7 Adaptive Exploration: What You See Is Up to You

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7.1 The Adaptive Explorer Hypothesis

What you see is all there is. According to psychologist and Nobel Prize winner Daniel Kahneman (2011), this principle is the key to understanding how people make decisions. It captures how the human mind tends to construct a belief or a preference from only the information that is seen or available at the time, even when that information is sparse and unreliable. In other words, the mind jumps to conclusions based on the limited information in front of it. Kahneman's principle would seem to help explain why people ignore base rates (Kahneman & Tversky, 1973), use irrelevant anchors (Tversky & Kahneman, 1974) and, in the case of risky decisions, construct a preference from the described gamble in front of them without regard to the norms of expected utility theory (Kahneman & Tversky, 1979).

Indeed, this principle may help to reveal how people make decisions when they can consult convenient descriptions to learn about their options: when a patient checks a pamphlet from the doctor's office to decide whether to take a certain treatment, a commuter scans the morning weather report to determine whether to bring a jacket, or a consumer inspects the safety rating of a vehicle they are thinking of buying. Yet most of the decisions people face do not come with thorough, close-at-hand descriptions. Instead, whether choosing what to order for dinner or hiring a new employee, the possible outcomes of the decision and the probabilities of those outcomes occurring are not known. As a result, people have to search their memory for prior experiences with the options or generate new experiences with them on the fly. They have to explore the options and learn from experience before making a decision. These types of decisions are what we call *decisions from experience.*

These two different types of decisions—decisions from description and decisions from experience—have important consequences for the decisions people make and how they make them. For instance, consider the choice between an 80% chance of winning €4 (vs. a 20% chance of winning nothing) and a guaranteed €3. This type of decision has been well studied in the behavioral laboratories of psychologists (see E. U. Weber, Shafir, & Blais, 2004). It is here that Kahneman's (2011) principle seems to hold: people make decisions based on the information before them—nothing more, nothing less. They take the outcomes and probabilities and use that information, or merely subsets of it, to make a decision (see, e.g., chapter 8).

However, when people make a decision from experience, there is much more to know than meets the eye; they have to explore the options and learn from experience before deciding. In order to understand how these decisions are made, it is crucial to understand how people explore. In this chapter, we show how people actively seek out experiences to inform their decisions, and we suggest a new principle to help make sense of these decisions: what you see is up to you.[1] People control both the source and the extent of their experiences and adjust their search based on their goals, their cognitive abilities, their past experience, and even their evolving preferences. They are, we propose, adaptive explorers.

To support our claim, we first review some of the empirical evidence for people being adaptive explorers. We then present a model called *Choice from Accumulated Samples of Experience* (CHASE), which formally describes search and choice in the process of adaptive exploration. A key aspect of the model is that search and choice in decisions from experience are an integrated system where experiences are accumulated over time to form a preference. This preference, in turn, helps determine how people search and when they stop searching. In the final section, we show how CHASE helps capture some of the properties of adaptive search, and how it provides new insights into the ways people make decisions from experience.

1. Note that Kahneman's (2011) "what you see is all there is" principle is written as a guide for an observer of a decision maker (e.g., a scientist) to help make sense of decisions. Our principle, "what you see is up to you," is written from the perspective of an individual making decisions from experience.

7.2 The Sampling Paradigm

One way researchers study how people make decisions from experience is by taking the monetary gambles often used to study decisions from description and turning them into experience generators (Barron & Erev, 2003; Busemeyer, 1982; Edwards, 1956; Hertwig, Barron, Weber, & Erev, 2004; E. U. Weber et al., 2004). For example, when researchers ask people to make decisions from description they present them with gambles like the one discussed in section 7.1: a choice between an 80% chance of winning €4 or a guaranteed €3. Each gamble produces payoffs with different probabilities. People are then asked to choose the one they prefer (see figure 7.1). When researchers ask people to make decisions from experience they show them the same set of gambles, but without the descriptions. Instead, people have to learn about the distribution of payoffs by sampling from them (Hertwig & Erev, 2009; Wulff, Mergenthaler-Canseco, & Hertwig, 2018).

There are, however, many different ways people can learn from experience. Box 7.1 describes some of the laboratory paradigms that have been developed to study decisions from experience. Here we focus on an implementation

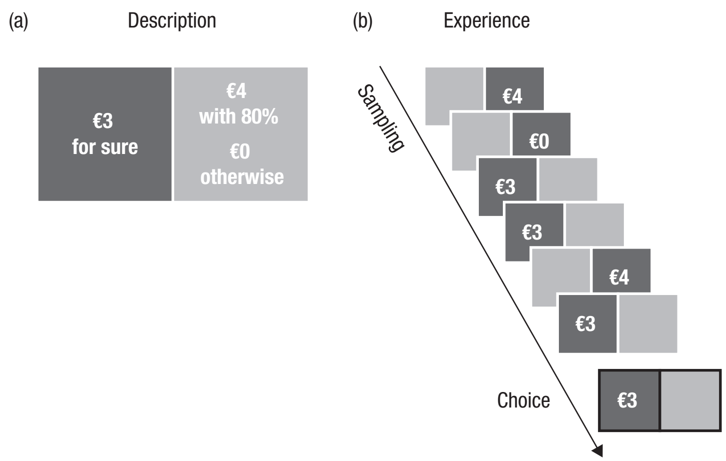

Figure 7.1
The sampling paradigm in (a) decisions from description and (b) decisions from experience. In decisions from experience, people sample one of the possible options (gambles; represented here in light and dark gray), and experience an outcome as a function of the possible outcomes' probability.

