Vol. 17 No. 2 (2026) 59–64
Letters on Evolutionary Behavioral Science

Successful Social Learners Can Choose the Better of Two Options: An Agent-Based Simulation

Masayuki Fujita[*], **Yohsuke Ohtsubo**

The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033 Japan

[*]Author for correspondence (marc-fm618@g.ecc.u-tokyo.ac.jp)

It has been argued that the presence of social learning does not increase population-level fitness because its advantage is frequency-dependent: Social learners cannot flourish unless a sufficient number of individual learners make valid information available. However, recent studies suggest that social learners can achieve higher fitness than individual learners even when individual learners are rare. This study investigated the effects of two mechanisms that confer an advantage on social learners over individual learners: information filtering by social learners and information aggregation through a preference for popular options. Using Smolla et al.'s (2015) model of social learning, which incorporated these two mechanisms, we systematically removed either or both of these mechanisms, rendering the study comparable to a 2 (information filtering: absent vs. present) × 2 (information aggregation: absent vs. present) factorial design. In addition, we tested these effects under the conditions with and without resource competition among agents, which was the original variable of interest in Smolla et al.'s study. The results showed that information filtering conferred a fitness advantage on social learners over individual learners especially when no resource competition was involved. In contrast, information aggregation alone was insufficient to help social learners outcompete individual learners.

Keywords
social learning, information filtering, information aggregation, Rogers's paradox, agent-based simulation

Introduction

Social learning refers to a mode of learning through the observation and/or imitation of others. It is widespread across a range of species, from insects and fish to birds and mammals, and humans are no exception (Kameda & Nakanishi, 2002; Kendal et al., 2018; Laland, 2004; Seeley & Buhrman, 2001; Whiten et al., 2022). Despite its prevalence, Rogers's (1988) game-theoretic analysis showed that social learning does not increase population-level fitness (i.e., Rogers's paradox). Social learners benefit from the presence of individual learners who produce valuable information, whereas individual learners do not benefit from the presence of social learners. Accordingly, the fitness of individual learners remains constant regardless of the proportion of social learners. At equilibrium, both social and individual learners have exactly the same level of fitness, which is equivalent to that of individual learners. That is, the population-level fitness at this mixed equilibrium is no different from that of a population dominated entirely by individual learners.

Enquist et al. (2007) challenged Rogers's paradox by introducing a new strategy, critical social learning. An implicit assumption of Rogers's (1988) original model is that individual learners can always choose the best option, whereas social learners simply copy others' behavior regardless of its consequences. In contrast, critical social learners assess the consequences of their copied behavior, and if it proves to be unsuccessful, they switch to individual learning. A population of critical social learners achieves higher fitness than a population of individual learners because they can balance two distinct modes: costly individual learning and cheap social learning. The key to the success of critical social learners is thus their conditional engagement in information production.

Rendell et al.'s (2010) social learning strategies tournament also revealed that social learning can achieve higher fitness in a multi-armed bandit context. Although this setting differs substantially from the context analyzed by Rogers (1988: e.g., individual learners in the multi-armed bandit problem may choose suboptimal options), one of the key features of the winning strategy was again a form of information production: choosing the better option among the options an agent had already learned, which we refer to as *information filtering*. Another notable characteristic of the winning strategy was its discounting of older information in favor of recently acquired information. Based on these results, we surmised that the effect of information filtering might emerge even in the most extreme situation where social learners can only choose between the two most recently learned options.

Rendell et al. (2010) articulated why information filtering is essential for the success of social learners. The comparative advantage of social learners arises from the fact that individual learners search for the better options from the entire set of available options, whereas social learners consider only options chosen by other agents (i.e., options that have already been proven to be better than those agents' previous choices). It is noteworthy that this effect is independent of the effect of *information aggregation*, by which we refer to the tendency for options preferred by a greater number of individuals to be superior to those preferred by a smaller number of individuals (Hastie & Kameda, 2005; Kameda et al., 2022).

doi: 10.5178/lebs.2026.140
Received 07 August 2026.
Accepted 04 September 2026.
Published online 22 September 2026.

