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Trends in Cognitive Sciences

Opinion

Bringing cumulative technological culture beyond copying versus reasoning

François Osiurak,[1,2,5,*,@] Nicolas Claidière,[3] and Giovanni Federico[4]

The dominant view of cumulative technological culture suggests that high-fidelity transmission rests upon a high-fidelity copying ability, which allows individuals to reproduce the tool-use actions performed by others without needing to understand them (i.e., without causal reasoning). The opposition between copying versus reasoning is well accepted but with little supporting evidence. In this article, we investigate this distinction by examining the cognitive science literature on tool use. Evidence indicates that the ability to reproduce others' tool-use actions requires causal understanding, which questions the copying versus reasoning distinction and the cognitive reality of the so-called copying ability. We conclude that new insights might be gained by considering causal understanding as a key driver of cumulative technological culture.

Highlights

Cumulative technological culture, which describes the increase in the efficiency and complexity of tools and techniques over generations, is at the root of the evolution of human technology and is considered one of the most important scientific topics of our time.

High-fidelity transmission is commonly thought to be the key driver of cumulative technological culture. The cultural niche hypothesis assumes that this transmission rests upon copying abilities, which allow individuals to reproduce others' tool-use actions without the need of understanding them.

We investigate whether the opposition between copying versus understanding possesses a cognitive reality by examining the cognitive science literature on tool use.

Evidence suggests that the ability to reproduce others' tool-use actions requires causal understanding, which challenges the validity of the copying hypothesis.

On the cognitive origins of cumulative technological culture

Cumulative technological culture (CTC) (see Glossary) refers to the transmission of techniques or tools over generations that is accompanied by an increase in their complexity and/or efficiency [1–3]. The dominant view, called the cultural niche hypothesis [4,5], assumes that CTC requires a **high-fidelity transmission** mechanism, with the rationale that **innovations** are quickly lost if they cannot be faithfully transmitted to others. Under this view, high-fidelity transmission rests upon high-fidelity **copying** (also called imitation), which reflects the cognitive ability to reproduce the actions performed by others with a high degree of fidelity [6,7]. This copying mechanism is associated with a bias-based selection mechanism, which orients the learner to the most appropriate models to be copied (e.g., prestige or conformity bias [5]). The corollary is that 'complex technologies such as bows result from the accumulation of many, mostly small, often poorly understood improvements made across generations' ([8] p. 1). In some cases, the transmission can be accompanied by an understanding of how the tool works, but **causal understanding** is not necessary for CTC [4,5,8,9]. Instead, it is the selective transmission of occasional experiments and lucky errors that drives much of the evolution of technology [10].

The cultural niche hypothesis has been mainly developed from evidence from anthropology, economics, and biology. Yet, it is also a cognitive view of CTC given the marked cognitive distinction drawn between high-fidelity copying and causal understanding. Surprisingly, this view is relatively silent on the cognitive origins of these abilities, particularly on the copying ability (for a similar criticism, see [11]). For a cognitive scientist, understanding how people copy the actions of others is not the end, but the beginning of the story [12]. In this article, we investigate the cognitive science literature on **tool use** to examine the concept of copying. The question raised here is whether the so-called concept of copying possesses a cognitive reality in the domain of technical cognition and whether it can be easily opposed to the concept of causal understanding. To answer this question, we will focus on the literature on the use of physical tools (e.g., stone tool, bow, knife). The study of how modern humans use these tools offers a better proxy to understanding

[1]Laboratoire d'Étude des Mécanismes Cognitifs, Université de Lyon, 5 avenue Pierre Mendès France, 69676 Bron Cedex, France
[2]Institut Universitaire de France, 1 rue Descartes, 75231 Paris Cedex 5, France
[3]Aix-Marseille Univ, CNRS, LPC, 3 Place Victor Hugo, 13331 Marseille, France
[4]IRCCS Synlab SDN S.p.A., Via Emanuele Gianturco 113, 80143, Naples, Italy
[5]https://emc.univ-lyon2.fr/fr/equipes/cognition-outils-systemes/francois-osiurak/

*Correspondence: francois.osiurak@univ-lyon2.fr (F. Osiurak).
[@]Twitter: https://twitter.com/osiurakf (F. Osiurak).

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how technologies could have been transmitted and improved during human evolution than more recent tools, which require interfaces and arbitrary rules to work (e.g., washing machines, smartphones). In addition, physical tools are commonly employed to make other tools. Thus, their use also reflects another facet of CTC (i.e., tool making).

The idea that high-fidelity copying/imitation is crucial for cumulative culture is not unique to the cultural niche hypothesis but widespread in the community ([13–15]; see also [16]). The consequence is that less time has been devoted to the study of causal understanding, but the literature on this aspect is far from absent. For instance, archeologists have stressed that early hominins [17–21] may have shown signs of causal understanding of stone fracturing and knapping skills. Others have also argued that imitation is a good candidate for the cultural inheritance of communicative gestures but not of technology [22]. In this vein, the present discussion can contribute to building bridges between these different bodies of literature and cognitive sciences with the aim of developing a specific framework for the role played by technical cognition in CTC [23,24].