Box 7.1
A taxonomy of dynamic decision making.

Decisions from experience can be understood as a special case of dynamic decision making, a class of decision situations that has been studied since the dawn of behavioral decision science (Busemeyer & Pleskac, 2009; Edwards, 1954, 1961; Rapoport, 1964). Edwards (1962b) proposed a taxonomy of dynamic decision making with three dimensions: (a) the nature of the options—whether options remain constant or change over time (stationary/nonstationary); (b) the source of information—whether information is freely available or acquired only through feedback on options chosen (search/feedback); and (c) the nature of the interaction between individuals and options—whether the individual's choice affects the properties of the available options or not (interactive/passive). As illustrated in table 7.B1, current research on dynamic decision making covers all cells of Edwards's (1962b) taxonomy. Notably, however, separate disciplines are involved. For instance, interactive decisions from feedback are commonly studied by neuroscientists interested in the neural representation of model-free versus model-based decision making (e.g., Gershman &

Table 7.B1
A taxonomy of dynamic decision making.

	Search		Feedback	
	Passive	Interactive	Passive	Interactive
Stationary	Sampling paradigm (Hertwig et al., 2004; Wulff et al., 2018)	—	Repeated choice paradigm (Barron & Erev, 2003; Gershman & Daw, 2017)	—
Nonstationary	Observe-or-bet task (Navarro, Newell, & Schulze, 2016; Tversky & Edwards, 1966; chapter 10)	Rivals-in-the-dark game (Markant, Phillips, Kareev, Avrahami, & Hertwig, 2018; Phillips, Hertwig, Kareev, & Avrahami, 2014; chapter 12)	Repeated choice paradigm (Estes, 1959; Plonsky, Teodorescu, & Erev, 2015)	Reinforcement learning (Gershman & Daw, 2017) Foraging tasks (e.g., Mata & von Helversen, 2015)

Note. Interactive contradicts stationary. Hence, cells with both of these features necessarily remain empty.

Box 7.1 (continued)

Daw, 2017), but less so by behavioral decision researchers. Another dimension that has emerged in the literature is the rate of sampling (e.g., Pleskac, Yu, Hopwood, & Liu, 2019; Tsetsos, Chater, & Usher, 2012; Zeigenfuse, Pleskac, & Yu, 2014). Here, participants are shown a sampled outcome anywhere from every 0.05 s to every 0.5 s. The aim is both to understand how decisions are made when information is presented rapidly (e.g., by a stock ticker) and to test some basic assumptions of the sequential sampling models that have been applied to model preferential choice (see Pleskac et al., 2019).

known as the *sampling paradigm*. In it, people can freely explore the options (at no cost) by sampling possible outcomes (typically by pressing a button; see figure 7.1 for an example or visit interactive element 7.1 at https://taming-uncertainty.mpib-berlin.mpg.de/). For each sample, a single outcome is drawn (with replacement) from the option's distribution. People are instructed to sample until they feel confident enough to choose an option for a final draw involving real monetary payoffs. Once they finish sampling, they indicate their preferred option.

Comparing the choices people make from experience to those they make from description has revealed systematic differences between the two, known as the *description–experience gap* (Hertwig & Erev, 2009). The description–experience gap, described next, highlights that decisions from description and decisions from experience are two different animals.

7.3 The Description–Experience Gap

In terms of monetary gambles, the description–experience gap corresponds to a systematic difference between decisions from description and experience in terms of deviances from choosing the option with the greatest expected value (Barron & Erev, 2003; Hertwig et al., 2004; E. U. Weber et al., 2004; see also Hertwig & Pleskac, 2018; Regenwetter & Robinson, 2017). This difference is perhaps best exemplified with reference to what has been called the fourfold pattern of risk attitudes (see Hertwig, 2012a; Tversky & Fox, 1995; Tversky & Kahneman, 1992). This pattern is shown in table 7.1, which summarizes people's preferences from Wulff et al.'s (2018) meta-analysis for four different choices between a risky gamble and a safe option. Focusing first on decisions from description, in the "gain" domain (top two

Table 7.1
The original and reversed fourfold pattern, information search, and predictions of CHASE.

		Gamble options		Percentage preferred risky option		Sample size
Problem	Domain	Risky	Safe	Description	Experience	
1	Gain	4, .8*	3, 1.0	34	**70 (63)**	19 (20)
2	Gain	32, .1*	3, 1.0	**58**	14 (18)	22 (17)
3	Loss	–4, .8	–3, 1.0*	**69**	45 (38)	22 (20)
4	Loss	–32, .1	–3, 1.0*	55	**83 (82)**	24 (17)

Note. The gambles are simple gambles of the format *x* with a probability *p* otherwise 0 and are noted as *x, p*. The higher expected value option is denoted by *. Boldface indicates proportions for which the fourfold pattern and its reversal predict a modal preference for the risky option. Sample sizes are average. Predicted choice proportions and sample sizes in parentheses come from fitting the CHASE model to the same aggregated dataset. Observed data are from Wulff et al. (2018), aggregating the data across studies of the description–experience gap.

rows of table 7.1), people were risk averse, preferring the safe option when the probability of winning was high (.8). However, when the gamble had the same expected value but the probability of winning was low (.1), people reversed their preference and chose the risky option. The fourfold aspect to this pattern emerged when people were presented with the same choices but with outcomes in the loss domain; in this case, preferences flipped. This is shown in the bottom two rows of table 7.1. Relatively speaking, people were risk-averse when the stated probability of losing was low but risk-seeking when it was high. Looking at the gambles and choice proportions in table 7.1 can also help reveal the source of this fourfold pattern. In particular, in description-based choices people appear to choose as if they overweight rare events (e.g., overweighting the probability of .2 of obtaining a 0 in problems 1 and 3), which results in the fourfold pattern (Tversky & Kahneman, 1992; van de Kuilen & Wakker, 2011).

