COGNITIVE SCIENCE

# Complex cognitive algorithms preserved by selective social learning in experimental populations

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**Many human abilities rely on cognitive algorithms discovered by previous generations. Cultural accumulation of innovative algorithms is hard to explain because complex concepts are difficult to pass on. We found that selective social learning preserved rare discoveries of exceptional algorithms in a large experimental simulation of cultural evolution. Participants (*N* = 3450) faced a difficult sequential decision problem (sorting an unknown sequence of numbers) and transmitted solutions across 12 generations in 20 populations. Several known sorting algorithms were discovered. Complex algorithms persisted when participants could choose who to learn from but frequently became extinct in populations lacking this selection process, converging on highly transmissible lower-performance algorithms. These results provide experimental evidence for hypothesized links between sociality and cognitive function in humans.**

Reading, counting, cooking, and sailing are just some of the human abilities passed from generation to generation through social learning (*1*, *2*). Complex abilities like these often depend on learned cognitive algorithms: procedural representations of a problem that coordinate memory, attention, and perception into sequences of useful computations and actions. Accumulation of complex algorithms—from ancient tool-making techniques to bread making, boat building, or horticulture—is central to human adaptation (*3*–*5*) yet challenging to explain because algorithmic concepts can be difficult to discover, communicate, and learn from observation (*6*), making them vulnerable to loss (*7*–*10*). Theories of cultural evolution suggest that human social learning may help overcome this fragility (*11*, *12*). For example, mathematical models (*13*) predict that choosing to learn from successful or prestigious individuals can prevent the loss of rare innovations. However, this potential link between sociality and complex abilities (*14*) is challenging to establish.

We conducted large-scale simulations of cultural evolution with human participants to assess how selective social learning influenced the evolution of cognitive algorithms. Prior research (*15*–*22*) shows that social learning can improve decisions in multiple-choice tasks (*23*), perceptual judgments (*24*), and search problems (*25*) and can improve artifacts such as physical structures (*26*) or computer programs (*27*). However, the evolution of cognitive algorithms at the population level has been difficult to study (*28*). We developed custom software to recruit large numbers of participants online and organize them into evolving societies facing a common problem. Twenty populations tackled a sequential decision problem (Fig. 1A and materials and methods 1.1). Presented with six images, participants attempted to establish hidden arbitrary orderings using pairwise comparisons. Out-of-order pairs swapped positions when compared. Participants were rewarded for establishing the ordering using fewer comparisons. This task poses a sorting problem, requiring a strategy for executing appropriate sequences of actions, analogous to culturally evolved strategies for making tools or food.

Participants transmitted their strategies across 12 generations (Fig. 1B). Initial asocial generations completed the task individually. Participants in generations 2 to 12 were randomly assigned to either the experimental selective social learning (SSL) treatment (participants could choose demonstrators from the previous generation based on demonstrator performance) or to a control random mixing (RM) treatment (demonstrator performance was not visible). Participants were incentivized to improve on strategies that they observed and provide a helpful description and demonstration of their own strategy (materials and methods 1.1.13).

Figure 2 shows task performance. Asocial participants achieved the lowest scores [mean over scored trials = 0.33, SD = 0.19, relative to a theoretical maximum of 1; supplementary materials (SM) 3; mean number of successful trials = 6.45 of 10 scored trials, SD = 2.89; SM 2.1.1]. Asocial participants improved over trials, confirming within-task learning {regression coefficient posterior mean (β) = 0.14, 97% highest density interval (HDI) = [0.11, 0.16]; SM 2.1.1}. Participants who learned socially (generations 2 to 12) achieved higher performance [mean (M) = 0.446, SD = 0.199] than asocial participants (β = 0.114, 97% HDI = [0.083, 0.145]; SM 2.1.2). RM participants (M = 0.399, SD = 0.167) outperformed asocial participants (β = 0.067, 97% HDI = [0.036, 0.098]; SM 2.1.3). SSL participants performed highest (M = 0.493, SD = 0.216), outperforming asocial (β = 0.162, 97% HDI = [0.13, 0.193]) and RM (β = 0.095, 97% HDI = [0.095, 0.107]; SM 2.1.3) participants.

