Enhancing Thoughts:

Culture, Technology, and the Evolution of Human Cognitive Uniqueness

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Abstract

Exactly how to characterize the nature and evolution of distinctively human cognition is still a matter of some dispute. However, three facts are widely thought to be key to this characterization (though a number of other factors are often cited as well): (a) humans have the ability and disposition to be cultural learners; (b) humans have the ability and disposition to rely on mental states with rich representational contents to make decisions, and (c) humans have the ability and disposition to make and use tools. What is not clear exactly is how these three elements work together so as to explain the nature and evolution of specifically human cognition. In response, this paper argues that cultural learning, representational decision-making, and technology create a positive feedback loop: sophisticated cultural learning makes possible the manufacture of tools that increase the sophistication of representational decision-making, which in turn allows for yet further increases in the sophistication of cultural learning and tool manufacture.

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I. Introduction

Saying that humans are cognitively unique is bordering on a triviality; what is far from a triviality is characterizing the nature of human cognitive uniqueness and explaining its evolution. However, that said, it is widely accepted that this characterization and explanation need to appeal to the following three facts: (1) humans are sophisticated cultural learners (Tomasello, 1999; van Schaik & Burkart, 2011; Boyd & Richerson, 2005; Heyes, 2018; Henrich, 2015; Sterelny, 2012); (2) humans have the ability and disposition to rely on mental states with rich representational contents (Millikan, 2002, 1989; Papineau, 2003; Schulz, 2018), and (3) humans are sophisticated tool-users and tool-makers (Vaesen, 2012; Osiurak & Reynaud, forthcoming; Režek et al., 2018; Wimsatt, 2007). What is not yet clear is how these ingredients work together to explain the nature and evolution of specifically human cognition. Making progress in determining this is the goal of this paper.

Before getting started with this, though, it needs to be stressed that there are also some other elements that are often thought to underlie human cognitive uniqueness. Most notable among these are the abilities to communicate in a natural language (Friederici, 2017) and to attribute mental states to other organisms (Tomasello, 1999), but also frequently mentioned is the ability for sophisticated causal and technological reasoning (Osiurak & Reynaud, forthcoming; Vaesen, 2012). Two points about these abilities should be noted here.

First, some of what follows directly touches on these other abilities: in particular, mental state and causal concepts are an example of the rich representational contents in (2), and the ability to communicate in a natural language is certainly part of what underlies (1). Second and most importantly, the point in what follows is not to argue against the importance of these other human abilities in explaining human cognition. Rather, the point is to show that there are *further* important relationships among facts (1)-(3). So, while it may well be true that next to or underlying (1)-(3) are linguistic, mindreading, or causal reasoning abilities (among other things), the goal here is just to show that there are important *interrelations* among (1)-(3)—independently of whatever else may be true about these facts or the features giving rise to them.

The paper is structured as follows. Section II presents the relevant aspects of cultural learning, representational decision-making, and technology. Section III lays out some of the key ways in which technology can enhance representational decision-making. Section IV adds cultural learning to the picture and shows that the upshot is a positive feedback loop between technology, representational decision-making, and cultural learning. Section V contrasts the resultant account with existing treatments in the literature. Section VI concludes.

II. Cultural Learning, Representational Decision-Making, and Technology

I here sketch the core aspects of cultural learning, representational decision-making, and tool use. No attempt at a systematic literature review is made; the goal is just to develop the necessary basis for the rest of the discussion in this paper.

1. Cultural Learning

Humans learn many different things from others, from particular behaviors to high-level psychological traits (Boyd & Richerson, 2005; Henrich, 2015; Heyes, 2018; Nisbett et al., 2001; Piccinini & Schulz, 2019). A number of different models for how this cultural learning (CL in what follows) can proceed are defended in the literature: for example, it may be based on the sharing of joint attention (Tomasello, 1999), an innate sense of pedagogy (Csibra & Gergely, 2011), or an apprenticeship of sorts (Sterelny, 2012). Similarly, it may be that individuals learn from their parental generation, their own generation, or both, and they could learn from individual models (their best friend), or sets of people (what their friends do on average), and they can be subject to various biases in their learning (Boyd & Richerson, 2005; Henrich & McElreath, 2007; Heyes, 2018; Godfrey-Smith, 2009, chap. 8). For present purposes, though, it is sufficient to note three key points about the human ability and disposition to learn from others—however, exactly, this ability and disposition is constituted.

First, while some other animals (such as crows, rats, and chimpanzees) also seem to engage in various kinds of CL, humans learn more and more complex facts from more and more different models (Tomasello, 1999; Tomasello & Herrmann, 2010; Tennie et al., 2009; Tennie & Over, 2012; El Mouden et al., 2014; van Schaik & Pradhan, 2003; Henrich & McElreath, 2011; Henrich, 2015; Boyd et al., 2011; Heyes & Galef, 1996; Creanza et al., 2012; Laland & Janik, 2006; Sterelny, 2012). This is one of the main reasons why the appeal to CL is widely thought to be a key element in the explanation of human cognitive uniqueness.

Second, CL can be cumulative: a behavioral or psychological variant can be improved successively, by letting improvements achieved up to the present become the basis for future improvements (Tomasello, 1999; Tennie et al., 2009).[1] In turn, this brings the acquisition of behavioral or cognitive variants with many different and complexly interacting parts within the scope of cultural learners—though they would be out of reach of individual learners (Tomasello, 1999; Tomasello et al., 2005; Tennie et al., 2009; Legare, 2019, 2017; Heyes, 2018; Henrich, 2015; Boyd & Richerson, 2005).

