20 The Adaptive Toolbox and Lifespan Development: Common Questions?

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Abstract

In this chapter, I explore the relationship between the vision of bounded rationality as an adaptive toolbox (e.g., Gigerenzer, Todd, & the ABC Research Group, 1999) and the vision of development as selection-optimization-compensation (Baltes, 1997, this volume). Both approaches are metatheories that advise us as to what questions to ask and what kinds of models to build. Both have an affinity for the use of evolutionary thinking as a guideline for what problems to address. Beyond this, however, are there similar ideas? Contradictions? And most important, is there a fruitful transfer of ideas and questions?

Visions of Rationality

Developmental, economic, and philosophical theories postulate, explicitly or implicitly, models of rational behavior and cognition. The Enlightenment view of rationality—that the laws of thought and the laws of probability are two sides of the same coin—has left its fingerprints on contemporary theories of human thinking that assume that mature thinking is content-independent, just as are the laws of logic and probability. For instance, Piaget and Inhelder (e.g., 1975) modeled the development of thinking in children as a cumulative process that ends at age 12 to 15 at the level of formal operations—at least in Geneva. Whereas Piaget, Inhelder, and many contemporary researchers in their wake have conducted experiments with textbook-type problems assuming that only logical operations, but not the content of the problem, should matter, others studied rationality in the real world where content-related knowledge does matter (cf. Wellman, this volume).

The move away from simple deductive or inductive reasoning problems has often resulted in visions of rationality in which organisms are assumed to be capable of computing probabilities and their joint distributions and also of having substantial knowledge about their environment, sometimes to the point of clairvoyance. Optimal foraging theory, for instance, models ants and bees *as if* they knew the distribution of all resources, conspecifics, and predators and could compute differential equations to choose the optimal patch and the moment to switch to the next patch (see Goodie, Ortmann, Davis, Bullock, & Werner, 1999). Real animals, of course, have to rely on rules of thumb (e.g., Seeley, 2001). Not only is the rationality of animals modeled by omniscience and massive mental computations; that of humans is portrayed in this way, too. Theories of human categorization, for instance, assume that a person stores all instances of, for example, cars she has ever seen—all Chevrolets, Hondas, Fords, Mazdas, and so on—in a multidimensional space of huge proportions. To categorize a new object—say, the car that just passed by—humans represent the new object as a new point in the same space. They then, ostensibly, compute the Euclidean distances between the new object and all stored ones and finally classify the new object as an instance of that class of stored objects that minimizes the average Euclidean distance (see Berretty, Todd, & Martignon, 1999). In many a vision, the rationality of cognition is equated with the three Os—omniscience, omnipotence, and optimization.

In Figure 20.1, I distinguish between two visions of rationality—*demons* and *bounded rationality*. Demons involve the three Os and enjoy great popularity in the social and behavioral sciences. There are two species of demons—those that exhibit *unbounded rationality* and those that *optimize under constraints*. Unbounded rationality describes decision strategies that ignore the fact that humans (and other animals) have

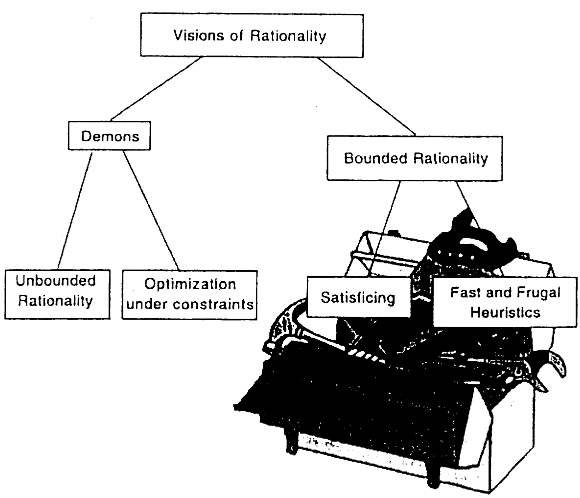

Figure 20.1 Visions of Rationality Underlying Cognitive Theories (from Gigerenzer, 2001; reprinted with permission of University of Nebraska Press).

limited time, knowledge, and computational capacities. In this framework, the question is, If humans were omniscient and had all eternity at their disposal, how would they behave? Maximizing expected utility, Bayesian models, Piaget's formal operations, and *Homo economicus* are examples of unbounded rationality frameworks. Unbounded rationality recreates humans in the image of God or in a secularized version thereof—Laplace's superintelligence. The weakness of unbounded rationality is that it does not describe the way real people think—not even philosophers, as the following anecdote illustrates. A philosopher from Columbia University was struggling with whether to accept an offer from a rival university or to stay where he was. His colleague took him aside and said: "Just maximize your expected utility: you always write about doing this." Exasperated, the philosopher responded: "Come on, this is serious."

