12 The ecological validity of fluency

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Abstract

This chapter reviews the ecological validity of processing fluency; that is, the extent to which we can draw valid inferences about the external world by paying heed to our internal experience of fluency. As a proximal cue, fluency can help us navigate an uncertain world because it reflects the statistical structure of our environment. We can use the ecological connection between fluency and the world to inform our judgments and decisions. For example, retrieval fluency—the speed with which we retrieve objects from memory—reflects numerical quantities of importance, the truth of statements, the danger of objects and social information about what other people are doing. We hope to complement our descriptive understanding of how and when people use fluency with an understanding of where fluency is an ecologically valid cue and where it is not.

All things are difficult before they are easy.

Dr. Thomas Fuller, Gnomologia, 1732; British physician (1654–1734)

Our cognitive machinery has evolved in the service of enabling us to navigate an often dangerous and uncertain world. How successfully we deal with this world depends, among other factors, on the fit between the cognitive machinery and environmental structures (Brunswik, 1956; Simon, 1990). In this chapter, we ask the question of whether a seeming by-product of the operation of our cognitive machinery—the fluency of our own processing experiences (the extent to which a cognitive operation feels easy or hard, swift or slow)—tells us something valid about the world we live in. For example, can we infer that companies whose names we recognize fluently tend to be more profitable than companies we hesitate to recognize? Or are we entitled to believe in assertions more, the more fluently we are able to process them? In other words, to what extent does the internal experience of fluency permit us to make valid inferences about our external world? This question concerns the *ecological validity of fluency* or lack thereof.

When we first asked the question about the ecological validity of fluency (Hertwig, Herzog, Schooler, & Reimer, 2008; Schooler & Hertwig, 2005), we thought that we would have no difficulty in finding an unambiguous answer in the large body of research conducted on the subjective experience of fluency (for reviews see e.g., Alter & Oppenheimer, 2009; Oppenheimer, 2008; Reber, Schwarz, & Winkielman, 2004; Schwarz, 2004; Winkielman, Schwarz, Fazendeiro, & Reber, 2003; for broader reviews on feelings in judgment and decision-making see e.g., Bless & Forgas, 2000; Greifeneder, Bless, & Pham, 2011; Pham, 2004, 2007; Schwarz, 2002, 2011; Schwarz & Clore, 2007; Shah & Oppenheimer, 2008). Our expectation, however, was quickly frustrated. Although some of the reviews cited above do bring up the question of fluency's validity, none aimed to present a systematic review or answer to our question. We found short discussions about the validity of affective feelings and feelings in general (e.g., Pham, 2004; Schwarz, 2011), but no discussions about cognitive feelings or fluency in particular (see Reber & Unkelbach, 2010, for an exception). In order to fill this void, we conducted a literature search (see Appendix A).

This chapter reviews the results of our literature analysis and suggests why fluency is an ecologically valid cue in domains that have not yet been investigated. We will discuss to what extent retrieval fluency—the speed with which we retrieve objects from memory—is a valid cue for predicting numerical quantities of importance, for assessing the truth status of statements, for assessing danger and for predicting other people's behavior. But before we start with our review, there is one question begging for an answer: Why has the potentially precious information encapsulated in a seemingly subjective experience received such scant attention?

Perhaps, the issue of validity is just utterly trivial and uninteresting because researchers simply have taken it for granted that fluency empowers valid inferences about the world. The literature, however, does not suggest such a concurrence of opinions. Clearly, there are researchers who believe in the usefulness of feelings for judgments and decisions. For example, Oppenheimer (2008, p. 237) suggested, "knowledge of our ease of processing can lead to useful inferences about the external environment." At the same time, others, for instance, Topolinski and Strack (2010, p. 722), have highlighted that in some cases "fluency is not a valid cue and may have powerful biasing effects" or "may even cause irrational behavior with substantial economic consequences." For example, correctly and repeatedly telling people that a consumer claim is actually false can, paradoxically, cause them to misremember it as true because repeated exposure to the false claim increases its fluency (Skurnik, Yoon, Park, & Schwarz, 2005). Similarly, people believe more in statements that rhyme than in their non-rhyming counterparts because rhyming increases the statements' fluency, which, in turn, increases the statements' perceived truthfulness (McGlone & Tofighbakhsh, 2000). We are thus left with a somewhat dissonant message. Although some fluency researchers seem to believe that fluency can be a valid cue (see also Unkelbach & Greifeneder, Chapter 2, this volume), they and others caution us to pay heed to the potentially biasing effects of fluency.

Two perspectives on fluency: Ecological correspondence vs. susceptibility to manipulation

We suggest that this seeming tension between fluency's positive and negative evaluations can be reconciled by recognizing that fluency's validity depends simultaneously on the answers to two questions. The first is the question of *ecological correspondence*: Can fluency, in principle, accurately reflect environmental criteria (e.g., the success of companies) and thus potentially enable valid inferences about our world? We believe that the positive statements in the literature on fluency's validity pertain to this ecological question: Many fluency researchers seem to think that fluency can reflect properties of our environment. As mentioned before, there is little research available to corroborate this belief. This dearth of evidence, we suspect, stems from researchers mainly focusing on the second question, which we call the *susceptibility to manipulation question*: Can fluency-based judgments and decisions, in principle, be influenced by obviously irrelevant factors (e.g., such as rhyming) that sabotage the potential correspondence between fluency and external criteria? As the extensive literature on fluency effects shows, the answer is unambiguously positive (e.g., Alter & Oppenheimer, 2009; Oppenheimer, 2008; Schwarz, 2004). Obviously, warnings about fluency's potential biasing effects in the literature are informed by research on fluency's susceptibility to manipulation. Ecological correspondence and susceptibility to manipulation together imply that fluency will only lead to valid judgments and decisions to the extent that there is both an ecological correspondence between fluency and environmental criteria *and* an absence of sabotaging influences, which would otherwise dilute fluency's validity.