Now consider what happens when people make decisions from experience with these same options (see table 7.1). The fourfold pattern reverses, suggesting that people make decisions from experience as if they underweight rare events. Wulff et al.'s (2018) meta-analysis synthesizing 27 datasets has shown that the choice proportions for the option consistent with underweighting the rare event differ by on average 9.7 percentage points between description and experience, with the magnitude of the gap varying considerably across problem types. In choices between safe and risky gambles—the problem type often used to measure people's risk preferences—the difference amounts to about 20 percentage points. In choices between two risky gambles, in contrast, it is about 6 percentage points. To experience this gap yourself or explore the large collection of data from Wulff et al., visit interactive elements 7.1 and 7.2 online.

The largest contributor to the description–experience gap in terms of the impact of rare events in decisions from experience is frugal exploration (e.g., Fox & Hadar, 2006; Hau, Pleskac, Kiefer, & Hertwig, 2008; Hertwig & Erev, 2009; Rakow & Newell, 2010). As table 7.1 shows, people took about 20 samples per problem, implying a sample size of about 10 samples per option. Frugal exploration has two important consequences. First, it means that many individuals will not experience the rare event. For instance, if people take 10 samples from an option offering $4 with a probability of .8 and $0 with a probability of .2, 11% of them will never experience the rare event ($0). Second, the majority of people, including those who do experience the rare event, will see it less often than expected given its objective probability. In the example above, the expected number of experiences of the rare event in 10 samples is two, with 30% of individuals expected to see the rare event exactly twice and 32% to see it more often. But a larger proportion of individuals—38%—are expected to experience the rare event only once or not at all. This is because the binomial distribution of samples is right-skewed for events with a probability smaller than .5, implying more mass below the expected value than above. Due to this statistical regularity, frugal search can result in decisions made from experience appearing as if rare events are underweighted.

Sample size, however, is not the only driver of the description–experience gap when it comes to rare events. This gap, while smaller, persists when sampling error has been accounted for (Camilleri & Newell, 2011a; Hau, Pleskac, & Hertwig, 2010; Hau et al., 2008; Kellen, Pachur, & Hertwig, 2016; Rakow, Demes, & Newell, 2008; Ungemach, Chater, & Stewart, 2009; for an overview, see Wulff et al., 2018). Other potential contributors discussed in the literature include the tendency to place more weight on recent than on earlier experience (Hertwig, Barron, Weber, & Erev, 2006); tallying strategies, which compare the options for small subsets of experiences and choose the option that wins most often (Hills & Hertwig, 2010); and differential probability weighting for stated probabilities and experienced relative frequencies (Abdellaoui, l'Haridon, & Paraschiv, 2011; chapter 8).

Notwithstanding these other drivers of the description–experience gap, the finding that sample sizes is key to the description–experience gap highlights the important role that search plays in decisions from experience. In contrast to decisions from description, where what you see is all there is, decisions from experience afford people the freedom to gather information and terminate their search whenever they see fit. This freedom impacts the information available and as a result, what you see is up to you. But which factors affect how people explore and when they decide to terminate search? Put differently, what are the mechanisms behind adaptive exploration?

7.4 Adaptive Exploration

7.4.1 Small Samples Can Be Smart

Never observing a rare event or observing it less often than expected can have profound consequences on how people evaluate the attractiveness of different options. Why then do people tend to break off their search so soon, forgoing the opportunity to gain a more accurate picture of the available options? For one, it is difficult, if not impossible, for individuals to know when their accumulated experience suffices to afford them a veridical picture of their options. Moreover, the incremental value of further search often diminishes drastically over time, and after a certain point increasing sample size will only marginally improve the understanding of a given option (see also chapter 4). To illustrate this point, we calculated the likelihood of picking the option with the higher expected value as a function of the number of samples drawn in the four problems presented in table 7.1. We assumed that the option with the higher experienced sample mean was chosen. Drawing 40 to 50 samples per option in problem 1 (and its reversal, problem 3) resulted in a mean chance of selecting the higher expected value option of 81.2%. But drawing only 10 to 20 samples per option resulted in a mean chance of 70.7% (see also Hertwig & Pleskac, 2010). Thus, in this case, drawing about one-third of the samples produced two-thirds of the gains in accuracy. In problem 2 (and its reversal, problem 4), the situation was even more extreme. Here, drawing 40 to 50 samples per option resulted in an improvement of 4.7 percentage points over drawing 10 to 20 samples per option and just 2.8 percentage points over chance. Considering that exploration is commonly associated with opportunity costs and, at the very least, processing costs, relying on small samples is thus often the smart thing to do (Hertwig & Pleskac, 2010; Ostwald, Starke, & Hertwig, 2015; Vul, Goodman, Griffiths, & Tenenbaum, 2014).