In 1961, the economist George Stigler made the image of *Homo economicus* more realistic. He introduced the fact that humans need to search for information—rather than being omniscient—which costs time and money (cf. Behrman, this volume). However, Stigler chose to retain the ideal of optimization and assumed that search is stopped when the costs of further search exceed its benefits: in other words, an optimal stopping point is calculated. This vision of rationality is known as *optimization under constraints* (such as time) and is prominent in models of domains ranging from animal foraging to human memory (Anderson & Milson, 1989). Even devoted proponents of optimization under constraints, however, have pointed out that the resulting models generally become more demanding than models of unbounded rationality, both mathematically and psychologically: The more constraints one introduces, the more complex the optimization calculations become. In optimization under constraints, humans are recreated in the image of econometricians, one step above the gods.

Most theories of cognition are based, at least implicitly, on the assumption of unbounded rationality: they do not model the search for information or stopping rules but rather assume that the organism already has all the relevant information (omniscience). The trick in the experiments is to use reasoning problems that exclude information search because (1) they have no content, as with logical problems, or (2) they have content, but it consists of artificial stimuli that vary only on two or a few dimensions, thereby excluding search for relevant knowledge. Textbooks on thinking and reasoning overflow with this type of problem. In the rare cases where search for information is actually modeled, optimization under constraints seems to be the favorite model.

An alternative vision is that of bounded rationality (see Figure 20.1). Herbert Simon (e.g., 1956, 1992), the father of "bounded rationality," argued that a theory of rationality has to be faithful to the actual cognitive capacities of humans—to their limitations in knowledge, attention, memory, and other resources. To Simon's dismay, his term *limitations* has mostly been taken to mean "constraints," and the term "bounded rationality" became confused with "optimization under constraints." In personal conversation, he once remarked, with a mixture of humor and anger, that he had considered suing authors who misused his concept of bounded rationality to construct even more complicated and unrealistic models of the human mind.

The Adaptive Toolbox

I propose the concept of the *adaptive toolbox*, which can help to avoid the misapprehension that making rationality more realistic just means making optimization more difficult. The adaptive toolbox of a species contains heuristics, not a general optimization calculus. These heuristics do not compute utilities, nor do they involve optimization. When used in the proper environment, these heuristics can be fast and effective. The heuristics consist of building blocks—such as rules for search, stopping search, and decision—and these building blocks can be recombined to generate new heuristics (see Gigerenzer & Selten, 2001; Gigerenzer & Todd, 1999). Some are inherited; others are learned or designed.

In Figure 20.1, I list two classes of tools in the adaptive toolbox. One class, Simon's *satisficing*, involves search and an aspiration level that stops search. For instance, when searching for a house, satisficers search until they find the first house that meets their aspiration level, stop search, and go for it. No attempt is made to compute an optimal stopping point (where the costs of further search exceed its benefits). A second class are fast and frugal heuristics (see Gigerenzer et al., 1999). The difference is this: satisficing involves search across alternatives, such as houses and potential spouses, assuming that the criteria are given (the aspiration level). Fast and frugal heuristics, by contrast, search for criteria or cues in situations in which the alternatives are given. For instance, classifying heart attack patients into high- and low-risk categories is such a situation: the alternatives are given (high or low risk), and one has to search for cues that indicate the alternative category a patient belongs to (Gigerenzer & Todd, 1999). A heuristic is said to be *fast* when it does not involve much computation and *frugal* when it searches for only some of the information.

The adaptive toolbox contains heuristics that help humans to deal with their social and physical environments. Heuristics are simple strategies—shortcuts or rules of thumb that can solve a class of problems, even when there is only limited time, knowledge, and other resources.

An example of a fast and frugal heuristic is the recognition heuristic. This heuristic is in the adaptive toolbox of both animals and humans. For instance, when a wild Norway rat has to choose between two foods—one that it recognizes because it had tasted it before and another that it does not recognize—the rat prefers the recognized food. Similarly, when humans choose between two similar goods—one whose brand name they recognize and one that they do not recognize—they tend to prefer the first. More generally, consider the class of tasks required to infer which of two alternatives has a higher value on a criterion and those situations in which recognition is positively correlated with the criterion (for example, having heard of a city indicates that it has a larger population). If a person recognizes one alternative but not the other, the recognition heuristic advises inferring that the recognized alternative has the higher value on the criterion. The heuristic is, of course, not foolproof; the proportion of correct inferences can be theoretically predicted on the basis of an individual's knowledge and empirically tested (Goldstein & Gigerenzer, 2002).