Although the distinction between these two key questions can resolve the tension between the positive and negative evaluations of fluency's claim to truth, there still seems to be a mismatch between what fluency researchers seem to believe and what they actually study: Although some researchers suggest that fluency can be a valid cue (e.g., Oppenheimer, 2008; Unkelbach, 2006), most of the empirical work demonstrates how fluency is influenced by irrelevant factors and thus that by relying on fluency people risk going astray. The resulting literature paints a rather bleak picture of the utility of fluency and leaves the reader with the impression that fluency is a potentially misleading cue and should be passed up.

The focus on fluency's susceptibility to manipulations and the resulting fluency illusions is reminiscent of the *heuristics and biases* research program's focus on the dark side of cognitive heuristics (Gilovich, Griffin, & Kahneman, 2002; Kahneman, Slovic, & Tversky, 1982). This program explicitly invoked the analogy between research in perception and research in judgment and decision making to motivate its guiding notion of *cognitive illusions* (e.g., Kahneman & Tversky, 1982): Just as visual illusions afford us insights into the working of our perceptual system that we will not gain under normal conditions, clever experimental paradigms can generate cognitive illusions that grant us insights into reasoning's opaque ways that we otherwise would not enjoy (but see Gigerenzer, 1996, for a critical discussion of cognitive illusions). However, cognitive illusions have been seductive far beyond their methodological utility. In Kahneman and Tversky's (1982, p. 124) words: "Although errors of judgments are but a method by which some cognitive processes are studied, the method has become a significant part of the message," and the use of heuristics became to be seen as leaving human reasoning prone to "severe and systematic errors" (Tversky & Kahneman, 1974, p. 1124).

When researchers construct paradigms whose very goal is to produce perceptual or cognitive illusions, they are—by design—collecting samples of situations that are not representative of what people normally experience. Although those studies can reveal some of our mind's operations, and undoubtedly can also provide an existence proof of perceptual or cognitive illusions, they do not afford us an unbiased assessment of how consequential such illusions are in our natural environment. And indeed, although researchers of human vision are masters in constructing ever more impressive perceptual illusions, they do not conclude from those illusions that our visual system is flawed or that we should not rely on it to navigate the world. On the contrary, vision researchers often marvel about the cleverness and elegance of our visual system and how well its in-built assumptions—which are revealed through visual illusions—match the informational structure of our environment. In fact, the very reason why we are fascinated by visual illusions is that we do not encounter them in our daily life—at least, for example, outside of 3D cinemas. In other words, just because "illusions" can be evoked in the lab, they need not wreak havoc outside of it (e.g., Funder, 1987; Krueger & Funder, 2004).

In stark contrast to vision researchers, scholars of human cognition have often concluded from famed demonstrations of cognitive illusions in the laboratory that those illusions indeed *are* a problem outside of the laboratory (e.g., Dawes, 2001; Piattelli-Palmarini, 1994). Although this conclusion could, of course, be true in principle, the appeal to findings from paradigms that, by their very design, were bound to produce cognitive illusions does not suffice. Such conclusions should be informed by studies using a *representative design*, that is, studies that randomly sample the stimuli from their respective environments (Brunswik, 1952; Dhami, Hertwig, & Hoffrage, 2004). Representative designs aim to preserve the natural properties of environments and thus allow us to assess the accuracy of judgments under representative circumstances. Furthermore, field studies can add external validity to the conclusions based on laboratory work (see, for example, Alter & Oppenheimer, 2006; Green & Jame, 2011).

We conjecture that what has been said about cognitive illusions can be generalized to research on fluency. Fluency researchers often—perhaps almost exclusively—decouple fluency and the criterion (e.g., the truth status of a statement) in their studies to show the "pure" contribution of fluency. To achieve this decoupling, fluency researchers use methods to manipulate fluency that have no ecological connection to the environmental criterion, thus creating "fluency illusions." For example, Reber and Schwarz (1999) orthogonally varied whether or not a statement was easy to read (i.e., color contrast of text) and whether a statement was true or not. They found that people believed more in statements that could be fluently read. Similar to the heuristics-and-biases program, the method became a significant part of the message; namely, fluency has come to be seen as an invalid cue that one should not rely on. But fluency's vulnerability, that is, findings indicating that people's judgment and decisions *can* be influenced by irrelevant sources of fluency, does not speak to the question of how ubiquitous and pernicious fluency illusions are beyond the confines of the experimental paradigms designed to demonstrate the very existence of those irrelevant influences. Consequently, we conjecture that the ecological question of whether and when fluency is an ecologically valid cue remains—after a vast number of investigations of fluency—by and large an open question. The myriad results stemming from the susceptibility paradigm simply fail to tell us much about fluency's ecological correspondence to environmental criteria.

