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Impact of technical reasoning and theory of mind on cumulative technological culture: insights from a model of micro-societies

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Our technologies have never ceased to evolve, allowing our lineage to expand its habitat all over the Earth, and even to explore space. This phenomenon, called cumulative technological culture (CTC), has been studied extensively, notably using mathematical and computational models. However, the cognitive capacities needed for the emergence and maintenance of CTC remain largely unknown. In the literature, the focus is put on the distinctive ability of humans to imitate, with an emphasis on our unique social skills underlying it, namely theory of mind (ToM). A recent alternative view, called the technical-reasoning hypothesis, proposes that our unique ability to understand the physical world (i.e., technical reasoning; TR) might also play a critical role in CTC. Here, we propose a simple model, based on the micro-society paradigm, that integrates these two hypotheses. The model is composed of a simple environment with only one technology that is transmitted between generations of individuals. These individuals have two cognitive skills: ToM and TR, and can learn in different social-learning conditions to improve the technology. The results of the model show that TR can support both the transmission of information and the modification of the technology, and that ToM is not necessary for the emergence of CTC although it allows a faster growth rate.

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Introduction

The increasing efficiency and complexity of tools over generations (i.e., cumulative technological culture, hereafter shortened as CTC) enables humans to be successful ecologically and demographically, allowing them to develop powerful technologies that are too complex to have been invented by a single individual (Boyd and Richerson, 1985; Derex et al., 2013; Tomasello et al., 1993). Even though technological culture has been observed in other animals, such as nonhuman primates (Whiten and Boesch, 2001), corvids (Holzhaider et al., 2010), and insects (Danchin et al., 2018), the cumulative component resulting in products that could not be invented by a single individual of human culture seems unique in the animal kingdom (Reindl et al., 2020, but see also Reindl et al., 2018; Derex, 2022), raising the question of the specific human cognitive skills underlying CTC. Historically, CTC has been primarily investigated through mathematical and computational modelling. Numerous models of cumulative culture have been proposed, which explore key factors, such as demographic factors (Henrich, 2004), social-learning strategies/copying biases (Acerbi and Alexander Bentley, 2014; Boyd and Henrich, 2002; McElreath et al., 2005; Rendell et al., 2010), population structure (Kolodny et al., 2015c), language evolution (Kolodny et al., 2015b), number of technological traits (Lehmann et al., 2011), migration (Creanza et al., 2017), transmission fidelity (Lewis and Laland, 2012), personality (Acerbi et al., 2009), or creativity (Kolodny et al., 2015a). These models undoubtedly bring new insights into the origins of CTC at a macroscale level. However, they leave open the question of the role of cognitive skills such as theory of mind, meta-cognition, technical reasoning and working memory (i.e., microscale level, for a similar view, see Acerbi et al., 2011). As Heyes (2018) stressed, integrating the two scales is essential to move the field forward. The present article seeks to go in that direction.

CTC is a specific form of cumulative culture, focusing on technology. Hence, as cumulative culture, CTC arises from the cultural transmission of knowledge and skills over time. Cultural transmission is supported by social learning, defined as learning about other conspecifics or the inanimate world that is influenced by observation of, or interaction with, another conspecific or its products (Heyes, 1994). Here, we borrow the terminology from Heyes (2018) and call the individual who is learning the receiver and the source from which it is learning the sender. Social learning depends in part on the amount of information the receiver gets from the sender (Osiurak and Reynaud, 2020). It can be divided into different social-learning forms: reverse-engineering (RE) where only the technology is present; observation (OBS) where a receiver witnesses a demonstration of the building of the technology by a sender; and communication (COM) with verbal interaction between a receiver and a sender. These three forms of social learning differ in the amount of information that is provided to the receiver, in ascending order of amount of information transmitted (RE, OBS, and COM). On the other hand, the learner-oriented dimension varies between two processes: emulation (copying of "results") and imitation (copying of "actions" and "results"), where imitation has higher fidelity than emulation (Whiten et al., 2009).

One might wonder where teaching takes place in the three social-learning forms. If we take the layman use of the term, teaching is a form of communication that implies language and is included here in the COM social-learning form. However, teaching in the social sciences literature is defined as the modification of a behaviour that facilitates learning in others (Kline, 2015). In some cases, teaching can be based on communicative behaviour (e.g., pointing to key features of the demonstration to make them more salient, providing verbal or gestural feedback or information). However, teaching does not necessarily require communicative behaviour between individuals (Franks and Richardson, 2006; Thornton, 2006). Thus, teaching can also take place in a context of observational learning, for instance when a sender slows down or repeats a specific movement.

At a cognitive level, a link has been repeatedly drawn between CTC and a specific social-cognitive skill, namely theory of mind (ToM) (Herrmann et al., 2007; Tennie et al., 2009; Tomasello et al., 1993). ToM refers to the ability to attribute mental states to oneself and others (Harris, 1991; Mead and Mead, 1985; Piaget, 1932; Premack, 1988; Tomasello et al., 1993; Whiten, 1991). The ability to share intentions allows the sender to orient the receiver toward the relevant features of the technology, what O'Madagain and Tomasello (2022) called intentional teaching. In addition, the receiver can also pay more attention to what the sender attempts to intentionally transmit. In sum, these social-cognitive skills favour the faithful transmission of technical content (i.e., imitation), which has been said to be the necessary condition for the emergence of CTC (Dean et al., 2012; Reindl and Tennie, 2018; Tennie et al., 2009; Tomasello et al., 1993, 2005; see also Reindl et al., 2020). As explained above, (intentional) teaching can take place in the context of observational learning in which there is no direct communicative behaviour between the sender and the receiver. For this reason and as our model will be based on micro-society studies in which the presence of teaching behaviour has not been documented in the OBS condition, we preferred (1) to keep the term "COM" for those conditions in which communication is allowed, and not to merge it with teaching although (2) we acknowledge that the COM conditions reported in the literature necessarily engaged more teaching behaviour than the OBS condition. Thus, we will also assume that ToM is more heavily involved in COM than OBS conditions.