The adaptive toolbox is, in two respects, a Darwinian model of human functioning:

- *Domain-specificity* Heuristics are domain-specific, not domain-general. Evolution does not follow a grand plan but results in a patchwork of solutions for specific problems. The same holds for the adaptive toolbox. Like hammers and wrenches, its tools—the heuristics—are specifically designed to solve a class of problems but not all problems.
- *Ecological rationality* Heuristics are not good or bad or rational or irrational per se. Their performance is relative to an environment, just as adaptations are not good or bad per se but are relative to an environment. The rationality of the adaptive toolbox is not logical but *ecological.*

For instance, the recognition heuristic is domain-specific in the sense that it can help to quickly solve problems that involve choosing between known and unknown objects. If one has to choose between two colleges—one that has a good reputation and the other that does not have a recognizable name—mere name recognition is a valid (although never perfect) cue for the quality of education. More generally, competitive situations—such as in stock markets, education, and sports—belong to the domain of the recognition heuristic. This heuristic can be used only by people who are sufficiently ignorant about the task at hand. An expert who knows all colleges, all brand names, or all sports teams cannot use the recognition heuristic: she has to rely on knowledge beyond recognition. And in a class of situations that have been defined, not being able to use the recognition heuristic can cause the counterintuitive less-is-more effect: more knowledge leads to less accurate inferences (Goldstein & Gigerenzer, 2002).

Ecological Rationality

The human color-constancy mechanism—which allows us to see an object as having the same color in the bluish sunlight at noon as well as the reddish light of the setting sun—is an adaptation. An adaptation is always with respect to an environment: it is not a good or bad mechanism per se. For instance, in situations with certain artificial lights, such as sodium vapor lamps in parking lots, our color-constancy mechanism breaks down. Those who have seen their green car turn blue know of this shocking experience. More generally, a Darwinian notion of rationality is always relative to an environment—that is, rationality is not logical but ecological. Face recognition, voice recognition, and name recognition are adaptations that help us to identify conspecifics that engage with us in social exchange and cooperation and to ostracize cheaters, among other functions. The recognition heuristic feeds on these psychological adaptations; it is not derived from logic, nor does it use an optimization calculus. The use of this heuristic is ecologically rational in environments where recognition is correlated with the criterion one wants to know—that is, where the recognition validity is better than chance (see Goldstein & Gigerenzer, 2002).

Domain-specificity and ecological rationality go hand in hand. In fact, the concept of ecological rationality provides a quantitative framework for understanding which structures of environments a heuristic can exploit. It also helps us to better understand the notion of domain-specificity and, moreover, define it mathematically (Martignon & Hoffrage, 1999). So far, however, domain-specificity has meant many things to many people (e.g., Hirschfeld & Gelman, 1994).

Simon expressed the ecological nature of bounded rationality by using a pair of scissors as a metaphor. The cognitive capabilities are one blade; the other is the structure of environments. One blade alone does not cut. Studying solely the cognitive capabilities—as most research in cognitive, developmental, and social psychology still does—will not help us understand how the mind works. Without ecological rationality, the study of bounded rationality is reduced to that of irrationality.

The Adaptive Toolbox in Lifespan Development

Thus far, I have briefly introduced the vision of bounded rationality as an adaptive toolbox—a collection of fast and frugal heuristics that uses simple rules for search, stopping, and decision as building blocks. I have also discussed the concept of ecological rationality rather than logical rationality and a toolbox with domain-specific, middle-range heuristics rather than one general-purpose tool. In what follows, I suggest several questions, not answers, that emerge from the intersection of the study of bounded rationality and the selection, optimization, and compensation framework.

What Is in the Adaptive Toolbox at Birth?

What heuristics are present at birth, and which emerge in the course of early development? Which social and physical environments are helpful in eliciting prepared heuristics? One challenge is to describe the content of the adaptive toolbox in early infancy in a precise and testable way (cf. Singer, this volume; Wellman, this volume). A description of a heuristic involves (1) its initial purpose (which may generalize later), (2) the environmental stimuli (including social stimuli and, if necessary, the inner physiological states of the infant) that elicit the heuristic, and (3) the search, stopping, and decision rules of which the heuristic consists. A baby's social smile, for instance, can be seen as a heuristic that emerges after a few months for the purpose of eliciting a parent's commitment, bonding, and the emotion of parental love. Once elicited, parental love prevents a parent from acting like *Homo economicus* making a cost-benefit analysis every morning of whether to invest time and resources in an infant or in some more promising venture or offspring.

