Title
On the Problems Solved by Cognitive Processes.

Journal
Cognitive science, 47(6)

ISSN
0364-0213

Authors
Smaldino, Paul E
Pietraszewski, David
Wertz, Annie E

Publication Date
2023-06-01

DOI
10.1111/cogs.13297

COGNITIVE SCIENCE
A Multidisciplinary Journal

Cognitive Science 47 (2023) e13297

ISSN: 1551-6709 online
DOI: 10.1111/cogs.13297

This article is part of the "Progress & Puzzles of Cognitive Science" letter series.

On the Problems Solved by Cognitive Processes

Paul E. Smaldino,[a,b] David Pietraszewski,[c] Annie E. Wertz[d]

[a] *Department of Cognitive and Information Sciences, University of California, Merced*
[b] *Santa Fe Institute*
[c] *Center for Adaptive Rationality, Max Planck Institute for Human Development*
[d] *Max Planck Research Group Naturalistic Social Cognition, Max Planck Institute for Human Development*

Received 31 October 2022; received in revised form 24 March 2023; accepted 24 April 2023

Abstract

Cognitive scientists have focused too narrowly on the acquisition of data and on the methods to extract patterns from those data. We argue that a successful science of the mind requires widening our focus to include the problems being solved by cognitive processes. Frameworks that characterize cognitive processes in terms of instrumental problem-solving, such as those within the evolutionary social sciences, become necessary if we wish to discover more accurate descriptions of those processes.

Keywords: Cognitive science

Until the 1950s, there was little scientific vocabulary for describing complex processes in which larger numbers of simpler procedures are combined (Minsky, 2011). This would change with the advent of computer science, foundational work in complex systems (Anderson, 1972; Simon, 1962; Wimsatt, 1974), and, of course, cognitive science (Gardner, 1985; Marr, 1982; Minsky, 1961, 1974). Now, almost a quarter of the way through the 21st century, cognitive science is highly rigorous and formalized, reaping theoretical and technological gains when combined with conceptual advances in artificial intelligence and computer science. For example, predictive coding, Bayesian inference, and the various flavors of machine learning all represent a revisiting of hierarchical prediction-with-error principles derived from mid-20th century thinkers like Minsky and Wiener (Clark, 2013; Minsky, 1961,

Correspondence should be sent to Paul Smaldino, Department of Cognitive and Information Sciences, University of California, Merced, 5200 North Lake Rd., Merced, CA 95343, USA. E-mail: paul.smaldino@gmail.com

1974; Tenenbaum, Kemp, Griffiths, & Goodman, 2011; Wiener, 1948/1961). These and other information-processing principles offer algorithmic solutions to information-processing problems and thereby identify functions that we might seek to discover within natural intelligences or build within artificial intelligences (Lake, Salakhutdinov, & Tenenbaum, 2015). They also provide us with tools to describe the relationships between dependent and independent variables observed within experimental studies, as in drift-diffusion models of decision-making (Pleskac & Busemeyer, 2010).

However, in our rush to build a rigorous science, we worry that a misstep is currently taking place: That too much emphasis is being placed on descriptive or predictive research, with not enough emphasis being placed on what cognitive processes are *for*—the problems that these processes have been genetically and culturally evolved to solve.

Imagine an alien scientist presented with a modern earth car. The car has all sorts of complicated machinery, from the pistons in its engine to the circuits in its computer. The alien's task is to figure out how it works. Of course, if they did not know that its function was transportation, the task would be nearly impossible, but our alien is no dummy. They know that the car is involved in transporting humans from one place to another and that the humans need to move, stop, turn, etc. So they quickly figure out that the steering wheel is for turning, which it does by controlling the alignment of the front wheels. They figure out that the engine is to give the car thrust, and the brakes are for stopping. Other design features are more mysterious. What about the airbags? Why are there big sacs inside compartments at the front interior of the car? Why are there lights on the ceiling, and why do the red exterior lights on the car's rear illuminate whenever the brake pedal is depressed? Why does a lever by the steering wheel activate blinking indicator lights, and why does the car emit a beeping sound when those indicator lights are activated if there is an object near the side of the car? The alien scientist may need to head to the alien pub and have a think over a tall frosty glass of Pan-Galactic Gargle-Blaster.

Understanding the design of a car is difficult if you do not know that its design must accommodate human anatomy and cognition. But even if you do know those things, understanding remains difficult if you do not also know that cars sometimes crash at high velocities, or that passengers sometimes need to find things at night, or that cars often drive directly behind one another and awareness of other drivers' braking helps drivers to initiate braking behavior, or that cars drive on roads arranged into multiple parallel lanes between which drivers must sometimes move. In other words, you need to understand not only the goals, capabilities, and constraints of the human drivers but also the broader social and physical contexts in which driving occurs. Knowledge of the general function "transporting humans" only gets you so far.