We employ Smolla et al.'s (2015) model of social learning (henceforth, the Smolla model) to test the effects of information filtering and aggregation. The Smolla model was proposed to test the effect of resource competition, which is not directly relevant to the purpose of the present study. Nonetheless, it is suited for our purpose because it not only incorporates both information filtering and aggregation by social learners, but also demonstrates that social learners outcompete individual learners regardless of the proportion of individual learners in the population. Thus, the Smolla model provides an adequate context to test the importance of information filtering—whether filtering alone accounts for the superiority of social learning or requires the accompaniment of information aggregation.

Pilot study: replication of the Smolla model

Model

The Smolla model involved 100 agents consisting of individual and social learners, who faced a multi-armed bandit problem in a non-stationary environment. The multi-armed bandit problem was implemented as an exploration-exploitation dilemma across an environment of 100 patches. The resource value of each patch (π) changed with a probability of τ in each round.

At the beginning of round t, each agent decided whether to engage in either exploration or exploitation—learning the resource value of a single patch with probability β (exploration) or collecting payoffs from one of the patches they already knew with probability $1 - \beta$ (exploitation). Those who decided to exploit moved first. Regardless of whether they were individual or social learners, all agents chose the patch from which they anticipated the highest payoff. This operationalization introduced information filtering by social learners, because they stored all learned resource values in memory and selected the best patch to exploit.

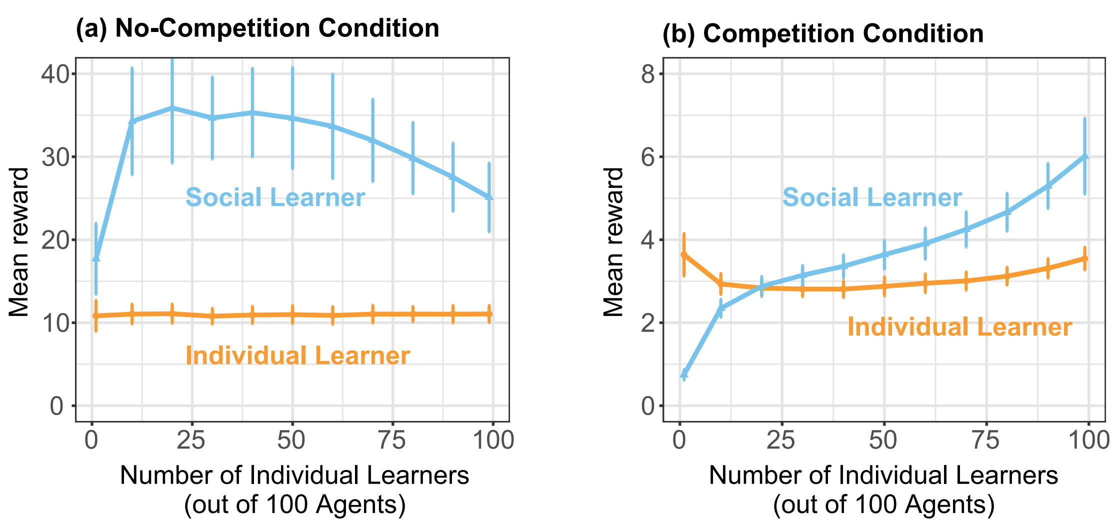
After all exploiting agents completed their moves, the remaining agents learned the resource value of a single new patch without collecting any resources in that round. Individual learners randomly chose one of the 100 patches, whereas social learners chose one of the exploiting agents in round t and learned the resource value π of the patch that the chosen agent was exploiting. This operationalization introduced the information aggregation effect, as social learners were more likely to explore the patches that attracted a larger number of agents in round t.

To investigate the effects of information filtering and aggregation for the main study, we first replicated part of Smolla et al.'s (2015) basic simulation (corresponding to their Analysis 1 and Figures 1a and 1c). Following Smolla et al. (2015), we conducted 100 runs for each frequency of individual learners in the set {0.01, 0.1, 0.2, …, 0.9, 0.99}. For all runs, we set $\tau = 0.01$ and $\beta = 0.2$. The resource value of each patch (π) was independently drawn from a gamma distribution with $k = 0.16$ and $\theta = 25$, which yields an extremely uneven resource distribution across patches with an expected resource value of 4 (see Figure S1): More than 60% of patches contained resource values smaller than 1, while approximately 1% of patches contained resource values greater than 50. Each exploiting agent earned either π in the no-competition condition or π/n in the competition condition, where n is the number of agents who were simultaneously exploiting the same patch. Each run lasted 10,000 rounds, and the last 2,500 rounds were used to determine each agent's fitness (i.e., accumulated resource value).