The heuristics in the adaptive toolbox are concrete instructions to both infants and parents telling them what to do, not general capabilities or attitudes. The notion of a theory of mind, for instance, is not a heuristic; it is a description of a capability, just like episodic memory or fluid intelligence.

Are Heuristics Acquired and Lost During Development?

I distinguish four ways to acquire new heuristics. Heuristics can be genetically coded or prepared, they can be acquired during the life course by learning, they can be designed, and they can be created from the building blocks of other heuristics. Let me give one example of each of these.

Female guppies choose between two potential mates using a simple heuristic that decides using only one reason, such as whether they have seen the one candidate mating with another female but not the other (Dugatkin & Godin, 1998). These females prefer the male that other females also preferred. This mate copying is genetically coded, although not observable at birth. Note that mate copying exemplifies the *interaction* between culturally based preferences and genetic preferences. Social copying heuristics can also be observed in humans, from the pop idols whom teenagers favor to the hiring of star professors.

When you learn to fly an airplane, you are taught a heuristic for avoiding collisions: when another plane approaches, look at a scratch in your windshield and see whether the other plane moves relative to that scratch. If it does not, dive away quickly. This heuristic is faster and more frugal than the "rational" procedure of computing the trajectories of both planes in four-dimensional space (including time) and determining whether they intersect. Learning, including observational learning, imitation, and instruction, is a second way to acquire new heuristics.

Besides observation and imitation, there is a third possibility for designing heuristics from scratch. For instance, emergency room physicians must decide whether a patient with suspected acute ischemic heart disease should be admitted to the coronary care unit. The Heart Disease Predictive Instrument (HDPI) has a documented validity for this decision and consists of a logistic formula for calculating the probability that the patient has the disease from a table with almost 50 probabilities. Because of this complexity, however, physicians tend neither to use nor to understand this tool and often rely on pseudodiagnostic cues that lead to inferior predictions. Yet there is a third method aside from confusion through complexity and mere intuition. Green and Mehr (1997) designed a fast and frugal heuristic, based on the Take The Best heuristic (Gigerenzer & Goldstein, 1996), which turned out to be more accurate in classifying patients than the HDPI and, moreover, could easily be understood and used by physicians.

Finally, new heuristics can be constructed from the building blocks—rules for search, stopping, and decision—of old heuristics. This recombination of the building blocks is described in Gigerenzer et al. (1999).

One might assume that, during development, the adaptive toolbox becomes more and more filled with new tools and that nothing gets lost. Can heuristics or their building blocks ever be lost? When and to what degree this happens is still an open question. Tasks in which children outperform adults suggest that there might indeed be heuristics that are lost between childhood and adult life.

Do Heuristics Change in Old Age?

Old age is characterized by losses in several functions, and the concept of compensation in the SOC framework refers to these losses. One form of compensation can be the shifting of tools in the adaptive toolbox so that certain classes of tools are on the top—that is, more often used. For instance, when the daily activities and the organization of a social life become difficult to manage because of losses in sensory and motor functions, heuristics that involve less planning and less attention to the outside world may be preferred. Heuristics involving routines and imitation rather than judgments and informed choice may become more frequent (cf. Kliegl, Krampe, & Mayr, this volume). If this change of heuristics does not occur automatically, one might systematically teach older people to reorganize their adaptive toolbox and switch to more robust heuristics that can reduce complexity into manageable parts. The divide-and-conquer heuristic is one example. When complex tasks (such as maintaining a conversation while maneuvering around an obstacle) tend to become difficult with age, the divide-and-conquer heuristic advises splitting such tasks into manageable parts or sequences (for example, first maneuver around the obstacle while stopping the conversation, and then take up the conversation again). This heuristic can prevent a type of accident in older people that results from their trying to solve everyday problems in the same way as they did when they were young.

