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The Castaway Island: Distinct Roles of Theory of Mind and Technical Reasoning in Cumulative Technological Culture

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Running Head:

Theory of Mind, Technical Reasoning, and Cumulative Culture

Abstract

Cumulative technological culture is an intriguing phenomenon whose cognitive bases remain a matter of debate. For the influential shared-intentionality theory, this phenomenon originates in theory-of-mind skills. Evidence challenges it, stressing the role of learners' technical-reasoning skills. This discrepancy might be explained by a more specific role of theory-of-mind skills, notably in situations where the teacher communicates with the learner without visual access to what the latter is doing. We tested this hypothesis using a micro-society paradigm where participants ($n = 200$) had to build the highest possible tower in two conditions: Monitoring (communication with visual access) and Blind (communication without visual access). We also assessed participants' theory-of-mind and technical-reasoning skills. Results indicated that learners' technical-reasoning skills predicted cumulative performance in both conditions, whereas teachers' theory-of-mind skills were involved only in the Blind condition. These findings confirm the distinct but complementary roles of theory-of-mind and technical-reasoning skills in cumulative technological culture.

Keywords: Cumulative Technological Culture; Theory of Mind; Technical Reasoning; Social Learning.

Introduction

Imagine you were shipwrecked and washed up on a desert island, with other castaways including Robinson, Alexandre, Daniel, Tom, and Wilson. To increase your chance of survival, it is very likely that you attempt to make tools (e.g., knife) and build constructions (e.g., shelter). Interestingly, a phenomenon seems to take place: You progressively share information between castaways so the amount of techniques developed on that island goes beyond what you were able to invent individually. This phenomenon, called cumulative technological culture, corresponds to the accumulation of socially learned information over generations, allowing humans to develop technologies (i.e., tools and constructions) that are too complex to have been invented by a single individual (Boyd & Richerson, 1996; Dean, Kendal, Shapiro, Thierry, & Laland, 2012; Tomasello, Kruger, & Ratner, 1993). It is driven by two engines (Legare & Nielsen, 2015): Imitation (i.e., copying a trait with high fidelity) and innovation (i.e., improving that trait). Although technological culture is relatively common in nonhuman animals, there is little evidence of cumulative technological culture in species other than humans (Whiten, 2011; Whiten, Horner, Marshall-Pescini, 2003; Whiten & van Schaik, 2006), raising the intriguing issue of the cognitive bases underlying this phenomenon.

The influential shared-intentionality theory posits that cumulative technological culture – and particularly the underlying imitative component – originates in the human ability to understand and share intentions with conspecifics (i.e., theory-of-mind skills; Hermann, Call, Hernandez-Lloreda, Hare, & Tomasello, 2007; Tomasello, Carpenter, Call, Behne, & Moll, 2005; Tomasello et al., 1993). By sharing intentions with a learner, a teacher can grasp the cognitive representations of the learner's behavior and, therefore, give appropriate feedback to help the learner copy the end-product. Therefore, to take place, cumulative technological culture

necessarily needs people to have face-to-face interactions to exchange information. For instance, because of his ability to understand your intentions, Robinson can give you appropriate feedback to help you build a shelter. Thus, Robinson, who is the best pedagogue of your group, should transmit the greatest number of techniques among your group.

In recent years, this prediction has been partially invalidated by studies using micro-society paradigms that have reported cumulative performance in reverse engineering conditions, where participants can only scrutinize predecessors' end-products (e.g., you stumble upon a knife made by Wilson and, after scrutinizing it very carefully, you reproduce it; Caldwell & Millen, 2009; Caldwell, Renner, & Atkinson, 2017; Zwirner & Thornton, 2015), and, to a lesser extent, in observational conditions where communication is not allowed (e.g., you observe Wilson making a knife without communicating with him; Caldwell & Millen, 2008, 2009; Osiurak et al., 2016). These findings have led to consider that technological cumulative culture might be mainly supported by the ability to reason about physical object properties, hereafter called technical-reasoning skills (Osiurak et al., 2016; Zwirner & Thornton, 2015). These skills might help the learner to extract relevant information from either the end-product itself or teacher's demonstration/advices in order to reproduce the end-product (i.e., imitation) but also to detect irrelevant information in order to improve the end-product (i.e., innovation). Said differently, technical reasoning might be critical not only in reverse engineering conditions (e.g., Wilson's knife) but also in observation conditions (e.g., observing how Wilson makes his knife) or teaching (e.g., Robinson teaches you how to build a shelter). This interpretation is consistent with evidence from neuropsychology and neuroimaging demonstrating that technical-reasoning skills are critical to tool use and tool making (Goldenberg & Hagmann, 1998; Goldenberg & Spatt, 2009; for reviews, see Osiurak & Badets, 2016; Osiurak & Heinke, 2018; Osiurak, Jarry, & Le Gall, 2010; Reynaud, Lesourd, Navarro, & Osiurak, 2016). Support for this view also

comes from a recent study showing that technical-reasoning skills (particularly learners') are a better predictor of cumulative performance than theory-of-mind skills in both an observation condition (the learner could observe the teacher without communicating) and a communication condition (the teacher could both observe the learner and communicate with her/him; Osiurak et al., 2016).