This chapter reviews what we currently know about the ecological validity of fluency; namely, the extent to which we can predict the external world by relying on fluency. The details of our literature search can be found in Appendix A. In this review, we have only included studies that used a *representative design*, that is, a representative or random sample of stimuli from a reference class of objects (Brunswik, 1952; Dhami et al., 2004). The ecological validity of fluency pertains to inferences about environmental criteria (e.g., the success of companies or the truth of a statement) as opposed to inferences concerning one's own past experiences, such as whether or not one has previously encountered an object (e.g., Whittlesea & Leboe, 2000). In the latter case, fluency can be a valid cue for inferring prior exposure to an object because prior exposure enhances processing fluency (e.g., Jacoby & Dallas, 1981).

Although many different phenomena have been subsumed under the broad notion of fluency (Alter & Oppenheimer, 2009), most of what we know about the ecological validity of fluency comes from investigations of *retrieval fluency* (e.g., Hertwig et al., 2008; Schooler & Hertwig, 2005). Retrieval fluency refers to the time it takes a person to access and retrieve an item from memory. This time is empirically operationalized as *recognition speed*, that is, the time it takes a person to decide that she recognizes an object (Hertwig et al., 2008). Thus, the next part of this chapter is devoted to the ecological validity of retrieval fluency. We will discuss to what extent retrieval fluency is a valid cue for predicting numerical quantities of importance, for assessing the truth status of statements, for assessing danger, and for predicting other people's behavior. Before we turn to our review, one more clarification is in order. In the fluency literature, a distinction is made between objective fluency (e.g., in terms of objective retrieval speed) and fluency-based feelings (e.g., the subjective experience of familiarity), which depend on the discrepancy between processing expectations and objective fluency (e.g., Whittlesea, 2004). In this chapter we assume that objective fluency approximates the actual fluency experience well enough in the context of our ecological analysis. Future research should directly investigate the ecological validity of (reported) fluency experiences.

The ecological validity of retrieval fluency

Human memory is a notorious gambler. Each and every day it operates based on a wager about the world around us. Memory bets that one is more likely to need a piece of information again, the more often one has encountered it in the past (Anderson & Milson, 1989; Anderson & Schooler, 1991, 2000; Schooler & Anderson, 1997). The more often one encounters some piece of information, the higher is its activation strength in memory and the more likely will one be able to retrieve or recognize it and—should one retrieve it—the faster that retrieval will take place. Thus memory mirrors the frequency of past encounters with information and reveals these encounters in the probability of recognition and the amount of retrieval fluency. But why would memory do this?

If one reads the headline of a randomly drawn article from the *New York Times*, then the probability that it will contain a specific word (e.g., "Washington") is larger the more often this word previously had appeared in *New York Times* headlines (Anderson & Schooler, 1991). Similarly, if one receives a new email message, then the probability that this message was sent by a specific person will be larger the more often he or she has contacted us in the past (Anderson & Schooler, 1991; Pachur, Schooler, & Stevens, 2012). These two and many more examples illustrate a fundamental statistical property of our world: The odds of encountering a piece of information increases the more often one has encountered it in the past. Thus by mirroring environmental frequencies and successfully betting on this statistical property, our memory can make information more accessible that we are currently likely to need (e.g., Anderson & Schooler, 2000). Metaphorically speaking, human memory is like a public library that organizes its books according to their predicted popularity (see Anderson & Milson, 1989; Anderson & Schooler, 2000). Frequently checked out books, that is, popular books (e.g., the Dan Brown blockbusters), will be made available in special spaces near the entrance of the library to make it easy for members to find them. In contrast, less popular books (e.g., the books by Herta Müller, recipient of the 2009 Nobel Prize in literature), the ones rarely checked out in the past, will be relegated to the back of the library. Because of the environment being thus reflected in our memory, we can exploit our memory to make inferences about the environment. We can infer, for example, that the more fluently we retrieve an item from memory, the more often we must have encountered it in the past. Retrieval fluency, however, can do much more than that.

Predicting numerical quantities of importance

Given that in an environment, say, encompassing of the world's 20 most profitable companies, a criterion (e.g., a company's revenue) is correlated with how often we have encountered the names of these companies in the past (e.g., through newspapers and magazines), then retrieval fluency can act as a cue for that criterion (Hertwig et al., 2008; see also Schooler & Hertwig, 2005): The more fluently we retrieve an object (e.g., a company's name), the larger its

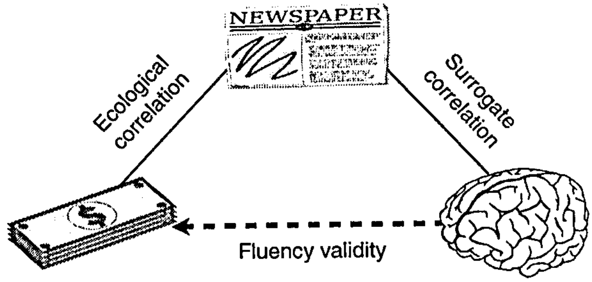

Figure 12.1 The ecological validity of retrieval fluency. An inaccessible or unknown criterion (e.g., a company's sales volume) is reflected by a mediator variable (e.g., the number of times the company is mentioned in the news), and the mediator influences the fluency of retrieval. The mind, in turn, can use retrieval fluency to infer the criterion (*fluency validity*). The degree to which the criterion is reflected in the environment is called the *ecological correlation*; the degree to which the environmental frequencies are reflected in memory is termed the *surrogate correlation*. The figure is adapted from Figure 1 in Goldstein and Gigerenzer (2002).