A second heuristic whose scope might increase in old age is the recognition heuristic. Aging affects recall more than recognition memory. For instance, at a party, a friend of mine once wanted to introduce his wife to a colleague and said, "This is my wife—um, ah, um . . . " at which point his wife helped him out and said, "Susan." Note that recall, not recognition, of her name was the problem. In general, the more recall fades, the more an aging person has to rely on mere name recognition in everyday life. For instance, when information about the quality of products becomes hard to recall, aging consumers nevertheless do not have to rely on guessing; they can choose among the products in supermarkets and department stores using the recognition heuristic: buy the product you recognize. Therefore, older people, just like younger and yet fairly ignorant people, may have a great use for the recognition heuristic to guide their decision making.

How Should Environments Be Designed During the Life Span?

Theories of thinking and problem solving assume that solving a problem occurs inside a person's head. The concept of ecological rationality, in contrast, emphasizes that the structure of the environment can do part of the work when a person solves a problem. For instance, consider a person who takes a hemoccult test, a screening test for colorectal cancer, that comes out positive. He wants to know his chances for actually having colorectal cancer. When we gave experienced physicians the relevant information in conditional probabilities, which is common in medical training, their answers varied from 1% to 99%. When we gave the physicians the same information in natural frequencies, all of them gave the same answer of about 5%, which is consistent with Bayes's rule (Gigerenzer, 2002; Hoffrage & Gigerenzer, 1998). Insight comes, in part, from outside—in this case, how one presents information in the physicians' environments.

If it is true that heuristics and their building blocks change in a predictable way during lifespan development, one can imagine designing environments so that these heuristics can work better at each stage of development. For instance, if in old age routines dominate everyday affairs, then it may be important to not change a person's home environment with new technology, even if this would improve a younger adult's life.

What Is the Role of Emotions as Heuristic Strategies over the Course of Life?

Heuristics can include cognitive and emotional building blocks. Emotions can fulfill the same functions in the adaptive toolbox as do cognitive building blocks. They can provide tools for search (what information to look for), stopping search, and decision making, in order to prevent the organism from getting stuck in an endless search for information or a cost-benefit analysis. But why would one need emotion in addition to cognition? There is a class of adaptive problems in which emotions can guide decisions more effectively than cognitive building blocks. Consider three women searching for a partner to start a family and rear children.

Ms. Economicus proceeds by rational-choice theory. She first tries to determine all possible partners and list for each all possible consequences—whether he likes children, will help parenting, be tender, be humorous, become an alcoholic, beat her up, get depressed, divorce her, and so on. Then she must do extensive research with each candidate to reliably determine the probability of each of the consequences actually occurring. Next, she needs to estimate quantitative utility for each of these consequences—say, helping parenting is plus 4 and becoming an alcoholic is minus 3. Finally, she multiplies the probabilities by the utilities of each consequence, sums these up to the expected utility for each candidate, and chooses the man with the highest expected utility. When she is finished with her research, she may be years older, and the chosen man happily married to someone else who was less rational.

Ms. Satisficing, in contrast, gets things done because she does not attempt to optimize. She simply has an aspiration level, which experience may modify, and she picks the first man that meets her aspiration level. So far, so good. However, when another man comes around the corner and looks even better, nothing keeps Ms. Satisficing from dropping her current husband and embracing the next one. Satisficing does not result in commitment.

Ms. Love, our third woman, is similar to Ms. Satisficing in that she does not try to maximize expected utility but rather uses a sequential search process. However, she has a different stopping rule: she stops her search by falling in love. Unlike the cognitive process of comparing a man to an aspiration level, love stops search more efficiently and for a longer time and, most important, can generate a high degree of commitment to the loved one.

This example illustrates that emotions can be highly effective tools for decision making. Emotions are involved in important adaptive problems, such as finding a mate, caring for children, or choosing food. Since the relevance of some of these adaptive problems rises and declines over the life course, the kinds of emotions that are in a person's repertoire may change in accordance to intensity and frequency of use over the life course (cf. Roberts & Caspi, this volume).

Concepts

Recently, Baltes and Freund (in press) suggested interpreting SOC in terms of heuristics. One way to do this is to specify strategies of, say, selection of means and ends and then to specify their building blocks, such as search, stopping, and decision rules. Here, I use the three key concepts of SOC and investigate what these terms mean in the bounded rationality framework. The meanings can differ substantially, and to recognize this is a first step to exploring the relationship between the two frameworks.