Although these findings have emphasized the key role of technical reasoning, they do not rule out the importance of theory-of-mind skills in cumulative technological culture, particularly in at least two specific contexts. The first concerns the opacity/transparency of the end-product (i.e., the amount of information directly provided by the end-product to understand how it is built). Theory-of-mind skills may be far more involved when the end-product is opaque than transparent because of the need for additional information to infer the making process (Wasielewski, 2014; see also Caldwell et al., 2017; Morgan et al., 2015; Stout & Hecht, 2017). The second is fully within the scope of the present study and concerns the amount of visual information available to the teacher. To grasp this second aspect, let us distinguish between two extreme situations, namely, "everything-is-present" situations and "nothing-is-present" situations. The former correspond to situations where visual information about what the learner is doing is available to the teacher in real time (e.g., both the learner and the teacher are side by side during the task). The latter correspond to situations where this visual information is absent (e.g., the teacher cannot observe what the learner is doing). Based on the aforementioned findings, teacher's theory-of-mind skills might be useful but not necessarily fundamental in everything-is-present situations, because learner's technical-reasoning skills can be sufficient to extract relevant information from the teacher's demonstration/advice (for a somewhat similar view, see Tennie, Braun, Premo, & McPherron, 2016). In addition, in such situations, the teacher can understand more easily learner's intentions by observing what s/he is doing and can also

provide direct feedback (e.g., pointing) if s/he is staying by the learner's side. So, the role of teacher's theory-of-mind skills may be limited in this case in that even people with a low level of theory of mind can succeed to transmit information. Things are different for nothing-is-present situations. If a teacher intends to transmit to a learner how to build an artifact, without watching what the learner is doing, theory-of-mind skills might be required in order to allow the teacher to understand the learner's mental states if only to know what the learner knows about the building process. Those situations demand a high level of pedagogy: If you meet Robinson by the lake, he could explain you how to build a shelter even in the absence of any raw material, simply because he is a good pedagogue, able to understand your cognitive representation and to guide you along the building process only with his words. As illustrated in this example, theory-of-mind skills might also be implicated in the choice of the terms used in order to ensure that the terms expressed are comprehensible by the learner. Even if learners' technical-reasoning skills might remain critical whatever the context, we hypothesize that theory-of-mind skills (particularly teachers') are more heavily and specifically engaged in nothing-is-present situations.

The aim of the present study is to test this hypothesis in order to provide new insights into the cognitive bases of cumulative technological culture. To do so, we used a micro-society paradigm where participants had to build the highest possible tower. They performed the task as a member of a chain of 10 participants. There were two conditions. In both of them, the teacher and the learner could communicate verbally, but the teacher could not see *directly* the learner's actions. In the Monitoring condition, teachers could nevertheless observe in real time what the learner was doing on a computer screen via a webcam focused on the learner's actions. This condition was introduced in order to prevent the teacher from interacting directly with the learner, thereby increasing the distance of transmission compared to previous conditions we tested elsewhere (i.e., observation and communication, see above; Osiurak et al., 2016). In the

Blind condition, the teacher had no visual information about what the learner was performing. This condition is very close to the description of nothing-is-present situations presented above. We also added a Control condition to verify that social transmission allowed significant improvement over generations compared to individual learning with a single participant (Mesoudi & Whiten, 2008; Miton & Charbonneau, 2018). We also measured participants' technical-reasoning and theory-of-mind skills. We predicted that learners' technical-reasoning skills were the best predictor of cumulative performance in both micro-society conditions. We also hypothesized that teachers' theory-of-mind skills should also predict cumulative performance, but only in the Blind condition, an instance of nothing-is-present situations.

Method

Participants

Two hundred and ten undergraduate students in cognitive sciences at the University of Lyon ($M_{\text{age}} = 19 \pm 1.4$; 132 females) took part in the experiment. Two hundred were assigned to the Monitoring and Blind conditions of the micro-society paradigm ($n = 100$ for each condition) and the remaining 10 to the Control condition. The sample size was estimated from the results of Caldwell and Millen (2009) and Osiurak et al. (2016) who used the same paradigm as in the present work (i.e., conditions with 10 chains of 10 participants each). The study was approved by the local ethics committee, and informed consent was obtained from all participants.