A series of experimental studies using micro-society paradigms reporting cumulative performance in reverse engineering conditions, where the receiver can only scrutinize the senders' technology (Caldwell and Millen, 2009; Derex et al., 2019; Osiurak et al., 2021a, 2022; Zwirner and Thornton, 2015) challenges the social-cognitive view of CTC. Recently, it has been shown that learners' technical-reasoning skills are the best predictor of cumulative performance in different social-learning conditions (e.g., observation, communication; De Oliveira et al., 2019; Osiurak et al., 2016, 2020, 2021b) and that the improvement of a physical system is accompanied by an increase in its understanding (Osiurak et al., 2021a, 2022; see also Derex et al., 2019; Harris et al., 2021). Given these results, it is proposed that CTC can arise from the interaction between specific non-social cognitive skills and less elaborated forms of social learning (i.e., which do not require specific social-cognitive skills). This is the technical-reasoning hypothesis (Osiurak and Reynaud, 2020). This hypothesis does not exclude the role of social-cognitive skills in CTC but considers it as a catalyst that will boost its growth, without being necessary for its emergence. This catalyst might be even more important in an opaque situation, where the receiver has no direct access to the technology (Osiurak et al., 2020). Before going deeper into the article, we want to give a quick definition of technical reasoning (for a more complete definition, see Osiurak, 2014; Osiurak et al., 2010). Technical reasoning (TR) is the ability to reason about physical object properties (Osiurak, 2014; Osiurak et al., 2010). It is both analogical (i.e., transfer from one situation to another e.g., using a knife to cut a tomato → using a saw to cut a wooden board) and causal (i.e., predicting the effects on the environment, e.g., the tomato is cut in half). It is based on mechanical knowledge, i.e., the knowledge of physical principles. It has been hypothesized that the lack of elaborated forms of TR in nonhumans might explain their difficulties in understanding mechanical actions (Osiurak and Reynaud, 2020). It is important to note that TR concerns only mechanical actions (i.e., tool–object relationships) and not motor actions (i.e., hand–tool relationships), meaning it does not intervene in the actual motor realization of an action. Finally, TR is not specific to the use of familiar tools, but also concerns any situation in which a physical problem has to be solved, such as when making tools or during construction behaviour.

Understanding the specific cognitive skills involved in CTC is fundamental to developing a computational model integrating both the macroscale and microscale of CTC. The goal of this article is to capitalize on existing literature to provide a computational model focusing on TR and ToM. We are aware that other cognitive skills might also influence CTC, such as metacognition or working memory (Dean et al., 2012; Dunstone and Caldwell, 2018; Fay et al., 2019; Osiurak and Reynaud, 2020), but we chose to focus on the two main cognitive skills at play for now. To do so, we will first replicate the classical results of the micro-society literature, which have been obtained in contexts of close-ended solution space (i.e., the presence of an optimal solution). The goal of this model is to solidify the results observed in said literature. Using modelling allows us to expand experimental results to a society of hundreds of generations and to manipulate precisely the social-learning conditions under which the individual will exchange information. Above all, the interest of modelling is to go beyond the real-world limitation of experimental paradigms. As recently pointed out by Derex (2022, see also Mesoudi and Thornton, 2018; Whiten et al., 2022), the potential of our CTC is endless due to both our capacity to gradually improve technology and our unmatched ability to innovate. This description of CTC implies the existence of an open-ended solution space, which diverges from the type of CTC observable in micro-society experiments (i.e., close-ended solution space). Thus, we will build a second model that goes beyond what is possible using the micro-society paradigm, namely, a model with an open-ended solution space.

Our model thus implements a micro-society paradigm with three social-learning forms—RE, OBS, and COM—and compares their success (i.e., the quality of the technology yielded) in various settings. To build a model that is consistent with the empirical data of the literature, we conducted beforehand a synthesis of 9 experimental studies (more details in supplementary material *S1: Synthesis*) using the micro-society paradigm. In these experiments, receivers learn vertically (i.e., parents to offspring transmission) from their senders to improve a single technology, under different social-learning forms. An issue with the literature is that OBS is not clearly defined and can change depending on the study, varying from no access to the quality of a technology (Zwirner and Thornton, 2015) to access to both the quality and the last two technologies of the transmission chain (Caldwell and Millen, 2009). Here, what we call "quality of a technology" refers to the overall efficiency of a technology, for example, the distance of flight of a paperplane (Caldwell and Millen, 2009, 2010b; De Oliveira et al., 2019; Fay et al., 2019), the height of a tower (Caldwell and Millen, 2008, 2010a; Osiurak et al., 2020; Reindl et al., 2017, 2018) or the number of rice grains a basket may contain (Zwirner and Thornton, 2015). The definition of OBS on which we base our analysis is as follows: a receiver observing a sender building its technology, without the possibility to communicate, and having access to the quality of the technology afterwards.

In the next section, we describe our model and simulations under four conditions:

1. First, we use a model with refinement only. This means that we are in a close-ended space (there exists a unique optimal solution), where the maximum quality of the technology is fixed. In this model, the individual can only refine the technology. This model is the closest to the micro-society literature, where the technology a participant may build is often limited either by the material at its disposition or by the number of solutions. In this regard, the technology either has a defined optimal solution (the wheel system of Derex et al., 2019) or cannot exceed a certain quality (the height of the tower is limited to the length and number of spaghetti at disposition, Osiurak et al., 2016, 2020; Reindl et al., 2017, 2018). We expect the three social learning forms to reach a different optimum quality, with RE, OBS, and COM, in ascending order.

2. Then, we add innovation to the model. Contrary to the first model, this model departs from experiments but is more ecological, as humans' CTC is made of refinement and innovation. We predict similar results as with only refinement, with RE having the lowest technology's quality, followed by OBS and then at the top COM. Notice that here we do not expect an optimum quality. Indeed, adding innovation makes our solution space open-ended, meaning there is no maximum quality or optimal solution. Furthermore, we expect RE and OBS to achieve fewer innovations than COM.

3. After that, we focus on a single transmission chain. Indeed, in the two previous models, we will be looking at the mean results of multiple transmission chains. This has the effect of reducing the amount of randomness introduced into the model. But this is at the cost of making the precise behaviour of a transmission chain more opaque. Therefore, we need to focus on a single chain to get a better grasp of the mechanisms underlying social transmission. To control the randomness of the model, we used random seeds to generate beforehand all its random values. In this model, we expect RE and OBS to follow a linear growth in terms of technology's quality, whereas we anticipate COM to have brief bursts of increases followed by long periods of stasis, something that is often seen in our cultural lineage evolution (Henrich, 2004; Klein, 2008; Kline and Boyd, 2010; Kuhn, 2012; Mesoudi, 2011; Shennan, 2001).