Third and relatedly, the major adaptive benefit of CL is that it allows organisms to adapt faster to local conditions (Boyd & Richerson, 2005; Henrich, 2015; Henrich & McElreath, 2011, 2007; Fogarty & Creanza, 2017). In particular, the fact that CL is cumulative, but yet not dependent on the origination and then spread of suitable genetic variants, makes it adaptive for enabling organisms to determine the biologically advantageous ways to think and act in certain environments. These environments can be broadly characterized as those changing sufficiently quickly and drastically (either spatially or temporally) to make it adaptive for individuals to change their behaviors and thinking in the light of this environmental variation, but not so quickly that any information received from others is outdated by the time it is received (Boyd & Richerson, 2005; Piccinini & Schulz, 2019).

2. Representational Decision-Making

Representational decision-making (RDM in what follows) is the determination of behavior based on mental states with content. Exactly what it means for a mental state to

[1] This is sometimes called "Tomasello's ratchet" (Tennie et al., 2009; Tomasello, 1999).

have content is still a matter of some dispute (Millikan, 1984, 2002; Papineau, 1987; Fodor, 1990; Dretske, 1988; Prinz, 2002). However, for present purposes, a detailed discussion of this is not necessary—any generally satisfactory account of mental content will do here.

What is important is that RDM can involve contents (i.e. "concepts," on a common construal of this notion: see e.g. Margolis & Laurence, 2015; but see also Machery, 2009) of different degrees of complexity. On one extreme, it can involve purely perceptual concepts: the organism makes it behavior dependent on how it perceives the world. On the other extreme, it can involve highly abstract and complex concepts—i.e. concepts that only have a highly tenuous connection to perceptual states, and / or which are constructed out of other (perhaps themselves complex) concepts (Fodor, 1990; Prinz, 2002). Key among these latter concepts are indexical ones, self-referential concepts, aesthetic and moral concepts, scientific and metaphysical concepts, epistemic and mental concepts, and mathematical concepts (Millikan, 1989; Carey & Spelke, 1996; de Hevia et al., 2014; Gilbert, 2018; Papineau, 2003).

It is furthermore important to note that it is a key feature of the latter, non-perceptual form of RDM that it is, broadly speaking, *inferential* in nature: instead of simply mapping particular perceptual states to particular behavioral outcomes, organisms infer what to do—either by making an inference from their perceptual states to the state of the world, or by inferring what they ought to, given how they perceive the world, or both (Millikan, 2002; Sterelny, 2003; Carruthers, 2006; Schulz, 2018). Now, it is not entirely clear to what extent this inference is *computational*—and what the relevant sense of "computation" here is—rather than *inferential* in a non-computational sense (Piccinini &

Scarantino, 2010). However, since settling this is not important for present purposes, I shall sidestep further discussion of this issue and just refer to "representational inferences" (or its cognates) in what follows.

As far as the evolution of RDM is concerned, there is good reason to think that one of its key drivers is cognitive efficiency (Lieder & Griffiths, forthcoming; Schulz, 2018) (though improved causal or counterfactual decision-making may also be a contributing factor: Dickinson & Balleine, 2000; Papineau, 2003; Millikan, 2002; Schulz, 2018). RDM allows an organism to streamline its cognitive and neural system in specific ways: instead of relying on a large battery of individual perception / action connections that need to be maintained and updated individually, it "chunks" some of these connections and / or *infers* the appropriate behavioral response to the situation it is in. This streamlining allows an organism to save costly neural and physical resources, as well as to save time adjusting to changes in its environment (Levy & Baxter, 1996; Lennie, 2003; Niven & Laughlin, 2008; Wang et al., 2016; Schulz, 2018; Lieder & Griffiths, forthcoming).

Importantly, though, these benefits of RDM are offset with costs. RDM, generally, comes with reductions in decision-making speed and increases in the reliance on cognitive resources like concentration and attention (Lieberman, 2003; Greene, 2008; Ramsey, 2014; Epstein, 1994; Schulz, 2018; Wynn & Coolidge, 2011; Coolidge & Wynn, 2009). It is the balance of these costs and benefits that, plausibly, is a key driver of the evolution of RDM (Schulz, 2018; Lieder & Griffiths, forthcoming). This point can be illustrated by appeal to two-systems accounts of cognition (though there is no need to commit to the details of these accounts here): system-2 thinking can streamline cognition, but will generally be time-, attention- and concentration-hungry, whereas system-1 thinking tends to be faster and more resource-frugal, but requires a myriad of specific perception / action to be stored and maintained (Epstein, 1994; Kahneman, 2003; Lieder & Griffiths, forthcoming).

In short: while RDM can be relatively fast and frugal—e.g. if it is highly practiced or based on decision rules that are tailored to the specifics of the environment in question (Gigerenzer & Selten, 2001; Schulz, 2018, chap. 8)—the evolution of RDM in general is driven by the balance of the benefits of streamlining cognition and the costs of increased need for cognitive and physical resources. An important corollary of this is that there will be selection for ways of *lessening* the cognitive and temporal costs of this way of interacting with the environment (while keeping its advantages) (Gigerenzer & Selten, 2001; Gigerenzer et al., 2000; Schulz, 2018, chap. 8; Wynn & Coolidge, 2011; Lieder & Griffiths, forthcoming).