Materials and Procedure

The task of the main experiment was to build the highest possible tower with 15 metal wires (20-cm long). Participants carried out the task as a member of a chain of 10 participants, each of whom performed the task one after the other. After completing the task, each participant

could help the subsequent participant by communicating verbally with her/him. So, each participant was first a learner (Building; 5-min long) and then a teacher (Teaching; 5-min long), except Participants 1 who had to perform the task alone without help from a teacher and Participants 10 who were only learners (**Figure 1**). Each pair of participants was sitting on two chairs back to back so that the teacher could not see *directly* the learner's actions. In the Monitoring condition, the teacher could nevertheless observe in real time what the learner was doing on a computer screen via a webcam focused on the learner's actions (**Figure 1**). In the Blind condition, the teacher had no visual information about what the learner was performing (i.e., back to back without the webcam feedback; **Figure 1**). In the Control condition, each participant had to build 10 different towers, without any interaction with other participants. The main measure was the height of towers in cm. After each building phase, each tower was positioned vertically and the measure was taken only after 10s. Therefore, the measure was sometimes taken on towers that had fallen down. The height corresponded to the distance between the table and the highest vertical point of the tower, but not to the total length of the tower.

< INSERT FIGURE 1 ABOUT HERE >

After the main experiment, participants took part in an additional testing session in order to assess their technical-reasoning and theory-of-mind skills (for a similar procedure, see Osiurak et al., 2016). For technical-reasoning skills, they had to complete two sub-tests of the NV7 battery (Bernaud, Priou, & Simonnet, 1994; NV7a: e.g., selecting among four pictures depicting four different nails the easiest one to hammer; 24 items; time limit: 5min; NV7b: e.g., selecting among four 3D geometrical shapes the one corresponding to a given 2D pattern; 38 items; time limit: 5min). These two sub-tests are psycho-technical tests aiming to assess the understanding of

how the physical world works (particularly the NV7a sub-test). The items are very similar to those used in experimental studies on mechanical reasoning (e.g., water pouring problems or pulley problems; for more detail, see Hegarty, 2004). Besides, even if these sub-tests may seem close to non-verbal, logical reasoning tests (e.g., matrix tests), they are not, because they clearly require understanding mechanical principles to be solved (e.g., knowing which nail is the easiest one to hammer necessarily needs a good understanding of the underlying mechanical principles such as percussion), which is not required in logical reasoning tests (e.g., solving matrix problems needs inductive and deductive reasoning, but no specific mechanical knowledge). We also have unpublished data from 400 participants, which confirm the orthogonality between technical-reasoning skills (assessed with both NV7a and NV7b sub-tests) and logical-reasoning skills (assessed with matrix and domino series tests) from correlational and factorial analyses. Theory-of-mind skills were measured with two tests. The first is the “Reading-the-Mind-in-the-Eyes” (RME) test (Prevost et al., 2014). It consists in choosing which of four words best describes what the person in the photograph is feeling or thinking (36 items; time limit: 3min). The second, the comic strip (CS) task (Sarfati, Hardy-Baylé, Besche, & Wildlöcher, 1997), corresponds to short three-pictures comic strips, showing a character performing a very simple action. The task is to choose which one of three answer cards is the most logical to complete the comic strip sequence (28 items; time limit: 2min). For each test, we recorded the number of correct responses given within the time limit. We conducted a factorial analysis with varimax rotation to confirm that each pair of tests (NV7a and NV7b versus RME and CS) was associated with the specific cognitive skills expected. We obtained a two-factor solution accounting for 73% of total variance (Factor 1: 39%; Factor 2: 34%). Factor 1 loaded on NV7a (.85) and NV7b (.84) and Factor 2 on RME (.91) and CS (.71). These results replicated those previously obtained with the same procedure by Osiurak et al. (2016; Pilot study [$n = 190$]: Factor 1: 39% of

variance; NV7a: .82; NV7b: .78; Factor 2: 32% of variance; RME: .94; CS: .61; Main study [$n = 200$]: Factor 1: 36% of variance; NV7a: .80; NV7b: .82; Factor 2: 35% of variance; RME: .90; CS: .73). To sum up, these analyses confirmed that NV7a/NV7b and RME/CS were orthogonal measures of technical-reasoning and theory-of-mind skills, respectively. We used the factor scores obtained from the corresponding factorial analysis as indicators of participants' technical-reasoning and theory-of-mind skills.