criterion value tends to be. That is, environmental frequencies (e.g., acquired through newspapers and magazines) can act as a *mediator* that connects an unknown criterion with our memory (Goldstein & Gigerenzer, 2002; Schooler & Hertwig, 2005). In such cases, retrieval fluency can predict a variable that is not itself a frequency, but could be anything from the population size of a city or the revenue of a company to the income of athletes (Hertwig et al., 2008)—as long as the criterion variable is reflected in environmental frequencies. The triangular relationships between criterion, mediator and retrieval fluency is depicted in Figure 12.1.

This ecological approach to retrieval fluency, of course, begs the question, which environmental criteria can retrieval fluency predict? That is, which criteria are reflected in mediators in the environment and which are not? The following two perspectives shed light on this issue. First, from a *statistical perspective* (Pachur, Todd, Gigerenzer, Schooler, & Goldstein, 2012), mediators in the environment (e.g., newspapers, people) reflect only those dimensions well, for which people's proclivity to communicate about an object either substantially increases or decreases as we move from objects with minimum values on the dimension to objects with maximum values on the dimension. For example, assuming that newsworthy things tend to happen in metropolitan areas, then it follows that national newspapers will offer their readers more information about large cities relative to hicksvilles. Consequently, mediators such as frequency of mentions in newspapers strongly reflect a city's population size (e.g., Goldstein & Gigerenzer, 2002). In contrast, when objects with especially low *and* high values, respectively, pique our curiosity, then the mediators will not adequately reflect the respective criteria dimensions. For example, not only very common animals, such as house cats, but also very rare and endangered animals, such as giant pandas, attract our attention (Richter & Späth, 2006). Similarly, the mediator will not reflect the true relation when people face two negatively correlated dimensions within one domain. For example, people frequently talk about very common yet relatively innocuous ailments, such as a cold or a migraine, but are also concerned with rare and frightening diseases, such as cholera or swine flu (Hertwig, Pachur, & Kurzenhäuser, 2005; Pachur & Hertwig, 2006).

Second, from a *topic perspective*, mediators in the environment (e.g., other people, the media, the entertainment industry) will expose us preferentially to objects that are "important" to those mediators. What is important to them? People and, by extension, the media talk and gossip about news that is, in one way or another, pertinent to human survival and reproduction, such as hazards, diseases, food, social status, attractiveness, competition, alliances, reputation and so on (e.g., Baumeister, Zhang, & Vohs, 2004; Davis & McLeod, 2003; Dunbar, 2004; Foster, 2004). Together with the statistical principle, we can predict that mediators—and thus retrieval fluency—will reflect those dimensions that both are important and do not correlate negatively with other important dimensions. Because, for example, in social environments, many important dimensions are positively correlated (resources, money, status, success, etc.), one can expect the mediators to reflect such social dimensions. Indeed, the income of athletes, the wealth of the richest people, the revenue of companies, and the success of tennis players are well reflected in the mediators (Hertwig et al., 2008; Scheibehenne & Bröder, 2007). In contrast, one can predict that the mediators will not reflect, for example, the incidence of disease rates (as discussed above) because people care about frequent, but also about rare, yet frightening diseases (e.g., Pachur & Hertwig, 2006). Furthermore, mediators will obviously not reflect obscure criteria that are of little interest to people (e.g., the distance between one European city and another arbitrarily chosen European city; Pohl, 2006).

What is the empirical evidence concerning the ecological validity of retrieval fluency? We searched for studies that reported on the validity of retrieval fluency among the references identified in our literature search (see Appendix A) and identified 25 domains with representative samples of objects (Brunswik, 1952; Dhami et al., 2004). In all these studies, retrieval fluency was operationalized as the time (in ms) that a participant took to judge whether or not she recognized a name (e.g., the music band Led Zeppelin). The retrieval *fluency validity* is defined as follows (Hertwig et al., 2008; Schooler & Hertwig, 2005): The resulting proportion of correct decisions if one always infers that the more fluently retrieved object has the larger criterion value (among all possible pairings of objects in the environment where both objects are recognized). Because decision-makers cannot discriminate differences in retrieval speed below 100 ms (Hertwig et al., 2008), we restricted the calculation of the fluency validity to pairs of objects for which difference in retrieval speed was equal to or larger than 100 ms (see Hertwig et al., 2008). We obtained the raw data and then calculated the fluency validities and other statistics for all domains (see Table 12.1).