Results

We successfully replicated Smolla et al.'s (2015) results. In the no-competition condition, social learners outcompeted individual learners regardless of their frequency (Figure 1a, which corresponds to Smolla et al.'s Figure 1a). In contrast, with resource competition, the result was closer to Rogers's model: Social learners performed poorly when individual learners were rare (see Figure 1b, which corresponds to Smolla et al.'s Figure 1c). Conversely, when individual learners were common, social learners outperformed them.

Figure 1
Replication of Smolla et al.'s (2015) results. (a) No-competition condition. (b) Competition condition



Main study

Overview

The purpose of this study was to test the effects of information filtering and aggregation on the performance of social learning. In addition, since Smolla et al. (2015) focused on the effect of resource competition in developing the model we employed, our simulation can be characterized by a 2 (filtering: present vs. absent) × 2 (aggregation: present vs. absent) × 2 (competition: present vs. absent) factorial design.

Conditions

In Condition 1 (filtering and aggregation), both information filtering and aggregation were retained, making this condition similar to the original Smolla model. However, we made one key modification. In the Smolla model, agents could memorize the resource values of all patches they had explored. However, as argued in the introduction, the minimum requirement for information filtering is to compare the two most recent options. Therefore, we restricted social learners' memory capacity to two slots. Consequently, when deciding which patch to exploit in round t, social learners could compare the resource values of only the two most recently learned patches (e.g., Patch A explored in round $t-1$ and Patch B exploited in round $t-2$; Patch C explored in round $t-1$ and Patch D explored prior to Patch C). In contrast, individual learners retained the ability to store the resource values of all patches they had explored. In each round, agents compared the patches in their memory and chose the one that maximized their expected payoff (i.e., π or π/n in the no-competition and competition conditions, respectively).

In Condition 2 (filtering and no aggregation), although social learners were able to store the resource values of the two patches and choose the best patch (as in Condition 1), they no longer retained a preference for popular patches. Instead, social learners in this condition chose a patch for exploration from the currently exploited patches with equal probability, irrespective of the number of agents exploiting those patches.

In Condition 3 (no filtering and aggregation), we deprived social learners of memory capacity. Therefore, social learners in this condition kept blindly exploiting the same patch until they explored another patch with probability $\beta = 0.2$. After exploring a new patch, they again kept exploiting it. Thus, this change removed information filtering by social learners. Nonetheless, as in the original model, social learners were more likely to explore popular patches (i.e., patches currently being exploited by more agents). This tendency usually drives the information aggregation effect.

In Condition 4 (no filtering and no aggregation), social learners were deprived of both memory capacity and the preference for popular patches. Therefore, neither information filtering nor aggregation by social learners was present in this condition.

Results

(1) Without competition

Figure 2 combines four panels, each corresponding to Conditions 1 to 4 in the no-competition condition. It is clear that information filtering was the key to making social learning advantageous over individual learning. With information filtering (Figures 2a and 2b), social learners outcompeted individual learners irrespective of the frequency of individual learners. In contrast, without it (Figures 2c and 2d), individual learners outcompeted social learners irrespective of their frequency. Therefore, it can be concluded that social learning with the information filtering feature is more adaptive than individual learning and this effect does not depend on the frequency of individual learners.

Figure 2 also revealed a generally positive, albeit nuanced, effect of information aggregation. In the presence of information filtering, information aggregation accentuated the advantage of social learners over individual learners (Figures 2a vs. 2b). Conversely, in the absence of information filtering—where individual learners performed better—the presence of information aggregation served to narrow the gap between the two learning strategies (Figures 2c vs. 2d).

(2) With competition

Figure 3 combines four panels, each corresponding to Conditions 1 to 4 in the competition condition. The results revealed that information filtering was necessary for social learners to outcompete individual learners. In the original Smolla et al.'s (2015) simulation, the fitness of social learners exceeded that of individual learners when social learners comprised 20% or more of the population. This pattern was reproduced as far as information filtering was present (Figures 3a and 3b). However, when resource competition was present, the positive effect of information filtering was not enhanced by information aggregation as much as it was when competition was absent (i.e., the difference between Figures 3a and 3b was smaller than that between Figures 2a and 2b). This is understandable because social learners with a preference for popular patches were more likely to concentrate on a small number of patches, thereby reducing each agent's earning (i.e., π/n decreases as n increases). In support of this explanation, individual learners performed slightly better when social learners did not exhibit a preference for popular patches (Figure 3a and 3b).