The cultural niche hypothesis

The cultural niche hypothesis argues that our technological adaptations mainly come from 'networks of diverse minds sharing information, lucky insights and chance recombinations in cumulative fashion' ([25] p. R383). This hypothesis rightly emphasizes that social learning is a much more effective catalyst than asocial learning for individuals to acquire new information. Elegant evidence demonstrates that collective intelligence is greater than the sum of individual intelligence [26] and that it can be optimized with specific network dynamics ([27,28]; see also [29,30]). We do not question these aspects. Instead, the question concerns the cognitive processes at play when people acquire, or even improve, technical content. The cultural niche hypothesis argues that 'complex technologies can evolve without causal understanding' ([9] p. 1), even if 'in some cases elements of causal understanding may be passed along, but this is not necessary' ([4] p. 10923). This hypothesis has been supported by four main arguments.

- Partial-knowledge argument: skilled tool makers can have no idea of whether alternative designs would be better [4,9,25].
- Absence-of-increased-understanding argument: experimental evidence indicates that the improvement of a physical system over generations is not necessarily accompanied by an increase of its understanding [8].
- Cultural-practices argument: many examples suggest that humans often do not understand why some cultural practices (mostly food practices) are effective (e.g., use of chili peppers, cassava processing, Fijian taboos about some toxic marine species) [4,5].
- Serendipity argument: a great number of inventions and discoveries have resulted from accidents or luck [31].

We will come back to each of these arguments at different times in this Opinion, but our discussion will concentrate on the cognitive reality of the copying versus causal understanding distinction. If people can copy without understanding, then this implies that technical cognition is supported by two distinct cognitive processes: copying and causal understanding. The question is whether the cognitive science literature on tool use supports this distinction.

Causal understanding

Causal understanding/reasoning serves two main functions: to predict events and to control their occurrence ([32–34]; see also [35,36]). Causal reasoning refers to the ability to reason about cause–effect relationships, usually by deriving predictions for interventions ('doing') after learning by observing events ('seeing') [37,38]. It is generally opposed to the concept of **associative**

Glossary

Apraxia of tool use: tool-use disorder; inability to select appropriate familiar tools for a given tool-use action or to perform effective mechanical actions, even when suitable familiar tools and objects are provided. This disorder appears after brain damage.
Asocial learning: learning that does not result from the observation of, or interaction with, another conspecific or its product.
Associative learning: ability to learn associations between passively observed events (i.e., classical conditioning) or between interventions and outcomes (i.e., operant conditioning). Associative learning involves representations about proximal relations (i.e., observable events).
Causal understanding: causal reasoning; ability to infer causal structure by observing the patterns of conditional probabilities among events, by examining the consequences of interventions or, usually, by combining the two. Causal reasoning involves representations about distal relations (i.e., unobservable entities; e.g., physical forces). Causal reasoning possesses multiple forms in the human brain, depending on the domain (e.g., social, physical). Here, we use the terms causal reasoning and technical reasoning as synonyms because of our focus on the role of causal reasoning in the technological domain.
Copying: imitation; ability to copy a technical behavior with a high degree of fidelity (also called propensity fidelity). In the literature, the term copying, and more specifically the term imitation, does not imply the absence of causal understanding. Here, we refer to the conception proposed by the cultural niche hypothesis, according to which copying does not require causal understanding, which justifies the distinction between these two cognitive abilities.
Cumulative technological culture (CTC): accumulation of socially learned technical content over generations, allowing humans to develop tools/technologies that are too complex to have been invented by a single individual.
High-fidelity transmission: transmission of information between a model and a learner with a relatively high degree of fidelity (also called episodic fidelity). This describes the whole

learning. Causal reasoning possesses different forms in the human brain. If you meet an unhappy friend, you can infer, from your knowledge of them, that the cause of their unhappiness is the defeat of their preferred football team. In this case, you have used your mentalizing skills, which involve a well-identified brain network (notably the dorso-medial prefrontal cortex and the temporo-parietal junction [39]). If, however, you attempt to understand why your knife cannot cut a piece of meat, you will use another form of causal reasoning, directed to the physical object properties. This reasoning is called **technical reasoning** and is associated with another brain network [notably the left inferior frontal gyrus (IFG) and the area PF within the left inferior parietal lobe (IPL)] [40]. We will hereafter use the terms causal understanding and technical reasoning interchangeably because of our emphasis on the technological dimension. The concept of technical reasoning has been supported by evidence from experimental psychology, neuropsychology, and cognitive neuroscience (for review, see [40,41]). Technical reasoning is not only causal but also analogical, allowing individuals to transfer what is understood in one situation to another. It is based on **mechanical knowledge** that is acquired through experience (i.e., **asocial learning** and **social learning** [42]) and which refers to partial knowledge we have about how our physical environment works. This knowledge is nondeclarative and difficult to make explicit (just take a few moments to think about a definition of 'cutting') and, therefore, differs from **semantic knowledge**. The distinction between mechanical knowledge and semantic knowledge mirrors the distinction repeatedly stressed in the archaeological and anthropological literature between knowledge and know-how [43–46] or, more precisely, ideational know-how [43].

