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Remarks Regarding Charles Catania's 1981 Discussion Article "The Flight From Experimental Analysis"

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Charles Catania (1981) makes the valid point that excessive focus on the creation of mathematical models in behavior analysis can crowd out experimental analysis. This point can, perhaps, be elaborated by considering how the utility of quantitative formulations depends on how they are used.

In the physical sciences, the laws of thermodynamics, the laws of motion, and the gas laws state simple relationships among 3–5 variables to which numbers can be assigned. The fact that such equations form the basis of modern technology may have inspired many of the mathematical modeling efforts in the behavioral sciences.

But the type of modeling used in physics is not applicable in the behavioral sciences. Constructs like drive, habit strength, response strength, reflex reserve, reinforcement magnitude or probability, behavioral momentum, and so forth (e.g., Bush & Mosteller, 1955) do not behave and are not measurable the way temperature, force, mass, distance, or pressure are. Long before we reach the mind-boggling non-linearities and interactions of such behavioral constructs, we face the problem that their operational definitions are necessarily arbitrary and non-unique. Drive, for instance, can refer to hours of deprivation of food, water, oxygen, or sex, or to blood sugar level or hydration level. The definitional problem is even greater for the concepts of reinforcement and response (Mechner, 1992). The wide range of possible definitions of the variables used in mathematical models of behavior limits the models' usefulness for prediction and control in situations beyond the particular ones to which they are fitted.

The underlying reason why mathematical models cannot be used in the behavioral sciences in the way they are used in the physical sciences is that organisms are responsive to myriad variables, both internal and external. This responsiveness—a product of evolution—gives organisms the ability to adapt and survive in complex and fast-changing circumstances. It is the reason why 2–4 "free parameters" (generally used as coefficients and/or exponents), are commonly required to fit a particular mathematical model of behavior to a particular set of data (Mazur, 2006). Free parameters, used in this way, are plug factors that correct for the action of any number of unknown variables, including the organism's current physiological state, learning history, adaptations, species, age, prevailing environmental contingencies, and physical variables in the prevailing environment. A wide range of equations can be fitted to a wide range of data by using 2–4 free parameters. Such free parameters don't correspond to independently defined and measurable entities (if they did they would no longer be "free")—they only reflect the joint action of the innumerable variables to which

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organisms are responsive and the particular ways in which the equations' main variables are defined.

James Mazur, in his article *Mathematical Models and the Experimental Analysis of Behavior* (2006), cites some elegant examples of this mathematical modeling in behavior analysis—studies of the initial-link effect, comparisons of quantitative implications of two theories of punishment, and of two alternative mathematical formulations of temporal discounting—hyperbolic versus exponential decay. He also discusses how Killeen's compelling MPR model can be fitted to a wide range of behavioral data by varying a small number of parameters.

While all of this work is impressive within its circumscribed domain, it would seem that any equation that requires 2–4 free parameters to fit a particular set of data is tantamount to a qualitative statement. For instance, the mathematical formulation of the matching law doesn't seem to add significant information to the qualitative statement that there is a general proportionality between most response strength measures and most measures of reinforcement rate or probability. Mazur quotes Herrnstein himself as having said, "If the matching law accounts for 90% of the variance, that's good enough for me." Similarly, it seems to me that the mathematical statement that temporal discounting functions are hyperbolic doesn't add significant information to the qualitative statement that reinforcing value tends to be inversely related to delay. Neither mathematical formulation enables us to make *numerical* predictions as to the behavior that will occur in any particular set of circumstances without assigning, to the free parameters, numerical values specific to those particular circumstances and to the particular definitions used for the formulation's main variables. In economics, too, the insights that mathematical formulations have provided have been mainly qualitative, for the same kinds of reasons. But the fact that mathematical formulations in behavioral science have limited generality does not mean that they have no value. It just means that the information they provide is qualitative.

Catania's point is that excessive focus on mathematical modeling can deflect effort from the laboratory research work needed to gain a greater understanding of organisms' relationship to the countless as-yet-undiscovered variables to which they are responsive. I would add that the "free parameter" adjustment approach can also deflect effort from the development of new conceptualizations of a model's basic variables like response and reinforcement. Let me illustrate with a concrete example. Many efforts to fit Herrnstein's matching law to data have run into deviations from theory described as "undermatching." "overmatching," and "bias." Baum's "generalized matching law" (Baum, 1974) seeks to correct for these deviations by the use of two free parameters. An alternative, more experimentally oriented approach to correcting these deviations would be to focus on the definition of the behavior variable—for instance, to consider features of the individual operant response unit. Examples of such features are response duration, required response effort, interresponse times that exclude response duration, or response clusters that come to function as larger units, as happens in some ratio-like schedules (Mechner 1992, pp. 24-27). That is just one example of the search for alternative conceptualizations of a basic variable. Others are (a) Davison's and Baum's recent work on the nature of reinforcement (2003); (b) the experimentally testable proposal that reinforcer presentations operate on changes of certain response parameters rather than on the absolute values of those parameters (Mechner 1992, pp. 37–46); and (c) equivalence research that examines the processes involved in concept formation (Sidman, 1994; Fields et al., 2012).

When Catania implies that the overarching task of behavior analysis is to conduct the experimental work required to broaden our understanding of operative variables and their interactions, he raises the question of whether some research strategies are more likely than others to lead to advances. I would suggest that particularly promising experimental research and mathematical modeling endeavors have been ones that bring behavior analysis into contact with other behavioral/biological disciplines, like physiology or chemistry. Killeen put it succinctly—models are useful when they have "reference to systems that exist in a different domain than the thing studied."

One familiar example is human dark adaptation, where two decay functions describe the recovery of retinal rods and cones from the bleached state. The first segment corresponds to the recovery of cones and the second to the recovery of rods. Details of the mathematical functions' shapes have been able to provide information about the contribution of variables other than the purely chemical ones (Lamb & Pugh, 2004). A second example is Killeen's recent work on ADHD, in which he relates mathematical formulations of such behavioral data as the mean and SD of response-time, and attentional inertia, to such physiological phenomena as the reuptake of various neurotransmitters, neural energetics, and the size and number of astrocytes (Killeen et al., 2012). Mazur also cites studies in which mathematical models of temporal discounting were used to assess effects of brain lesions on temporal discounting in rats, and an application of the matching law to examine the relationship between the neural control of monkeys' saccadic eye movements and the probability that eye movements would be followed by a fruit juice delivery. A particularly prominent example of domain bridging is Eric Kandel's elucidation of the neural mechanisms of learning and memory (Kandel, 2006).

It should be noted that quantitative approaches to discipline bridging need not be limited to mathematical models. For example, behavioral contingencies provide conceptual bridges between behavior analysis and other behavior-based disciplines. Codification and modeling of these bridges requires the use of a formal symbolic language (Mechner, 2011). Examples are bridges to economics (Mechner, 2010), and to locomotion, reading and listening (Mechner, 2009).

In summary, Catania correctly points out that mathematical modeling activity can deflect research effort from laboratory work. However, we have also seen that quantitative formulations can be used to identify research questions raised by new conceptualizations, and serve as a tool for bringing experimental studies into fruitful contact with other disciplines, thereby contributing to conceptualizations that extend the reach of behavior analysis.

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