7.4.2 Moderators of Exploration

Relying on small samples can be smart. Nonetheless, it is often beneficial to adapt exploratory effort to the resources available and the peculiarities of the environment. Research using the sampling paradigm has shown that decision makers indeed adapt their exploration systematically. Table 7.2 summarizes the factors known to affect how much people explore. The table features environmental factors (which pertain more to the choice environment) at the top, contextual factors (which are more related to the choice context) in the middle, and individual factors (which have more to do with the decision maker) at the bottom. For instance, people draw larger samples in the presence of potential losses (Lejarraga, Hertwig, & Gonzalez, 2012), in the affective state of fear (Frey, Hertwig, & Rieskamp, 2014), or when faced with many options (Hills, Noguchi, & Gibbert, 2013; Noguchi & Hills, 2016).

The strongest effects result from manipulating the potential upside of a choice or the downside of exploration. For instance, sample size has been shown to increase when payoffs are increased by an order of magnitude (Hau et al., 2008) or when decision makers are incentivized to maximize the long-term rather than the short-term return (Wulff et al., 2015a). Conversely, the risk of being beaten to the punch by a competitor can slash exploration efforts to just a single draw (Phillips et al., 2014; see also chapters 12 and 15). These results suggest that individuals evaluate whether to terminate or continue sampling as a function of the benefits (or costs) associated with the available options and, more generally, their goals.

7.4.3 Routes to Terminating Search

There are many ways in which people can determine when they will stop searching. In the sampling paradigm and the situations it embodies, perhaps the two most straightforward routes to terminating exploration are a *planned stopping rule* and an *optional stopping rule*. With a planned stopping

Table 7.2
Moderators of search and their potential representation in CHASE.

		Sample Size		
Moderator	Manipulation	Treatment	Control	CHASE
Environmental				
Complexity[a]	32 vs. 2 options	34	5	Unknown
	32 vs. 2 options	51/38	6/4	Unknown
	8 vs. 2 options	113	41	Unknown
Domain[b]	Loss vs. gain	11	9	Possible increase in thresholds for losses
Problem order[c]	1st vs. 30th problem	25.5	9.1	Increased familiarity reduces variability in preference accumulation OR later problems result in lower thresholds
Variance[b]	Variance experienced	16	11	Increased payoff variance leads to a decrease in rate of change in preference
Contextual				
Affect[d]	Fearful vs. happy	45/45	28/6	Fear leads to higher thresholds and greater attention to extreme outcomes (see section 7.6.4)
Competition[e]	Social competition (yes or no)	1	18	Competition leads to a lower decrease in the threshold for making a choice
Health[f]	Medical vs. monetary	17	22	Health domain should increase thresholds, but may change attention to outcomes
Incentives[g]	Incentives×10	33	11	Increased incentives lead to higher thresholds
Social context[h]	Ultimatum game vs. standard paradigm	8	24	Unknown

Table 7.2 (continued)

Moderator	Manipulation	Sample Size		CHASE
		Treatment	Control	
Individual				
Age[i]	Younger vs. older adults	46	58	Unknown
Aspirations[j]	Long vs. short run	34	23	Long-run aspirations result in higher thresholds
Numeracy[k]	High vs. low	23	15	Unknown
Rational ability[k]	High vs. low	22	18	Unknown
Moderator	Predictor	Correlation		CHASE
Fluid intelligence[l]	DSST & 2 options	< .1		Unknown
	DSST & 8 options	~.2 to .4		Unknown
Working memory[m]	Digit span	.38		Unknown
	Operation span	.04		Unknown
	Operation span	–.19/.13/19		Unknown

Note. DSST: Digit–symbol substitution task. a: Frey, Mata, & Hertwig (2015), Hills et al. (2013), Noguchi & Hills (2016). b: Lejarraga et al. (2012). c: Lejarraga et al. (2012). d: Frey et al. (2014). e: Phillips et al. (2014). f: Lejarraga, Woike, & Hertwig (2016). g: Hau et al. (2008). h: Fleischhut, Artinger, Olschewski, Volz, & Hertwig (2014). i: Frey et al. (2015). j: Wulff, Hills, & Hertwig (2015a). k: Lejarraga (2010). l: Frey et al. (2014), Frey et al. (2015). m: Rakow et al. (2008), Wulff, Hills, & Hertwig (2015b), Wulff et al. (2015a). Table adapted from Wulff et al. (2018).

rule, people decide beforehand how many samples to take; with an optional stopping rule, they choose to stop on the basis of incoming information and its significance for their current goals. Evidence suggests that people take both routes. For instance, ongoing analyses of the Wulff et al. (2018) data show that samples in multiples of 10 occur much more frequently than would be expected by chance, suggesting that many people plan to terminate their search at a round number.

Findings of a phenomenon analogous to the gaze cascade effect in the sampling paradigm suggest that people also use an optional stopping rule (Wulff et al., 2018). The term *gaze cascade effect* comes from eye-tracking studies, which have shown that when people make a choice their gaze gradually shifts to the option eventually chosen before the choice is made (Shimojo, Simion, Shimojo, & Scheier, 2003). A similar effect can be seen in decisions from experience, where people sample more often from the chosen option toward the end of a sampling sequence (see figure 7.2) and switch to a different option when they experience negative outcomes (see figure 7.4).