Goal versus means

When an individual observes another carrying out a tool-use action, two components of the demonstration can be copied: the **motor action**, namely the body movement executed by the model, or the **mechanical action**, namely the physical action that generally involves at least two external objects (e.g., a hammer and a nail). In a way, the former can be viewed as the means and the latter as the goal. The question is which of these components is preferentially processed by an observer/learner. Many experimental psychology and cognitive neuroscience studies have tackled this question by designing experiments in which each component is manipulated independently. For instance, participants can have to 'imitate' a model performing a tool-use action while either the motor action or the mechanical action is congruent with the participant's tool-use action [47] or to judge the appropriateness of a model's tool-use action while the motor action is correct versus incorrect and/or the mechanical action is correct versus incorrect [48–51]. The conclusions drawn from these studies are that: (i) it is easier to 'imitate' a model when the mechanical action is congruent, (ii) the correctness of the mechanical action has a larger impact on the judgment of what the model is doing than the correctness of the motor action, and (iii) the mechanical action is processed earlier than the motor action. These findings suggest a goal-first effect in action observation, which has also been found when participants merely scrutinize tools [52–54] or use tools in a non-action-observation condition [55,56], including in stone-knapping contexts [57]. This effect is also generalizable to non-tool-use actions (e.g., imitation of meaningless gestures [58]), confirming the early intuition of Bernstein [59], a pioneer in the motor-control field, who claimed that 'one must concentrate on the "what" of the movement, the "hows" come later by themselves' (p. 234; see also [11]).

Neuroimaging studies have also helped us specify the neural network associated with the observation of the mechanical actions performed by others. When someone observes another individual carrying out an action directed toward an object (i.e., tool-use actions but also non-tool-use actions such as grasping an object), a well-identified fronto-temporo-parietal network is recruited, also known as the action observation network [39]. However, watching someone else performing tool-use actions spontaneously engages an additional tool-use network that includes the left IFG

process, which involves both the information sent from the model and the learner's ability to process this information.

Innovation: production of a new technology either through novel invention, modification, or recombination.

Logical intelligence: logical intelligence encompasses different forms of reasoning (e.g., induction) that apply to relations that are not necessarily causal (e.g., taxonomic relations; lions have property X, mammals have property X).

Mechanical action: interaction between physical objects (e.g., a hammer pounding a nail).

Mechanical knowledge: nondeclarative knowledge about physical principles that is acquired through experience. This knowledge is necessarily partial.

Micro-society experiment: an experiment in which participants must improve a physical system collectively through the social transmission of technical content. The transmission can be indirect (i.e., reverse engineering; only the product is transmitted) or direct (i.e., observation, teaching). The definition proposed here focuses on the technological dimension, but micro-society experiments can also be conducted in other domains, such as language.

Motor action: movements executed by an individual. These movements can be involved in tool-use actions or not (e.g., grasping an object to move it).

Psychotechnical test: test that assesses individuals' understanding of physical events.

Semantic knowledge: declarative knowledge about facts, concepts, people, or social usages.

Social learning: learning that is influenced by observation of, or interaction with, another conspecific or its product.

Technical reasoning: ability to reason about the physical world. This reasoning is both causal and analogical.

Tool use: use of any handheld physical implement that is used to make changes in the environment.

and the area PF within the left IPL [60] (Figure 1A). Importantly, this tool-use network is specific to the processing of the mechanical actions performed by the model and not to the processing of the model's intentions (i.e., the mentalizing network). This mentalizing network can be engaged when participants are explicitly requested to think about the reasons 'why' the model is doing the tool-use actions [61], which confirms the existence of different forms of causal reasoning in the human brain (see earlier).