4. Finally, we focus on the role of ToM in CTC. To test whether ToM has an impact on the technology's quality, we construct two different models, one with ToM and one without ToM. We expect both models to yield CTC with similar results in terms of technology's quality, hinting that ToM may not be a necessary cognitive skill for the emergence of CTC.

The model

In our model, we assume an environment composed of a single technology. We further assume that this technology can be decomposed into components, called traits. For example, if the technology represents a vehicle, traits represent the wheels, the seating, the steering wheel, etc. At each generation, an individual appears in the environment, intending to improve as much as possible the technology. To do so, the individual beforehand learns the technology's traits from the previous individual using one of three different social-learning forms (RE, OBS, COM). This learning phase depends on the cognitive skills (TR and ToM; depending on the social-learning form) of both the sender and the receiver. Afterwards, the individual tries to improve the technology by refining its traits. Refining the technology's trait equals increasing its quality toward a fixed arbitrary limit. Subsequently, the individual disappears from the environment and is replaced with a new one. This process is repeated for N generations ($N = 1000$ if not stated otherwise), creating transmission chains.

Technology and environment. Consider a single technology T composed of n distinct traits, such that $T = \{trait_1, trait_2, \cdots, trait_n\}$. Each trait has a *quality* and a *limit*. The *quality* represents the overall efficiency of a trait, taking some value between 1 (the minimal value, e.g., a coarse square-like stone wheel for our vehicle) and the *limit*, being the maximum quality that a trait may achieve, set to an arbitrary natural number greater than 1. We assume that each trait is semi-independent[1] (the quality of each trait is independent of one another, but we will see later that innovative traits will impact the overall limit of all existing traits) and contributes equally to the overall quality of the technology denoted *quality*(T), given by

$$\text{quality}(T) = \sum_{i=1}^{n} \text{quality}\left(\text{trait}_i\right).$$

The same logic follows for the limit of each trait and the technology, denoted limit(T).

The quality of technology generally reflects the quality of the technological environment to which this technology belongs. In our model, only the technology T is present in the environment. Thus, the quality of the environment is extrapolated from a noisy representation of the technology T. Then

$$\text{env} = \text{quality}(T) + \varepsilon,$$

where ε represents the noise, drawn from a uniform distribution in the range $\left[-\frac{\text{quality}(T)}{10}, \frac{\text{quality}(T)}{10}\right]$.

Individual. Consider an individual I defined as $I = \left\{\text{cog}_1, \text{cog}_2, \ldots, \text{cog}_n\right\}$ where cog_i represents the knowledge about the mechanism underlying the trait_i of the technology T, taking some value between 0 (no knowledge at all) to the limit of trait_i (a total understanding of trait_i).

Individuals also have two cognitive skills: TR and ToM. Each of these skills is represented by a value, denoted I_{TR} and I_{TOM}, respectively. I_{TR} is drawn from a gaussian distribution, such that I_{TR} belongs to [0, env]. We use env to compute I_{TR} because TR has been shown to be acquired through interaction with the physical environment and, as a result, the technological environment (Osiurak and Reynaud, 2020). It is important to note that, with each generation, quality(T) may increase and may therefore lead to an increase of env and I_{TR}. This is not to say that we consider that all new individuals can understand the entire technology. However, we assume that their environment allows them to understand the current state of the technology sufficiently to improve it. I_{TOM} is also drawn from a normal gaussian distribution centred at 0.5 with s.d. $= \frac{0.5}{3}$, such that I_{ToM} belongs to [0, 1], with $I_{\text{ToM}} = 0$ when the individual has no ToM and $I_{\text{ToM}} = 1$ when the individual has perfect ToM.

The initial value of each cog_i (i.e. before learning) depends on I_{TR}. Indeed, I_{TR} acts as a pool of knowledge, from which we randomly sample without replacement the quality of each cog_i (more details in Supplementary material S2: *Random sampling of cogs*) until the pool of I_{TR} is empty. At the end of this process

$$\sum_{i=1}^{n} \text{cog}_i = I_{\text{TR}}.$$

Learning methods. Learning involves the receiver directly interacting with various sources, for example, the technology T, or the individual present in the environment at generation $t{-}1$. We consider three forms of learning RE, OBS, and COM.

In RE, the receiver only interacts with the technology T present at generation t. Thus, there is no impact of I_{ToM} because there is no direct social interaction between the receiver and the sender. Therefore

$$\text{cog}_i' = \text{cog}_i + \left(\delta_{\text{RE}} * \frac{I_{\text{TR}}}{\text{env}}\right),$$

where cog_i' is the updated cog_i, δ_{RE} represents the information that can be obtained by learning from the sender using RE, obtained by computing difference $\text{quality}\left(\text{trait}_i\right) - \text{cog}_i$, and $\frac{I_{\text{TR}}}{\text{env}}$ represents the impact of the receiver's TR. Growing evidence suggests that the receiver's TR is the best predictor of cumulative performance in transmission chains irrespective of the social-learning form (Acerbi et al., 2009; Caldwell and Millen, 2009: Derex et al., 2019; Osiurak et al., 2021b). This explains why TR plays here a critical role in the learning process.

In OBS, the receiver directly observes its predecessor (the sender) while the latter improves the technology. However, no form of communication is permitted between them. Because of the absence of communication, the receiver is not able to explicitly access the sender's knowledge. Nevertheless, the receiver may notice the improvement in technology brought about by the sender, by directly comparing the technology at generation $t{-}1$ and the technology at generation t. Given that the receiver is watching someone improve the technology, it is logical to consider that it is monitoring the technology itself, and therefore it will be able to use RE. We consider that OBS necessarily implies RE, which gives

$$\text{cog}_i' = \text{cog}_i + \left(\delta_{\text{RE}} * \frac{I_{\text{TR}}}{\text{env}}\right) + \left(\delta_{\text{OBS}} * \frac{I_{\text{TR}}}{\text{env}}\right),$$

where $\delta_{\text{OBS}} = \text{quality}\left(T_i\right) - \text{quality}\left(T_{i-1}\right)$.