In the absence of information filtering, social learners never outperformed individual learners, regardless of whether they exhibited a preference for popular patches (Figures 3c and 3d). The effect of information aggregation was consistent with that in the no-competition condition. That is, the presence of information aggregation improved social learners' fitness unless individual learners were rare.

Discussion

This study demonstrated the fitness-enhancing effect of information filtering by social learners. With this ability, social learners were able to achieve higher fitness than individual learners. This pattern was not predicted by Rogers's (1988) classic model, which did not incorporate the possibility of information filtering by social learners. Importantly, achieving this advantage required only a minimal capacity: the ability to choose the better patch from just two options. When resource competition was absent, this minimal level of information-filtering ability enabled social learners to outcompete individual learners

Figure 2
Mean rewards of social and individual learners under no competition as a function of information filtering and aggregation (dotted lines indicate Smolla et al.'s (2015) results)

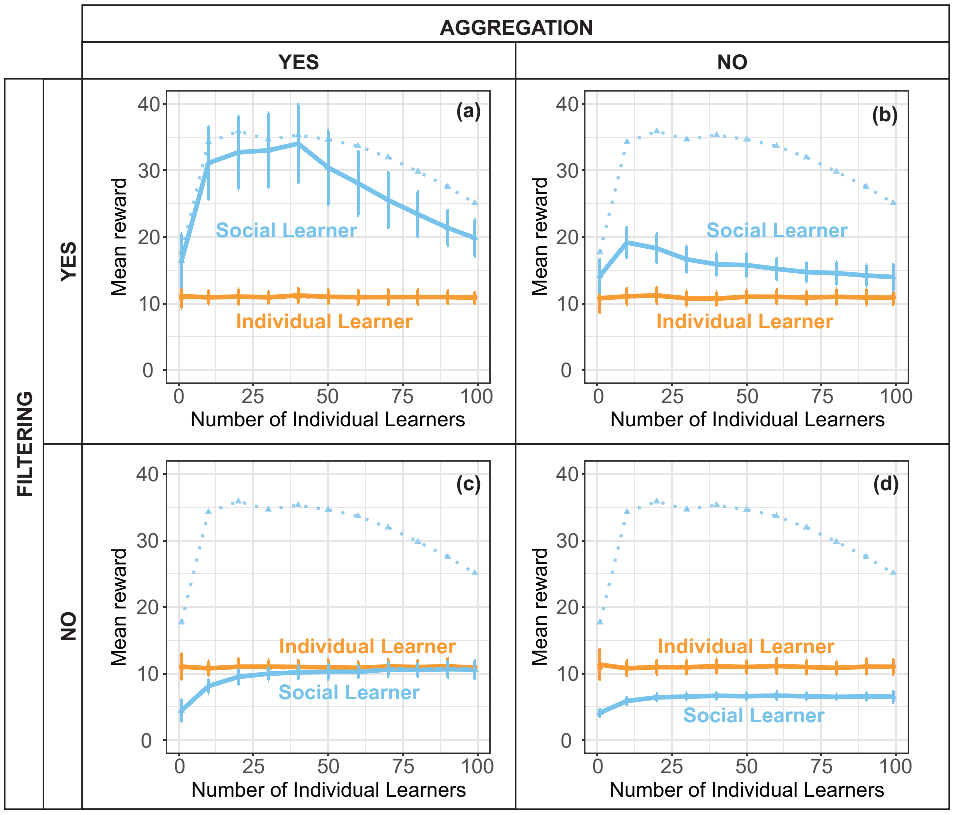
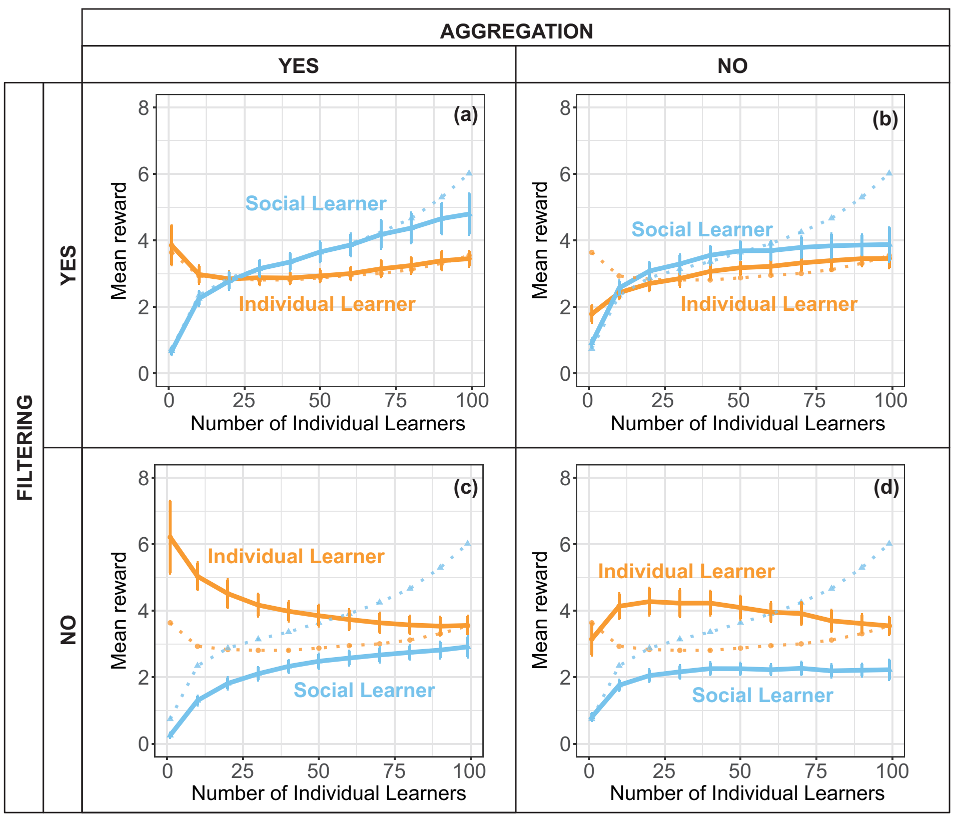