Selection

In the adaptive toolbox, selection occurs at three levels—the selection of cues for making a decision, the selection of an alternative or action (the decision itself), and the selection of a heuristic (which defines both of these selections) from those available in the adaptive toolbox. The selection of cues is defined by two rules: a *search rule* that determines where to look for cues and what cues to look at first, and a *stopping rule* that determines when to end search. The selection of an object or an action is determined by one rule, the decision rule. For instance, the Take the Best heuristic searches cues in the order of their subjective validity and stops search the moment a cue is found that provides evidence for one alternative but not for the other. The decision rule uses just this reason (one-reason decision making) and does not integrate several reasons (it is noncompensatory). The selection of a particular heuristic over another depends on extent of knowledge about cues (some heuristics assume less, others more knowledge), on the task (heuristics are domain-specific and can be applied to a bounded class of tasks), and on earlier experience with various heuristics. The general concept of "selection" in the SOC framework can easily be connected with the more specific models of search, stopping, and decision rules in the adaptive toolbox.

Optimization

The concept of optimization, however, means different things in the two frameworks. In mathematics, statistics, and the theory of fast and frugal heuristics, optimization means computing a maximum or minimum of a function, such as to maximize the expected utility of alternative actions. Fast and frugal heuristics differ from models of unbounded rationality and optimization under constraints in that they do *not* involve optimization computations (see Figure 20.1). Heuristics and optimization are opposites of each other.

Optimization as a computational process needs to be distinguished from an *optimal* outcome. Heuristics try to achieve good-enough outcomes without optimization. They do so by exploiting the structure of environments. Note that heuristics do not try to get a complete representation of the environment in the first place; they just "bet" that it has the right structure—and learn from failure. Note also that optimization (as a process) does not guarantee an optimal outcome. The reason is that most real-world environments are highly uncertain, unpredictable, and incompletely known; therefore, one has to make simplifying assumptions in order to be able to apply the differential calculus. As a consequence, optimization has to "bet" on the assumptions, and that bet may prove wrong, just as with a heuristic. In SOC theory, optimization seems to refer to choosing the right tool for the right goal. Thus, it may refer to the outcome of behavior and not to an underlying optimization computation. If so, the term is used in opposite ways, but the underlying ideas need not be contradictory.

Compensation

The notion of compensation in the SOC framework refers to situations in which losses of goal-relevant means occur and in which a person acquires and invests in alternative means. Compensation here means *substitution* in the sense of vicarious functioning: one strategy is substituted for another. Compensation of means (as opposed to goals) would correspond to the substitution of one heuristic, or class of heuristics, for another one. For instance, cognitive heuristics that require amounts of memory that are no longer available due to age-dependent losses might be substituted with emotion-driven heuristics that exhibit anger or induce feelings of guilt to achieve the same goal.

In the theory of fast and frugal heuristics, compensation has a second, different meaning. A heuristic can process reasons (or cues, predictors) in a compensatory or noncompensatory way. Most cognitive models assume compensatory processing—that is, a negative or positive value on one reason can always be compensated by the values on other reasons. Multiple regression, neural networks, analysis of variance, factor analysis, Euclidean distances, and the expected utility calculus are all examples of models that specify how several reasons or cues are combined—that is, they assume compensatory cognitive processes. But not all cognitive, emotional, and moral processes are compensatory in nature; not everything can be reduced to one common currency. Love, honor, military medals, and Ph.D.s are said to be without price: You cannot buy them with money. Many of the heuristics we study are noncompensatory: only one reason decides, and no attempt is made to weight and sum all possible reasons. Is this distinction between compensatory and noncompensatory strategies a relevant issue for lifespan development? It may well be. Noncompensatory forms of decision making pose fewer demands on memory because they typically involve only a limited search for information. Thus, noncompensatory heuristics may be particularly fit to guide decisions at that point of the life span where recall memory gets more and more difficult to access.

Bringing Ideas Together

It is evident that there are both parallels and differences between SOC and the adaptive toolbox. These can be observed at various levels—as a metatheory, as concrete models of heuristics, and in the terminology. My attempt to explore some of the parallels in this chapter is very preliminary. But it may provide a starting point for a deeper exploration of the potential of a connection between the two frameworks. And both research programs can benefit. First, the study of bounded rationality could eventually be extended into a lifespan perspective. That is, one can study the ontogenetic change of the adaptive toolbox of *Homo heuristicus*. Such a developmental perspective is still missing today, just as the program of unbounded rationality has never been concerned about what happens when their demons are aging. And demons, after all, do not seem to age. Second, the study of bounded rationality with its emphasis on decision making with limited time and resources can provide a heuristics perspective to lifespan development. Because the individual heuristics are not just verbally but also formally defined, the study of the adaptive toolbox can also provide a new analytic framework for modeling the cognitive and emotional processes in development.

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