RDM is important for explaining human cognitive uniqueness, as human cognition plausibly is at least partially characterized by the reliance on particularly abstract and complex concepts in particularly many different decision situations (Millikan, 1984, 2002; Papineau, 2003; Schulz, 2018).[2] In fact, a large number of the decisions humans make feature a large number of particularly complex and abstract concepts (e.g. whether a [[RANDOM] [SAMPLE]] is [REPRESENTATIVE] of its [POPULATION], or whether an [INHERITED] [[PROPERTY] [ARRANGEMENT]] is [JUST]).[3] Note that the distinction between human and non-human cognition is one of degree, not of kind, in

[2] This is not to say that all decisions that humans make must feature many highly abstract and complex concepts—just that many (including many everyday) ones do.
[3] The reliance on these kinds of concepts may have an innate basis (Carey & Spelke, 1996; de Hevia et al., 2014; Margolis & Laurence, 2015). However, for present purposes, this is not so central. See also below.

this regard. It is not that humans can do something—such as have abstract thoughts—that non-human animals cannot. Rather, the point is that humans can think more thoughts that feature more concepts, many of which are more abstract or complex than what is true of non-human animals.

3. Technology

The manufacture and use of tools—i.e. objects designed to fulfil a given function—is a well-known major adaptive advantage of many different organisms (van Schaik & Pradhan, 2003; Vaesen, 2012; Režek et al., 2018; Wadley et al., 2009; Wimsatt, 2007; Muthukrishna & Henrich, 2016). For present purposes, it is sufficient to make three points about the nature and evolution of tool use ("technology" in what follows).

First, the adaptive benefits of technology come in degrees (Biro et al., 2013; Stout & Hecht, 2017; Sterelny, 2012). Technology can lead to slight gains in the speed or energetic efficiency with which organisms retrieve food from a given source, but they can also make completely new food sources available to organisms.

Second, technology comes in different degrees of complexity (Biro et al., 2013; Renfrew & Scarre, 1998; Martinez, 2013; Coolidge & Wynn, 2009). On the one hand, the *manufacture* of a tool can be more or less difficult (Wadley et al., 2009; Režek et al., 2018; Stout & Hecht, 2017). On the other hand, the *use* of a tool can similarly vary in terms of foresight and skill (Churchill & Rhodes, 2009; Sterelny, 2012).

Third, there is no question that humans stand out in terms of their ability to make and use technology. While many different kinds of animals (see e.g. Mann & Patterson, 2013; Haslam, 2013; Sanz & Morgan, 2013; Fragaszy et al., 2013; McGrew, 2013; Hansell &

Ruxton, 2008; Cheke et al., 2011; Shumaker et al., 2011) have been shown to use or manufacture tools, humans are able to build and use tools of particularly high degrees of complexity (Shea, 2017). In particular, humans are able to build and use tools whose function it is to build *other* tools—they build robots that build computers that navigate airplanes. More abstractly, humans have also developed a device for storing and transmitting precise information about (nearly) anything: written language (Gibson & Ingold, 1993; Mullins et al., 2013). For these reasons, it is unsurprising that it is widely recognized that humans build and use tools that have vast adaptive value: indeed, it is widely thought that humans achieve much of their fitness *through* technology (Henrich, 2015; Boyd & Richerson, 2005; Landy et al., 2014; Tennie & Over, 2012; van Schaik & Pradhan, 2003; Osiurak & Reynaud, forthcoming; Muthukrishna & Henrich, 2016).

All in all, therefore, it is plausible that human cognitive uniqueness can be (if only partially) characterized by the fact that it draws on extensive CL, highly complex and abstract RDM, and sophisticated technology. However, this leaves open several questions. Key among these are the following three:

(1) *Why* is it that humans are able to build tools of such complexity, rely on concepts with such complexity, and be cultural learners of such complexity?
(2) Why do other organisms *not* have these abilities?
(3) Why do humans have extensive abilities *in all three* of these dimensions?

These questions have not yet been cogently answered. While technology, RDM, and CL have been investigated individually, and while some connections between these three have been pointed out before (see e.g. Tomasello, 1999; Sterelny, 2012; Heyes, 2018; Boyd & Richerson, 2005; Fabry, 2017; Clark, 1997; Schulz, 2018; Klein & Edgar, 2002; Legare, 2019; Tennie & Over, 2012; van Schaik & Pradhan, 2003; Fogarty & Creanza, 2017; Reindl et al., 2018; Muthukrishna & Henrich, 2016; Osiurak & Reynaud, forthcoming), there is a set of mutually reinforcing interactions among the three that has not yet been clearly documented. As I show what follows, laying out this set of mutually reinforcing interactions is key for getting at cogent answers to each of the above three questions. To bring this out, I begin by considering some of the major dynamic relations just between RDM and technology. Once that is done, I bring CL back into the picture.

III. Technologically-Enhanced RDM

The availability of technology allows for RDM to be drastically enhanced.[4] Two different types of this sort of technology can be distinguished.

First, technology might be available that allows organisms to store, for the long-term, some or all of the information its RDM relies on. This will be called technology of type (a) in what follows.

To see the benefits of technology of type (a), assume an organism makes foraging decisions by comparing the food recovery rate at the current locale with the (relatively

[4] It is sometimes suggested that certain forms of technology allow organisms to use the environment directly to make a decision about what to do, and thus make it *less* adaptively valuable to rely on RDM (Brooks, 1991; Beer, 1990; L. B. Smith & Thelen, 1994; Silberstein & Chemero, 2012). There is a lot that can be said about this dynamical systems perspective on these issues; however, for now, it just needs to be noted that it does not exhaust the relationship between technology and RDM: as the rest of this section makes clearer, there are also adaptively positive connections between technology and RDM. See also Schulz (2007, chap. 7).

constant) average rate for the surrounding area. Assume also that the organism had technology available that allowed it to store this average rate for long-term usage, once it had it estimated. Then, instead of needing to estimate the latter rate over and over again, the organism just needs to do it once, and can then refer back to it whenever needed. This can the lower the *average* costs of making the relevant representational inferences significantly: after the initial setup, these costs can drop to near-zero. Importantly, given the complexity of some representational inferences, reducing the need for them can (though of course need not) come with major improvements in cognitive efficiency.