The gaze cascade effect has been taken as evidence that "gaze is actively involved in preference formation" (Shimojo et al., 2003, p. 1317). But it is also indicative of an optional stopping rule where people sample information until their preference reaches a threshold (Mullett & Stewart, 2016). The logic behind this claim is this: if a person employs an optional stopping process, the last sample of information they encountered will be consistent with the choice they make because their preference has reached the threshold required to choose that option. This pattern is more likely to happen when a person is looking at the option (so long as the information they sample from the option they are looking at is favorable). The strength or valence of the second-to-last sample does not have to obey quite the same logic, but it likely will (otherwise, the preference state would not be close to the threshold). The third-to-last will, on average, point to the chosen option but less so, and so on, giving rise to a gaze cascade effect. Thus, the gaze cascade effect is indicative of a link between search and choice, a property that is reflected in our integrated model of decisions from experience, CHASE, to which we return in section 7.6. Corroborating this interpretation, this phenomenon analogous to the gaze cascade effect only occurs in self-terminated sampling and not in environments where sample size is predetermined by the experimenter (see figure 7.2).

In sum, when decision makers are actively involved in exploration, search and choice are intimately connected. People do not just passively tally experiences as they stream past, particularly when afforded the freedom to control the process of exploration (Wulff & Pachur, 2016). By adapting information search to the internal and external characteristics of the situation, people shape the environment they observe and, as a consequence, their final decision (see also Denrell, 2005; Denrell, 2007; March, 1996; Pleskac, 2015). The evidence for adaptive exploration described in the previous section shows that the degree to which description and experience diverge depends on a number of factors. Aside from driving the

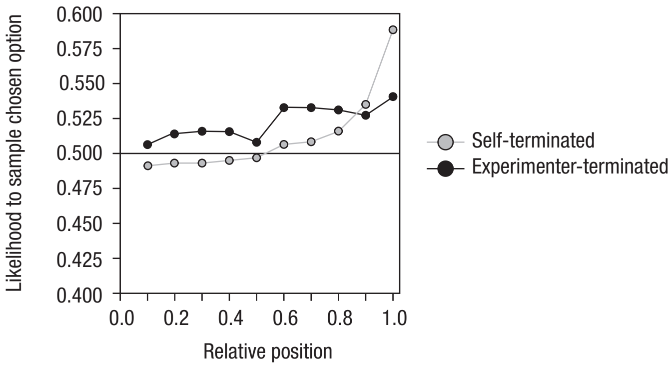

Figure 7.2
Likelihood of sampling from the option eventually chosen over the course of the sampling sequence in self-terminated versus experimenter-terminated sampling. Based on the combined data of Wulff et al. (2018).

description–experience gap, active exploration in decisions from experience presents a thorny problem for many current models of decision making that act according to Kahneman's (2011) "what you see is all there is" principle. Specifically, it implies that models can only successfully describe, predict, and explain decisions from experience if they account for how people learn from experience and make choices from what they have learned.

7.5 Modeling Search and Choice in Decisions from Experience

The link between exploration and choice has been noticeably absent from previous attempts to model decisions from experience in the sampling paradigm. Nearly all models treat experience as a given—like a memory bank that passively records sampled outcomes and is called upon only to make a final choice. In two-stage prospect theory, for instance, the observed relative frequencies of outcomes are merely used as proxies for their objective probabilities (Fox & Hadar, 2006; Tversky & Fox, 1995; see also chapter 8). These subjective frequencies are then entered into prospect theory's probability weighting function to determine the value of the option. Thus, the same model that is used for stated probabilities in decisions from description is recruited to account for choices involving experienced relative frequencies. This approach has frequently been used to understand final choices and the probability weighting pattern in the sampling paradigm (e.g., Fox & Hadar, 2006; Glöckner, Hilbig, Henninger, & Fiedler, 2016; Kellen et al., 2016). However, it offers no account of how people explore in the context of experience-based choice, including when they decide to stop sampling. This limitation is also present in various forms in other models. For instance, reinforcement learning models do not have a stopping rule (Sutton & Barto, 1998), and instance-based memory models treat choice and search as independent processes (C. Gonzalez & Dutt, 2011; Hawkins, Camilleri, Heathcote, Newell, & Brown, 2014). We now present a model that was designed to address this limitation and examine its predictions for decisions from experience.

7.6 Choice from Accumulated Samples of Experience (CHASE)

CHASE models decisions from experience as a sequential sampling process in which experiences are accumulated over time to form a preference (Busemeyer & Townsend, 1993; Laming, 1968; Ratcliff & Smith, 2004; Wald, 1947). As such, it provides a new window onto the process of active exploration and choice in decisions from experience. Full details of the model can be found in the online supplement to this chapter (at https://taming-uncertainty.mpib-berlin.mpg.de/; see also Markant, Pleskac, Diederich, Pachur, & Hertwig, 2015). In brief, outcomes are generated from gambles depending on how a person searches (the frequency and order with which they sample each option). Each observed outcome could, in principle, contribute to the accumulated preference in direct proportion to the payoff amount. However, previous work has suggested that outcomes may be weighted differently in decisions from experience depending on how they compare with other possible outcomes (see also Ludvig, Madan, & Spetch, 2014; Pleskac et al., 2019; Zeigenfuse et al., 2014). To account for this possibility, CHASE models each outcome's impact, referred to as its *subjective valence*, based on its likelihood and its desirability relative to the other possible outcomes. Over the course of search, subjective valences are accumulated to form a preference for one option over the other, creating a random walk across preference states as depicted in figure 7.3. Under an optional stopping rule, preference at some point reaches one of two thresholds. The final choice is determined by the threshold reached, and the sample size is determined by the number of steps taken to reach it (see figure 7.3).