By the final generations (9 to 12), performance among SSL (M = 0.514, SD = 0.216) and RM (M = 0.433, SD = 0.163) participants increased substantially relative to asocial participants (SSL: β = 0.181, 97% HDI = [0.147, 0.221]; RM: β = 0.101, 97% HDI = [0.071, 0.132]; SM 2.1.5 and 2.1.6). This was not just a consequence of accumulating more knowledge of the task: In a follow-up experiment, asocial participants completed 52 trials (equivalent to four generations) yet performed worse than SSL participants (but better than RM participants; SM 1.3). In the SSL group, but not the RM group, a distinct population of high performers emerged (performance > 0.6; Fig. 2B). Most of these participants (85.2%) learned from a high-performing demonstrator (Fig. 2C). However, most people who learned from

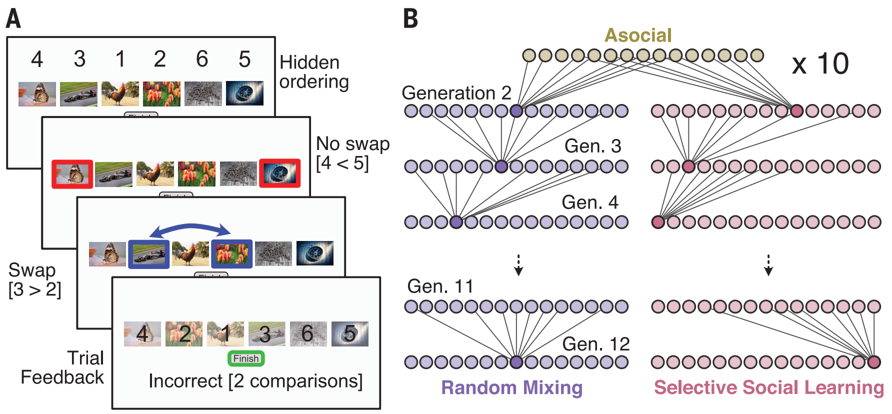


**Fig. 1. Problem-solving task and study design.** (**A**) Sorting task. (**B**) Participants chose up to three demonstrators from a sample of eight (out of 15) members of the preceding generation. Ten SSL networks were paralleled by 10 RM networks yoked to shared initial generations.

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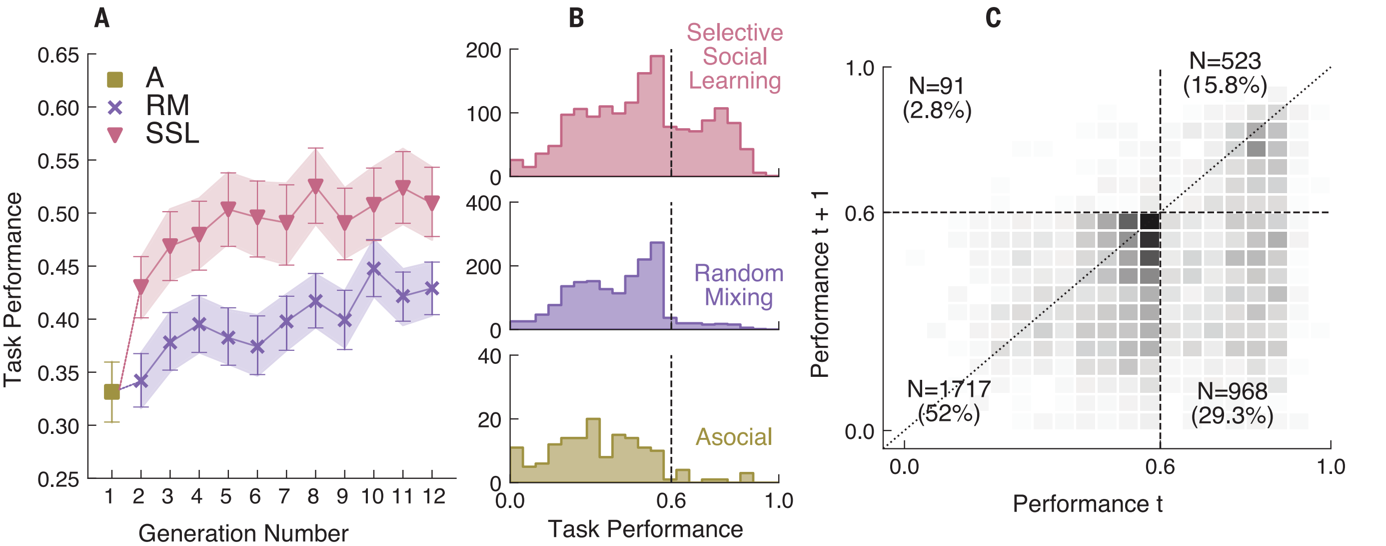