Of course, this assumes that the organism in fact needs to make the same type of representational inference multiple times. However, while not universally plausible, this is plausible at least sometimes: streamlining repeated decision-making is precisely one of the drivers of the evolution of RDM (Millikan, 2002; Schulz, 2018; Whiten, 1995).

The second type of technology that can significantly enhance RDM is one that itself makes some or all of the needed representational inferences for the organism. This will be called technology of type (b) in what follows.

To see the benefits of this kind of technology, note that if an organism can access technology—some form of calculator, say—that is able to estimate the average food recovery rate of the area, then the organism *never* has to make the relevant inferences. In fact, the organism does not even need *to be able to* make the relevant inferences (or at least not within ecologically realistic timescales), and could still rely on complex RDM to interact with its environment. In this way, the availability of technology that makes some of the relevant representational inferences for the organism can also make RDM much faster and less concentration- and attention-hungry.

Technology of type (a) and (b) are especially noteworthy in this context, as it is plausible that the complexity—and thus the costliness—of a representational inference is, *ceteris paribus*, related to the abstractness and complexity of the concepts involved (Schulz, 2018; Ramsey, 2014). The closer a concept is to being perceptual, the easier it tends to be to relate it to the state of the world. Highly abstract concepts do not have a straightforward empirical signature, and thus tend to require more work to connect to the environment of the organism (Fodor, 1983, 1990; Prinz, 2002; Margolis & Laurence, 2015).[5] Similarly, more complex concepts—i.e. concepts with more parts—generally require more in the way of tracking the different parts in representational inferences than concepts with fewer parts (Fodor, 1983, 1990; Prinz, 2002; Margolis & Laurence, 2015). Two further points are worthwhile to note about technology of types (a) and (b).[6]

First, some of the key examples of human technology are of type (a) and (b). So, as far as technology (a) is concerned, humans have long found ways of creating symbols that can be stored, transported, and manipulated (Muthukrishna & Henrich, 2016; Kelly, 2015). Indeed, technology of this type is quite old: on a conservative estimate, symbolic cave art, figurines, and musical instruments appear in the material record about 40-50 Kya (Bednarik, 2008; Renfrew & Scarre, 1998; Shea, 2017; Klein & Edgar, 2002;

[5] This does not mean that this trade-off is linear or one-sided. Some kinds of reasoning with abstract concepts can be quite easy (if I know that I have a hammer, and if I know that this a bone, then I can infer that I can break the bone with the hammer to obtain marrow). Still, the key point here is that the cognitive labor involved in RDM is *generally* an increasing function of the abstractness and number of abstract concepts employed: while determining how to use a [HAMMER], while non-trivial, might be relatively easily done. it remains true that determining whether a [PROPERTY] [ARRANGEMENT] is [JUST] is harder.

[6] The distinction between technologies (a) and (b) need not be sharp. For example, an organism might use tallying sticks first as a calculating device and then as a mobile storage device for the results of such a calculation.

Mellars, 1989; Lawson, 2012; Pike et al., 2012; Kelly, 2015; Morley, 2013).[7] Technology of type (b)—i.e. broadly computational technology—is newer, but even that goes back several thousand years. For example, the "Senkereh Tablet" is a Babylonian calculating device about 5000 years old (Sugden, 1981), and the first sundials date from about 3000 years ago (King, 1955); needless to say, recent human history has seen an explosion of suchlike computational tools.

Second, it is plausible that precisely this is a key factor underlying the human ability to rely on many highly complex and abstract concepts in many of their representational decisions.[8] Because they can outsource key aspects of the cognitive labor associated with their RDM, they can rely on concepts like "cause," "just," "knows," or "number" so extensively (Landy et al., 2014; Stout & Chaminade, 2012; Muthukrishna & Henrich, 2016).

In some cases, the use of these concepts themselves is underwritten by the use of technology. For an obvious example, much of science (in a broad sense) is and has been conducted with the aid of written symbols—including (especially) mathematical ones—and computational devices (Fabry, 2017; Hutto & Myin, 2012; Menary, 2007). However, many other examples can be cited as well, from making representationally difficult investment decisions (Benbasat & Dexter, 1982; Todd & Benbasat, 1992) (including in Babylonian times—Sugden, 1981) to determining where a ship is located (Pacey, 1992).

[7] This also fits well to Kelly's (2015) argument that external devices of various kinds (such as the building complexes in the Chaco Canyon of New Mexico) have been constructed as memory aids. While Kelly focuses on using technology as an aid for remembering, rather than as information storage itself, this difference is not so important for present purposes. What matter here is that technology of this type enables humans to reduce the costs of making various kinds of representational inferences and decisions.
[8] Note that the claim is just that cognitive technology underwrites the reliance on *many highly complex and abstract concepts*—not that that *all* (representational) cognition depends on external aids, as it is often argued in the literature on embedded or situated cognition (Menary, 2007; Hutto & Myin, 2012; Haugeland, 1999; Clark, 2013).