In COM, the receiver is in direct interaction with the sender and can communicate with it. The sender, therefore, acts as a teacher and tries to share their knowledge. It has been repeatedly stressed that ToM (or ToM-like process) might play a critical role in teaching situations (Herrmann et al., 2007; Tomasello, 1999; Tomasello et al., 1993, 2005), and particularly the teacher's ToM (Osiurak et al., 2020) in the context of transmission chains, therefore only S_{ToM} (the sender I_{ToM}) is included in the model under COM. We also consider that since the sender and the technology are present in the environment, the receiver can use OBS and RE. This gives

$$\text{cog}_i' = \text{cog}_i + \left(\delta_{\text{RE}} * \frac{I_{\text{TR}}}{\text{env}}\right) + \left(\delta_{\text{OBS}} * \frac{I_{\text{TR}}}{\text{env}}\right) + \left(\delta_{\text{COM}} * \frac{I_{\text{TR}}}{\text{env}} * \left(S_{\text{ToM}} + 1\right)\right),$$

where $\delta_{\text{COM}} = \text{sender.cog}_i - \text{receiver.cog}_i$. $\left(S_{\text{ToM}} + 1\right)$ represents the impact of the ToM of the sender. We consider that the S_{ToM} acts as a catalyst for the COM, enabling individuals to acquire technical information more efficiently than through RE or OBS (Osiurak and Reynaud, 2020). However, if $S_{\text{ToM}} = 0$ (i.e., a teacher without any ToM), COM becomes similar to RE and OBS and only depends on I_{TR}. Therefore, if a receiver has a good TR, it will be able to acquire all the technical information of the sender, regardless of its ability to transmit them. However, in the opposite case, no matter if the sender has a good ToM, he will not be able to pass all its technical information to a receiver with low TR. This assumption is directly derived from previous works using micro-society paradigms that have shown that the receiver's TR (I_{TR}) is the best predictor of cumulative performance (Acerbi et al., 2009; Caldwell and Millen, 2009; Derex et al., 2019; Osiurak et al., 2021b) and that the sender's ToM is only significant when the task is too opaque (Acerbi et al., 2009).

Modification of the technology and innovation. The individual can modify the technology in two ways: improving it or deteriorating it. In addition to understanding the technology, TR is also necessary when modifying the technology because it shapes the mental simulation of the mechanical actions required (Osiurak and Reynaud, 2020). Furthermore, the receiver's TR is the best predictor of cumulative performance in transmission chain paradigms, as has been evidenced by several studies (De Oliveira et al., 2019; Osiurak et al., 2016). Thus, the probability p_{improve} of improving the technology is obtained by computing

$\frac{I_{\mathrm{TR}}}{\mathrm{env}}$. It follows that the probability of deteriorating the technology is given by $p_{\mathrm{deteriorate}} = 1 - p_{\mathrm{improve}}$. Furthermore, we assume that individuals with I_{TR} above average (i.e. $I_{\mathrm{TR}} > \frac{\mathrm{env}}{2}$) have sufficient TR to at least faithfully copy the technology, meaning that they cannot deteriorate the technology. Indeed, we assume that, in a random population possessing a range of technologies, an average individual will be able to at least reproduce most of these technologies (i.e., only a worse than average individual will not be able to reproduce any technologies present in their environment). After the direction of the modification is determined, modifications for each trait are computed independently with

$$\mathrm{quality}(\mathrm{trait}_i)' = \begin{cases} \mathrm{quality}(\mathrm{trait}_i) * \beta_{\mathrm{improve}} & \text{if } \mathrm{cog}_i' \geq \mathrm{quality}(\mathrm{trait}_i), \\ \mathrm{quality}(\mathrm{trait}_i) & \text{otherwise.} \end{cases}$$

For the improvement, where β_{improve} is arbitrarily set at some value >1, and

$$\mathrm{quality}(\mathrm{trait}_i)' = \begin{cases} \mathrm{quality}(\mathrm{trait}_i) * \beta_{\mathrm{deteriorate}} & \text{if } \mathrm{cog}_i' < \mathrm{quality}(\mathrm{trait}_i), \\ \mathrm{quality}(\mathrm{trait}_i) & \text{otherwise.} \end{cases}$$

For the deterioration, where $\beta_{\mathrm{deteriorate}}$ is arbitrarily set at some value <1.

Another way in which the technology can be modified is through innovation. After modifying the technology using its knowledge, the individual may have the opportunity to innovate. Innovation is a different process compared to modification. The latter is comparable to refinement: the individual changes the quality of the trait (whether it is by improving or deteriorating it). It is a small change of the pre-existing traits of the technology. Innovating on the other end brings a great change in the technology, adding a new trait while also increasing the limit of the already existing ones (we will explain this phenomenon in greater detail later). The innovation opportunity comes with a probability $p_{\mathrm{innovation}} = 0.01$. Once this opportunity appears, the individual tries to seize it. To do so, the individual can either have a good TR, allowing it to achieve the innovation by itself or have an almost optimal technology, ready for innovation. As a result, we assume that either I_{TR} or quality(T) needs to be in the top 20% (i.e., $\frac{I_{\mathrm{TR}}}{\mathrm{env}} > 0.8$ or $\frac{\mathrm{quality}(T)}{\mathrm{limit}(T)} > 0.8$) for innovation to occur. Indeed, if the technology is at its maximum, just a little tweak will bring it up to the next step. In the case of an individual with low I_{TR} innovating, this represents serendipity. If not, it can simply be interpreted as the logical consequence of the progress of time. But if the technology is not at its maximum, we want to make sure that an individual with high I_{TR} (e.g., an expert) may still be able to innovate right away, leaping directly to the next step. In our model, innovation has two effects: the first is that it adds a brand-new trait to the technology, which refers to as *groundbreaking innovation* (Kolodny et al., 2015c). The second is that, because a new trait appears, the limits of all the traits increase, an effect called *innovative combination* (Kolodny et al., 2015c). The value by which the trait increases is called the strength of the innovative combination, denoted by θ and set to an arbitrary positive integer.

Results

To evaluate the performance of a transmission chain, we average the quality of the technology over multiple simulation runs. Below are the main results of the model. First, we run the model with refinement only to investigate the impact of the different social-learning forms in a space with a finite number of solutions. Then, we extend the model by adding innovations to observe the model's results in a more ecological situation. Next, we examine a single-run simulation to compare the effect of the different social-learning forms. Finally, we compare the model with a version without ToM to learn more about its importance for CTC. Except when stated otherwise, the results discussed in this section are obtained using simulations with the following parameters: limit(tech) = 2, $n = 2$, $\theta = 5$, $\beta_{\mathrm{improve}} = 1.2$, $\beta_{\mathrm{deteriorate}} = 0.8$, and $p_{\mathrm{innovation}} = 0.01$.