Results

Results of the two micro-society conditions (Monitoring and Blind) and the Control condition are displayed in **Figure 2**. In each condition, we tested for cumulative performance by using the nonparametric Page's test (Caldwell & Millen, 2009). There was a significant improvement over generations for the two micro-society conditions (Monitoring: $p < .001$; Blind: $p < .05$) as well as for the Control condition ($p < .05$). The Page's test is very sensitive in that even a single step-wise increase can lead to a significant test result (Reindl & Tennie, 2018). So, as recommended by Reindl and Tennie (2018), we confirmed our results from Page's test with an Linear Mixed Model (LMM) using R (R Core Team, 2013) with tower height as dependent variable, generation (i.e., position of the participant in the chain) as fixed effect and chain number as a random effect using the "lmer" function of the R package lme4 (Bates, Maechler, Bolker, & Walker, 2013)¹. For each condition, we tested the overall significance of the model by comparing the conditional model to a null model lacking generation and chain

¹ LMM allows to combine in a single predictive model both random and fixed effects. The dependent variable, in our case tower height, can be modeled as a linear combination of the variables in the model, with fixed coefficients (i.e., slope and intercept of the regression) for the fixed factors, in our case the generation (i.e., position of the participant in the chain) and coefficients that can vary within certain limits for the random effects, in our case the chains (i.e., chain number). The LMM regresses data with a fixed slope and intercept for all generations, pooled over all chains, but also assumes that intercepts and slopes can vary within each chain. This allows to take into account the possible variation that can exist between different chains of participants: If chains were not considered as a random effect, and, as a consequence, all data from all chains were pooled together, then the trend within each chain would not be considered by the model. In other words, modeling the chain factor as a random effect allows each chain to behave similarly but not strictly identically with each other.

number as a random effect with an F -test. This analysis confirmed the results obtained from Page's test with an effect of generation for the three conditions (Monitoring: $p < .001$; Blind, $p = .05$; Control: $p = .02$). To examine whether cumulative performance was higher in the micro-society conditions than in the Control condition, we computed for each condition a Δ -score defined as the mean performance of the last 3 participants (attempts in the Control condition) minus the mean performance of the first 3 participants (attempts in the Control condition; **Figure 2**). This measure inspired from Caldwell and Millen (2009; see also Reindl & Tennie, 2018) allows to better reflect the general increase of performance between early and late generations compared to a global measure of cumulative performance taking into consideration all the generations, which can mask differences between conditions, notably if these differences emerge later in the chains. This Δ -score was submitted to Mann-Whitney comparisons, indicating that the Δ -score was higher ($p = .03$) in the Monitoring condition ($M = 17.73\text{cm}$, $95\% \text{ CI} = 10.41\text{cm}–25.05\text{cm}$) than in the Control condition ($M = 6.40\text{cm}$, $95\% \text{ CI} = -5.41\text{cm}–18.21\text{cm}$). The Blind condition ($M = 8.20\text{cm}$, $95\% \text{ CI} = 1.48\text{cm}–14.92\text{cm}$) did not differ significantly from the two other conditions (both $p > .30$).

< INSERT FIGURE 2 ABOUT HERE >

As mentioned, we were interested in predicting cumulative performance based on technical-reasoning and theory-of-mind skills. Our four predictors were as follows:

- ToM_L: Learner's theory-of-mind skills;
- ToM_T: Teacher's theory-of-mind skills;
- Tech_L: Learner's technical-reasoning skills;
- Tech_T: Teacher's technical-reasoning skills.

As mentioned above, we hypothesized that (1) learners' technical-reasoning skills were the best predictor of cumulative performance in both micro-society conditions and (2) teachers' theory-of-mind skills should also predict cumulative performance, but only in the Blind condition. Given that we did not have any documented evidence of potential interactions between technical-reasoning skills and theory-of-mind skills, we considered their influence as additive. So, for each micro-society condition (Monitoring and Blind), the influence of the aforementioned four predictors on tower height was tested using a LMM, in which they were included as fixed factors, while generation and chain number were included as random factors using R (see above). All the 15 possible additive models were considered, exploring the whole possible model space. All models were then ranked according Akaike's Information Criterion corrected for small samples (AICc). Following Burnham and Anderson (2002), we considered models with $\Delta_i < 2$, Δ_i being the distance to the best-ranked model according to AICc, as having substantial support (evidence). For both conditions, we selected the two top candidate models with $\Delta_i < 2$ (see model selection table in **Table 1**). We conducted conditional-model averages based on AICc (**Table 2**) using package AICcmodavg. We estimated for each predictor variable its relative importance (Importance weight + CI) by summing the Akaike weights (model probabilities) of the selected models including the variable. As a result, the variable with the biggest predictor weight is supposedly the most important predictor and, at the contrary, the one with the smallest sum is estimated to be the weakest predictor. The only statistically significant predictors of cumulative performance are Tech_L in the Monitoring condition (Importance weight: 0.95; Estimate±Standard Error: 5.89±2.12) and both ToM_T and Tech_L in the Blind condition (Importance weight: 0.95 and 0.80, respectively; Estimate±Standard Error: 4.99±1.70 and 3.82±1.67, respectively). All these variables were significant at the 95% confidence level (the intervals did not contain the null value).