Interacting with the world based on concepts such as “the procession of the perihelion of Mercury,” “maximizes revenue streams in risky environments,” or “is at longitude 156.3319°” is only made possible by the use of technology like mathematical written calculations, the abacus, or the marine chronometer (Pacey, 1992; Schliesser & Smith, 1996; G. E. Smith, 2005; Benbasat & Dexter, 1982).

In other cases, it is the fact that technology exists that allows *other* decisions to be made quickly and efficiently that the above abstract and complex concepts can be relied on. Humans can spend time assessing what is “just,” for example, because they have tools available that allow them to track quickly and easily exactly who *owns* what: written records in a natural language. It is a lot harder to determine whether an inherited property arrangement is *just* if it is not clear what the property arrangement is, or how it came about—not to mention if our cognitive and other resources are already extremely taxed by the needs for organizing the basics of survival (Mithen, 1990, 1999; Wynn & Coolidge, 2011; Gilbert, 2018; Landy et al., 2014). Technology of type (a) or (b) can help make this kind of determination.

Note that the point here is not that *all* uses of complex or abstract concepts in humans must directly or indirectly rely on this kind of technology, or that this the only thing this use depends on. In particular, it is entirely possible that various innate capacities are necessary to make decisions by relying on concepts like [KNOWS], [BELIEVES], [CAUSES], [IS A NUMBER] (Cosmides & Tooby, 1992; Carruthers, 2006; Margolis & Laurence, 2015; Carey & Spelke, 1996; de Hevia et al., 2014; but see also Sterelny, 2003;

Heyes, 2018; Cowie, 2003).[9] Also, it is plausible that organisms can use other organisms as aides in streamlining their RDM (Schulz, 2018, chap. 7).

The point is just that the reliance on technology of type (a) and (b) generally is one of the major components that makes it possible to often rely on RDM with many especially complex and abstract concepts. Whatever else is needed, without technology of type (a) or (b) it would generally be too time-consuming or take too much concentration and attention to use *many differen*t, *highly abstract or complex* concepts like [KNOWS] or [IS JUST] for *many different* decisions—which is precisely what it characteristic of distinctively human cognition.

This is important to note, as the availability of technology (a) and (b) cannot be taken for granted. While many features of the organism's environment can be used to *temporarily* store information in some form (Rowlands, 2010; Griffiths & Stotz, 2000; Clark, 1997, 2008), the long-term storage or computational enrichment of information is unlikely to be easily obtainable.

So, when it comes to technology of type (b), it is just not generally the case that features of the environment themselves perform appropriate representational inferences.[10] Only deliberately generated tools are likely to be able to do this. Furthermore, building such tools is not straightforward. To be usable as an inferential aid, a tool needs to actually be able to perform the needed inferences, and it needs to be able to do so sufficiently efficiently. This implies that finding or building tools that can play this role is

[9] Relatedly, it is of course also true that an increase in working memory would also aid the reliance on complex and abstract concepts—and that it would thus be selected for (Coolidge & Wynn, 2009; Mithen, 1999).
[10] Of course, some features might perform some kinds of calculations (Reed, 1996). The point is just that this will not be so for many of the representational inferences organisms might need to make.

unlikely to be easy (van Schaik & Pradhan, 2003; Reindl et al., 2018; Muthukrishna & Henrich, 2016; Osiurak & Reynaud, forthcoming; Tennie et al., 2009).

Much the same holds for technology of type (a). To be useful in enhancing RDM, such technology needs to be able to store information in a way that buffers it from environmental contingencies—both inorganic and organic—and it needs to be able to store this information in a way that makes it easily and reliably accessible. This rules out many features of the environment, as these two demands pull in opposite directions: the need to buffer information from external influences favors storage that is not easily and reliably accessible, and the need for easily and reliably accessible information favors storage that is open to external influences.

To overcome this, organisms are likely to need to manipulate the environment in some form. One of the major ways to do so is by devising or finding *mobile* sources of long-term information storage (Shea, 2017; Kelly, 2015). With mobile long-term storage, external influences can be minimized, and the information remains easily accessible. However, devising suitable mobile information storages is not trivial: to be mobile, they need to be light, but to remain stable, sufficiently robust. Apart from some classic human examples, few such mobile information stores are known (Bednarik, 2008; Renfrew & Scarre, 1998; Fragaszy et al., 2013; Shumaker et al., 2011; Shea, 2017; Morley, 2013). Another way of solving this problem is by relying on technology that stores the information in places that are *only* accessible to the relevant organisms, but which *are* easily accessible to the latter. Such places are rare, and need to be constructed: generally, if one organism can access a given locale, so can at least several other organisms—not to mention the weather, etc.—and among the places that are only accessible to a given organism, few are *easily* accessible to this organism. Apart from human examples (such as paintings in strategically located caves: Miyagawa et al., 2018; see also Kelly, 2015), it is therefore unsurprising that few examples of such forms of long-term storage have been found (Shea, 2017).[11]

In sum: technology that strongly enhances RDM—through the provision of long-term storage of elements of representational inferences, or which does some or all of the needed representational inferences for the organism—plausibly is quite rare and can only be constructed with difficulty. So, given that (as just noted) humans have been able to manufacture and use technology of type (a) or (b), how did they manage to do this? It is here where CL enters the picture.

IV. CL, Technology, and RDM: A Positive Feedback Loop

CL interacts with both of the other two aspects of human cognitive uniqueness that are the forefront of this paper, and does so in both directions. To see this, consider the three pairs of relationships (CL – technology, technology – RDM, and CL – RDM) separately at first, and then combine them to get an overview of their overall interplay.