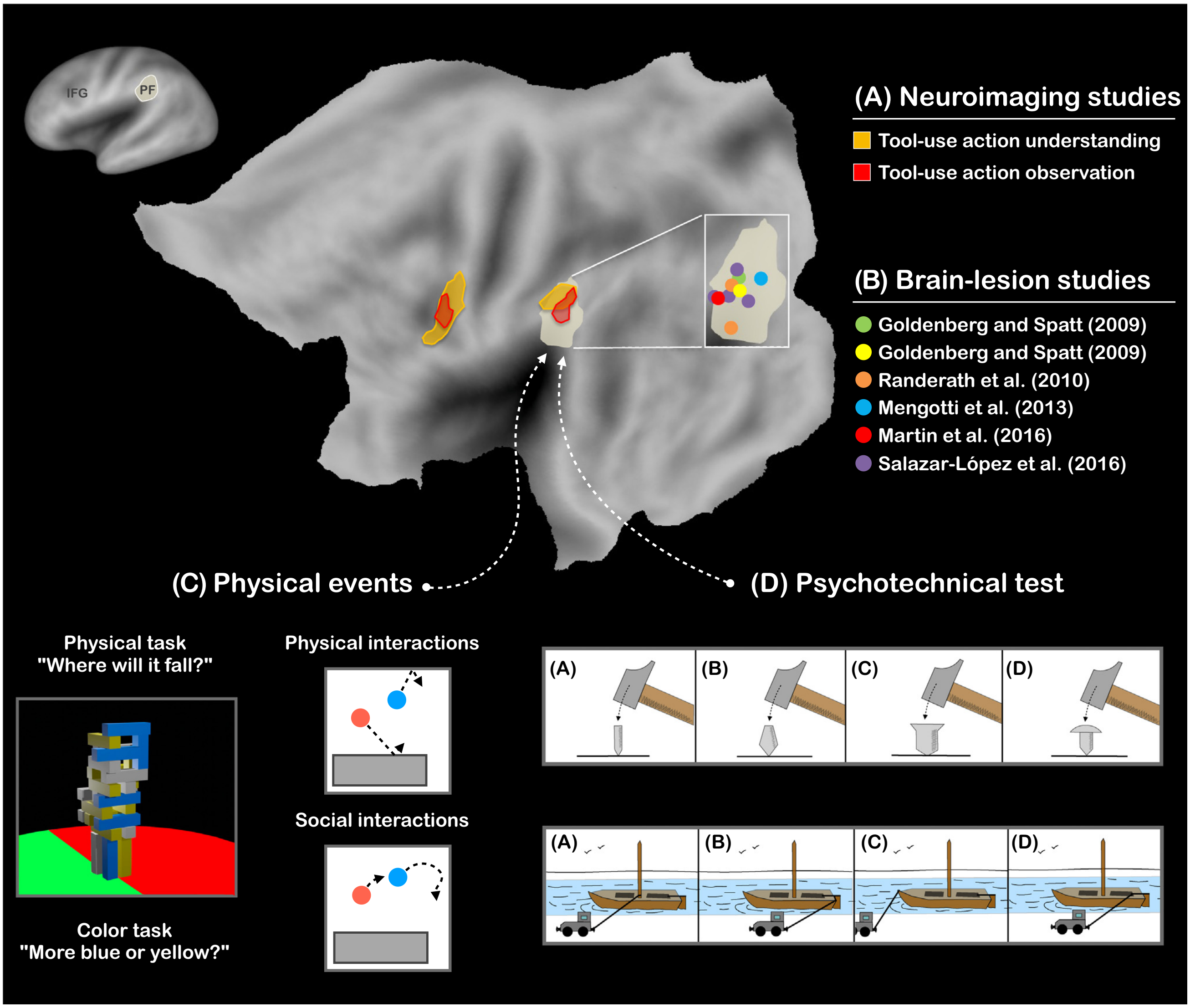

Figure 1. Neurocognitive bases of technical reasoning. (A) Neuroimaging studies have revealed a brain network specific to tool-use action understanding [67] and observation [60]. This network is left-lateralized and includes the area PF within the inferior parietal lobe and the inferior frontal gyrus. The cognitive processes associated with these areas need to be specified. (B) Brain-lesion studies have found that familiar and novel tool use/making is systematically impaired after damage to the left area PF (green: novel tool use; other colors: familiar tool use [65,123–126]), stressing the critical role of this area in the ability to reason about mechanical actions during tool use. (C) Neuroimaging evidence also indicates that the left area PF, along with bilateral premotor cortex and superior parietal lobes, is recruited when people reason about physical events (i.e., physical task or physical interactions) compared with nonphysical events (i.e., color task or social interactions) [69]. (D) The involvement of the left area PF in understanding physical events was also confirmed by a specific link between the cortical thickness of the left area PF and performance on a psychotechnical test [71].

Do we copy the goals?

Taken together, these findings indicate that people preferentially process the goal of a demonstration and that this processing involves a specific tool-use brain network. Although instructive, these findings do not rule out the idea of the so-called copying ability. After all, one may consider that people simply encode and store (i.e., 'copy') for future uses the information associated with the mechanical action observed, without understanding the underlying causal effects. If that were the case, then two distinct networks could be identified, one specialized in the copying of mechanical actions with no associated understanding, another engaged when people use tools in 'asocial' conditions, such as when they solve mechanical problems by using or making novel tools while no demonstration is provided or when they reason about physical events. Such a finding would confirm the distinction drawn by the cultural niche hypothesis between copying that is involved in social learning and the use of familiar tools versus causal understanding that is involved in asocial learning and the use of novel tools/reasoning about physical events. However, the cognitive science literature does not support this distinction.

It has long been observed that some left brain-damaged patients can suffer from tool-use disorders, also called **apraxia of tool use** [62]. These patients can attempt to cut a piece of bread with a spoon, to pound a nail by rubbing the hammer against the nail instead of hammering with it, to put their glasses on upside down, to try to power an electrical coffee machine by plugging in a kettle as if the kettle was connected to the coffee machine, to try to brush their hair with a toothbrush, or to shave their moustache by pressing strongly the razor against the skin instead of making the expected shaving movements. Interestingly, there is a strong link in these patients between the ability to use familiar tools and the ability to use or make novel tools to solve mechanical problems [63–66] (for review, see [40]). Brain-lesion studies have demonstrated that the difficulties in using both familiar and novel tools occur commonly after damage to the tool-use network (notably the left area PF; Figure 1B). In other words, the same brain network is recruited irrespective of whether the tools are familiar (presumably learned through social transmission) or novel (presumably requiring asocial learning). This tool-use network is activated when people focus on the appropriateness of mechanical actions involved in tool-use actions [67,68] (Figure 1A), reason about physical events [69] (Figure 1C), or view physical events without being explicitly asked to reason about them [69,70]. The cortical thickness of the left area PF also predicts the performance on **psychotechnical tests**, in which participants reason about physical events [71] (Figure 1D). This tool-use network, therefore, supports our ability in 'using, making, and reasoning about tools and more generally shaping the physical world to our ends' ([72] p. 29309; see also [73]). Said differently, we do not only copy mechanical actions, but we also attempt to understand them.