Figure 3
Mean rewards of social and individual learners under competition as a function of information filtering and aggregation (dotted lines indicate Smolla et al.'s (2015) results)



irrespective of their frequency.

Given the implication of Rogers's (1988) classic model, it may seem counterintuitive that social learners' fitness exhibited an inversed-U shape—beyond a certain threshold, it declined as the frequency of individual learners increased in the no-competition condition (Figures 1a, 2a and 2b). This trend is driven by a key assumption of the Smolla model: Only individual learners explore new patches. In other words, the total number of exploited patches monotonically increases as the frequency of individual learners increases. Interestingly, this simple assumption creates two opposing forces. On one hand, social learners benefit from having a larger pool of exploited patches (Figures S6a and S6c). On the other hand, too many options overload social learners' information-filtering capacity—since they compare their current patch with a new patch only once every five rounds on average ($\beta = 0.2$). Consequently, as the frequency of individual learners increases, social learners end up exploiting lower-ranked options (Figures S6b and S6d).

Despite its crucial influence, information filtering was operationalized at its minimal level in this study. To remove this minimal ability, in the no-filtering conditions, we deprived social learners of their ability to compare the patches—leaving them to blindly exploit any patch they happened to visit, regardless of its resource value. Unsurprisingly, such incapacitated social learners were unable to outcompete individual learners who made those patches available. Yet, a puzzling result is that information aggregation still benefited the social learners lacking the ability to evaluate patches, particularly when individual learners were abundant. The apparent puzzle can be resolved by considering who produces information and how. Suppose there are 99 individual learners. An individual learner may discover a highly beneficial patch and exploit it persistently until its resource value changes (with probability $\tau = 0.01$). As the first discoverer stays there for a long time, other individual learners may independently discover the same patch and start exploiting it. This process leads to a positive correlation between patch quality and density. Accordingly, social learners equipped only with a preference for popular patches can still benefit from the information aggregation effect.

One may wonder whether these results are peculiar to the highly skewed resource distribution generated by the gamma distribution with $k = 0.16$ and $\theta = 25$. In Smolla et al.'s (2015) original study, they also employed a different gamma distribution with $k = 16$ and $\theta = 0.25$, which yielded a far less skewed distribution with the same expected mean of 4.00 (see Figure S1). Under this parameter set, approximately 69% of resource values fell between 3 and 5, and less than 0.01% of resource values exceeded 10. We also ran our simulation using this less skewed gamma distribution and report the results in the Supplementary Material. As shown in Figures S2 and S3, the less skewed resource distribution did not change the qualitative conclusions. In addition, as further robustness checks, we performed two sets of supplementary simulations: first, repeating the basic simulation (Figures 2a) under varying values of τ, and second, reproducing the information aggregation simulations (Figures 2b and 3b) with social learners endowed with full memory capacity (see Robustness Checks 1 and 2 in Supplementary Material). These modifications did not alter any of the qualitative conclusions.