1. The CL – Technology Nexus

First and most straightforwardly, CL allows for the piecemeal, cumulative manufacture and refinement of technology of type (a) and (b) (Boyd & Richerson, 2005; Henrich, 2015; Sterelny, 2012; Heyes, 2018; Tennie et al., 2009; Tomasello, 1999; Tennie & Over,

[11] It is possible that humans made paintings in many different places, but that these paintings only survived in caves. In that case, these paintings would not be an example of technology (a). However, the most common view of cave paintings is that they were, indeed, deliberately created in caves. I thank an anonymous referee for useful discussion of this point. See also Kelly (2015).

2012; van Schaik & Burkart, 2011; van Schaik & Pradhan, 2003). In this way, the answer to the question of how humans managed to build this kind of technology, despite the difficulties that come with designing, manufacturing, and using it, becomes easy to see. No individual human needs to be able to fully grasp the details of the representational inferences it is seeking to outsource. Rather, the appropriate kind of long-term storage and the external representational inference machines can be built slowly and over time.[12]

However, there is also a set of reverse influences from complex technology to more sophisticated CL. This set of influences is less widely recognized, but it is very important still. As organisms become able to rely on tools that help them make some or all of their representational inferences, their ability to culturally learn from others is expanded, too.

On the one hand, they can now learn more *efficiently* from others. Given the fact that learners have technology available that allows them to make some of the needed representational inferences, more information can be transmitted to them in a given time period and with a given level of effort. Models or teachers can just provide outlines of the needed information, and let the learners fill in the details as needed on their own. In this way, the *effective* (though not the actual) bandwidth of the transmission channel is being increased (see also Sterelny, 2012). In turn, such increases in the effective bandwidth of the CL channel mean that more information, and more complex information, can be obtained from others.

On the other hand, cognitive technology can increase the set of possible sources of CL. Scrolls and books and other instances of technology of type (a) can be passed on to others, preserved over time, and carried across mountains. Cave paintings can be found

[12] This is not to say that technology does not also get enhanced by other things—including humans' technological competence (Reindl et al., 2018; Osiurak & Reynaud, forthcoming; Tennie et al., 2009).

by future generations or strangers travelling through a given area. Technology of type (b) may provide organisms with ways of inferring what those only distantly related to them (in temporal, spatial, social, or epistemic position) are likely to think: ruins of a previous building can be used as the basis of a representational inference about where and how early generations thought it would be good live. Clothing worn by travelers can be used as the basis for of a representational inference about how those in other places live. However achieved, an increase in the number of possible sources of cultural information is important, as it makes the institution of CL more resilient (Sterelny, 2012). As there are more models, the probability is lessened that cultural information is being lost. This is of major adaptive importance for a cultural species like the human one (Heyes, 2018; Henrich, 2015).

2. The Technology – RDM Nexus

The idea that technology can enhance RDM was the topic of section III, and thus does not need to be restated here. However, what is important to note is that there is also a reverse impact from more complex and abstract RDM to more sophisticated technology. In particular, as organisms are able to rely more often on more complex or abstract concepts like [CAUSES], [FULCRUM], or [IS A PRIME NUMBER] they are able to build more complex kinds of technology (Osiurak & Reynaud, forthcoming; Tennie et al., 2009; Reindl et al., 2018). As noted earlier, understanding the causal, epistemic, or mathematical structure of the world is crucial for manipulating the world so as to manufacture complex tools—including tools that aid the understanding of the causal, epistemic, or mathematical structure of the world (Muthukrishna & Henrich, 2016;

Reindl et al., 2018; Osiurak & Reynaud, forthcoming; Bender & Beller, 2019, 2016; Tennie et al., 2009). In short: more complex & abstract RDM enhances the technological competences of an organism—and thus enables them to build more complex technology.[13]

3. The CL – RDM Nexus

Finally, there is a direct relationship between CL and complex / abstract RDM. Given the fact that CL can be cumulative, if the starting place of the CL can be highly abstract and complex thoughts, then CL can make these yet more abstract and complex (Tennie et al., 2009; Tomasello, 1999; Heyes, 2012, 2018). This thus makes for another explanation for why human RDM has the complexity it has: the ability to start the process of CL with complex and abstract RDM (e.g. because it has been harnessed by sophisticated technology) enables humans to cumulatively learn ever more complex and abstract representations from others.

Putting these three sets of interrelations together creates an overall positive feedback loop between CL, technology, and RDM. CL can make it possible to cumulatively manufacture and use the kinds of complex technology that, directly and indirectly, can be used to drastically enhance RDM, and which in turn significantly expands the quantity and stability of CL.

[13] The present account thus combines the perspectives of Tennie and Over (2012); van Schaik and Pradhan (2003); Osiurak and Reynaud (forthcoming); and Vaesen (2012): both individual competence and CL matter to technological competence, as these can reinforce each other.

[Figure 1]

It is also possible to put at least a rough timeline on this looping evolutionary trajectory. It is reasonable to see the feedback cycle as coming into existence somewhere around 3.5 Mya; at this point, cranial capacity (e.g. of *A. afarensis*) was only slightly larger than that of *P. troglodyte*, and early hominins are generally thought not to have been too different from non-human primates (Shultz et al., 2012). A handful of iterations of the feedback loop then take place until about 1 Mya-500 Kya; at this point, complex tools (such as weighted javelins) are being made and human encephalization greatly increases (Anton et al., 2014; Barham, 2013). The feedback process then starts to really bite, and the cycle accelerates by at least 40 Kya: at this point, humans create musical instruments and other complex tools that enhance and which are enhanced by RDM and CL (Adler, 2009; Morley, 2013; Killin, 2018). Finally, with the advent of writing and sophisticated computational devices about 5 Kya (Nissen, 1985), the loop is put into full swing, and advances in RDM, technology, and CL greatly accelerate each other.