Model with refinement only. We define the *optimized-technology level* as the maximum quality technology can theoretically achieve (i.e., quality (T) = limit (T)) and a *plateau* of a learning form as the maximum technology's quality it achieves (see Fig. S3.1 in Supplementary material for more information on the plateau). Results for the model with refinement only are shown in Fig. 1A. When there is no innovation, the learning forms differ in the way they plateau, with RE and OBS reaching the optimized-technology level after COM (RE: $M = 42.55$, SD = 2.92; OBS: $M = 35.71$, SD = 22.68 and COM: $M = 8.68$, SD = 25.01). Once a plateau is reached, the average quality of the technology remains the same. However, this quality fluctuates for RE and OBS but not for COM. Further investigations reveal that these fluctuations are related to the capacity of the social-learning form to maintain CTC (Supplementary material Table S3.1, Figs. S3.1 and S3.2). While we are in a close-ended solution space, we argue that the ability (through social learning) to maintain the optimized-technology level is still crucial for CTC. Indeed, except for COM, the quality of the technologies oscillates between limit(T) and the minimum quality it can have, which explains why when taking the average of 1000 simulations of RE and OBS (we will look at a single transmission chain later), it does not reach the optimized-technology level even after 1000 generations. Finally, in addition to achieving lower quality of technology, RE and OBS plateau after COM (see supplementary material Fig. S3.1). This result is even stronger when increasing the limit (Fig. 1B). Taken together, these results show that in addition to allowing the CTC to be maintained over time, communication also allows an optimal solution to be reached much more rapidly.

Model with refinement and innovation. Adding innovations to the model allows for much higher technology quality in transmission chains. As shown in Fig. 1C, all the learning forms yield an initially exponential increase in technology quality. Notice that both RE and OBS produce lower technology quality than COM, the former both having very similar behaviours and results (at the last generation: RE: $M = 213.11$, SD = 141.13; OBS: $M = 266.39$, SD = 166.06; COM: $M = 591.87$, SD = 322.39), which agrees with the classical results of the literature on transmission chains (Fig. 1D; see also S1: *Meta-analysis* in supplementary material), where RE has the lowest technology quality, closely followed by OBS and then well ahead COM. When we decrease β_{improve} so that an individual deteriorates more severely than it improves (i.e. $\beta_{\mathrm{improve}} - 1 < 1 - \beta_{\mathrm{deteriorate}}$), only RE and OBS show a significant drop in technology's quality, although still exhibiting CTC (with $\beta_{\mathrm{improve}} = 1.2$, $\beta_{\mathrm{deteriorate}} = 0.8$: RE: $M = 212.11$, OBS: $M = 266.39$, COM: $M = 591.87$; with $\beta_{\mathrm{improve}} = 1.1$, $\beta_{\mathrm{deteriorate}} = 0.8$: RE: $M = 24.67$, OBS: $M = 45.41$, COM: $M = 601.87$; see also Fig. S2.4 in Supplementary material). This result demonstrates that even in an environment where the potential loss of information is greater than the gain, communication may overcome this problem and still leads to strong CTC. Conversely, increasing β_{improve} (i.e. $\beta_{\mathrm{improve}} - 1 > 1 - \beta_{\mathrm{deteriorate}}$) increases the quality of the technology for RE and OBS, but not for COM (with $\beta_{\mathrm{improve}} = 1.2$, $\beta_{\mathrm{deteriorate}} = 0.8$: RE: $M = 212.11$, OBS: $M = 266.39$, COM: $M = 591.87$; with $\beta_{\mathrm{improve}} = 1.3$, $\beta_{\mathrm{deteriorate}} = 0.8$: RE: $M = 321.67$, OBS: $M = 368.43$, COM: $M = 635.56$; see Supplementary material Fig. S3.3). This is simply because, for COM, the limit of the technology is already reached, so an increase in β_{improve} has no impact.

