show that the transmission of such heuristics is likely to have very different consequences on exploratory behaviors and cultural variation compared to the transmission of solutions. This calls for more investigation of the different types of knowledge that can be culturally transmitted, and on how they differentially influence cultural evolutionary dynamics.

4 Material and Methods

4.1 Participants

A total of 418 adult participants took part in the study. 18 participants were excluded from the analysis according to preregistered exclusion criteria, either because of technical issues (17 participants) or because they failed the attention check (1 participant). Analyses were therefore performed on 400 participants, which was the pre-registered targeted sample size (Mean age = 29.74; SD = 10.04 – Women: 195; Men: 199; Other: 6).

The experimental protocol was approved by the ethic committee of the *Institute for Advanced Study in Toulouse*. All participants provided informed consent by checking a box before beginning the study.

4.2 Online Task

Participants completed the task online using a web-interface programmed using *oTree* [29]. Eight guests (represented by letters from A to H) had to be placed in eight rooms, with each room containing exactly one guest (Figure 2.a). Participants were informed that each guest has preferences regarding the room in which they sleep, and that some but not all guests have strong preferences regarding who their neighbors are. However, participants were not told what those preferences were. To submit a configuration, participants used a drag-and-drop interface to assign each guest to a room. After submitting a configuration, participants were informed about the score associated with this configuration, i.e. the summed preferences of guests (see Appendix B for details).

The experiment contained two successive phases (Figure 2.c):

- **Exploration phase:** Participants completed ten trials, submitting one configuration per trial. After each submission, they received feedback in the form of a score(Figure 2.a). They could see the history of all configurations they had already submitted and the score associated with each configuration. This phase ended once participants had submitted 10 configurations. Participants were incentivized to maximize their cumulative score over those 10 trials.

- **Transmission phase:** Participants were asked to provide a heuristic specifying a detected regularity, such as "*X and Y must be neighbors*". They were informed that providing an accurate heuristic (that is, a heuristic that indeed has an impact on guests satisfaction) would increase their bonus payment. During this phase, they could see the 10 configurations they submitted during the previous phase and the associated scores. After they had submitted a heuristic, they were asked to submit an additional configuration.

Participants were informed that the score associated with this configuration would be multiplied by 3 to incentivize them to submit what they believed to be the best configuration. The *heuristic* and *solution* produced during this phase constitute the two types of social information that would then be transmitted to the next participants.

4.3 Treatments

Participants were assigned to one of three treatments (*Asocial*, *Solution* and *Heuristic*) and were attributed a position in the chain. Chains were 3-geenration long but involved 5 participants: one participant in the first position, two participants in the second position and two participants in the third generation (Figure 2.c).

Participants in the first position were all part of the *Asocial* treatment. They did not receive any social information and completed the task exactly as described in section 4.2.

For each chain, one of the participant in second position was assigned to the *Solution* treatment, and the other participant in second position was assigned to the *Heuristic* treatment. In the same way, one of the participant in third position was assigned to the *Solution* treatment, and the other participant in third position was assigned to the *Heuristic* treatment (Figure 2.b).

Participants in both *Solution* and *Heuristic* treatments were informed that a participant had played the exact same game before them. Participants in the *Solution* treatment were told that they would receive the last configuration submitted by the previous participant. Participants in the *Heuristic* treatment were told that they would receive the heuristic submitted by the previous participant. In both treatments, social information remained visible throughout the whole exploration phase.

4.4 Analyses

4.4.1 Parametric and structural similarity measures

We defined two metrics capturing how similar two configurations are. We defined one measure of *parametric similarity*, and one measure of *structural similarity*. The *parametric similarity* between two configurations is defined as the fraction of guests that are assigned to identical rooms in both configurations. The *structural similarity* between two configurations is defined as the fraction of pairs of guests that are neighbours in both configurations. Figure 2.b provides examples of parametric and structural similarities between different configurations.

4.4.2 Individual exploration measures

To quantify frequency of exporation at the individual level, we counted the number of unique configurations submitted by participants among the 11 configurations submitted in total. To quantify breadth of exploration at the individual level, we computed the pairwise parametric and structural similarities between configurations submitted by a participant, and averaged it over all pairs. We use this value to define within-individual parametric (respectively structural) diversity as 1− (average pair-wise parametric (respectively structural) similarity).

4.4.3 Statistical Analyses

Data analysis was performed using R v. 4.3.1 [30]. We used Bayesian multi-level models to conduct statistical analyses. Models were fitted using the *Statistical Rethinking* package [31]. We used samples from the posterior to compute contrasts between treatments. 89% credible intervals of the posterior contrasts are reported. Unless explicitly labelled as exploratory, all statistical models were registered on OSF prior to data collection (*https://osf.io/gxvnq*). Full details of the statistical models are provided in Appendix C.

References

[1] Lewis G. Dean, Gill L. Vale, Kevin N. Laland, Emma Flynn, and Rachel L. Kendal. Human cumulative culture: a comparative perspective. *Biological Reviews*, 89(2):284–301, 2014. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/brv.12053.

[2] Claudio Tennie, Josep Call, and Michael Tomasello. Ratcheting up the ratchet: on the evolution of cumulative culture. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1528):2405–2415, August 2009.

[3] Michael Tomasello. *The cultural origins of human cognition.* The cultural origins of human cognition. Harvard University Press, Cambridge, MA, US, 1999. Pages: vi, 248.

[4] Joseph Henrich. *The Secret of Our Success: How Culture Is Driving Human Evolution, Domesticating Our Species, and Making Us Smarter.* Princeton University Press, Princeton, December 2016.

[5] Susan Perry, Alecia Carter, Marco Smolla, Erol Akçay, Sabine Nöbel, Jacob G. Foster, and Susan D. Healy. Not by transmission alone: the role of invention in cultural evolution. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 376(1828):20200049, July 2021.

[6] Cristine H. Legare and Mark Nielsen. Imitation and innovation: The dual engines of cultural learning. *Trends in cognitive sciences*, 19(11):688–699, 2015. Publisher: Elsevier.

[7] Elizabeth Bonawitz, Patrick Shafto, Hyowon Gweon, Noah D. Goodman, Elizabeth Spelke, and Laura Schulz. The double-edged sword of pedagogy: Instruction limits spontaneous exploration and discovery. *Cognition*, 120(3):322–330, 2011. Publisher: Elsevier.

[8] Nathan Crilly and Carlos Cardoso. Where next for research on fixation, inspiration and creativity in design? *Design Studies*, 50:1–38, 2017. Publisher: Elsevier.

[9] Kyanoush Seyed Yahosseini, Samuli Reijula, Lucas Molleman, and Mehdi Moussaid. Social information can undermine individual performance in exploration-exploitation tasks. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, volume 40, 2018.

[10] Daniel Barkoczi and Mirta Galesic. Social learning strategies modify the effect of network structure on group performance. *Nature communications*, 7(1):13109, 2016. Publisher: Nature Publishing Group UK London.

[11] Maxime Derex, Bernard Godelle, and Michel Raymond. Social learners require process information to outperform individual learners. *Evolution*, 67(3):688–697, 2013. Publisher: Blackwell Publishing Inc Malden, USA.

[12] Roope O. Kaaronen. Mycological rationality: Heuristics, perception and decision-making in mushroom foraging. *Judgment and Decision Making*, 15(5):630–647, 2020. Publisher: Cambridge University Press.