CTC and technical reasoning

Evidence that people do not simply 'copy' others' actions but use their technical-reasoning skills to understand what they are doing also comes from the literature on CTC, particularly from **micro-society experiments** [74–76]. It has been repeatedly shown that cumulative performance over generations can be observed in reverse-engineering conditions in which participants can only scrutinize the predecessors' product [8,77–79], even if the progressive improvement is slower than in observation and teaching conditions in which participants can interact together directly ([80]; for somewhat similar results, see [81]; see also [13,18,82]). In reverse-engineering conditions, participants cannot copy because they cannot see the mechanical actions performed by their predecessors. Therefore, technical-reasoning skills are the best candidate to explain how people can gradually improve a physical system in such conditions. As mentioned earlier, the left area PF is engaged in the observation of the mechanical actions performed by others and evidence has demonstrated that its cortical thickness predicts performance on psychotechnical tests. Interestingly, performance on these tests is the best predictor of cumulative performance in micro-society paradigms [83–85]. By contrast, creativity or **logical intelligence** scores do not predict cumulative performance [83]. Initial experimental evidence has suggested that the improvement of a physical system over generations is not necessarily accompanied by an increase in its understanding [8] (the absence-of-increased-understanding argument). Partial replications have nevertheless revealed the presence of a parallel improvement of the physical system over generations and its understanding [78,86], not only when this understanding is assessed with a test analogous to the system but also with a test in which the characteristics of the system change (i.e., transfer test; for discussion on the link between analogical reasoning and CTC, see [87]). In other words, these findings stress that it is the 'abstract' understanding of the physical system that improves over generations. It is noteworthy that, in micro-society experiments in which participants have access to several models, the participants do not focus only on the best one but screen a great number of them to obtain more accurate information [88]. This spontaneous strategy, which is based on intervention (one of the two components of causal reasoning, see earlier), is counterproductive if people simply copy the best model and rather suggests that people seek to form a causal representation of how the physical system works. It has also been reported that people do not explore randomly the space of solutions ([8,89]; see also [90]). These findings indicate that people seek to enrich their causal understanding by watching others, leading them to extract relevant and reject irrelevant information. Finally, if the level of technical-reasoning skills plays a role in the ability to reproduce and improve a technical solution over generations, it can be predicted that signs of cumulative performance should be difficult to observe in children, who are supposed to possess a lesser level of technical expertise. However, this level of technical expertise may be sufficient to reproduce the technical solution of an adult model. A couple of experimental studies have confirmed these predictions in reporting that young children can reproduce an adult model's technical solution (even in a reverse-engineering condition) they could not reach just by themselves [91] and show signs of cultural lineages in transmission chains but not of cumulative performance [92].

Can we copy without technical reasoning?

As discussed so far, it appears difficult to consider that we learn technical content from others without using our technical-reasoning skills. Another way of testing this hypothesis is to see if individuals with technical-reasoning deficits (i.e., difficulties in using familiar tools or solving mechanical problems by using or making novel tools) can recruit their copying skills to solve technical problems. Two studies [93,94] provide an answer to this question. These studies included left brain-damaged patients with tool-use disorders. Like most neurological patients, these patients had additional sensorimotor or cognitive deficits (e.g., hemiplegia, aphasia), whose nature was heterogenous because it depended on the location of lesions. It is known that these additional deficits do not provoke apraxia of tool use. In other words, the difficulties faced by these patients in using tools reflected the impairment of their technical-reasoning skills. They were trained to carry out simple everyday tool-use activities, such as cutting a slice of bread and spreading margarine and jam on it. For each activity, three distractors were also presented (e.g., a tin-opener) to make the activity closer to the ecological/home context. The activities were trained for several weeks, several days a week with specific sessions as well as for 20–40 minutes during the daily sessions of occupational therapy. The training consisted of either errorless completion of the whole activity (step-by-step demonstration; i.e., a kind of observational learning) or training of details (i.e., directing the patient's attention to the functional significance of critical features of the actions; i.e., teaching). The results showed a post-therapy decrease in fatal errors (i.e., errors that made patients unable to proceed without help) and needs for assistance but not of reparable errors (i.e., the error did not prevent the patient from continuing the activity). In other words, although the patients committed fewer errors after the therapy, they still had difficulties carrying out the activities and were not able to 'copy' faithfully the tool-use actions. There was no generalization of training effects from trained to nontrained activities and the rate of errors increased when the trained activities were evaluated with a partially different set of tools (e.g., another knife). The success of training was preserved at follow-up (6–30 months after the end of the therapy) only in patients who had practiced the activity at home. In others, fatal errors reappeared.

Two conclusions can be drawn from these results, which unfortunately stress the difficulties of these patients to recover from their tool-use disorders. The first is that patients with technical-reasoning deficits encounter severe difficulties in acquiring tool-use skills through social learning (the model being here the occupational therapist). It is noteworthy that these difficulties might reflect the more general inability to copy others' actions. This possibility is not supported by neuropsychological and neuroimaging evidence, which has indicated that tool-use skills versus imitation of gestures (symbolic and meaningless) involve distinct neurocognitive processes [95,96]. The second is that, if we consider that the improvement of performance over therapy, which was nevertheless prone to many errors, reflects a potential copying ability, then this copying ability is characterized by a high learning cost (several hours here for simple activities) and degrades if not frequently practiced. In addition, this copying ability would be very sensitive to the lesser environmental changes (e.g., a new knife).