One important property of the accumulation of subjective valences is that preference is relative. Experiencing an attractive outcome for one

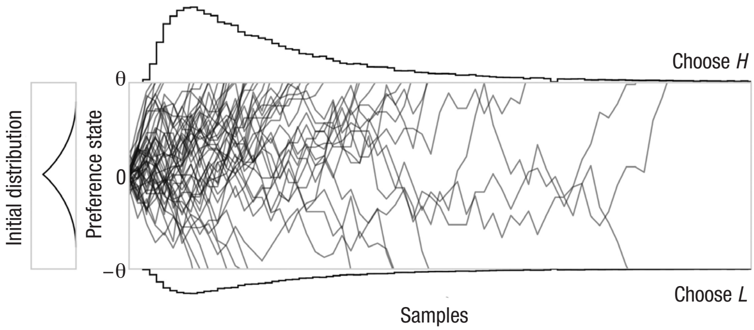

Figure 7.3
Preference accumulation for a choice between options *H* and *L* with higher and lower expected values, respectively. Each trajectory represents a different trial, with preference moving up or down after each draw based on the subjective valence of the observed outcome. The initial distribution captures the variability between trials at the starting point. The distributions at the top and bottom edges represent the probability that search ends as a function of sample size, conditional on either a higher expected value choice (*H*, top) or a lower expected value choice (*L*, bottom).

option will shift preference toward that option and away from the other. This property is consistent with an empirical result observed in the sampling paradigm. In particular, in self-terminated search in the sampling paradigm, experiencing negative outcomes for one option increases the chance of choosing the other option (see figure 7.4). Note also that, like other sequential sampling models with optional stopping, CHASE predicts a gaze cascade effect like that shown in figure 7.2.[2] Finally, as we will now show, CHASE accounts for some key properties of adaptive exploration, such as adapting to costs and benefits and adapting to environmental uncertainty.

7.6.1 Adapting to Costs and Benefits

Under optional stopping, CHASE assumes that people may adjust their decision threshold depending on their goals or the presence of any implicit or explicit costs. Control over the decision threshold is a common feature

2. The use of an optional stopping rule is not necessary in self-terminated sampling conditions: A person could, as we discussed in section 7.4.3, decide on a sample size before beginning to search. Such planned stopping can also be modeled with CHASE.

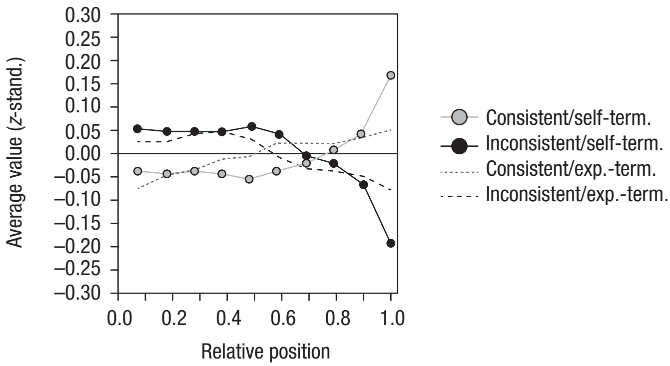

Figure 7.4
Average observed outcome value (*z* standardized within trial) over the course of the sampling sequence as a function of whether or not the last sampled option was consistent with the chosen option for self-terminated and experimenter-terminated sampling. Based on the combined data of Wulff et al. (2018).

of sequential sampling models of decision making. If, for example, errors in a perceptual decision are associated with high costs, people would adopt a high threshold, leading to the accumulation of more evidence and, in turn, a higher proportion of correct responses. But demanding more evidence also means that it will take longer to reach a decision. Consequently, the decision threshold helps control the speed–accuracy trade-off in perceptual decisions (Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; Ratcliff & Smith, 2004).

CHASE predicts the same sort of trade-off between sample size and the proportion of choices that maximize expected value. In this case, higher thresholds lead to larger sample sizes and more choices that maximize expected value. Consistent with this prediction, Hau et al. (2008) showed that increasing the magnitude of rewards by a factor of 10 was associated with larger sample sizes and more choices that maximize expected value (and a decrease in the description–experience gap; we will return to this point shortly). Adjustments in the decision threshold may underlie how people adapt their exploration to a wide array of variables (see table 7.2), including monetary (dis)incentives, opportunity costs (J. W. Payne, Bettman, & Luce, 1996), the effort involved in gathering information (Fu & Gray, 2006), competition (Phillips et al., 2014), or even motivational and emotional factors (Frey et al., 2014).

7.6.2 Adapting to Environmental Uncertainty

Another reason for adopting an optional stopping rule is uncertainty about how much experience is needed to reach a conclusion (Edwards, 1965). CHASE predicts that both choice and sample size depend on the degree of uncertainty in the environment. If outcomes unambiguously favor one option over the other, preference will quickly reach the corresponding decision threshold. If outcomes sometimes favor one option and sometimes the other, preference will tend to ebb and flow, and sample sizes will increase. This implies that larger outcome variance will cause both larger sample sizes and a lower proportion of choices of the higher expected value option. Indeed, people making decisions from experience tend to sample for a longer period of time when they experience high variance in outcomes (Lejarraga et al., 2012; Pachur & Scheibehenne, 2012).

This prediction depends on variance actually being experienced. High-variance options (as calculated based on their objective description) do not per se lead to more information search (see Wulff et al., 2018). Options with rare outcomes that are never experienced may in fact be associated with low experienced variance and thus with smaller sample sizes. An unlucky decision maker may happen to experience outcomes that unambiguously favor an option without knowing that a disastrous (but rare) outcome is just around the corner. This brings us back to the description–experience gap and how CHASE accounts for it.