Table 12.1 The Ecological Validity of Retrieval Fluency: Overview of Empirical Findings From 25 Domains

Domain	*Reference class*[a]	*N*	*M*	*Rec. rate*	*Pairs*	*Val*	*d_R val*	*Val for quartiles of Δ fluency*				*% val > 50%*	*Source*
								1st	*2nd*	*3rd*	*4th*		
						POPULATION SIZE							
City population: Austria	14 largest Austrian cities[b]	66	14	0.51	18	0.63	0.69	0.54	0.62	0.63	0.72	0.71	Hilbig et al (2011)
City population: Austria	28 largest Austrian cities[c]	175[d]	28	0.28	22	0.65	0.82	0.59	0.68	0.61	0.73	0.77	Marewski & Schooler (2011, Studies 1-3)
City population: France	36 largest French cities[c]	175[d]	36	0.57	130	0.61	0.91	0.57	0.58	0.63	0.67	0.78	Marewski & Schooler (2011, Studies 1-3)
City population: Germany	30 largest German cities[c]	175[d]	30	0.97	192	0.65	1.50	0.61	0.63	0.66	0.70	0.92	Marewski & Schooler (2011, Studies 1-3)
City population: Italy	50 largest Italian cities[c]	175[d]	50	0.47	189	0.69	1.66	0.63	0.67	0.71	0.75	0.90	Marewski & Schooler (2011, Studies 1-3)
City population: Poland	14 largest Polish cities[b]	66	14	0.46	13	0.59	0.35	0.66	0.53	0.61	0.70	0.58	Hilbig et al (2011)
City population: Spain	38 largest Spanish cities[c]	175[d]	38	0.34	53	0.61	0.73	0.58	0.59	0.61	0.70	0.75	Marewski & Schooler (2011, Studies 1-3)
City population: Switzerland	14 largest Swiss cities[b]	68	14	0.64	27	0.73	1.35	0.64	0.70	0.78	0.87	0.88	Hilbig & Pohl (2009, Study 3)
City population: U.K.	30 largest U.K. cities[c]	175[d]	30	0.56	86	0.57	0.49	0.54	0.55	0.57	0.60	0.69	Marewski & Schooler (2011, Studies 1-3)
City population: U.S.	118 largest U.S. cities	120[e]	118	0.52	147	0.67	2.07	0.60	0.63	0.69	0.74	0.93	Hertwig et al. (2008, Study 1)

City population: U.S.	261 largest U.S. cities	68	261	0.30	1,152	0.64	2.51	0.59	0.64	0.66	0.68	0.97	Hilbig et al (2010)
City population: U.S.	28 largest U.S. cities[c]	175[d]	28	0.77	133	0.64	1.27	0.59	0.62	0.66	0.69	0.89	Marewski & Schooler (2011, Studies 1-3)
City population: Worldwide	61 largest cities worldwide	29	61	0.63	518	0.54	0.47	0.51	0.52	0.53	0.56	0.72	Hilbig (2010)
						ECONOMIC SUCCESS							
Athletes' income	50 richest athletes	40	50	0.24	51	0.61	0.72	0.55	0.62	0.63	0.60	0.75	Hertwig et al (2008, Study 1)
Billionaire's fortune	100 wealthiest people	40	100	0.09	44	0.62	0.70	0.62	0.67	0.63	0.67	0.76	Hertwig et al (2008, Study 1)
Companies' market capitalization	Market capitalization of 80 companies	21	80	0.52	612	0.64	4.38	0.57	0.62	0.67	0.71	1.00	Marewski & Schooler (2011, Study 5)
Companies' revenue	100 German companies with highest revenue	40	100[f]	0.46	842	0.58	1.29	0.56	0.58	0.60	0.59	0.95	Hertwig et al (2008, Study 1)
Country's GDP	GDP of 162 countries	20	162	0.90	7,122	0.64	1.87	0.56	0.61	0.67	0.70	1.00	Marewski & Schooler (2011, Study 4)
Music artists' cumulative record sales	106 most successful artists in the U.S.	40	106[f]	0.69	1,684	0.57	1.32	0.55	0.57	0.58	0.60	0.98	Hertwig et al (2008, Study 1)

(continued)

Table 12.1 (continued)

Domain	*Reference class*[a]	*N*	*M*	*Rec. rate*	*Pairs*	*Val*	*d_R val*	*Val for quartiles of Δ fluency*				*% val > 50%*	*Source*
								1st	*2nd*	*3rd*	*4th*		
						FAMILIARITY & POPULARITY							
Familiarity: Companies	84 companies from the S&P 100 Index	22	84	0.84	1,884	0.68	2.93	0.60	0.66	0.72	0.76	1.00	Herzog et al (2011)
Familiarity: infectious diseases	54 infectious diseases' name recognition	20	54	0.46	222	0.78	3.77	0.64	0.76	0.83	0.90	1.00	Marewski & Schooler (2011, Study 6)
Familiarity: Politicians	189 German politicians' name recognition	19	189	0.36	1,757	0.76	5.13	0.67	0.74	0.80	0.85	1.00	Marewski & Schooler (2011, Study 7)
Popularity of sports	25 most popular sports in Germany	80	25	1.00	227	0.53	0.29	0.51	0.53	0.52	0.56	0.60	Pachur et al (2012)
						DISEASE INCIDENCE							
Incidence: Cancer	Incidence of 24 types of cancers in Germany	40	24	0.69	112	0.56	0.86	0.57	0.52	0.59	0.58	0.83	Hertwig et al (2005, Study 2)
Incidence: Infectious diseases	Incidence of 24 types of infectious diseases in Germany	100[g]	24	0.58	74	0.38	-1.33	0.47	0.38	0.34	0.33	0.07	Hertwig et al (2005, Study 2); Pachur & Hertwig (2006, Study 2)