< INSERT TABLES 1 AND 2 ABOUT HERE >

Discussion

The first key finding of our study is that learners' technical-reasoning skills are a good predictor of cumulative performance in both Monitoring and Blind conditions, corroborating previous results obtained in other contexts of social transmission (i.e., observation and communication) with a different task (i.e., airplane building; Osiurak et al., 2016). In other words, the role of technical-reasoning skills in cumulative technological culture might be both context-general and task-general. These findings suggest that even early signs of cumulative technological culture could have been mainly based on the ability to extract relevant and reject irrelevant technical information from teachers'/predecessors' demonstration/advice (Osiurak, 2017; Zwirner & Thornton, 2015; see also Enquist & Ghirlanda, 2007; Vaesen, 2012). The technical-reasoning hypothesis appears to be an appropriate alternative to the shared-intentionality hypothesis, providing a parsimonious way to explain not only how people copy predecessors' technologies but also improve them (i.e., the dual engines of cumulative technological culture; Legare & Nielsen, 2015). Moreover, it can also offer a new insight into how creative technical solutions can emerge from the interaction between individuals' technical-reasoning skills and social transmission/collaboration. For instance, an individual can provide an original, but unfeasible technical solution (because of poor technical-reasoning skills), which can be a source of inspiration for another one, who is able to make it feasible (because of good technical-reasoning skills), thereby generating an original and adapted technical solution, namely, the two key components of a creative production (Guildford, 1967). Nevertheless, the involvement of technical-reasoning skills might remain domain-specific, being involved only in the technological domain and not in other domains (e.g., mathematics), where other specific

cognitive skills could come into play (e.g., logical reasoning). Further research is needed to explore this issue.

The second key finding is the involvement of teachers' theory-of-mind skills in the Blind condition only, confirming our main hypothesis. As mentioned, this condition can be considered as an instance of nothing-is-present situation, where a heavy demand is placed upon the teacher to acquire and transmit information via verbal communication in order to form an accurate representation of what the learner is doing and intends to do. Although theory-of-mind skills might not be critical *per se* to cumulative technological culture, its potential influence in nothing-is-present situations should not be underestimated if we consider the frequency of such situations in everyday life. Just think about how knowledge, in general, is conveyed in schools, where teachers transmit information, without learners directly observing the phenomena described. This also implies that theory-of-mind skills could have boosted cumulative technological culture, freeing humans from being in concrete situations (i.e., presence of materials and demonstration) to acquire and transmit new information about, for instance, how to build a bridge or make a knife. Besides, contrary to technical-reasoning skills, theory-of-mind skills might not be domain-specific (i.e., specific to technology or mathematics, for instance) but rather context-specific, with a greater involvement in non-concrete situations (Morgan et al., 2015). Further research is needed to explore this possibility, which may help us to specify the role of theory of mind in human evolution.

The third and last key finding concerns the presence of greater cumulative performance in the Monitoring condition and not in the Blind condition, when compared to the Control condition. This confirms that cumulative technological culture is more likely to take place as the amount of information that teachers and learners exchange increases (i.e., Monitoring > Blind;

for somewhat similar results, see Caldwell & Millen, 2009; Morgan et al., 2015; Osiurak et al., 2016). A more tricky issue concerns the absence of difference between the Blind condition and the Control condition. This finding may be interpreted in terms of the ratio collaboration/competition that may occur in social learning (for discussion on social learning strategies, see Kendal et al., 2018; Laland, 2004). The added value of social learning is to provide learners with ideas they would not have thought of on their own (Tomasello et al., 1993). Ideally, this learning is collaborative when the learner can integrate progressively new information from the teacher while performing the task, as in the Monitoring condition or, more generally, in situations where both the learner and the teacher are side by side. This transmission may, however, be competitive if the learner has to spend considerable time to understand what the teacher is attempting to explain, the learner's focus being more on the adjustment of a shared representation of the task instead of on the task itself. This may be the case in the Blind condition or, more generally, in nothing-is-present situations. Whatever it might be, this finding tells us that social learning does not always outperform individual learning and that learners may need time and individual practice to integrate new social information as suggested by the helical curriculum mechanism depicted by Whiten (2015).

Context of the Research

More broadly, the present study offers original insights into the role played by learners and teachers in the social transmission process. In line with the literature, we have called “teacher” an individual using verbal communication to transmit information, the term “model” being generally preferred for an individual transmitting information without verbal communication (i.e., observation-only conditions). The notion of pedagogy is orthogonal to this verbal/non-verbal distinction. Simply, a pedagogue is an individual excelling in the ability to

transmit information whatever the context of social transmission, for instance, by presenting the learner with an organized and logical sequence of information as well as by slowing her/his actions/speech flow and using terms appropriate to the level of the learner. As suggested by the shared-intentionality theory, theory-of-mind skills might be the main determinant of pedagogical skills, and the present findings corroborate this, showing that non-concrete situations put heavy demands on pedagogy, revealing the need for a high level of theory-of-mind skills to ensure the transmission.