This, then, provides answers to the three questions at the heart of this paper:

(1) *Why* is it that humans are able to build tools of such complexity, rely on concepts with such complexity, and be cultural learners of such complexity?

Answer: It is (partly) because humans are cultural learners that they are able to build the kinds of tools that allow them to rely on highly complex and abstract concepts—and it is (partly) because they are able to build the kinds of tools that allow them to rely on highly complex and abstract concepts that they are cultural learners of such complexity.

(2) Why do other organisms *not* have these abilities?

Answer: For other organisms, the positive feedback loop did not get going. They were not sufficiently strong cultural learners to build the kinds of tools that would allow them to rely on highly complex and abstract concepts—and thus, they were not able to become sufficiently strong cultural learners to begin with.[14]

(3) Why do humans have extensive abilities *in all three* of these dimensions?

Answer: All three of these abilities co-evolve in a positive feedback loop. Advances in one of them are likely to be coupled with advances in others (Gibson & Ingold, 1993; van Schaik & Burkart, 2011; van Schaik & Pradhan, 2003; Tennie & Over, 2012).

V. Differences to Other Accounts

To get a better sense of this account of human cognitive uniqueness, it is useful to contrast it with some of the other ones in the literature. The goal in this is not a thorough literature review, but merely a focused contrast for purposes of elucidation.

First among these accounts is that of Tomasello (see e.g. Tomasello, 1999; Tomasello et al., 2005; Tennie et al., 2009; Tomasello & Herrmann, 2010).[15] The key to Tomasello's picture of the evolution of human cognitive uniqueness are the related human abilities to

[14] Since positive feedback loops need not be deterministic, this can explain why technological competence can sometimes decrease (Jagher, 2016; Premo & Kuhn, 2010). If one step in the cycle happens to fall below the needed threshold, the remaining steps are more likely to do so, too.
[15] See also Csibra and Gergely (2011); van Schaik and Burkart (2011); Legare (2019); Tennie and Over (2012).

attribute representational mental states to others (to see others as intentional agents of their own) and to *jointly* attend to some event in the world (to attend to an event in the explicit recognition that others are attending to that event as well). Tomasello argues that these abilities allow humans to learn more things, and more complex things, from others. He also argues that they underlie the human ability to express themselves in a natural language—which further enhances their ability to learn from others.

The account here defended is consistent with much that is in Tomasello's work. However, there are two key points of departure from the latter. First, there is little in Tomasello on the importance of physical tools for the enhancement of RDM. The present account fills this lacuna. Second and most importantly, there is little in Tomasello on the *interplay*—that is, the existence of a positive feedback loop—among technology, CL, and RDM.[16] Specifically, the present account adds an explicit treatment of the ways in which (i) CL not only allows for the manufacture of more complex tools, but is also amplified by the existence of complex tools, (ii) complex tools allow for more complex RDM, which in turns allows for the manufacture and use of more complex tools, and (iii) more complex RDM allow for more CL, which allows for more complex RDM. In this way, the present account can be seen as an expansion and deepening of the picture laid out in Tomasello.

A second major account to take note of here is that of Heyes (2018). According to the latter, CL is at the heart of human cognitive uniqueness. While there may be a handful of small differences between human and non-human animals in terms of their "psychological starter-kit"—e.g. in terms of their propensities towards social

[16] He sometimes hints at something like this see e.g. Tomasello (1999, pp. 208-209), but he does not spell out these hints in the way it is done here.

aggression—most of what distinguishes human and non-human animals is culturally learned. Importantly, this includes psychological capacities such as mindreading and the ability to speak a language (i.e. the underpinnings of CL itself: Heyes, 2012).

While there is again much that the present account shares with that of Heyes—such as the pride of place given to CL in explaining human cognitive uniqueness—it differs from the latter in three key respects. First, unlike Heyes's account, the present account is not *committed* to a strong anti-nativism about mindreading or language: as noted in section I, the present account can allow these abilities to have some innate presuppositions. Second, there is nothing much about the impact of the manufacture of physical tools—symbolic mnemonic devices, the abacus, sundials—on RDM and CL in Heyes's account.[17] Finally and relatedly, Heyes does not emphasize the *interplay* among RDM, CL, and technology: she does not note the positive feedback cycles connecting these three. This is the heart of the present account, though.

The third picture of the evolution of human cognition to mention here is the niche-constructionist one. There are a number of different versions of this picture (Sterelny, 2003, 2012, 2018; Fogarty & Creanza, 2017; Jablonka & Avital, 2010; see also Odling-Smee et al., 2003), but they all share the ideas that (a) humans alter the environments in which they live, and (b) these alterations supported the evolution of distinctively human cognitive capacities, such as technology, language, and culture.

The present account is broadly in this vein, too, but differs in important respects from others like it. In particular, the point emphasized here is less about altering the niche in

[17] Osiurak and Reynaud (forthcoming) discuss tool-use and tool-manufacture in a framework that is largely consistent with that of Heyes. However, they also do not integrate this into a positive feedback loop with CL and RDM.

which humans live, but concerns specifically the existence of a positive feedback loop among RDM, technology and CL. So, while Fogarty and Creanza (2017) note that agricultural food production can buffer human populations from environmental instability, thus supporting technological innovation even among small populations, they do not consider the ways in which technology can enhance and be enhanced by both CL and RDM—as is done here. Similarly, while Sterelny (2012) briefly notes that changes in technology can prepare the ground for enhanced CL, he does not consider in any kind of detail the kinds of connections among RDM, technology and CL here laid out. (Sterelny, 2012 also commits to a specific model of CL—the apprentice model—that is not central here.)