**Fig. 2. Performance in the sorting task.** (**A**) Performance over generations. Error bars show 95% confidence intervals. A, asocial. (**B**) Performance among SSL (top), RM (middle), and asocial (bottom) participants. The vertical axis shows the number of participants. The vertical dashed line indicates the high-performance threshold (0.6). (**C**) Participant performance relative to their demonstrators. t, time (generation number).

a high-performing demonstrator were not themselves high performing (64.9%). This asymmetry indicated an exceptional strategy that is rarely discovered and difficult to pass on.

To deepen our understanding of these strategies, we analyzed the algorithmic structure of participant responses. Using recurrent neural network models (SM 4), we identified eight classes of algorithms (SM 4.3). Participants discovered several known sorting algorithms. Two algorithms were more frequent than all others. The first algorithm is known in computer science as selection sort. Selection sort generates 15 specific comparisons (1-2, 1-3, 1-4, 1-5, 1-6, 2-3, 2-4, 2-5, 2-6, 3-4, 3-5, 3-6, 4-5, 4-6, and 5-6; Fig. 3A) that are guaranteed to succeed (performance = 0.55). The second algorithm is an even more efficient solution, known as gnome sort. The comparisons implied by gnome sort depend on the outcome of earlier comparisons, so its behavior varies. Participants using gnome sort made specific sweeps of adjacent comparisons until a pair failed to swap, remembering where each sweep started (Fig. 3B).

Overall, 80% of participants who used an identifiable algorithm used selection sort or gnome sort (SM 4.2.1). Figure 4 shows major independent lineages of algorithms in four networks (all networks are shown in the SM). Only 44% of asocial participants (66 of 150) used an identifiable algorithm: Among asocial participants, 16% (26) used selection sort and just 13% (20) used gnome sort. All other algorithms were even rarer. In early generations, selection sort began to spread in both the RM and SSL groups (SM 2.2.2), independently becoming the most frequent algorithm in 7 of 10 network pairs. In the RM group, selection sort continued to spread, dominating 9 of 10 populations by generations 9 to 12 (67% of identifiable algorithms). However, in the SSL group, selection sort began to decline after generation 3 (Fig. 4). In the SSL group, but not the RM group (SM 2.2.3), gnome sort dominated 8 of 10 populations. By the final two generations, more than half of all SSL participants used gnome sort.

Participants successfully transmitted selection sort and gnome sort from person to