Having said this, the key issue is what is the part of variance explained by teachers' theory-of-mind/pedagogical skills and learners' domain-specific cognitive skills (i.e., technical-reasoning skills here) in the social transmission process? Here we show that learners' technical-reasoning skills are a systematic predictor of cumulative performance in both conditions, confirming previous findings obtained in another communication condition but also in an observation condition (Osiurak et al., 2016). In other words and in the broader context of education, this questions the folk belief that social transmission is mainly based on pedagogy. Instead, most of the variance might be explained by learners' domain-specific cognitive skills rather than by teachers' pedagogical skills: Good Student*Good Pedagogue: 20/20 in statistics; Good Student*Poor Pedagogue: 16/20; Poor Student*Good Pedagogue: 5/20; Poor Student*Poor Pedagogue: 4/20; 80% of variance explained by Factor: Student; 20% of variance explained by Factor: Pedagogue. In a way, this hypothetical view might be reflected in the success of students of reputed universities or schools, which might much more depend on the quality of the selection of students – i.e., students who can compensate the lack of pedagogy of some of their teachers by understanding, for instance, what a teacher is explaining even if that teacher is explaining it very poorly – rather than on the quality of pedagogy of their teachers. At this point, the issue is: How does a learner develop domain-specific skills if, at each learning phase, the role of the teacher is

minimal? First, remind that teachers remain fundamental for social transmission. Even if they cannot be pedagogues, they can nonetheless be a source of information whose quality transmitted depends on learners' domain-specific skills. There is always something that is transmitted, so that everyone can learn new information even when confronted only with poor teachers. Second, the role of teachers might be limited to help learners to reach the upper limit of what they can learn in a given situation (i.e., the aforementioned 20% of variance), an idea very close to the concept of proximal developmental area (Vygotsky, 1978). In this case, a pedagogue following a learner on mid/long-term could help her/him to progressively increase her/his level of skills (e.g., from 5/20 to 7/20, then from 7/20 to 10/20, and so on). This optimistic view is however based on the idea of tutorial, which is not as frequent as it might be, particularly in the educational context where organizational pressure generally leads to group teaching instead to individualized programs. Future research is needed to explore these avenues, which could help us to better understand the real role played by pedagogy in cumulative technological evolution and, more broadly, in education.

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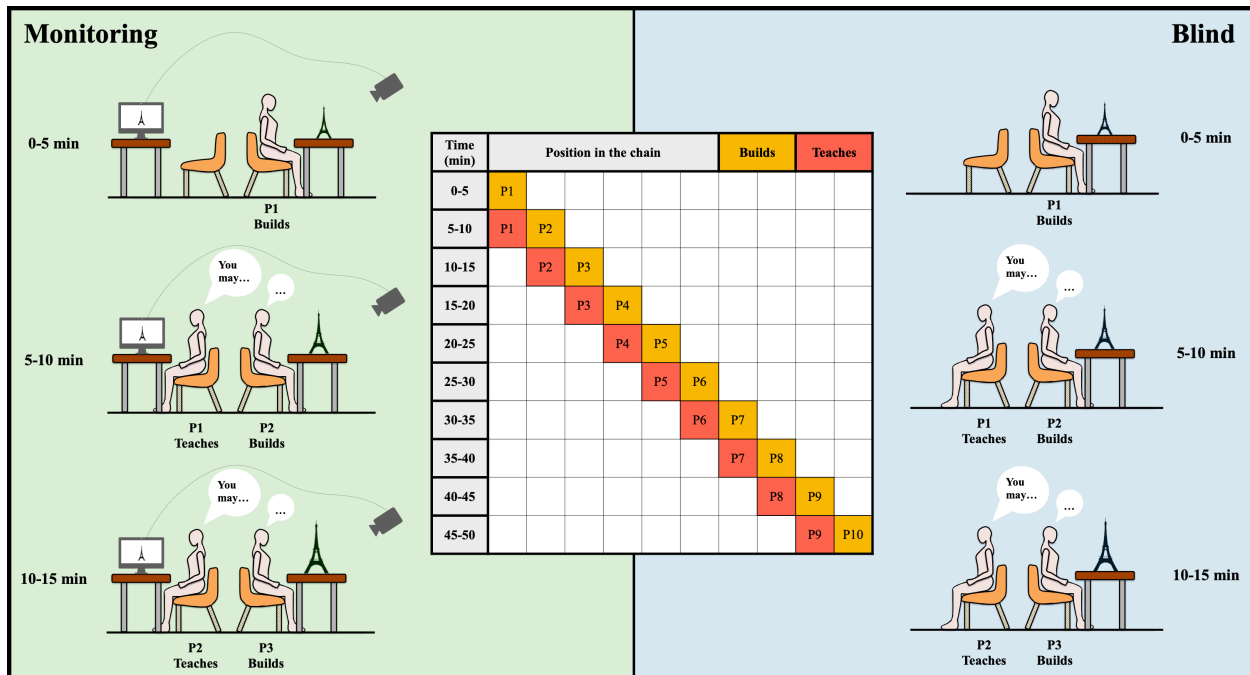