Escaping from the copying versus reasoning distinction

We conclude that the distinction between a high-fidelity copying mechanism and causal understanding does not find support from the cognitive science literature on tool use. While technical reasoning seems spontaneously engaged in the social transmission of technical content and critical for reproducing others' tool-use actions, an independent copying ability, if it exists in the domain of technical cognition (Box 1), would not support faithful transmission and its cognitive origins remain to be determined (Figure 2, Key figure). Put in more radical terms, the copying versus reasoning distinction may be a red-herring because high-fidelity transmission of technical content is driven only by technical-reasoning skills.

Box 1. Not one but several cumulative cultures with different cognitive origins?

Current evidence suggests that cumulative culture is not a unified phenomenon but might recruit a collection of domain-general [110–113] and domain-specific [22] cognitive mechanisms. Accordingly, the question 'is causal understanding necessary for cumulative culture?' makes little sense without specifying the domain of interest. For instance, the fact that people can follow some cultural (mostly food) practices without understanding why they are effective has been repeatedly used to support the cultural niche hypothesis (the cultural-practices argument) [4,5]. We do not dispute this evidence. Food processing needs to retrieve information about each recipe specifically (e.g., ingredients, steps, step order, and duration) that is stored in semantic memory, which refers to knowledge about facts, concepts, people, or social usages [114]. This memory, which is supported by ventral brain regions, notably the temporal cortex [115], is not involved in the technical dimension of tool-use skills. Thus, patients with selective semantic-memory deficits do not meet difficulties in solving mechanical problems with novel tools but can be unable to name or describe the function of familiar tools they can nevertheless use appropriately [116–119]. Importantly, contrary to technical skills, no evidence indicates that semantic knowledge needs causal understanding to be acquired. We can know that Saturn is a planet, dinosaurs exited million years ago, or cassava roots are commonly soaked in water for several days before eating them, without any causal understanding about how this knowledge was built. Note, however, that food practices are based on at least two cognitive components. The first is linked to semantic memory. The second is the technical-reasoning component because food processing requires tools (e.g., knives, plates) and techniques (e.g., fire making, cutting), which constitute a repertoire that people can exploit for different recipes. Using these tools and techniques involves technical reasoning and, therefore, causal understanding. The consequence is that the cultural evolution of food processing is linked to causal understanding, even if it plays an indirect role. The same is true for many cultural domains because cultural evolution in one domain (e.g., arts [120]) is often intertwined with cultural evolution in other domains ([121]; see also [122]). This technical-reasoning versus semantic-memory distinction provides one potential avenue to explain why part of cumulative culture can be passed along through high-fidelity copying and without understanding, whereas other parts require causal understanding.