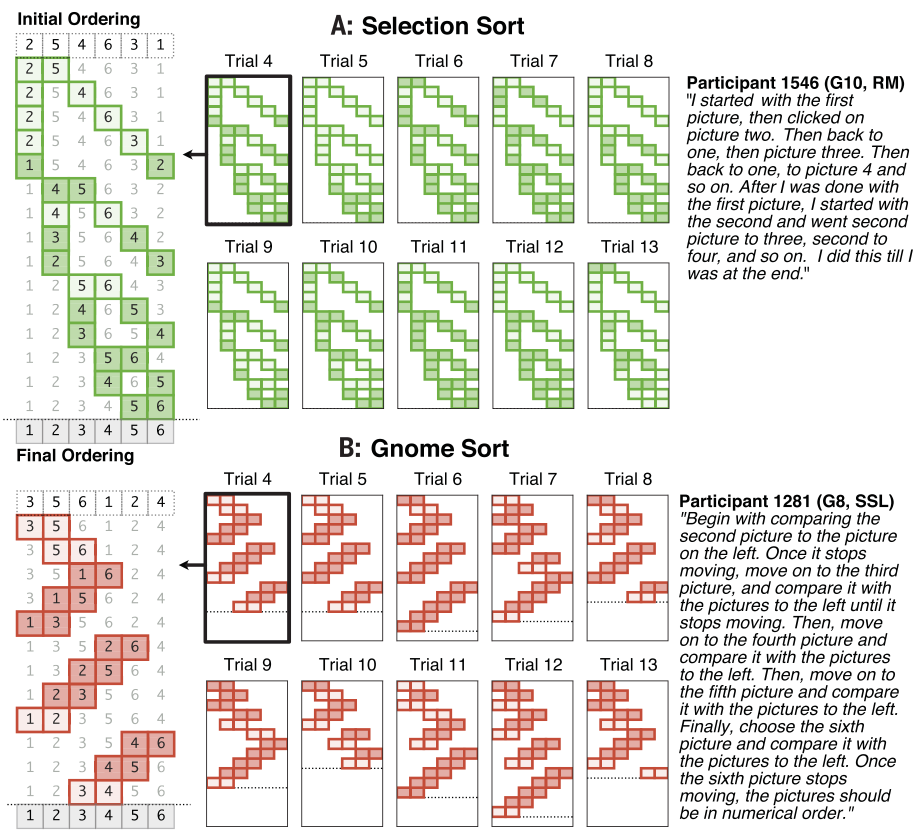


**Fig. 3. Selection sort and gnome sort.** (**A** and **B**) Strategy descriptions and executions by participants using selection sort [(A); participant 1546] and gnome sort [(B); participant 1281]. Squares show swap (solid) or no swap (transparent). G, generation.