Back to cognition. The analytical tools currently used by cognitive scientists, while powerful, are currently insufficient to understand the nature of mind and brain. See, for example, the modern classic paper, "Could a neuroscientist understand a microprocessor?" (Jonas & Kording 2017), which cleverly illustrates the limitations of associational techniques to discover processes. This limitation is not likely to be overcome until the broader contexts in which cognition occurs are appreciated for what they are: as entailing additional information-processing problems that must also be addressed in our models. In other words, the very thing that we seek to explain—a cognitive competence—cannot be adequately characterized without considering the broader context in which that competence occurs. The role of the environment in cognition *has* long been appreciated in some circles (Brooks, 1991; Clark, 2008), but even then the environment is often treated as a fixed influence rather than something that shapes the nature of cognitive algorithms themselves. A more holistic approach may require deeper engagement with disciplines that have historically been more peripheral to cognitive science, including anthropology, sociology, environmental science, and evolutionary ecology.

Stressing the importance of ecology and evolution in human cognition is hardly new (e.g., Boyd & Richerson, 1985; Cosmides & Tooby, 1987; Gibson, 1979; Tooby & Cosmides, 1992). However, recent focus on formalism and prediction (e.g. Hofman et al., 2021; Yarkoni & Westfall, 2017) often ignores the instrumental nature of cognition. Many authors have correctly emphasized the importance of understanding how the brain and related complex systems work so that we can understand what computations are *possible*. This should not be abandoned. But just as important is to ask, *which problems are cognitive competencies solving*? What are the evolutionary, cultural, and developmental histories of those competencies? And what are the current behavioral and social problems that such competencies allow the individual to master?

The most classic theory reference in cognitive science is probably Marr (1982). Marr challenged us to consider cognitive processes from three perspectives: computational, algorithmic, and implementational. One interpretation of our argument is that there has been too little focus on the computational aspects of cognition (see also Cosmides & Tooby, 1994; van Rooij & Baggio, 2021). In Marr's framing, "computational" does not refer to programs being executed on a computer, in the sense that "computational neuroscience" or "computational social science" uses the term. Rather, it refers to a description of function: the informational transformations happening in cognitive processing, such as the identification of object boundaries from a visual image. Marr correctly emphasized that cognitive scientists must understand *what* problems are being solved in order to characterize *how* they are being solved.

Ethologists and behavioral ecologists have different ways of carving up perspectives on the processes generating behavior. Mayr (1963) divided explanations into ultimate and proximate, where the latter emphasizes explanations from the perspective of evolution and the former emphasizes explanations involving more immediate physical and physiological mechanisms. Tinbergen (1963) further elaborated on this distinction by proposing that a complete explanation of a behavior requires consideration of four perspectives: proximate causal mechanism, ontogeny, adaptive value, and phylogenetic history. Most of cognitive science has focused only on the first of these. Our proposal is consistent with a cognitive science that unifies Marr's focus on multiple levels of analysis with Tinbergen's focus on multiple levels of temporal scale and causal pathway (see also Brase, 2014).

This approach offers alternative ways to think about function—even in areas already well-versed in functionalist thinking. For instance, considerations of the natural ecology and evolutionary histories of visual systems have led to algorithmic and implementational level insights that would have been difficult, if not impossible, to arrive at by looking at these systems in isolation (e.g., Niven, Anderson, & Laughlin, 2007; O'Carroll, Bidweii, Laughlin, & Warrant, 1996). The conceptual purchase is even greater when notions of function are either less clear or biased by intuitions divorced from our species' natural ecology. Plants, for instance, are easy to overlook as minor decorative aspects of modern living. But, through an evolutionary lens, it becomes clear that plants have long been an indispensable part of human existence that can be life-sustaining food, raw materials for tools, or fatal poisons. Recent work using an evolutionary approach has uncovered a host of novel design features of human learning, categorization, and inference procedures centered around the problems posed by plants (Gerdemann & Wertz, 2021; Wertz, 2019).

Much work in cognitive science focuses on short-term processes and their mechanistic explanations. Such work should continue. But researchers can also integrate social, ecological, and evolutionary approaches to produce a deeper understanding of the instrumental nature of cognitive processes. One enduring benchmark in cognitive science is whether our models describe or predict data. But we can also add to this whether we have adequately asked, and then answered, what cognitive processes are *for*. This is not just another puzzle to solve; understanding function can open new doors for understanding mechanism (Smith & Winterhalder, 1992). Evolutionary approaches offer this very thing: a broader, contextualized notion of function, grounded in the real-world problems solved by cognitive processes.

References

Anderson, P. W. (1972). More is different: Broken symmetry and the nature of the hierarchical structure of science. *Science*, *177*(4047), 393–396.