Key figure

Causal understanding and high-fidelity transmission

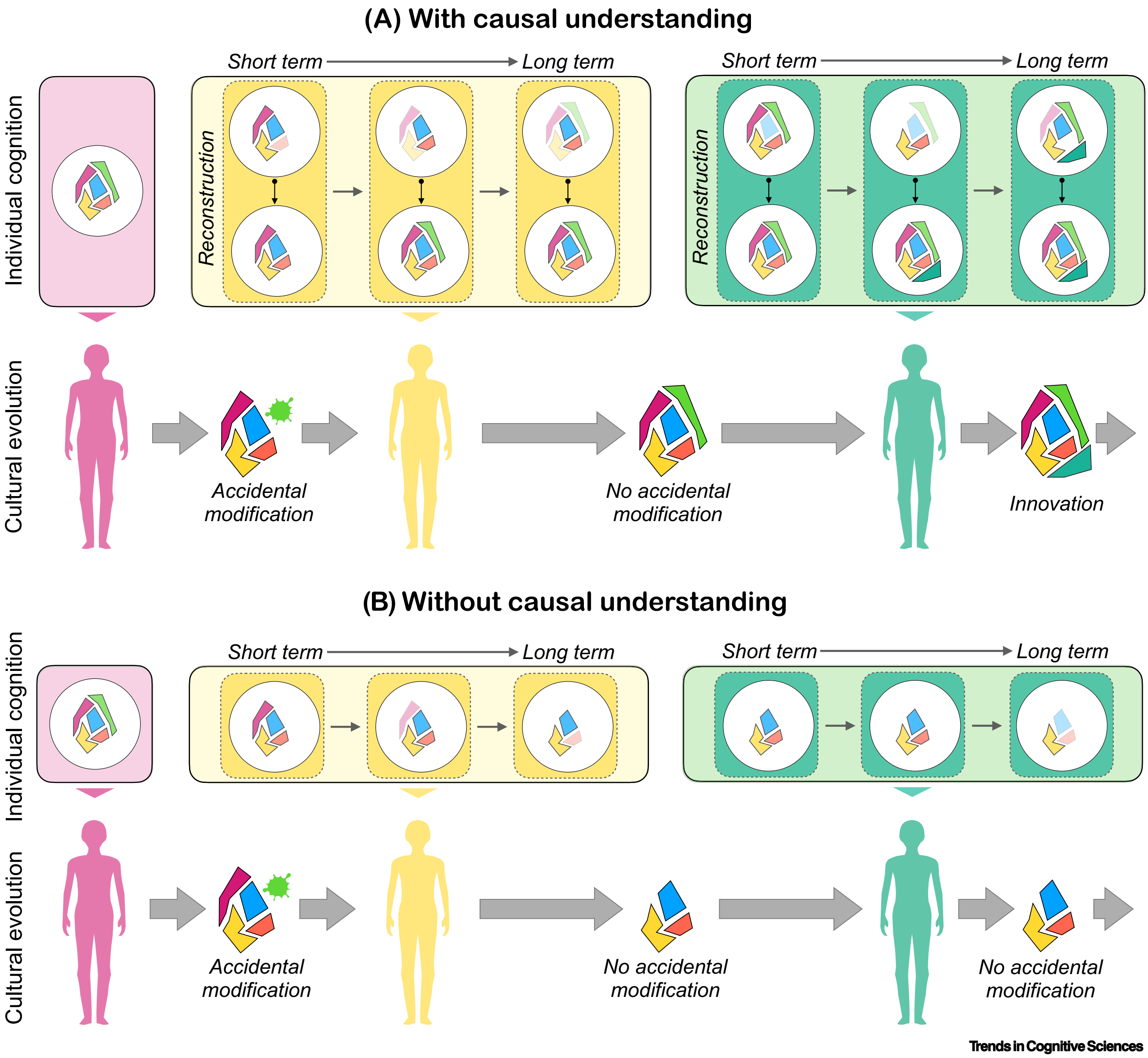

Figure 2. The technical-reasoning hypothesis (A) assumes that causal understanding is spontaneously engaged in social transmission of technical content and is critical for reproducing and improving upon others' tool-use actions and technologies. Thus, the phenomenon of high-fidelity transmission does not necessarily need to have a strict correspondence at the individual level but can be supported by a reconstruction process implemented through causal understanding, which can be particularly useful when the technical content transmitted is degraded or incomplete (e.g., accidental modification [86]). This hypothesis does not exclude the potential role of memory (i.e., working memory and episodic memory) to store the information transmitted and/or reconstructed over the individual's lifetime. However, the technical behavior can be maintained only if the individual understands it. This is consistent with evidence indicating that children reproduce both the relevant and irrelevant actions performed by a model in the short term (immediately after the demonstration) but only the relevant actions in the long term (after a delay of 1 week) [127]. Without causal understanding (B), the information is progressively lost in the long term, suggesting that high-fidelity transmission can take place only if the technical content is quickly transmitted between individuals (i.e., in the short term) and without the presence of accidental modifications.

In our opinion, the literature suggests that participants use their technical-reasoning skills to develop their own causal understanding of the situation and use this understanding to solve technical problems. We are born with limited causal understanding of physical principles (e.g., support) and that understanding evolves during infancy and adulthood through experience [97–99]. Asocial (or individual) learning and social learning are two ways of acquiring experience and enriching our understanding and they provide complementary information, with social learning guiding learners toward more effective solutions and asocial learning allowing individuals to adapt that knowledge to their own constraints and goals. Inter-individual variability in terms of causal understanding/technical-reasoning skills can explain the presence or absence of high-fidelity transmission. High-fidelity transmission is a mechanism that involves both the information sent by the model and the learner's ability to process it. This transmission can be disrupted if some information is incompletely sent and/or if the learner cannot process appropriately the information received. The more advanced the causal understanding of the problem is, the more individuals can transmit, acquire, and maintain the technical behavior over time. This may lead to faithful transmission when the technique is optimal and causal understanding is easily accessible, but it can also lead to improvement over time (e.g., technique suboptimal and understanding is easily accessible), adaptation to one's own needs, divergence through the use of a completely different solution, or the loss of technical knowledge (e.g., when the understanding is advanced and difficult to acquire).

Considering that causal understanding can drive CTC does not mean that individuals must have a perfect causal representation of physical events since we necessarily only possess a partial causal understanding of a technique (Box 2). The question is one of degree: what is the degree of understanding necessary to sustain cultural transmission? Interestingly, our view predicts that the loss of technical knowledge along cultural transmission chains is not irreversible because participants with higher technical reasoning abilities and/or more elaborate causal understanding can reconstruct the technical knowledge that has been lost [86]. In other words, the phenomenon of high-fidelity transmission does not necessarily need to have a strict correspondence at the individual level but could be supported by a reconstruction process [6,100–102] implemented through technical reasoning. New population-based experiments, computational modeling, and empirical research are needed to provide support for these cultural dynamics.

Concluding remarks

The cultural niche hypothesis claims that CTC is driven by both copying and selection mechanisms and minimizes the role played by causal understanding. The cognitive science literature depicts a different scenario, in which the degree of understanding might explain the quality of the transmission, thereby reintroducing the role played by individual cognition in CTC and, more generally, cultural evolution (see [103,104]), a view compatible with the cultural attraction theory [100,105,106]. More broadly, our discussion also leads us to revisit the classical high-fidelity transmission versus innovation distinction (for discussion on the innovation component, see [107]). If we envisage that technical reasoning plays an active role in the transmission, we can also envisage that it is also engaged in innovation, by supporting the recombination process that characterizes most innovations [31,108]. Even if some innovations result from 'lucky errors', 'the inventor also [has] a mind prepared to recognize the discovery embedded in chance observation' ([31] p. 5). Future research could be envisaged to examine whether people with better understanding are more prone to detect these lucky errors or perform recombination (the serendipity argument; see Outstanding questions). If such findings were obtained, then this could lead to an extended scenario in which causal understanding in concert with asocial and social learning drives both the transmission and innovation components of CTC [109].

Outstanding questions

What are the neurocognitive foundations of innovation? Is innovation supported by causal understanding? Do high-fidelity transmission and innovation involve distinct cognitive processes?