[13] Roope O Kaaronen, Mikael A Manninen, and Jussi T Eronen. Rules of thumb, from Holocene to Anthropocene. *The Anthropocene Review*, 10(3):685–709, December 2023.

[14] H. C. Petersen and Gillian Fellows Jensen. *Qaanniornermut ilitsersuut*. Kalaallit Nunaata Katersugaasivia, 1981.

[15] Roope O. Kaaronen, Mikael A. Manninen, and Jussi T. Eronen. Body-based units of measure in cultural evolution. *Science*, 380(6648):948–954, June 2023.

[16] Saxton Temple Pope. *Yahi archery*, volume 13. Berkeley: University of California Press, 1918.

[17] Thomas Dhoop and Juan-Pablo Olaberria. Practical Knowledge in the Viking Age: the use of mental templates in clinker shipbuilding. *International Journal of Nautical Archaeology*, 44(1):95–110, 2015. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1095-9270.12081.

[18] Michael W. Carter and Craig A. Tovey. When Is the Classroom Assignment Problem Hard? *Operations Research*, 40(1-supplement-1):S28–S39, February 1992.

[19] Abdullah Almaatouq, Mohammed Alsobay, Ming Yin, and Duncan J. Watts. Task complexity moderates group synergy. *Proceedings of the National Academy of Sciences*, 118(36):e2101062118, September 2021.

[20] Kerstin Schillinger, Alex Mesoudi, and Stephen J. Lycett. The impact of imitative versus emulative learning mechanisms on artifactual variation: implications for the evolution of material culture. *Evolution and Human Behavior*, 36(6):446–455, 2015. Publisher: Elsevier.

[21] Max Kleiman-Weiner, Felix Sosa, Bill Thompson, Bas van Opheusden, Thomas L. Griffiths, Samuel Gershman, and Fiery Cushman. Downloading Culture. zip: Social learning by program induction. In *Proceedings of the Annual Meeting of the Cognitive Science Society*, volume 42, 2020.

[22] Helena Miton and Simon DeDeo. The cultural transmission of tacit knowledge. *Journal of The Royal Society Interface*, 19(195):20220238, October 2022.

[23] Thomas Holding, Paul E. Smaldino, and Charlotte O. Brand. Analogies evolve by increasing transmission fidelity in the communication of complex information. Publisher: OSF.

[24] Mathieu Charbonneau. Understanding Cultural Fidelity. *The British Journal for the Philosophy of Science*, 71(4):1209–1233, December 2020.

[25] Anne Kandler and Enrico R. Crema. Analysing Cultural Frequency Data: Neutral Theory and Beyond. In Anna Marie Prentiss, editor, *Handbook of Evolutionary Research in Archaeology*, pages 83–108. Springer International Publishing, Cham, 2019.

[26] Enrico R. Crema, Eugenio Bortolini, and Mark Lake. How Cultural Transmission Through Objects Impacts Inferences About Cultural Evolution. *Journal of Archaeological Method and Theory*, 31(1):202–226, March 2024.

[27] Donald Norman Sull and Kathleen M. Eisenhardt. *Simple rules: How to thrive in a complex world.* Houghton Mifflin Harcourt, 2015.

[28] Monica Tamariz. Replication and emergence in cultural transmission. *Physics of Life Reviews*, 30:47–71, 2019. Publisher: Elsevier.

[29] Daniel L. Chen, Martin Schonger, and Chris Wickens. oTree—An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, 9:88–97, March 2016.

[30] R Core Team. *R: A Language and Environment for Statistical Computing.* R Foundation for Statistical Computing, Vienna, Austria, 2023.

[31] Richard McElreath. *Statistical Rethinking, A Course in R and Stan.* 2015.

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Appendix A Additional results

Individual curves In section 2.2, we observed that for participants in the *Solution* treatment, the similarity between their configurations and the configuration received appears to plateau after trial 1. To explain this observation, we looked at the simalirity curves for each participants (Figures S1 and S2). This revealed a high diversity in participants' behavior. While some gradually move away from their demonstrator, other start by exploring and only then revert to copying the configuration received. Others alternate between exploring around it and far from it. We believe that this high diversity is due to the interaction of several factors. First, some participants may be more risk-averse than others, thus limiting the extent to which they diverge from the information received. Participants may also explore in a more or less structured manner: some may make one change at a time, while others may explore more chaotically. Finally, how lucky participants are in their exploration should also lead to significant differences: if a participant discovers a better solution that is very different from their demonstrator's, it is unlikely that they would revert back to the solution received. In reverse, a participant that explores widely but unsuccessfully should be more likely to end up exploring in the neighborhood of the solution received.