SUMMARY ACROSS ALL DOMAINS											
1st quartile	40	28	0.46	53	0.58	0.70	0.55	0.57	0.60	0.60	0.75
M_R	76	53	0.54	239	0.62	1.18	0.58	0.61	0.64	0.68	0.85
3rd quartile	175	100	0.69	612	0.65	1.87	0.61	0.66	0.67	0.73	0.97

Note. *N* refers to the total number of participants in the dataset and *M* to the number of objects in the domain. The following columns show averaged values across participants (using a 20%-trimmed mean, M_R; Wilcox & Keselman, 2003; see also Note 1): *Rec. rate* refers to the recognition rate (proportion of objects recognized), *pairs* to the number of simulated fluency pairs, *val* to the fluency validity, *val for quartiles of* Δ *fluency* to the fluency validity for the first, second, third and fourth quartile of absolute differences in retrieval speed (within participants), respectively. d_R *val* refers to a robust one-sample Cohen's *d* effect size (cf. Algina et al, 2005) of the fluency validities (compared against 50%) and *% val > 50%* refers to the proportion of participants for which fluency validity was larger than 50%. Because people cannot detect differences in retrieval fluency below 100 ms (Hertwig et al, 2008, Study 2), all statistics were calculated only for object pairs with a difference of 100 ms or more. The retrieval fluency validity is defined as follows (Hertwig et al, 2008; Schooler & Hertwig, 2005): the proportion of correct decisions one would make if one would always infer that the more fluently retrieved object has the larger criterion value (among all possible pairings of objects in the reference class where both objects are recognized by a participant).

[a] See the referenced articles for detailed descriptions of the domains and reference classes.

[b] In the original study, the largest city was excluded from the reference class.

[c] In the original study, the capital city was excluded from the reference class and only one-word city names of similar word length (i.e., 5–8 letters) were used.

[d] We collapsed the respective datasets across Studies 1, 2 and 3 from Marewski & Schooler (2011).

[e] Participants were presented with a random third of the 118 cities.

[f] Unlike in the original analysis, we did not exclude objects with overly long names (see Hertwig et al, 2008, footnote 5, p. 1194).

[g] We collapsed the datasets from Hertwig et al (2005, Study 2) and Pachur and Hertwig (2006, Study 2).

All obtained fluency validities were above chance level (range [0.53, 0.78])—with the sole exception of the infectious diseases domain, where validity was only 38 percent; this low validity is consistent with the observation that the number of times infectious diseases are mentioned in the media is a poor predictor of the diseases' actual incidence (Pachur & Hertwig, 2006). Averaged across all 25 domains, the fluency validity was 62 percent (interquartile range or IQR: [.58, .65]).[1] Thus retrieval fluency enables people to draw inferences that clearly surpass chance level.[2] Robust Cohen's *d* effect sizes (cf. Algina, Keselman, & Penfield, 2005), comparing the fluency validities against chance level, averaged 1.18 across domains (IQR [0.70, 1.87]), thus indicating large effect sizes (see Cohen, 1988). Furthermore, fluency was a valid cue for the large majority of participants: Averaged across domains, 85 percent (IQR [0.75, 0.97]) of participants enjoyed validities above chance level.

Roughly half of the domains (13 out of 25) pertain to inferences about population size. To see whether our conclusions about fluency's validity are unduly influenced by this "drosophila" type of domain, we grouped the domains into four classes based on the type of criterion that was to be inferred (see Table 12.1): population size (13 datasets), economic success (e.g., people; six datasets), familiarity and popularity (e.g., politicians; four datasets), and disease incidence (two datasets). Three results emerged. First, retrieval fluency is also a valid cue in domains other than population size inferences (M_R = 61%, IQR [0.57, 0.65]). Second, fluency seems equally potent in inferring economic success (M_R = 61%, IQR [0.59, 0.63]) and population size (M_R = 63%, IQR [0.61, 0.65]). Third, fluency also enables inferences about familiarity and popularity (Mdn = 72%, IQR [0.65, 0.77]), which is not surprising given that familiarity and popularity are nearly synonymous with being frequently talked, written, and heard about. Given that we only have two domains about disease incidences (with fluency validities of 38 percent and 56 percent, respectively), it is difficult to draw any conclusions about this domain. Research on risk perception, however, suggests that media coverage of, for instance, incidents of infectious diseases is not necessarily a good proxy for actual incidence rates (e.g., Hertwig et al., 2005).