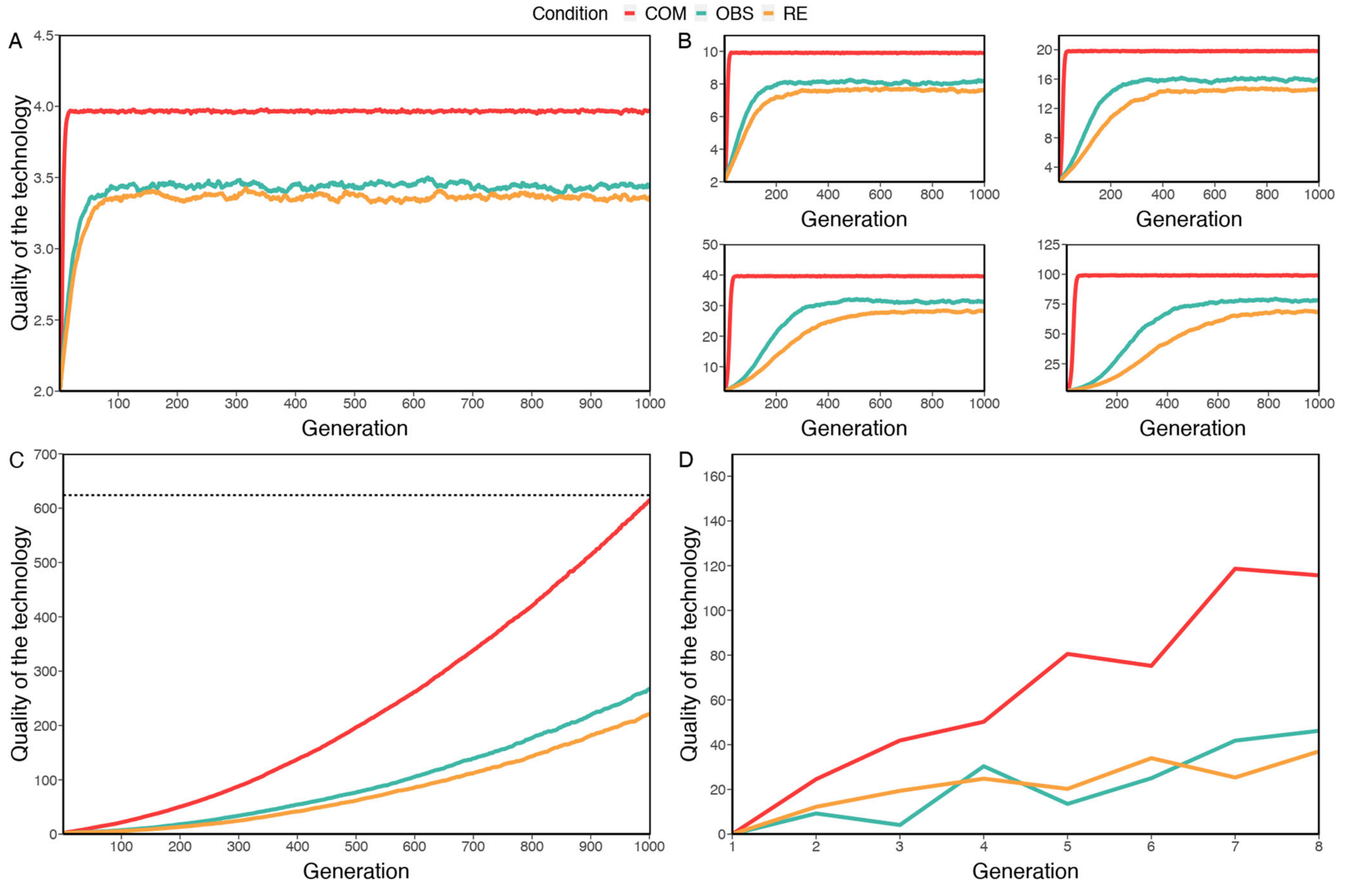

Fig. 1 Model results in terms of technology's quality as a function of generation. We run 1000 simulations of 1000 generations for each model and averaged the technology's quality between simulations. Common parameter values for all models: $n = 2$, $\theta = 5$, $\beta_{\text{improve}} = 1.2$, $\beta_{\text{deteriorate}} = 0.8$. **A** Model with refinement only, limit(tech) = 2. **B** Model with refinement only, where each model has a different *limit*: *top left*: limit(tech) = 2 (same as **A**); *top right*: *limit(tech)* = 5; bottom left: limit(tech) = 10; *bottom right*: limit(tech) = 20. **C** Model with refinement and innovation, limit(tech) = 2, $p_{\text{innovation}} = 0.01$. The black dashed horizontal line represents the maximal value the technology may take accounting for the parameters and ten innovations (an innovation every 100 generations; $p_{\text{innovation}} = 0.01$). **D** Results from the synthesis (for more information, see supplementary material *S3 Synthesis*), mean score as a function of generation.

We also investigate the effect of the innovative combination strength θ on the quality of the technologies (see Supplementary material Fig. S3.4). Increasing θ effectively increases the limit(T), thus improving quality*(T)* for all learning forms. However, the social-learning form that benefits the most is OBS, because an increase in θ brings OBS closer to COM (with $\theta = 5$: OBS: $M = 266.39$, COM: $M = 591.87$, percentage change = 122.18; with $\theta = 50$: OBS: $M = 4602.15$, COM: $M = 6161.22$, percentage change = 33.88). Moreover, we notice that the difference between RE and OBS increases with θ. Further analyses indicate that it is caused by the increase of limit(T), which has the direct effect of decreasing the probability of having a technology good enough to innovate (i.e., $\frac{\text{quality}(T)}{\text{limit}(T)} > 0.8$), making the process more dependent on I_{TR} (Supplementary material Fig. S3.5). However, this effect is not observed for RE because it lacks individuals with sufficient I_{TR} to innovate (Supplementary material Fig. S2.5), which explains this difference with OBS. Furthermore, having better technology leads to better I_{TR}, which leads to better technology, and so on (i.e., a snowball effect), further explaining the increase in quality for OBS.

Single simulation run. We modify the model so that the random parts of the model are fixed (for more detail, see S4: *Non-random model* in supplementary material) to ensure that the only difference between simulations is the social-learning form. The result of a single simulation run is shown in Fig. 2A. First, we see that for COM, a single simulation run alternates between long periods of stagnation and periods of rapid growth. During periods of stagnation, the technology has reached its limit, and therefore cannot be improved before an innovation appears. Interestingly, RE and OBS also reach this point, but later compared to COM (RE: $M = 63.2$, OBS: $M = 52.4$, COM: $M = 18.4$). These results are similar to those of the model with refinement only. Furthermore, neither RE nor OBS is characterized by a period of a very rapid increase in the quality of the technology, which appears only in COM. Conversely, the quality fluctuates for RE and OBS. Other simulations show that RE and OBS never reach the optimized-technology level, or do not exhibit CTC at all, whereas COM always reaches the optimized-technology level after a brief period of growth (Fig. 2B). It is these different simulations, varying from no CTC at all to an optimized-technology level, that, when averaged, gave poorer results for RE and OBS compared to COM.

Theory of Mind. The comparison between COM without ToM and COM with ToM shows that there is very little difference between the two, demonstrating a limited impact of ToM (Fig. 2C). Further analyses indicate that ToM has an impact only during the