Parametric similarity with first generation

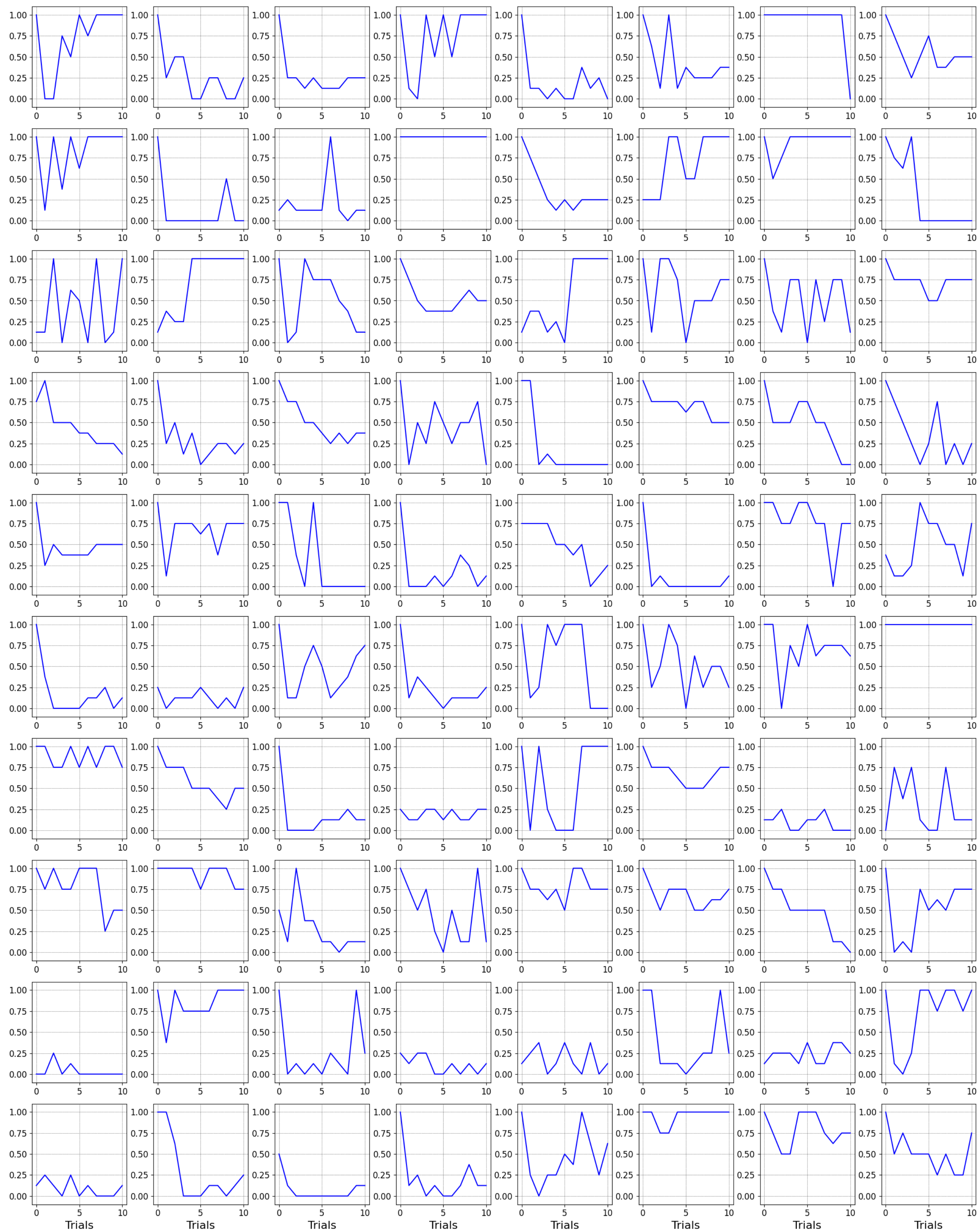

Figure S1: Parametric similarity between configurations produced and configuration received for each participant in the *Solution* treatment.

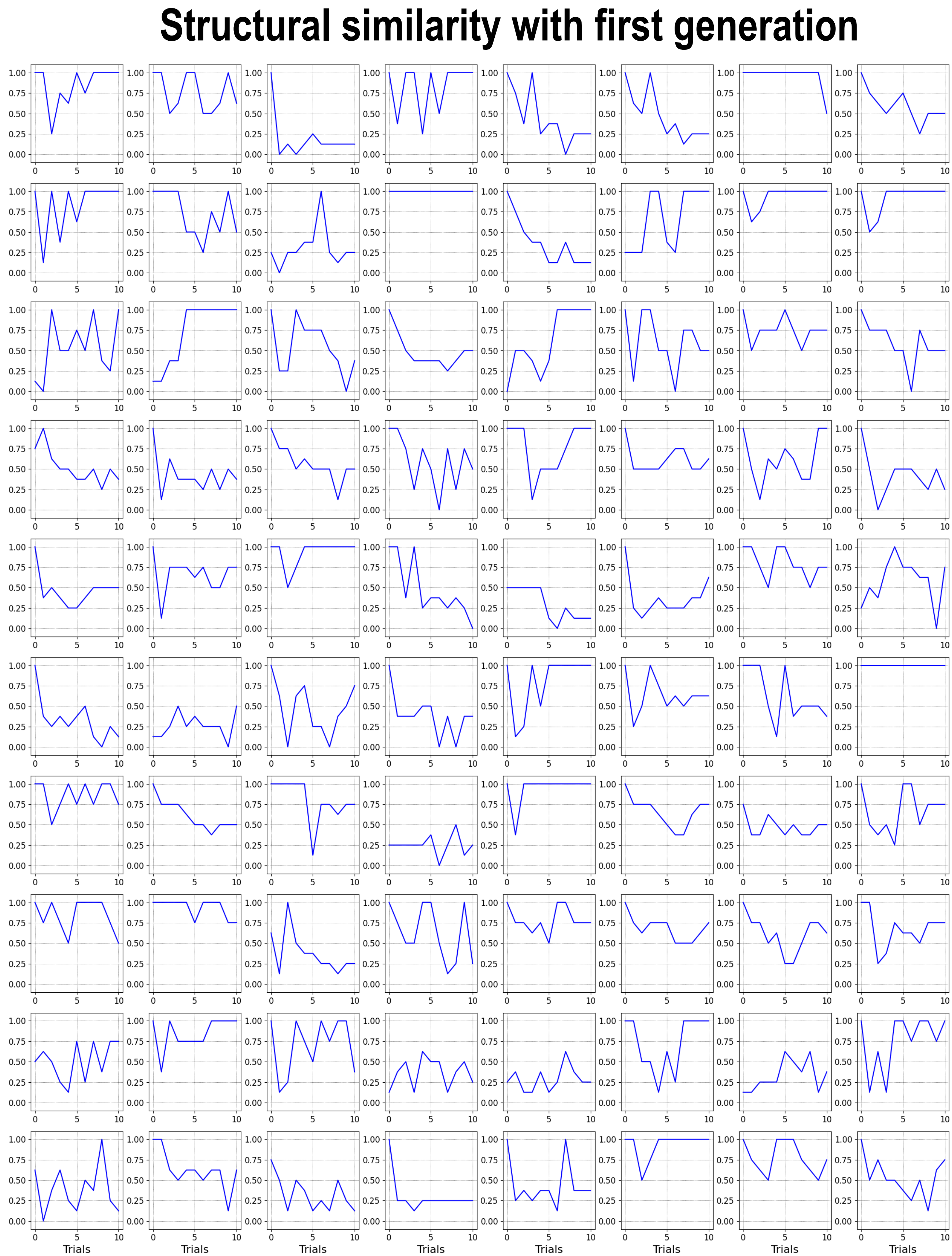

Figure S2: Structural similarity between configurations produced and configuration received for each participant in the *Solution* treatment.

Appendix B Additional details on the methods

Participants recruitment Participants were recruited by posting the online task on Prolific, which is an online platform that centralizes the recruitment of participants for online experiments and surveys. From Prolific, participants accessed a URL that directed them to the web-page of the study. The only requirements for selecting participants were that they were at least 18 years old and fluently speak English. Participants received £1.6 for completing the task and a bonus payment of up to £1.25 (mean = £0.77, SD = £0.27) depending on their performance (see bonus payment section below). Participants' age ranged from 18 to 68 (mean = 29.74; SD = 10.04). The sex indicated by users on Prolific was used to balance participants' sex between treatment.

Pre-experiment information and tutorial Before starting the experiment, participants were provided with information about the task (Figures S3) and S5). They were told that they would have to solve a room assignment problem, which would involve assigning 8 guests to 8 individual rooms. They were informed that the satisfaction

Information for participants

Please read the following information carefully. It outlines what you will be asked to do during the experiment, what data we will record and how they will be used and protected.

Title of study : Evaluating the stability of cultural information

Study description: This study investigates how the nature of the information that individuals receive influences how they solve a complex problem. Your task will consist in solving an optimization problem called « *room assignment problem* ». Results will be used to draw insights about how individual search for solutions to complex problems. It is estimated that the total length of the study will take 12 minutes. In addition to the payment that you will receive for taking part in this experiment, you will receive a bonus payment that will depend on your performance during the task.

Data collection and privacy : The data collected during this experiment is anonymous, no one will have access to the data apart from the researchers and there are no personal identifiers to link you to this research. Age, gender and task-related information (such as the solutions you will submit) will be collected. All recorded data will be protected by a password only known to the investigators of the present experiment. Anonymized data will be deposited in a public repository for an unlimited period of time but you will never be personally detectable. Anonymous, combined data (e.g. group averages) may be printed as part of an article in a scientific journal.

Consent Statement

If you would like to take part in this study, please read the consent statements below. If you agree with the statements, please check the box to begin the online task. Date and time of consent will be stored. If you do not want to take part, you can simply close the tab. In any case, you may still withdraw at any time during the experiment for any reason and without explanation by closing the tab.