7.6.3 Using CHASE to Explain the Description–Experience Gap

The decision threshold in CHASE is one mechanism that offers a (partial) explanation for the description–experience gap. To see this, we used CHASE to simulate choices for choice problems 1 and 2 in table 7.1 over a range of decision thresholds (the results for the corresponding loss problems are in this case symmetrical). As figure 7.5 shows, the probability of choosing the higher expected value option (i.e., the risky option) increases with the magnitude of the threshold. This is because sample sizes are smaller at lower thresholds, resulting in greater sampling error. At lower thresholds, a majority of individuals will experience the rare event less often than expected, leading to choices consistent with underweighting of the rare outcome and the reversed fourfold pattern of risk attitudes. At higher thresholds, the impact of sampling error is lessened, rare outcomes are more likely to be encountered and thus contribute to the accumulated preference, and

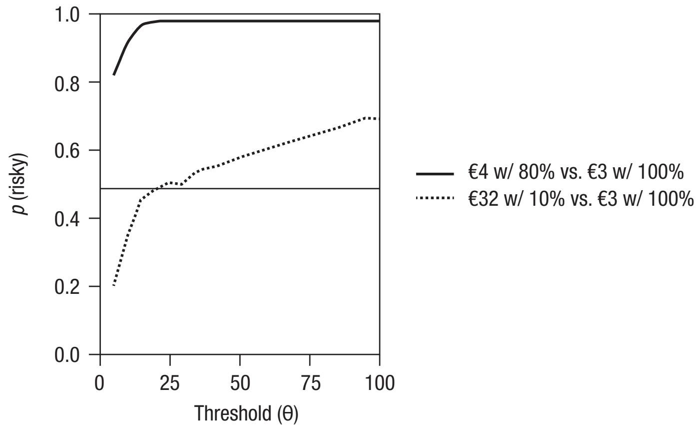

Figure 7.5
The predicted probability of choosing the risky option as a function of decision threshold θ, for the two choice problems in the gain domain used to illustrate the fourfold pattern of risk attitudes in table 7.1 (the results for the loss domain are symmetrical). Assuming an indifferent starting point, equal probability of sampling each option, linear weighting, and no internal noise in the accumulation process, a low threshold is sufficient to result in choices that appear to underweight rare events.

there is a higher likelihood of choosing the higher expected value option for both problems. Thus, CHASE provides a mechanistic understanding of how uncertainty in the environment and the decision threshold interact to drive exploration and choice—one consequence of which is the description–experience gap.

7.6.4 Understanding the Weight of Experience through CHASE

The decision threshold is an important lever for adapting exploration, but other mechanisms can also affect how people explore and choose in decisions from experience. One of them is the weight people award to each sampled outcome. According to CHASE, sampled outcomes do not necessarily get equal attentional weight. Instead, the attention people pay to each outcome depends on its likelihood and desirability relative to the other possible outcomes. This is implemented by making the weight a function of the probability of obtaining a particular outcome or a larger one (i.e., the decumulative rank in the gamble). For instance, rarer outcomes might be down-weighted relative to other outcomes, with the consequence that more frequent outcomes would receive more weight in the accumulated preference. This subjective weighting of outcomes can also drive the accumulation of preference, which in turn impacts which threshold is reached and when. It is possible to disentangle the influence of the decision threshold from the subjective weighting of outcomes by fitting CHASE to observed data.

To illustrate this point, consider Frey et al.'s (2014) manipulation of affective states during decisions from experience. Figures 7.6a and 7.6b display the choice and sample size data. Four of the choice problems are the same as were used to demonstrate the reversal of the fourfold risk pattern of attitudes (see table 7.1). In general, the reversed fourfold pattern holds (note that this figure plots the probability of choosing the higher expected value option). In the fearful condition, however, sample size was increased and choice proportions were shifted more toward maximizing expected value. In other words, the strength of the reversed fourfold pattern was weaker in the fearful condition. Is this weakened pattern solely the result of people setting a higher decision threshold in the fearful condition?

To answer this question and better understand the effects of affective states at the process level, we fit CHASE to the data from each condition. As figure 7.6 shows, the model accounts quite well for both the choice (7.6a) and sample size distributions (7.6b). The model indicates that participants in the fear condition indeed adopted a higher decision threshold ($\theta = 21.4$) than did happy participants ($\theta = 12.6$). However, fearful participants also appear to have given more attentional weight to the large (but less frequent) gains and losses (see figure 7.6c, left). This differential weight to different sampled outcomes has an important consequence: as sample sizes increase (i.e., thresholds increase), choices from CHASE mimic choices from rank-dependent expected utility models like prospect theory (see Pleskac et al., 2019). Figure 7.6d shows what the inferred decision weights would be for the two conditions (i.e., if people set very high choice thresholds and made choices then these would be the rank-dependent decision weights one would observe if prospect theory were fit to the choices).[3] The results illustrate that fearful emotional states would result in decision weights that give too much weight to rare events. Thus, according to CHASE, two factors

3. We emphasize that CHASE does not assume that people explicitly represent probabilities. Rather they make choices as if they do.