Even though an average fluency validity of 62 percent may not seem terribly impressive, it would be misleading to compare it to the utopian benchmark of making 100 percent correct inferences. Even strategies that can process large amounts of information and do so in a computationally expensive way (e.g., Bayesian networks) do not achieve perfect accuracy in real-world environments and often do not perform much better than simple heuristics (e.g., take-the-best; Martignon & Hoffrage, 2002). Thus rather than comparing fluency validities to perfect accuracy, one should compare them to the accuracy of inferences that are based on information *other* than retrieval fluency, that is, on cues drawn from our semantic knowledge (e.g., whether a city has an airport or not). For instance, when one calculates the accuracy of participants' actual decisions in three domains investigated in Hertwig et al. (2008, Study 3) and focuses on only those decisions in which participants concluded that the *less* fluently recognized object was larger (i.e., participants obviously relied on information other than retrieval fluency) one finds the following: Participants' inferences were actually *less* accurate than those that they would have made had they always relied on retrieval fluency (6, 7, and 11 percentage points lower accuracy, respectively; Hertwig et al., 2008, p. 1204). This result suggests that retrieval fluency can lead to inferences at least as accurate as those from knowledge-based strategies that "think harder" about the problem by using cue knowledge.

Another convenient property of retrieval fluency is that it is more likely to be correct when it becomes easier to use. Specifically, the larger the differences in, say, two company names' retrieval fluency, the more easily the retrieval fluency can be distinguished and the more likely the resulting inference will be correct. This is because larger differences in retrieval fluency translate into larger differences in the environmental frequencies and—given an ecological correlation between the criterion and the mediators in the environment—also into larger differences on the criterion (Hertwig et al., 2008). Figure 12.2 shows for the five domains investigated in Hertwig et al. (2008, Study 1) how the fluency validity increases as the difference in retrieval fluency increases. For example, whereas indistinguishable differences in retrieval fluency (i.e., below 100 ms) imply a validity of 54 percent when inferring which of two US cities is larger, validity rises to 71 percent for differences larger than 700 ms. This result also emerges in the other domains. Table 12.1 shows the fluency validity in each domain separately for quartiles of absolute differences in retrieval speed (i.e., for the first, second, third and fourth quartile of absolute differences within each participant). In all but one domain (infectious diseases), the fluency validity increased from

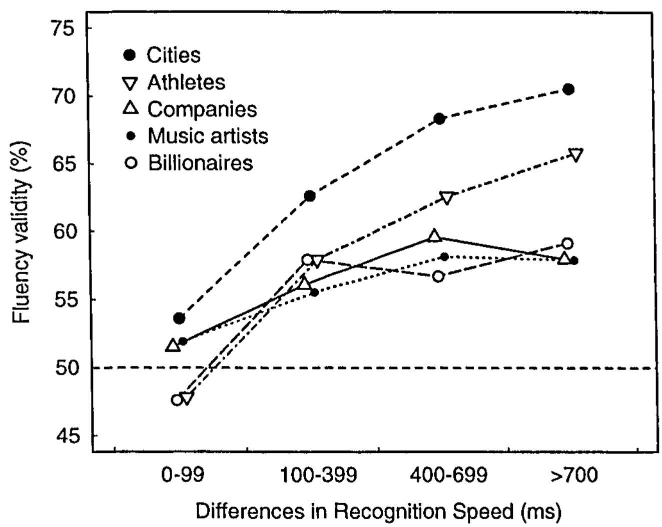

Figure 12.2 The validity of retrieval fluency as a function of increasing differences in retrieval fluency between the two objects (adapted from Hertwig et al.'s, 2008, Figure 2).

the smallest fourth of fluency differences (M_R = 58%, IQR [0.55, 0.61]) to the largest differences (M_R = 68%, IQR [0.60, 0.73]). This implies that inferences based on differences in retrieval fluency are most valid when they are most likely to be correctly assessed—that is, when the differences are large (Hertwig et al., 2008).

How and when do people use retrieval fluency in making quantitative inferences about the world? Clearly, people do not invariably rely on retrieval fluency for their judgments and decisions. Whether and how people use subjective experiences depends on the validity and the direction of the fluency cue, both of which people can extract from experience (i.e., Brunswikian cue learning; Unkelbach, 2006; Unkelbach & Greifeneder, Chapter 2, this volume) and their naïve theories about the mental processes that they apply to the task (e.g., people discount the informational value of their subjective experiences when they attribute them to a non-diagnostic source; Schwarz, 2004). Although there is extensive research on how and when people use cognitive and affective feelings (e.g., Greifeneder et al., 2011; Oppenheimer, 2008; Schwarz, 2004), there are only a few process models in the literature of how they take advantage of their sense of fluency. Schooler and Hertwig (2005; see also Hertwig et al., 2008; Marewski & Schooler, 2011; Volz, Schooler, & von Cramon, 2010) proposed the *fluency heuristic* that infers that the faster of two recognized object scores higher on a criterion, given that the retrieval difference is larger than 100 ms. This fluency heuristic is most useful when people merely recognize two objects, and thus cannot apply knowledge-based strategies; in those cases, using retrieval fluency leads to decisions that are clearly better than chance and people's decisions are well described by the fluency heuristic (Marewski & Schooler, 2011). In contrast, when further knowledge about the objects is available, people seem to use knowledge-based strategies, which tend to be more accurate than the fluency heuristic for such cases (Marewski & Schooler, 2011; see also Hilbig, Erdfelder, & Pohl, 2011).

As of now, we have analyzed the ecological validity of retrieval fluency when inferring numerical quantities of importance in the world. Next, we turn to a different kind of a criterion: the truth (or lack thereof) of a statement.