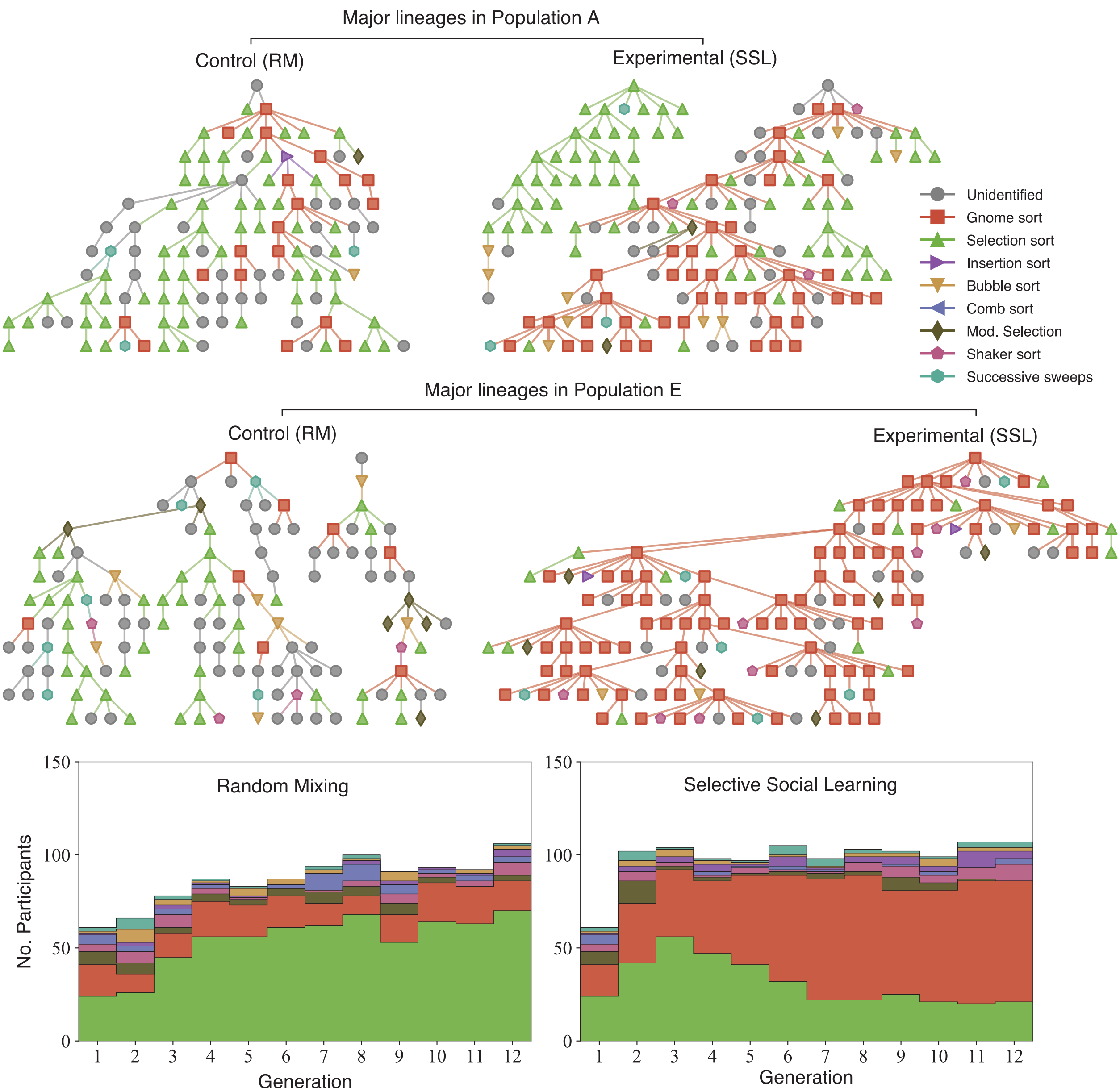


**Fig. 4. Algorithm lineages.** (**Top**) Major lineages (connected subcomponents exceeding 20 participants) in two network pairs. (**Bottom**) Algorithm frequencies under RM (left) and SSL (right).

person. However, transmission fidelity differed (SM 2.3). Selection sort uses a fixed comparison sequence, so it is easier to describe and learn. Several algorithms (e.g., comb sort, bubble sort, insertion sort; SM 4.3) share this property but were rare, suggesting that selection sort is particularly intuitive or memorable [consistent with sequence-learning studies (*29*) and mathematical analyses of attractors (*30*)]. Gnome sort was harder to pass on. Its conditional logic improved performance (sometimes needing only five comparisons) but made the algorithm harder to describe, learn, and use (SM 7). A follow-up study (SM 1.4) showed that transmission of complex algorithms in this task was primarily facilitated by participant demonstrations, not written descriptions (though descriptions do improve transmission; SM 2.1.8). Finally, we found that selective social learning counteracted differences in algorithm transmission fidelity. SSL participants chose higher-performing demonstrators and therefore encountered gnome sort more often (SM 2.4), offsetting the complexity disadvantage at the population level. Numerical simulations support this dynamic (SM 8).

Our study offers insight into one potential mechanism linking sociality and the transmission of complex discoveries, supporting assumptions of mathematical models (*31*). Random mixing led to an evolutionary process shaped by how difficult the algorithms were to learn and convey, favoring highly transmissible algorithms (e.g., selection sort). By contrast, selective social learning led to an evolutionary process heavily influenced by how efficiently participants could solve the underlying problem, favoring more complex algorithms (e.g., gnome sort).

Sequential decision-making problems arise in many higher cognitive functions such as planning, social interaction, navigation, and tool use. Like the sorting problem, these challenges call for procedural strategies that we can follow to reliably achieve a goal when interacting with a dynamic task. Our study showed that a simple form of selective social learning helped populations establish such solutions by increasing the take-up of rare but innovative algorithms. Alternative routes to increased uptake, such as forms of content-biased learning (*13*), may have analogous evolutionary consequences.

Our study does not address potential consequences of population size, demographic profiles, or more complex forms of demonstrator selection that may arise in richer contexts (e.g., strategies that account for potential relationships between expertise and teaching skills). Our findings highlight interactions between reconstructive and preservative aspects of cultural transmission (*30*). Choosing who to learn from helps complex ideas be preserved and built on by future generations in evolving populations.

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## SUPPLEMENTARY MATERIALS

science.org/doi/10.1126/science.abn0915
Materials and Methods
Figs. S1 to S55
Tables S1 to S15
References (*32*, *33*)


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**Humans succeed through social learning**
Our capacity to accumulate complex algorithms over generations allows human beings to adapt to diverse environments and solve challenges that go beyond our individual limitations. However, cultural accumulation of innovative algorithms is difficult to explain. Thompson *et al*. studied a large number of participants to explore the evolution of algorithms under different learning conditions (see the Perspective by Henrich). Selective social learning that involved knowledge of the success level of different strategies or of different models preserved difficult-to-invent, efficient algorithms more than random social learning or one-attempt asocial learning. Two efficient algorithms were used by many people, but the most efficient one only spread under selective social learning. —PRS