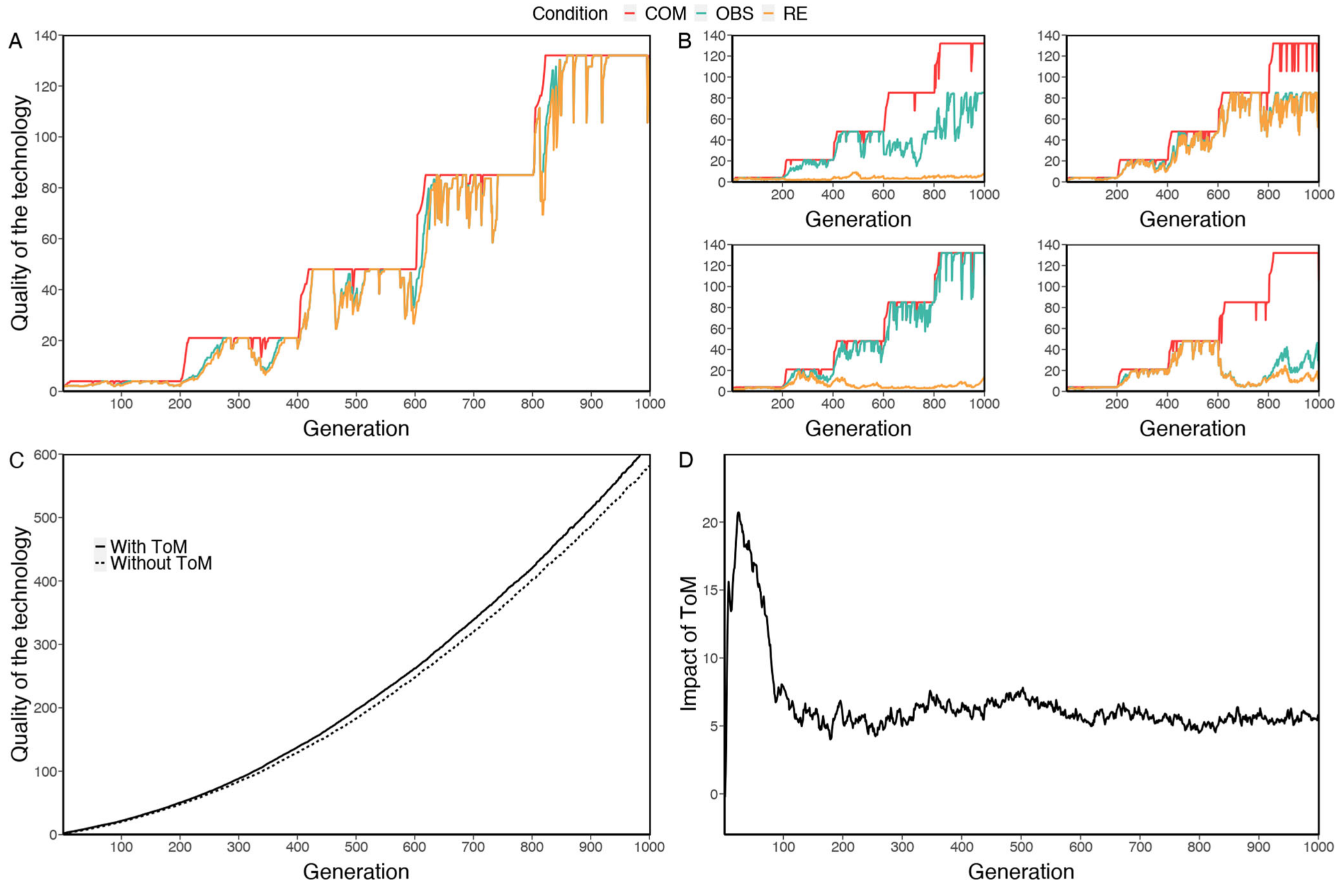

Fig. 2 Model results for single simulation run and impact of ToM. We run 1 simulation of 1000 generations for each social-learning form. Parameter values for all models: limit(tech) = 2 $n = 2$, $\theta = 5$, $\beta_{\text{improve}} = 1.2$, $\beta_{\text{deteriorate}} = 0.8$. We manually set innovations to occur once every 200 generations. **A** Model results in terms of technology's quality as a function of generation for a specific single simulation run where all three social-learning forms reach the *optimized-technology level* after each innovation. **B** Example of different model results in terms of technology's quality as a function of generation for multiple specific single simulation runs. **C** Model results in terms of technology's quality as a function of generation. We run 1000 simulations of 1000 generations for both models and averaged the technology's quality in-between simulations. Parameter values for both models: limit(tech) = 2 $n = 2$, $\theta = 5$, $\beta_{\text{improve}} = 1.2$, $\beta_{\text{deteriorate}} = 0.8$ and $p_{\text{innovation}} = 0.01$. **D** Impact of ToM as a function of generation. We compare **C** model technology's quality. The impact of ToM is calculated as follows: $impact = \frac{quality(T)\ with\ ToM - quality(T)\ without\ ToM}{quality(T)\ without\ ToM} * 100$.

first generations, indicating that its effect may be to accelerate the acquisition of an optimal technology (Fig. 2D). However, once this optimum is reached, ToM has a limited impact because, as seen above, it is only innovations and I_{TR} that allow CTC.

Discussion

What are the cognitive skills underlying CTC? Although essential to understand the origin of our culture and our evolution (Seife, 2005), this question remains insufficiently explored. Two answers have been put forward to address this question. The first one focuses on the imitation part of CTC and posits that faithful social transmission (Dean et al., 2012; Reindl and Tennie, 2018; Tennie et al., 2009; Tomasello et al., 1993, 2005), is potentially supported by ToM (Herrmann et al., 2007; Tomasello et al., 1993, 2005), is necessary for the emergence of CTC. The second proposes that CTC arises from TR, the ability to reason about physical object properties (Osiurak and Reynaud, 2020). TR might support both imitation and innovation (the dual engine of culture, see Legare and Nielsen, 2015) in CTC. It is important to note that neither side neglects the importance of both TR and ToM but disagrees on their role and significance for CTC. Although many models are investigating CTC, to date there is a lack of models focusing on the micro-scale level of CTC, and, in particular, cognitive skills underlying it.

Here, we propose a modelling framework integrating cognitive skills in the transmission of information. We base our model on the micro-society paradigm frequently used to study CTC and its different social-learning forms to investigate the impact of ToM and TR on CTC. It consists of a single micro-society, where receivers learn vertically from their senders to improve a single technology. The model results are qualitatively similar to those seen in the micro-society literature. Indeed, in both our model and the literature, RE and OBS conditions yield similar transmission chain scores (albeit OBS is often ahead by a small step), and both are significantly lower than COM.

Without innovation, our model exhibits a period of rapid growth of technology quality and then plateaus around a specific value. This result is alike those found in the literature (in replicator-dynamics, Boyd and Henrich, 2002; environmental learning, Henrich, 2001; the number of tools, Kolodny et al., 2015c; tool complexity, Mesoudi, 2011). However, the value at which they plateau differs between social-learning forms: RE plateaus at the lowest value, followed by OBS plateauing at a barely higher value, and COM plateaus at a significantly higher value, near the *optimized-technology level*. This is also in accordance with the transmission-chain literature, where communication conditions often outperform non-communication ones (Caldwell and Millen, 2009; De Oliveira et al., 2019; Lucas et al., 2020; Osiurak et al., 2020, 2021b). Further analysis shows that this difference in the value at which the social-learning forms plateau is in fact due to the capacity of the social-learning form to maintain a high-quality technology over time, something that only COM achieves constantly. This result is consistent with the idea that communication (and presumably teaching) is a very effective way of transmitting information (Kline, 2015; Thornton and Raihani, 2008). However, our results also show that CTC can emerge without communication. Indeed, all social-learning forms achieve a gradual increase in technology's quality. While they might not reach the *optimized-technology level* due to greater variation in technology's quality, all social-learning forms exhibit CTC behaviour. This pushes the role of the communication more towards a catalyst of CTC than towards a necessary cognitive skill for its emergence.