You can print this page by clicking here

- ***I have read and understood the above information and consent to take part in this study.***
- ***I understand that if I decide at any other time during the experiment that I no longer wish to participate in this project, I can withdraw from it immediately.***

☐ By checking this box you state that you agree with the above statements.

Figure S3: Pre-experiment information and consent form

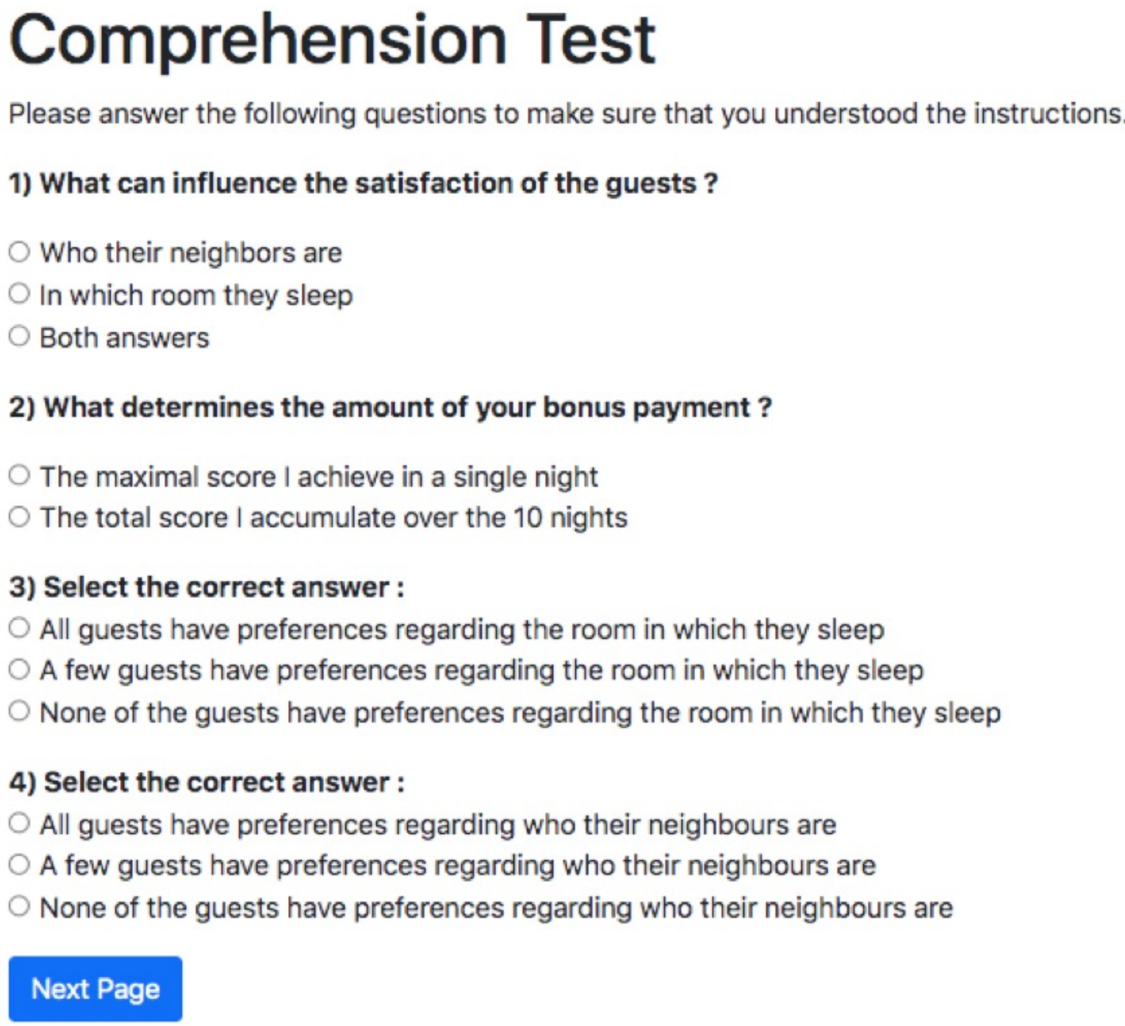

Figure S4: Comprehension test

of all guests depended on the room in which they slept, and that for some guests, who their neighbors are would significantly impact their satisfaction. They were told that they would have to maximize the satisfaction of the guests over N trials, and that their bonus payment would depend on the cumulated score. They were also informed that they had no time limit to complete the task. Participants were then asked to submit a test configuration to verify that they were able to use the drag-and-drop interface. They also had to answer a comprehension test of four questions (Figure S4) to verify that they understood and memorized the information provided.

Score Calculation The score associated with a given configuration depended on the total satisfaction of the guests. The satisfaction of all guests depended on the room to which they were assigned. For each room-guest pair, we draw uniformly at random a value between 0 and 50 to determine the satisfaction of this guest when assigned to this room. These values were randomly generated before the experiment, but were then fixed and