Boyd, R., & Richerson, P. J. (1985). *Culture and the evolutionary process*. Chicago, IL: University of Chicago Press.

Brase, G. L. (2014). Behavioral science integration: A practical framework of multi-level converging evidence for behavioral science theories. *New Ideas in Psychology*, *33*, 8–20.

Brooks, R. A. (1991). Intelligence without representation. *Artificial Intelligence*, *47*(1-3), 139–159.

Clark, A. (2008). *Supersizing the mind: Embodiment, action, and cognitive extension*. Oxford, England: Oxford University Press.

Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, *36*, 181–204.

Cosmides, L., & Tooby, J. (1987). From evolution to behavior: Evolutionary psychology as the missing link. In D. J. pré, (Ed.), *The latest on the best: Essays on evolution and optimality* (pp. 277–306). Cambridge, MA: MIT Press.

Cosmides, L., & Tooby, J. (1994). Beyond intuition and instinct blindness: Toward an evolutionarily rigorous cognitive science. *Cognition*, *50*, 41–77.

Gardner, H. (1985). *The mind's new science: A history of the cognitive revolution*. New York, NY: Basic books.

Gerdemann, S. C., & Wertz, A. E. (2021). 18-month-olds use different cues to categorize plants and artifacts. *Evolution & Human Behavior*, *42*, 304–315.

Gibson, J. J. (1979). *The ecological approach to visual perception*. London, England: Taylor & Francis.

Hofman, J. M., Watts, D. J., Athey, S., Garip, F., Griffiths, T. L., Kleinberg, J., … & Yarkoni, T. (2021). Integrating explanation and prediction in computational social science. *Nature*, *595*(7866), 181–188.

Jonas, E., & Kording, K. P. (2017). Could a neuroscientist understand a microprocessor? *PLoS Computational Biology*, *13*(1), e1005268.

Lake, B. M., Salakhutdinov, R., & Tenenbaum, J. B. (2015). Human-level concept learning through probabilistic program induction. *Science*, *350*, 1332–1338.

Marr, D. (1982). *Vision: A computational investigation into the human representation and processing of visual information*. New York, NY: W H Freeman.

Mayr, E. (1963). Cause and effect in biology. *Science*, *134*, 1501.

Minsky, M. (1961). Steps toward artificial intelligence. *Proceedings of the IRE*, *49*, 8–30.

Minsky, M. (1974). *A framework for representing knowledge* (Artificial Intelligence Memo No. 306). Cambridge, MA: Massachusetts Institute of Technology.

Minsky, M. (2011). The society of mind, Fall 2011. MIT OpenCourseWare. https://www.youtube.com/watch?v=-pb3z2w9gDg&list=PLUl4u3cNGP61E-vNcDV0w5xpsIBYNJDkU

Niven, J. E., Anderson, J. C., & Laughlin, S. B. (2007). Fly photoreceptors demonstrate energy-information trade-offs in neural coding. *PLoS Biology*, *5*(4), e116.

O'Carroll, D. C., Bidweii, N. J., Laughlin, S. B., & Warrant, E. J. (1996). Insect motion detectors matched to visual ecology. *Nature*, *382*, 63–66.

Pleskac, T. J., & Busemeyer, J. R. (2010). Two-stage dynamic signal detection: A theory of choice, decision time, and confidence. *Psychological Review*, *117*, 864.

Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society*, *106*, 467–482.

Smith, E. A., & Winterhalder, B. (1992). Natural selection and decision-making: Some fundamental principles. In E. A. Smith & B. Winterhalder (Eds.), *Evolutionary ecology and human behavior* (pp. 25–60). New York, NY: Walter de Gruyter.

Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: Statistics, structure, and abstraction. *Science*, *1192788*(1279), 331.

Tinbergen, N. (1963). On aims and methods of ethology. *Zeitschrift für tierpsychologie*, *20*(4), 410–433.

Tooby, J., & Cosmides, L. (1992). The psychological foundations of culture. In B. Jrkow, C. Lsmides, & T. Joby (Eds.), *The adapted mind: Evolutionary psychology and the generation of culture* (pp. 19–136). New York, NY: Oxford University Press.

van Rooij, I., & Baggio, G. (2021). Theory before the test: How to build high-verisimilitude explanatory theories in psychological science. *Perspectives on Psychological Science*, *16*(4), 682–697.

Wertz, A. E. (2019). How plants shape the mind. *Trends in Cognitive Sciences*, *23*, 528–531.

Wiener, N. (1961). *Cybernetics: Or control and communication in the animal and the machine* (2nd Ed.). Cambridge, MA: MIT Press. (Original work published in 1948)

Wimsatt, W. C. (1974). Complexity and organization. In *PSA: Proceedings of the biennial meeting of the Philosophy of Science Association* (Vol. 1972, pp. 67–86). Cambridge, England: Cambridge University Press.

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122.