Figure 1. Schematic illustration of the two micro-society conditions. The task was to build the highest possible tower. Participants performed the task as a member of a chain of 10 participants, each of whom completed the task one after the other. After completing the task, each participant could help the subsequent participant by communicating verbally with her/him. So, each participant was first a learner (Building; 5-min long; in orange) and then a teacher (Teaching; 5-min long; in red), except Participants 1 who had to perform the task alone without help from a teacher, and Participants 10 who were only learners (Central Panel). Each pair of participants was sitting on two chairs back to back so that the teacher could not see directly the learner's actions. In the Monitoring condition, the teacher could nevertheless observe in real time what the learner was doing on a computer screen via a webcam focused on the learner's actions (Left Panel). In the Blind condition, the teacher had no visual information about what the learner was performing (i.e., back to back without the webcam feedback; Right Panel). Only the three first building phases are illustrated for both conditions.

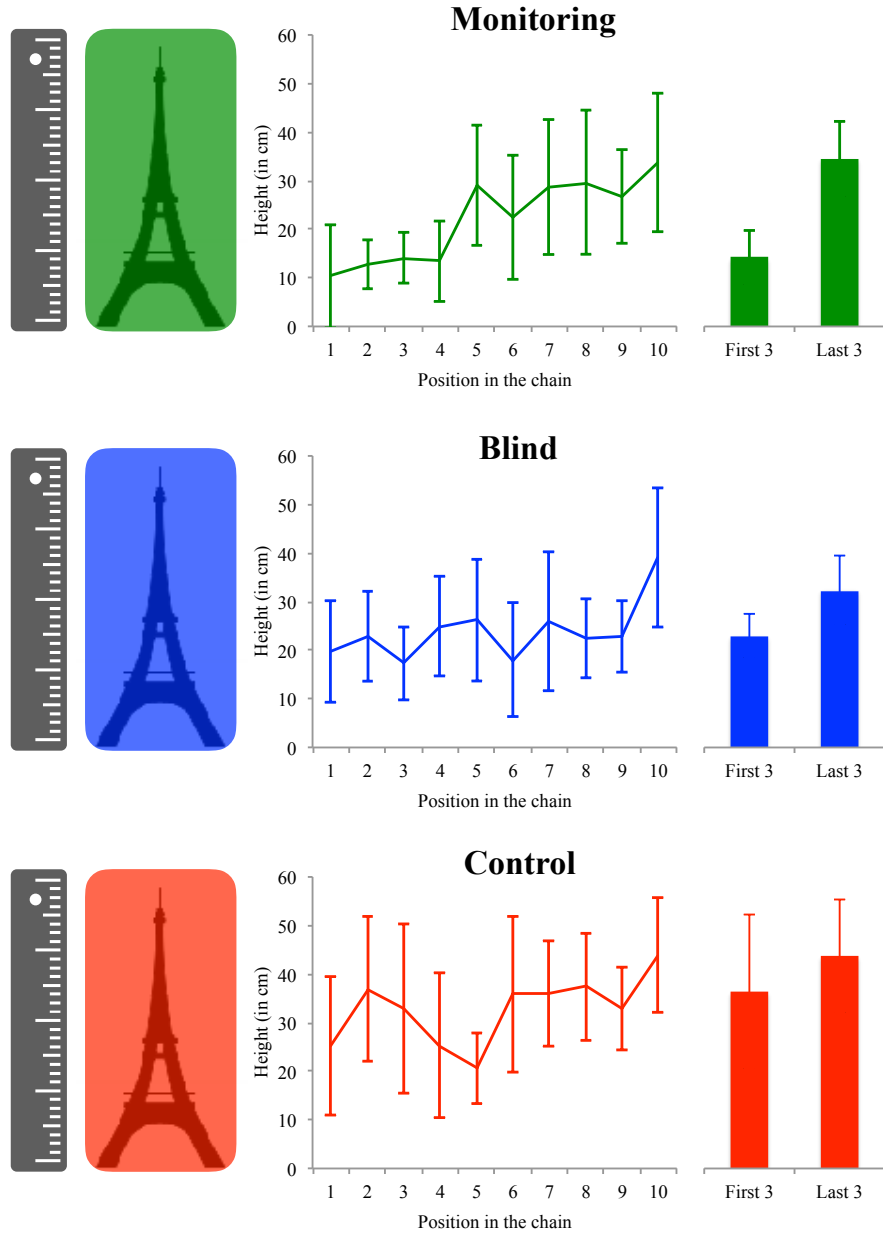


Figure 2. Results of the two micro-society conditions (Monitoring and Blind) and the Control condition. Performance (Tower height) is given for both each position in the chain and for the average of the first three and last three participants of the chain. Error bars represent 95% confidence intervals.