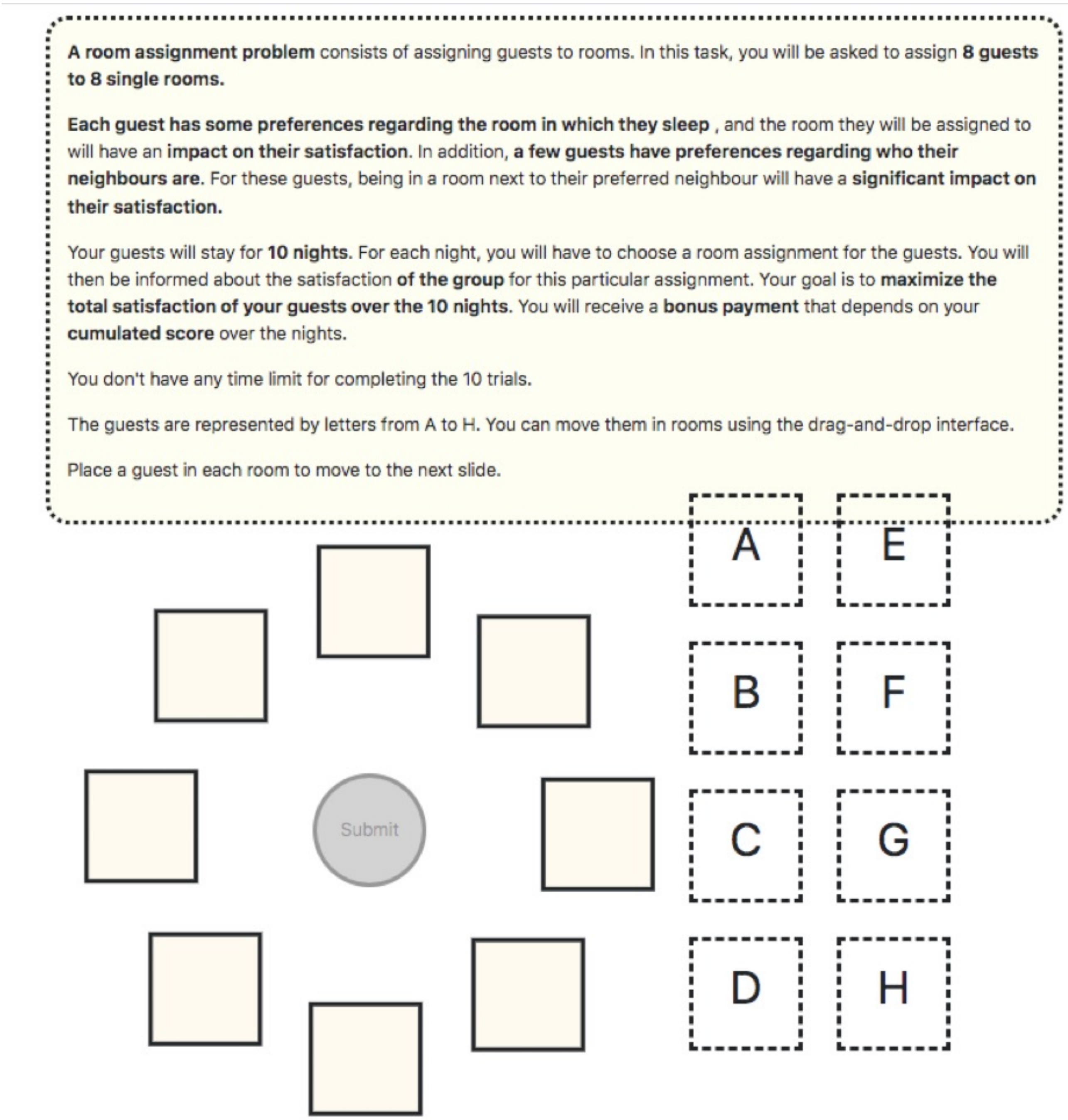

Figure S5: Pre-experimental tutorial

Figure S6: Screenshots of the Exploration Phase

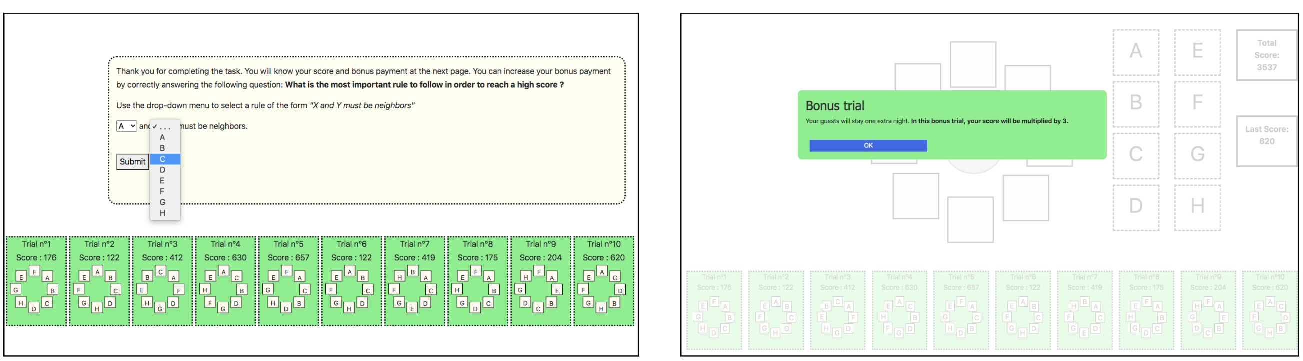

Figure S7: Screenshots of the transmission phase

identical for all participants. Additionally, when guests A and C were placed in neighboring rooms, the total satisfaction associated with the configuration was increased by 240. Similarly, when guests B and D were placed in neighboring rooms, the total satisfaction was increased by 240. The pairs A-C and B-D were chosen following pilot studies which revealed that they ensured that some participants, but not all, would discover them during the Exploration phase. The best configuration yielded a score of 931.

Bonus Payment To compute the amount of the payment awarded to participants, we divided the total score obtained over all trials (including the bonus trial which counted triple) by 9310 (corresponding to 10 times the maximal possible score on one configuration). This resulted in bonus payments ranging from £0.22 to £1.25 (mean: 0.77; std: 0.26). Bonus payment were then increased by £0.25 if the participant submitted an accurate heuristic. This total value represented the amount of their bonus payment in pounds.

Appendix C Statistical models

C.1 Pre-registered Analyses

Statistical models for pre-registered analyses were published on OSF (*https://osf.io/gxvnq*) prior to data collection.

Effect of social information on exploration frequency To investigate the effects of the two types of social information on exploration, we studied the number of different configurations submitted by each participant. This value ranges between 1 (all configurations submitted by the participant are identical) to 11 (all configurations submitted by the participant are different). We fitted a linear model predicting Exploration (number of different configurations) as a function of treatment (0: Asocial, 1: Configuration second-generation; 2: Rule second-generation).

Equation:

$\textit{Number of unique configurations} \sim \mathrm{N}(\mu_i, \sigma)$

$\mu_i = a_{\text{treatment}[i]}$

Priors:

$a_{\text{treatment}} \sim \text{Normal}(8, 2)$

$\sigma \sim \text{Exponential}(1)$

Effect of social information on exploration breadth To investigate the effects of the two types of social information on the variation generated by participants, we studied the parametric and structural distances between configurations submitted by each participant. We computed the parametric and structural distance between each pair of solutions, and summed these distances to obtain a measure of variation for each participant. We fitted a linear model predicting Aggregated parametric Variation (summed parametric distances between all pairs of configurations) as a function of treatment (0: Asocial, 1: Configuration second-generation; 2: Rule second-generation). Similarly, we fitted a linear model predicting Aggregated Structural variation (summed structural distances between all pairs of configurations) as a function of treatment.

Equation:

$\textit{parametric variation} \sim \mathrm{N}(\mu_i, \sigma)$

$\mu_i = a_{\text{treatment}[i]}$

Priors:

$a_{\text{treatment}} \sim \text{Normal}(250, 30)$

$\sigma \sim \text{Exponential}(10)$

Equation:

$\textit{Structural variation} \sim \mathrm{N}(\mu_i, \sigma)$

$\mu_i = a_{\text{treatment}[i]}$

Priors: $a_{\text{treatment}} \sim \text{Normal}(250, 30)$

$\sigma \sim \text{Exponential}(10)$

Effect of social information on inter-generation variation To investigate the effect of the type of social information on inter-generational variation, we studied the distance between a solution produce by a second-generation participant at a given trial with the last solution produced by the first-generation participant of the same chain. To do so, we computed the parametric and structural distances between each configuration produced by a participant with the last configuration submitted by the previous participant. We fitted two linear models (one for the parametric distance, and one for the structural distance) predicting distance as a function of treatment (1: Configuration second-generation; 2: Rule second-generation) and trial number (0-11), controlling for participant identity. To determine whether the first configuration produced by second-generation participants resembles the last solution produced by first-generation participants, we estimated the distance (both parametric and structural) between randomly generated configurations. If the confidence interval of the distance between random configurations falls completely inside the confidence interval of the effect of a treatment, this treatment is considered as having no effect on the distance. If this confidence interval for random configurations falls neither completely inside nor completely outside the estimated confidence interval for a treatment, we increased the number of random configurations generated until it falls either completely inside or completely outside.

Equation:

$\textit{parametric distance} \sim \text{N}(\mu_i, \sigma)$

$\mu_i = a_{\text{treatment}[i]} + b_{\text{trial}[\text{treatment}[i]]} \cdot \text{trial}_i + d$

In exploratory analyses, we included the third generation of participants in the analyses. The *Treatment* variable had thus 5 possible values: 1 corresponds to the *Asocial* treatment, 2 to the *Solution-2ndGeneration* treatment, 3 to the *Heuristic-2ndGeneration*, 4 to the *Solution-3rdGeneration* treatment and 5 to the *Heuristic-3rdGeneration*. We then ran the 7 pre-registered models described above with these 5 categories for *Treatment*.