What is the role of memory (notably working memory and episodic memory) in cumulative technological culture? And in conjunction with causal understanding? Is semantic memory necessary for cumulative technological culture?

If we assume that understanding differs from explaining, then what is the role of individuals' explaining skills in cumulative technological culture? What link do explaining skills have with teaching? How do implicit understanding and explicit understanding interact with each other?

How do social-learning strategies (e.g., model-based biases or 'who' strategies) interact with causal reasoning? Do the strategies differ depending on the learner's level of causal understanding?

How does individual cognition (e.g., technical reasoning) interact with demography (e.g., population size, population structure) to constrain cultural phenomena (e.g., cumulative technological culture)?

Box 2. Causal understanding is necessarily partial

Causal understanding refers to the ability to predict the effects of intentional modifications of a system and is necessarily partial. For instance, if you ask ten renowned engineering scientists specialized in archery mechanics to predict the effects of modifying the shape of present-day bows (Figure IA), you may observe that their predictions (i.e., noise reduction, arrow speed) are almost perfect, generating the illusion of complete causal understanding. Imagine now that a time travel machine transports them to the future (say 3500 AD), in which bows have remarkable shapes and are made of new materials (Figure IB). You question the ten scientists on these futuristic bows and notice that they meet difficulties in predicting the effects of modifications. You conclude that, after all, their causal understanding is not complete but partial as they cannot predict the effects of all the modifications. This conclusion is trivial because our causal understanding does not allow us to foresee all the effects that can occur in the physical world (for a somewhat similar discussion about the manufacture of Samurai swords, see [87]). Although indisputable, the partial knowledge argument has been repeatedly employed by the proponents of the cultural niche hypothesis to support the idea that causal understanding is not necessary for CTC [4,5,9]. For instance, Harris *et al*. [9] interviewed skilled Hazda bowyers and compared their bow-making beliefs to those revealed by engineering research. They found that Hazda bowyers were better than chance on seven of 13 questions but nevertheless concluded that 'expert-level causal understanding isn't necessary for cumulative culture in extant humans' ([9] p. 5). We cannot expect Hazda bowyers to have perfect and complete bow-making knowledge, who would have such knowledge? A basic assumption in psychometrics is to consider the measure as relative and not absolute. Psychologists do not compare individuals' performance on vocabulary tests with dictionary entries or academicians' vocabulary because the risk is to generate floor effects with performance far below the 'absolute' expert level. It is more revealing to compare an individual's performance relatively to a norm/control group to apprehend, all else being equal, what is specific to the individual studied. Harris *et al*. [9] did not use such a control group but if their purpose was to show that causal understanding is not necessary for CTC, it would have been more interesting to report that Hazda bowyers do not outperform a control group (e.g., Hazda non-bowyers) on a bow-making understanding test.

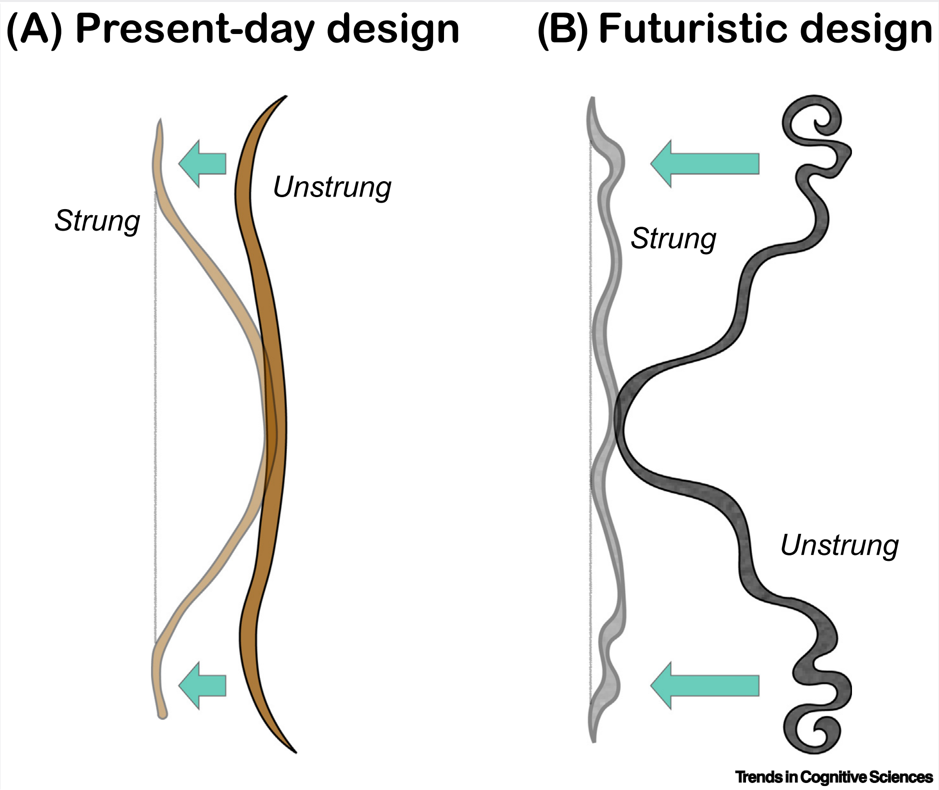

Figure I. Present-day (reflex–deflex) and futuristic (3500 AD) bow designs.

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Declaration of interests

No interests are declared.

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