Table 1
 Best models of cumulative performance (tower height) in the two micro-society conditions (LMM analysis)

| Monitoring condition | | | | | Blind condition | | | | |
|--|-----|--------|------------|------------|--|-----|--------|------------|------------|
| Models | k | AICc | Δ_i | ω_i | Models | k | AICc | Δ_i | ω_i |
| <i>Tech_L</i> | 6 | 784.81 | 0.00 | 0.33 | <i>Tech_L+ToM_T</i> | 7 | 775.98 | 0.00 | 0.34 |
| <i>Tech_L+ToM_T</i> | 7 | 785.92 | 1.10 | 0.19 | <i>Tech_L+Tech_r+ToM_T</i> | 8 | 776.58 | 0.59 | 0.25 |
| <i>Tech_L+ToM_L</i> | 7 | 786.84 | 2.02 | 0.12 | <i>Tech_L+ToM_L+ToM_T</i> | 8 | 778.38 | 2.40 | 0.10 |
| <i>Tech_L+Tech_r</i> | 7 | 787.00 | 2.18 | 0.11 | <i>ToM_T</i> | 6 | 778.65 | 2.67 | 0.09 |
| <i>Tech_L+ToM_L+ToM_T</i> | 8 | 788.04 | 3.23 | 0.07 | <i>Tech_L+ToM_L+Tech_r+ToM_T</i> | 9 | 779.04 | 3.05 | 0.07 |
| <i>Tech_L+Tech_r+ToM_T</i> | 8 | 788.23 | 3.42 | 0.06 | <i>Tech_r+ToM_T</i> | 7 | 779.54 | 3.56 | 0.06 |
| <i>Tech_L+ToM_L+Tech_r</i> | 8 | 789.11 | 4.30 | 0.04 | <i>ToM_L+ToM_T</i> | 7 | 781.00 | 5.02 | 0.03 |
| <i>Tech_L+ToM_L+Tech_r+ToM_T</i> | 9 | 790.40 | 5.59 | 0.02 | <i>Tech_L</i> | 6 | 781.69 | 5.70 | 0.02 |
| <i>ToM_L</i> | 6 | 790.90 | 6.08 | 0.02 | <i>ToM_L+Tech_r+ToM_T</i> | 8 | 781.95 | 5.97 | 0.02 |
| <i>ToM_T</i> | 6 | 791.74 | 6.92 | 0.01 | <i>Tech_L+Tech_r</i> | 7 | 782.87 | 6.88 | 0.01 |
| <i>Tech_r</i> | 6 | 791.87 | 7.06 | 0.01 | <i>Tech_L+ToM_L</i> | 7 | 784.00 | 8.01 | 0.01 |
| <i>ToM_L+ToM_T</i> | 7 | 793.13 | 8.32 | 0.01 | <i>Tech_r</i> | 6 | 784.32 | 8.33 | 0.01 |
| <i>ToM_L+Tech_r</i> | 7 | 793.19 | 8.38 | 0.01 | <i>ToM_L</i> | 6 | 785.21 | 9.22 | 0.00 |
| <i>Tech_r+ToM_T</i> | 7 | 794.05 | 9.24 | 0.00 | <i>Tech_L+ToM_L+Tech_r</i> | 8 | 785.22 | 9.23 | 0.00 |
| <i>ToM_L+Tech_r+ToM_T</i> | 8 | 795.48 | 10.67 | 0.00 | <i>ToM_L+Tech_r</i> | 7 | 786.54 | 10.56 | 0.00 |

Tech, technical-reasoning skills; ToM, theory-of-mind skills; L, learner; T, teacher; k , number of parameters in the model; AICc, Akaike's Information Criterion corrected, $\Delta_i = \text{AIC}_{c(i)} - \text{AIC}_{c(\min)}$; ω_i , Akaike weights explaining total variance. Models with $\Delta_i < 2$ are in italics.

Table 2
Predictors from the conditional-averaged model of cumulative performance (tower height)

| Monitoring condition | | | Blind condition | | |
|----------------------|-------------|-------------------|-------------------|-------------|-------------------|
| Predictors | Estimate±SE | Importance weight | Predictors | Estimate±SE | Importance weight |
| Tech _L | 5.89±2.12* | 0.95 | ToM _T | 4.99±1.70* | 0.95 |
| ToM _T | -2.36±2.07 | 0.36 | Tech _L | 3.82±1.67* | 0.80 |
| ToM _L | -1.35±2.15 | 0.28 | Tech _T | -2.07±1.55 | 0.42 |
| Tech _T | 0.83±2.16 | 0.25 | ToM _L | -0.10±1.70 | 0.23 |

Tech, technical-reasoning skills; ToM, theory-of-mind skills; L, learner; T, teacher; Estimate, Weighted parameter estimate; SE, Standard error; *, Variables that are significant at the 95% confidence level (the interval does not contain the null value).