When the possibility of innovating is added to our model, we observe an exponential growth of the technology's quality, something that is also observed in our cultural evolutionary history (Lehman, 1947). We posit that this exponential growth is due to a snowball effect: an increase in technology's quality is accompanied by an increase in the understanding of this technology, thus increasing in return the capacity of the individual to increase the technology's quality and so on. This snowball effect occurs because TR supports both the transmission of information and the modification of the technology. This effect of both the understanding and the technology's quality improving together is something that we have already shown in a recent study using transmission chains, where an increase in the speed at which a wheel rolls down an axis is correlated to the increase in the understanding of how mass repartition affects this movement (Osiurak et al., 2021a, 2022). An interesting case emerging from our model is that a single micro-society has a completely different pattern, where bursts of rapid increases in technology's quality alternate with long periods of stasis. This pattern is also observed in another model (Kolodny et al., 2016) and archaeological records (Henrich, 2004; Kline and Boyd, 2010; Kuhn, 2012; Mesoudi, 2011; Shennan, 2001), with known historical stasis phases such as in the Acheulean (Schick and Toth, 2017; Shipton, 2010, 2018). This result suggests that in a population composed of multiple micro-societies all following this pattern of rapid increases and stasis, the overall score of the population will follow an exponential trend.

Our results show that ToM has little to no impact on CTC. Our model without ToM predicts the same result in terms of technology's quality compared to the one incorporating it. This result seems surprising because ToM can only impact learning positively. However, further analysis showed that ToM has an impact early on in our model, acting as a catalyst for the first burst of increases in technology's quality. In this regard, we consider the impact of ToM as a launching pad for the snowball effect described earlier, being neither necessary nor sufficient for the emergence of a CTC. Having ToM equates to having better transmission of information. While we argue that this is not needed for the emergence of CTC, we posit that in its early stage ToM helps reducing the variance in information transmission. This helps carrying improvement to the next generation, thus reaching an optimal technology quality faster. In the later stage of CTC, ToM has less of an impact as TR can maintain and enhance CTC alone. These findings challenge the idea that faithful transmission of information (i.e., teaching) must be supported by ToM to be effective. In addition to these findings, our model predicts that micro-societies with COM are less susceptible to cultural losses, even in an unfavourable environment where losses are stronger than gains. This might be because when a cultural loss occurs (an individual deteriorates the technology), its successor could realize what went wrong, and then correct the damage. We suggest that it is because their TR allows this individual to grasp the mechanical mechanisms underlying the damage of its predecessor (Osiurak and Reynaud, 2020). This might not be possible in OBS and RE because of the lack of information exchange between the individual and its direct predecessor.

Recently, Derex (2022) challenged the classical definition of cumulative culture. He distinguished cumulative culture that only optimizes cultural traits exploiting a finite set of natural phenomena (named Type I) from cumulative culture that not only optimizes cultural traits but also expands the said set of natural phenomena, giving rise to an "infinite" solution-space (Type II). He proposed a dynamics underlying the improvement of technology, with long phases of technology refinement toward an optimal solution (i.e., a close-ended space solution or Type I CTC), punctuated by innovation that shatters this ceiling, only to bring another long phase of refinement toward an even higher point. Following these definitions, it is clear that our model with refinement falls into Type I CTC and that the model with refinement and innovation falls into Type II CTC. However, we want to point out that our second model merely implements innovation and the individual means of enacting it without diving deeper into the cognitive mechanisms underlying innovation. More modelling and experimental work are needed to explore the origin of innovation and the cognitive capacities behind it.

Like all models, ours is a simplification of reality and has limits. First, we modify the three social-learning forms seen in the micro-society paradigm to make them more appropriate, as we do not think that teaching can be dissociated from RE and OBS in a real setting. This is also motivated by the numerous variants of these social-learning forms encountered in the literature (Caldwell and Millen, 2008; Wasielewski, 2014; Zwirner and Thornton, 2015). Second, we focus on ToM and TR only. This is a significant simplification that allows us to investigate more closely the role of these two cognitive skills in CTC. However, this neglects other cognitive abilities that may have an impact on CTC, such as altruism (Dean et al., 2012), creativity (Gabora, 2019), or memory (Lotem et al., 2017). Third, as indicated earlier, implementing OBS is challenging as its definition is unclear in the literature, and there are certainly different ways of implementing it. Fourth, our environment is composed of a single technology. Overcoming this limit may require, for example, multiple distinct parallel micro-societies all having their specific technology, which combined would make up the environment. All these simplifications are justified as our goal was to replicate the micro-society paradigm but extending our model to include multiple populations and technologies is an important goal for future research.

Human technological culture has been essential to our success as a species and our results suggest that TR has been at the origin of this difference with our closest relative. Cumulative technological culture could have happened in the absence of ToM skills and language with other simple forms of social learning such as reverse-engineering or observation. However, our results also show that ToM skills, although not essential, may have been a major catalyst for the development of technologies by stabilizing the transmission of knowledge between individuals. An important outstanding question is why humans would have developed TR and no other non-human primates.

Data availability

A detailed methods description, the codes, and extended results are available in the online electronic supplementary material and at https://osf.io/g7uer/?view_only=338d7a86a8754414b37d39b1d7fcd86d.

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Note

1 This assumption is critical to our model. Adding traits dependence would not only be innovative (very few models have done it before, for an example see Buskell et al., 2019; Kolodny et al., 2015c) but also more realistic (indeed, it seems logical to think that any trait of a technology is needed to meet its purpose). However, this would make the analysis of the model much more ambiguous concerning what we are interested in (i.e., social-learning form and the impact of TR and ToM on CTC) as it introduces a higher level of complexity (Buskell et al., 2019). Note that this assumption has already been made for similar reasons in other models, although these models have not focused on technological traits (Lehmann et al., 2011; Strimling et al., 2009). We also believe that both types of models are complementing each other (a view shared by Buskell et al., 2019) and that both are needed to grasp the complex phenomenon that is CTC. All things considered, we certainly agree that implementing traits dependence in a model of micro-society would bear interesting results and that future work should try to do so.

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