C.2 Output of statistical models

We here report for each model the 89% credible intervals for each estimated parameter, as well as for contrasts between parameters.

	mean	sd	5.5%	94.5%
a[Asocial]	9.133	0.245	8.749	9.522
a[Solution]	7.845	0.235	7.472	8.22
a[Heuristic]	9.153	0.256	8.739	9.575
sigma	2.147	0.098	1.998	2.313
a[Solution] − a[Asocial]	−1.288	0.337	−1.844	−0.747
a[Heuristic] − a[Asocial]	0.02	0.358	−0.531	0.595
a[Heuristic] − a[Solution]	1.308	0.35	0.746	1.868

Model 1: Number of unique configurations submitted

	mean	sd	5.5%	94.5%
a[Asocial]	0.687	0.012	0.668	0.706
a[Solution]	0.547	0.012	0.528	0.566
a[Heuristic]	0.646	0.012	0.626	0.665
sigma	47.09	1.031	45.474	48.66
a[Solution] − a[Asocial]	−0.14	0.017	−0.166	−0.112
a[Heuristic] − a[Asocial]	−0.041	0.016	−0.067	−0.015
a[Heuristic] − a[Solution]	0.099	0.017	0.072	0.126

Model 2: Within-Individual parametric diversity

	mean	sd	5.5%	94.5%
a[Asocial]	0.512	0.01	0.496	0.527
a[Solution]	0.43	0.01	0.413	0.446
a[Heuristic]	0.478	0.01	0.463	0.493
sigma	38.46	0.972	36.905	40.032
a[Solution] − a[Asocial]	−0.082	0.014	−0.104	−0.06
a[Heuristic] − a[Asocial]	−0.034	0.014	−0.056	−0.012
a[Heuristic] − a[Solution]	0.048	0.014	0.025	0.071

Model 3: Within-Individual structural diversity

	mean	sd	5.5%	94.5%
a[Solution]	0.582	0.027	0.537	0.625
a[Heuristic]	0.153	0.025	0.112	0.192
b[Solution]	0.983	0.002	0.979	0.986
b[Heuristic]	0.998	0.002	0.994	1.001
sigma	1.73	0.031	1.681	1.779
a[Chance]	0.13	0.006	0.12	0.14
a[Heuristic] − a[Solution]	−0.429	0.037	−0.489	−0.37
b[Heuristic] − b[Solution]	0.015	0.003	0.009	0.02

Model 4: Parametric distance with demonstrator

	mean	sd	5.5%	94.5%
a[Solution]	0.667	0.022	0.632	0.701
a[Heuristic]	0.385	0.022	0.351	0.42
b[Solution]	0.991	0.002	0.988	0.994
b[Heuristic]	1.003	0.002	0.999	1.006
sigma	1.603	0.027	1.562	1.646
a[Chance]	0.269	0.008	0.256	0.282
a[Heuristic] − a[Solution]	−0.282	0.031	−0.331	−0.233
b[Heuristic] − b[Solution]	0.012	0.003	0.007	0.017

Model 5: Structural distance with demonstrator

	mean	sd	5.5%	94.5%
a[Asocial]	5156.131	43.003	5087.199	5224.872
a[Solution]	6081.134	44.372	6011.627	6150.692
a[Heuristic]	5958.768	43.377	5887.658	6028.95
sigma	391.034	3.498	385.58	396.873
a[Solution] − a[Asocial]	925.003	63.334	827.418	1023.829
a[Heuristic] − a[Asocial]	802.638	60.925	702.819	897.249
a[Heuristic] − a[Solution]	−122.366	63.229	−224.801	−22.538

Model 6: Total score

	mean	sd	5.5%	94.5%
a[Asocial]	502.174	8.997	487.379	516.011
a[Solution]	546.667	9.205	531.512	561.193
a[Heuristic]	527.149	9.056	513.029	541.491
sigma	80.855	1.489	78.377	83.306
a[Solution] − a[Asocial]	44.493	12.741	23.712	64.392
a[Heuristic] − a[Asocial]	24.975	12.65	4.501	45.456
a[Heuristic] − a[Solution]	−19.517	12.499	−39.575	0.061

Model 7: Score at the last trial

Figure S8: Output of pre-registered statistical models

	mean	sd	5.5%	94.5%
a[Asocial]	9.133	0.253	8.715	9.522
a[Solution_2d_gen]	7.854	0.251	7.454	8.254
a[Heuristic_2d_gen]	9.159	0.255	8.741	9.564
a[Solution_3rd_gen]	7.096	0.245	6.694	7.481
a[Heuristic_3rd_gen]	8.641	0.263	8.223	9.056
sigma	2.34	0.078	2.219	2.466
a[Solution_2d_gen] – a[Asocial]	−1.278	0.338	−1.8	−0.749
a[Heuristic_2d_gen] – a[Asocial]	0.026	0.36	−0.549	0.598
a[Heuristic_2d_gen] – a[Solution_2d_gen]	1.304	0.351	0.743	1.878
a[Heuristic_3rd_gen] – a[Asocial]	−0.492	0.357	−1.056	0.081
a[Heuristic_3rd_gen] – a[Solution_2d_gen]	0.787	0.365	0.194	1.357
a[Heuristic_3rd_gen] – a[Heuristic_2d_gen]	−0.518	0.361	−1.091	0.041
a[Solution_3rd_gen] – a[Asocial]	−2.036	0.34	−2.552	−1.483
a[Solution_3rd_gen] – a[Solution_2d_gen]	−0.758	0.357	−1.317	−0.198
a[Heuristic_3rd_gen] – a[Solution_3rd_gen]	1.545	0.349	0.992	2.113
Heuristic_3rd_gen] – a[Heuristic_2d_gen]) – (a[Solution_3rd_gen] – a[Solution_2d_gen])	0.24	0.495	−0.561	1.045

Model S1: Number of unique configurations submitted

	mean	sd	5.5%	94.5%
a[Asocial]	0.685	0.014	0.663	0.707
a[Solution_2d_gen]	0.548	0.013	0.527	0.569
a[Heuristic_2d_gen]	0.645	0.014	0.622	0.667
a[Solution_3rd_gen]	0.462	0.014	0.44	0.484
a[Heuristic_3rd_gen]	0.6	0.014	0.578	0.622
a[Solution_2d_gen] – a[Asocial]	−0.137	0.019	−0.167	−0.106
a[Heuristic_2d_gen] – a[Asocial]	−0.04	0.02	−0.073	−0.009
a[Heuristic_2d_gen] – a[Solution_2d_gen]	0.097	0.019	0.066	0.127
a[Heuristic_3rd_gen] – a[Asocial]	−0.085	0.019	−0.115	−0.053
a[Heuristic_3rd_gen] – a[Solution_2d_gen]	0.052	0.02	0.021	0.084
a[Heuristic_3rd_gen] – a[Heuristic_2d_gen]	−0.045	0.02	−0.078	−0.012
a[Solution_3rd_gen] – a[Asocial]	−0.223	0.019	−0.253	−0.194
a[Solution_3rd_gen] – a[Solution_2d_gen]	−0.086	0.019	−0.116	−0.056
a[Heuristic_3rd_gen] – a[Solution_3rd_gen]	0.139	0.019	0.109	0.17
Heuristic_3rd_gen – Solution_3rd_gen] – a[Heuristic_2d_gen – Solution_2d_gen]	0.042	0.027	−0.001	0.086