A final picture of human cognition that, while somewhat different in focus, is worth mentioning here is the work based on the "extended cognition" framework (Clark, 1997, 2008, 2013; Dennett, 1995, 2000; Sterelny, 2017; Colagè & d'Errico, 2018). According to the latter, understanding human cognition cannot be done by seeing it as limited to what is going on in human brains—either because human cognitive states literally *extend into* the social and non-social environment, or because they are so embedded in the social and non-social environment that not including the latter in our theorizing about them would lead us to miss important cognitive phenomena.[18]

There is no question that the present account of the evolution of human cognitive uniqueness, with its emphasis on CL and technology, has many affinities with the work on extended cognition. However, there are also several important differences to note. First, the present account, unlike some of the major accounts in the extended mind

[18] The extended-cognition-perspective partly cross-cuts some of the other accounts just mentioned (especially that falling under the niche constructionist framework: Sterelny, 2012, 1999, 2017, 2018).

literature (see e.g. Clark, 1997, 2008), is not metaphysical: no claims are being made here about where cognitive states begin and end. Second and most importantly, it is again the specifics of the account here—namely, the existence of a self-reinforcing enhancement process between RDM, CL, and technology—that set it apart from what is in the extended cognition literature to date.

All in all, therefore, the core of what makes the present account stand out from what has been in the literature up to now is that it expands the set of relationships that need to be recognized as influencing the evolution of human cognitive uniqueness. While other accounts have also looked at aspects of RDM, technology, and CL, they have not looked at these three as creating a positive feedback loop. That is (picking up a point made in section I), the goal of the present account is not to downplay the importance of mindreading and language (Tomasello), technological competence (Ossiurk & Reynaud), apprenticeships (Sterelny), or imitation (Heyes). Rather, the point is that without paying attention to the positive feedback loop among RDM, tools, and CL, a compelling account of human cognitive uniqueness cannot be provided. While these three elements may well have other underlying enablers and presuppositions, they also influence each other, and this needs to be kept in mind when making sense of human cognitive uniqueness.

VI. Conclusion

A plausible inroad into the explanation of the nature and evolution of distinctively human cognition lies in the set of complex and dynamic relationships between CL, technology, and RDM. CL enables humans to build the kinds of tools that allows their decision-making to be based on highly abstract and complex mental representations, and the ability to rely on highly abstract and complex mental representations, in combination with sophisticated technology, expands their CL in its possible content and sources. While other animals may also have some of these elements—they can engage in some CL, in some technology and manufacture, and in some kinds of RDM—none of these elements appears sufficiently far advanced so that it can enhance the remaining elements in a positive feedback loop. In short: what makes human cognition so different from that of other organisms is that CL, technology, and RDM have pushed—and continue to push—each other to new heights.

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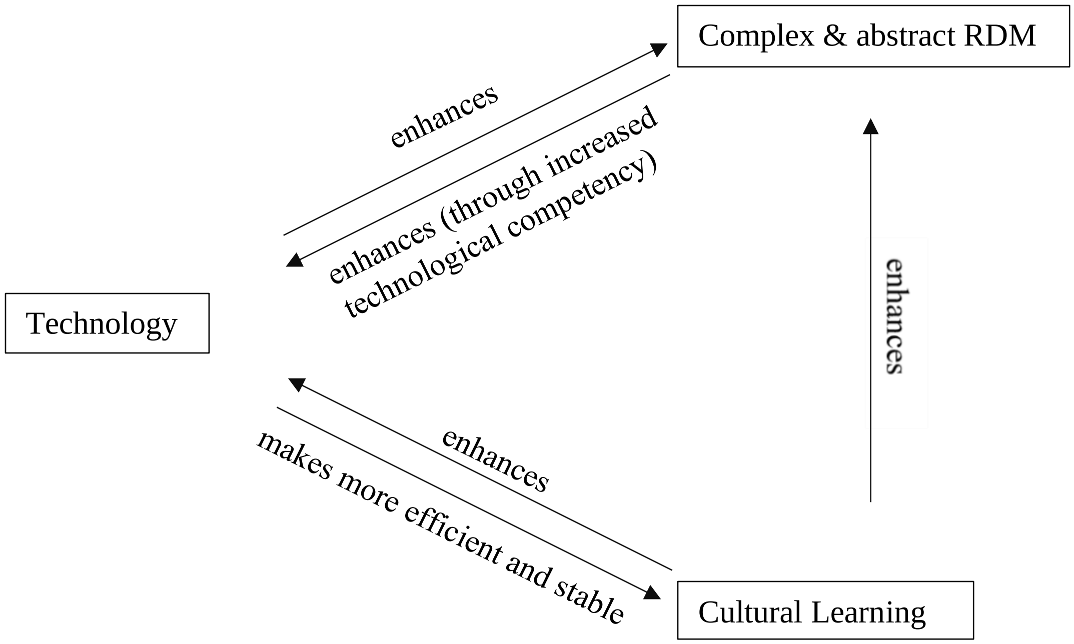

Complex & abstract RDM
enhances
enhances (through increased
technological competency)
Technology
enhances
enhances
makes more efficient and stable
Cultural Learning