In summary, this study highlighted the importance of information filtering in social learning. Despite its effectiveness, this minimal ability still critically relies on the exploration efforts of individual learners. Without their exploration, few options are made available to social learners, rendering their information-filtering ability useless. Future studies should investigate the optimal balance between individual learners' exploration and social learners' filtering.

Acknowledgments

We would like to thank the 2025 members of the Ohtsubo lab (University of Tokyo, Department of Social Psychology) for their helpful advice. This study was financially supported by the Ministry of Education, Culture, Sports, Science and Technology–Japan (Grant#: 24H02200).

Author contribution

Masayuki Fujita: Conceptualization, Methodology, Formal analysis, Investigation, Visualization, Writing – Original Draft. **Yohsuke Ohtsubo:** Conceptualization, Methodology, Supervision, Writing – Review & Editing.

Data accessibility & program code

All code (Python code for simulation and R code for visualization) is available on the Open Science Framework (https://osf.io/hf2xj/).

Supplementary material

Electronic supplementary materials are available online.

References

Enquist, M., Eriksson, K., & Ghirlanda, S. (2007). Critical social learning: A solution to Rogers's paradox of nonadaptive culture. *American Anthropologist*, *109*(4), 727–734. https://doi.org/10.1525/aa.2007.109.4.727

Hastie, R., & Kameda, T. (2005). The robust beauty of majority rules in group decisions. *Psychological Review*, *112*(2), 494–508. https://doi.org/10.1037/0033-295X.112.2.494

Kameda, T., & Nakanishi, D. (2002). Cost–benefit analysis of social/cultural learning in a nonstationary uncertain environment: An evolutionary simulation and an experiment with human subjects. *Evolution and Human Behavior*, *23*(5), 373–393. https://doi.org/10.1016/S1090-5138(02)00101-0

Kameda, T., Toyokawa, W. & Tindale, R. S. (2022). Information aggregation and collective intelligence beyond the wisdom of crowds. *Nature Review Psychology*, *1*(6), 345–357. https://doi.org/10.1038/s44159-022-00054-y

Kendal, R. L., Boogert, N. J., Rendell, L., Laland, K. N., Webster, M., & Jones, P. L. (2018). Social learning strategies: Bridge-building between fields. *Trends in Cognitive Sciences*, *22*(7), 651–665. https://doi.org/10.1016/j.tics.2018.04.003

Laland, K. N. (2004). Social learning strategies. *Learning & Behavior*, *32*(1), 4–14. https://doi.org/10.3758/BF03196002

Rendell, L., Boyd, R., Cownden, D., Enquist, M., Eriksson, K., Feldman, M. W., Fogarty, L., Ghirlanda, S., Lillicrap, T., & Laland, K. N. (2010). Why copy others? Insights from the social learning strategies tournament. *Science*, *382*(5975), 208–213. https://doi.org/10.1126/science.1184719

Rogers, A. R. (1988). Does biology constrain culture? *American Anthropologist*, *90*(4), 819–831. https://doi.org/10.1525/aa.1988.90.4.02a00030

Seeley, T. D., & Buhrman, S. C. (2001). Nest-site selection in honey bees: How well do swarms implement the "best-of-N" decision rule? *Behavioral Ecology and Sociobiology*, *49*, 416–427. https://doi.org/10.1007/s002650000299

Smolla, M., Gilman, R. T., Galla, T., & Shultz, S. (2015). Competition for resources can explain patterns of social and individual learning in nature. *Proceedings of the Royal Society B: Biological Sciences*, *282*(1815), Article 20151405. https://doi.org/10.1098/rspb.2015.1405

Whiten, A., Harrison, R. A., McGuigan, N., Vale, G. L., & Watson, S. K. (2022). Collective knowledge and the dynamics of culture in chimpanzees. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *377*(1843), Article 20200321. https://doi.org/10.1098/rstb.2020.0321