Model S2: Within-Individual parametric diversity

	mean	sd	5.5%	94.5%
a[Asocial]	0.512	0.012	0.493	0.53
a[Solution_2d_gen]	0.431	0.011	0.414	0.448
a[Heuristic_2d_gen]	0.479	0.011	0.462	0.496
a[Solution_3rd_gen]	0.366	0.011	0.348	0.384
a[Heuristic_3rd_gen]	0.441	0.011	0.424	0.458
a[Solution_2d_gen] – a[Asocial]	−0.081	0.016	−0.106	−0.055
a[Heuristic_2d_gen] – a[Asocial]	−0.033	0.016	−0.059	−0.008
a[Heuristic_2d_gen] – a[Solution_2d_gen]	0.048	0.015	0.024	0.073
a[Heuristic_3rd_gen] – a[Asocial]	−0.071	0.015	−0.095	−0.046
a[Heuristic_3rd_gen] – a[Solution_2d_gen]	0.01	0.015	−0.014	0.033
a[Heuristic_3rd_gen] – a[Heuristic_2d_gen]	−0.038	0.015	−0.061	−0.014
a[Solution_3rd_gen] – a[Asocial]	−0.146	0.016	−0.171	−0.121
a[Solution_3rd_gen] – a[Solution_2d_gen]	−0.065	0.016	−0.09	−0.04
a[Heuristic_3rd_gen] – a[Solution_3rd_gen]	0.075	0.015	0.051	0.099
Heuristic_3rd_gen – Solution_3rd_gen] – a[Heuristic_2d_gen – Solution_2d_gen]	0.027	0.021	−0.008	0.061

Model S3: Within-Individual structural diversity

	mean	sd	5.5%	94.5%
a[Solution_2d_gen]	0.48	0.02	0.448	0.513
a[Heuristic_2d_gen]	0.139	0.021	0.103	0.172
a[Solution_3rd_gen]	0.313	0.023	0.276	0.348
a[Heuristic_3rd_gen]	0.135	0.021	0.1	0.168
Chance	0.13	0.006	0.119	0.14
a[Heuristic_2d_gen] – a[Solution_2d_gen]	−0.341	0.029	−0.39	−0.295
a[Solution_3rd_gen] – a[Solution_2d_gen]	−0.166	0.031	−0.216	−0.118
a[Heuristic_3rd_gen] – a[Solution_2d_gen]	−0.345	0.03	−0.394	−0.298
a[Heuristic_3rd_gen] – a[Heuristic_2d_gen]	−0.004	0.03	−0.053	0.045
a[Heuristic_3rd_gen – Solution_3rd_gen]	−0.178	0.031	−0.227	−0.13
Heuristic_3rd_gen – Solution_3rd_gen] – a[Heuristic_2d_gen – Solution_2d_gen]	0.162	0.043	0.094	0.23

Model S4: Parametric distance with demonstrator

	mean	sd	5.5%	94.5%
a[Solution_2d_gen]	0.613	0.02	0.581	0.645
a[Heuristic_2d_gen]	0.399	0.019	0.37	0.431
a[Solution_3rd_gen]	0.474	0.02	0.442	0.506
a[Heuristic_3rd_gen]	0.361	0.019	0.33	0.391
Chance	0.269	0.008	0.256	0.282
a[Heuristic_2d_gen] – a[Solution_2d_gen]	−0.214	0.027	−0.256	−0.171
a[Solution_3rd_gen] – a[Solution_2d_gen]	−0.139	0.028	−0.183	−0.096
a[Heuristic_3rd_gen] – a[Solution_2d_gen]	−0.252	0.027	−0.294	−0.212
a[Heuristic_3rd_gen] – a[Heuristic_2d_gen]	−0.038	0.026	−0.08	0.003
a[Heuristic_3rd_gen – Solution_3rd_gen]	−0.112	0.027	−0.156	−0.069
Heuristic_3rd_gen – Solution_3rd_gen] – a[Heuristic_2d_gen – Solution_2d_gen]	0.101	0.038	0.04	0.163

Model S5: Structural distance with demonstrator

	mean	sd	5.5%	94.5%
a[Asocial]	5156.23	53.568	5071.916	5241.547
a[Solution_2d_gen]	6080.028	50.921	5998.726	6162.312
a[Heuristic_2d_gen]	5959.703	50.861	5876.025	6043.261
a[Solution_3rd_gen]	6494.217	49.961	6417.585	6575.126
a[Heuristic_3rd_gen]	6376.099	50.79	6298.032	6457.435
sigma	462.419	3.78	456.167	468.58
a[Solution_2d_gen] – a[Asocial]	923.798	74.29	805.618	1044.931
a[Heuristic_2d_gen] – a[Asocial]	803.474	72.459	682.96	920.725
a[Heuristic_2d_gen] – a[Solution_2d_gen]	−120.324	72.221	−236.987	−9.187
a[Heuristic_3rd_gen] – a[Asocial]	1219.87	76.882	1098.098	1344.109
a[Heuristic_3rd_gen] – a[Solution_2d_gen]	296.072	71.697	180.301	410.617
a[Heuristic_3rd_gen] – a[Heuristic_2d_gen]	416.396	71.628	302.843	534.324
a[Solution_3rd_gen] – a[Asocial]	1337.988	73.959	1218.541	1456.207
a[Solution_3rd_gen] – a[Solution_2d_gen]	414.19	70.524	308.48	526.831
a[Heuristic_3rd_gen] – a[Solution_3rd_gen]	−118.118	69.315	−227.317	−6.597
Heuristic_3rd_gen – Solution_3rd_gen] – a[Heuristic_2d_gen – Solution_2d_gen]	2.206	99.78	−154.416	163.965

Model S6: Total score

	mean	sd	5.5%	94.5%
a[Asocial]	502.492	10.427	485.308	518.858
a[Solution_2d_gen]	546.27	10.613	529.666	563.372
a[Heuristic_2d_gen]	526.521	10.214	509.691	542.744
a[Solution_3rd_gen]	558.383	10.4	541.344	574.389
a[Heuristic_3rd_gen]	544.924	10.2	528.85	561.358
sigma	93.032	1.625	90.351	95.617
a[Solution_2d_gen] – a[Asocial]	43.778	14.944	20.154	68.831
a[Heuristic_2d_gen] – a[Asocial]	24.029	14.396	1.2	47.111
a[Heuristic_2d_gen] – a[Solution_2d_gen]	−19.749	14.772	−44.023	3.967
a[Heuristic_3rd_gen] – a[Asocial]	42.432	15.238	17.351	66.884
a[Heuristic_3rd_gen] – a[Solution_2d_gen]	−1.346	14.684	−24.548	22.409
a[Heuristic_3rd_gen] – a[Heuristic_2d_gen]	18.403	14.571	−4.904	40.515
a[Solution_3rd_gen] – a[Asocial]	55.891	14.279	32.475	78.831
a[Solution_3rd_gen] – a[Solution_2d_gen]	12.113	15.167	−12.584	35.016
a[Heuristic_3rd_gen] – a[Solution_3rd_gen]	−13.459	14.832	−37.171	9.784
Heuristic_3rd_gen – Solution_3rd_gen] – a[Heuristic_2d_gen – Solution_2d_gen]	6.29	21.386	−28.078	39.685