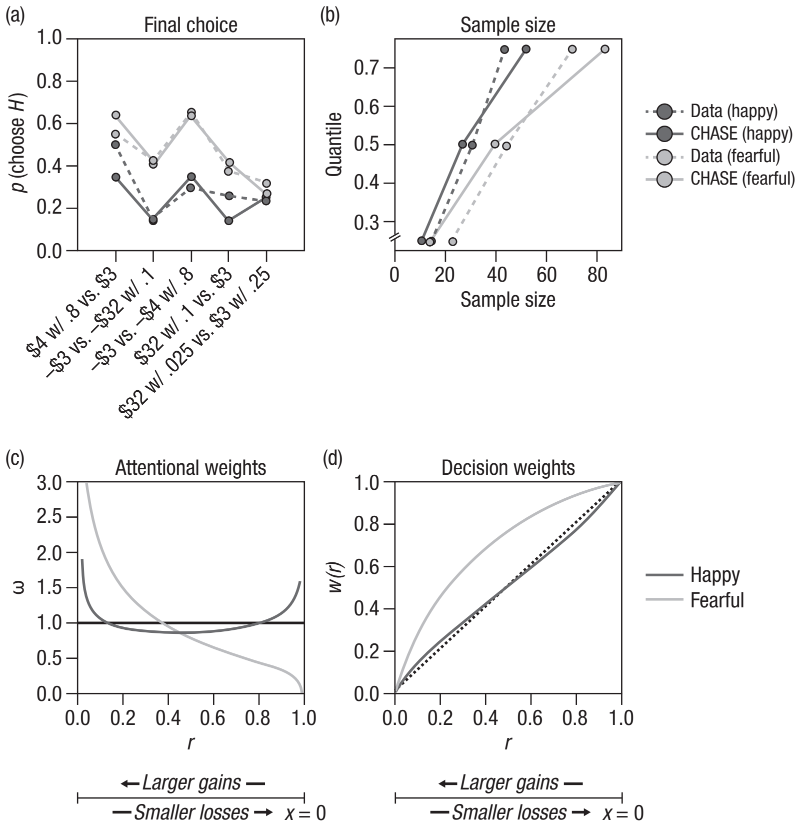

Figure 7.6

Results from fitting CHASE to data from Frey et al. (2014; Study 2, fearful and happy conditions only). (a) Observed and predicted proportion of *H* choices. (b) Quantiles of sample size distribution. (c) In addition to adopting a higher decision threshold, fearful participants weighted higher magnitude outcomes more heavily. The attentional weight is a function of the rank *r* of the outcome in the gamble. In gains, the rank is the decumulative rank such that outcomes decrease in magnitude with increasing rank *r*; in losses, the rank is the cumulative rank such that they also decrease in magnitude. (d) This weighting of extreme outcomes in the preference accumulation process can give rise to choices that appear to have an elevated probability weighting function.

are responsible for the weakened reversed fourfold pattern in the fear condition: people's higher thresholds and greater attentional weight to large (but less frequent) gains and losses. In fact, according to CHASE, all else being equal, if people in the fear condition had set higher thresholds then a fourfold risk pattern akin to what is seen in decisions from description would have been observed. Although more work is needed to understand the conditions that impact how people weigh each sample of experience, these results illustrate the importance of modeling search and choice together in order to distinguish alternative processes involved in preference formation.

To summarize, CHASE provides a framework for modeling search and choice together in decisions from experience, through the lens of a single evidence accumulation process. CHASE makes it possible to explain and predict a number of factors that reflect adaptive exploration during decisions from experience. We should note that, as listed in table 7.2, there are many other factors that impact search during decisions from experience. For some factors, like payoff domain (gain or loss) or familiarity with the problems, CHASE makes some straightforward predictions about how these factors impact search and choice. However, it is unclear if and how CHASE may account for other factors. We do not necessarily see this as a limitation of the model; instead, these unknowns are exciting areas to further explore in order to better understand adaptive exploration during decisions from experience.

7.7 Adaptive Exploration Helps Distinguish Decisions under Uncertainty from Decisions under Risk

By far the most common approach to understanding how people make decisions when the consequences of their choices are uncertain reduces uncertainty to risk—for example, by having people decide between descriptions of monetary gambles. Within this paradigm, the often cited distinction between risk and uncertainty is more semantic than real. To quote Lopes (1983), "this distinction made its way into the psychological literature a long time ago via Edwards' (1954) seminal article in *Psychological Bulletin* on decision theory, but it has since languished for want of empirical relevance" (p. 137). In our view, research on decisions from experience demonstrates the empirical reality of this distinction. People are constantly making decisions without the aid of actuarial tables, or even an awareness of the full set of potential outcomes. Instead they rely on direct experience. When their past experience is not enough, they take action to reduce uncertainty in a way that is adaptive. The wealth of data gathered on decisions from experience over the past 15 years has established that there is a gap between decisions from experience and decisions from description. This gap goes beyond the choices people make and, by extension, beyond their preferences. People making decisions from experience are adaptive explorers, tuning their search to the properties of the environment, their goals and abilities, and their experiences. In other words, in decisions from experience, what you see is up to you.

This empirical reality calls for models of adaptive exploration. CHASE is one such model, describing the interaction between preference and exploration in decisions from experience. It represents a significant step forward from models that have focused on final choices while treating exploration as a given (Erev et al., 2010; C. Gonzalez & Dutt, 2011). Yet it is just a first step. At present, the framework does not capture a number of factors that affect exploration in decisions from experience, including choices between more than two options, learning effects across trials, and individual differences in search and choice (see table 7.1). Nevertheless, CHASE offers a new approach to understanding how people both generate and exploit experience to make decisions in the midst of uncertainty.