Model S7: Score at the last trial

Figure S9: Output of exploratory statistical models including third generation participants

	mean	sd	5.5%	94.5%
a[Asocial]	9.99884667333333	0.420238332092207	9.31636505	10.6558975
a[Solution_2d_gen]	8.88066701333333	0.46915537037231	8.14106085	9.631793
a[Heuristic_2d_gen]	10.1724424533333	0.469853509845559	9.4285696	10.904322
a[Solution_3rd_gen]	8.19519797333333	0.499524265490979	7.3873237	8.9976955
a[Heuristic_3rd_gen]	9.72902472666667	0.492565005841711	8.9159085	10.5081175
sigma	2.31422222	0.0851444695640092	2.18280125	2.45605095
b[total_score]	−0.0001723952908	6.6638574582482e−05	−0.00028093144	−6.5941284e−05
a[Solution_2d_gen] − a[Asocial]	−1.11817966	0.357436297191426	−1.7087676	−0.562185199999999
a[Heuristic_2d_gen] − a[Asocial]	0.17359578	0.351259282205157	−0.3817632	0.72124765
a[Heuristic_2d_gen] − a[Solution_2d_gen]	1.29177544	0.355713052931747	0.7122074	1.8683938
a[Heuristic_3rd_gen] − a[Asocial]	−0.269821946666667	0.364454025351447	−0.85474195	0.3029652
a[Heuristic_3rd_gen] − a[Solution_2d_gen]	0.848357713333333	0.355072567305999	0.270323649999999	1.43506975
a[Heuristic_3rd_gen] − a[Heuristic_2d_gen]	−0.443417726666667	0.365696007363994	−1.04458435	0.15427115
a[Solution_3rd_gen] − a[Asocial]	−1.8036487	0.363843451246256	−2.3796896	−1.23648175
a[Solution_3rd_gen] − a[Solution_2d_gen]	−0.68546904	0.363241438448519	−1.27545815	−0.0858479000000003
a[Heuristic_3rd_gen] − a[Solution_3rd_gen]	1.53382675333333	0.36573918883793	0.97208855	2.1130829
[Heuristic_3rd_gen] − a[Heuristic_2d_gen]) − (a[Solution_3rd_gen] − a[Solution_2d_gen])	0.242051313333334	0.522294080395025	−0.592052049999998	1.07309075

Model S8: Number of configuration submitted

	mean	sd	5.5%	94.5%
a[Asocial]	0.708067854545455	0.0171646068963739	0.680962886363636	0.735499477272727
a[Solution_2d_gen]	0.575170401515152	0.0181003366818164	0.546528034090909	0.60513425
a[Heuristic_2d_gen]	0.671422763636364	0.0169673665806774	0.645221727272727	0.698871034090909
a[Solution_3rd_gen]	0.490780425757576	0.0178831488096377	0.463185125	0.5189555
a[Heuristic_3rd_gen]	0.628268859090909	0.0185817835405368	0.599353034090909	0.658616147727273
a[Solution_2d_gen] − a[Asocial]	−0.132897453030303	0.0201779385286903	−0.164648090909091	−0.0996869090909090909
a[Heuristic_2d_gen] − a[Asocial]	−0.0366450909090909	0.0210391505989654	−0.0701903181818182	−0.00295914772727277
a[Heuristic_2d_gen] − a[Solution_2d_gen]	0.0962523621212121	0.0192476406793893	0.0657189886363636	0.125946795454545
a[Heuristic_3rd_gen] − a[Asocial]	−0.0797989954545455	0.0196492300504847	−0.11118	−0.0484222386363636
a[Heuristic_3rd_gen] − a[Solution_2d_gen]	0.0530984575757576	0.0204740738693051	0.0212741250000001	0.0857892840909091
a[Heuristic_3rd_gen] − a[Heuristic_2d_gen]	−0.0431539045454545	0.0204391746279405	−0.0758386022727272	−0.0100633977272727
a[Solution_3rd_gen] − a[Asocial]	−0.217287428787879	0.0202420478279719	−0.249201227272727	−0.184959556818182
a[Solution_3rd_gen] − a[Solution_2d_gen]	−0.0843899757575758	0.0204494388183961	−0.117500227272727	−0.0515234090909091
a[Heuristic_3rd_gen] − a[Solution_3rd_gen]	0.137488433333333	0.0206497544156271	0.105894738636364	0.172524954545455
[Heuristic_3rd_gen] − a[Heuristic_2d_gen]) − (a[Solution_3rd_gen] − a[Solution_2d_gen])	0.0412360712121212	0.0285194324243253	−0.00432645454545455	0.0883530113636363
b[total_score]	−0.00203724566073333	0.000795989180518538	−0.0033191944	−0.000771210505

Model S9: Within-individual parametric diversity

	mean	sd	5.5%	94.5%
a[Asocial]	0.554038895454545	0.0136906838467765	0.532171738636364	0.574905772727273
a[Solution_2d_gen]	0.480285398484848	0.0151319122296429	0.455565420454546	0.5039415
a[Heuristic_2d_gen]	0.527856587878788	0.0146695234794727	0.503655	0.550558556818182
a[Solution_3rd_gen]	0.419327460606061	0.0153844971103216	0.393835159090909	0.442372977272727
a[Heuristic_3rd_gen]	0.493376448484849	0.0157684836737104	0.468676397727273	0.519302215909091
a[Solution_2d_gen] − a[Asocial]	−0.073753496969697	0.0159029298100001	−0.0996570681818182	−0.0490536022727273
a[Heuristic_2d_gen] − a[Asocial]	−0.0261823075757576	0.0159755614669881	−0.052798375	−0.000595238636363618
a[Heuristic_2d_gen] − a[Solution_2d_gen]	0.0475711893939394	0.0158361487787585	0.0222985227272727	0.0723491363636364
a[Heuristic_3rd_gen] − a[Asocial]	−0.060662446969697	0.0165070308843838	−0.0861606022727272	−0.0348283977272727
a[Heuristic_3rd_gen] − a[Solution_2d_gen]	0.01309105	0.0166451165114488	−0.0132703977272727	0.0393461477272727
a[Heuristic_3rd_gen] − a[Heuristic_2d_gen]	−0.0344801393939394	0.0160486410060713	−0.0605479431818182	−0.00809828409090909
a[Solution_3rd_gen] − a[Asocial]	−0.134711434848485	0.0156542394957645	−0.159994943181818	−0.110119965909091
a[Solution_3rd_gen] − a[Solution_2d_gen]	−0.0609579378787879	0.01507218812004	−0.0853560113636364	−0.036836375
a[Heuristic_3rd_gen] − a[Solution_3rd_gen]	0.0740489878787879	0.0159866385692	0.0481555568181818	0.0993734772727273
[Heuristic_3rd_gen] − a[Heuristic_2d_gen]) − (a[Solution_3rd_gen] − a[Solution_2d_gen])	0.0264777984848485	0.0212429142140733	−0.00743478409090906	0.0601818522727273
b[total_score]	−0.00370658942	0.000732768792330573	−0.0048820798	−0.00249677185

Model S10: Within-individual structural diversity

Figure S10: Output of exploratory statistical models controlling for total score