Is this really true? Inferring the likely truth of statements

"In Malaya, if a man goes to jail for being drunk, his wife goes too." Is this statement true or false? A simple rhetorical tool to increase the perceived truthfulness of such a statement is: repeat it (e.g., Arkes, Boehm, & Xu, 1991; Bacon, 1979; Begg, Anas, & Farinacci, 1992; Brown & Nix, 1996; Hasher, Goldstein, & Toppino, 1977; Hertwig, Gigerenzer, & Hoffrage, 1997; for a meta-analysis see Dechêne, Stahl, Hansen, & Wänke, 2010). As the character Bernard Marx in Aldous Huxley's (1932) *Brave new world* conjectured, "Sixty-two thousand four hundred repetitions make one truth!"

There are two complementary explanations for the effect that repetition increases the perceived truth of statements. First, people may conclude that repeated statements must be true *because* they recall having seen or heard them before (Brown & Nix, 1996; i.e., a form of convergent validity; Arkes et al., 1991). Second, people may unwittingly put more faith in repeated statements because repetition increases processing fluency (Feustel, Shiffrin, & Salasoo, 1983), which in turn increases the perception of truth (Begg et al., 1992). People may judge fluently processed statements as true because they have learned that the experience of fluency "correlates positively with the truth of a statement" (Unkelbach, 2007, p. 219).

But is it reasonable to assume that fluency is a cue to a statement's truth value? Some have argued that "there is no logical reason for repetition to affect rated truth" (Begg et al., 1992, p. 447). In fact, Ludwig Wittgenstein ridiculed the tendency to buy into the veridicality of a statement based on its mere repetition, comparing it to purchasing two copies of the same newspaper to double-check whether the information in the first copy is correct (Kenny, 2006; see Unkelbach, Fiedler, & Freytag, 2007, for an empirical demonstration of this phenomenon). To make matters worse, a statement's processing fluency can be influenced by factors that are totally unrelated to how often one has encountered it in the past. For example, people are more inclined to believe statements the more legible they are (Hansen, Dechêne, & Wänke, 2008; Reber & Schwarz, 1999) or when they rhyme (McGlone & Tofighbakhsh, 2000).

However, there are also arguments as to why there may be an exploitable association between repetition and truth (and thus also between fluency and truth). Russell (1940), Wittgenstein's teacher and colleague at Cambridge, for instance, noted that it is often difficult, if not even impossible, to obtain direct evidence regarding the truth of statements. Based on this premise, Russell argued that it may be reasonable to believe more strongly in a statement as a function of how many other people endorse it. Assuming that one is more likely to encounter a statement the more it is endorsed by people, one could then infer that the more often one encounters a statement, the more people believe it to be true; hence one may infer that the more likely it is to be true. Consistent with this chain of inferences, true factual statements tend to be processed faster (i.e., more fluently) than wrong factual statements (Shtulman & Valcarcel, 2012; Unkelbach & Stahl, 2009). This then implies that, holding everything else constant, true factual statements tend to be repeated more often than wrong factual statements.

Furthermore, a Bayesian analysis (Reber & Unkelbach, 2010) shows that evaluating fluent statements as true ones will result in beliefs that are more likely to be true than mere chance (50 percent) if one is *a priori* more likely to experience true than false statements in the world. The intuition behind the Bayesian argument is as follows (see Reber & Unkelbach, 2010, for a detailed discussion): Arguably, repeatedly encountered statements become more fluent regardless of whether they are actually true, that is, $p(\text{fluent} \mid \text{true}) = p(\text{fluent} \mid \neg\text{true})$. If this premise holds, the posterior probability that a statement is true given that it is fluently processed reduces to the prior probability of the statement being true in the first place (and its complement, the prior probability that the statement is *not* true).

$$p(\text{true} \mid \text{fluent}) = \frac{p(\text{true})}{p(\text{true}) + p(\neg\text{true})} \tag{1}$$

Equation 1 implies that the probability of a statement being true given that it is processed fluently is larger than 50 percent whenever the probability that a randomly encountered statement is true is higher than 50 percent. But why should this prior probability of a statement being true be larger than 50 percent?

To the extent that conversation is a cooperative venture, speakers aim to communicate relevant information (Sperber & Wilson, 1986) and this, among other things, implies that they say what they think is true (see Grice's, 1975, *maxim of quality*). If we can reasonably assume that most other speakers are cooperative in a certain domain, then we can also assume that statements we hear will more likely to be true than not. This in turn implies that the prior probability that a statement is true will be higher than 50 percent and thus fluency will be indicative of truth. Of course, there are domains (e.g., marketing, political campaigns) in which communication tends to be adversarial and competitive rather than cooperative and here fluency is not likely to be a valid cue to the truth status of statements.

Predicting numerical quantities and assessing the truth of statements are important tasks, but they pale in comparison to the importance of the criterion that we will discuss in the next section.

Is it going to kill me? Assessing danger

When organisms encounter an unknown living creature or a novel food, the question arises: Is this new thing dangerous? Is it going to kill me? This question is so important, so evolutionarily old and needs to be "answered" so swiftly that living creatures are likely to have some in-built mechanisms that spit out the answer (LeDoux, 1996). One strategy is to turn the inference—"Is it dangerous?"—into a hard-wired or learned preference—"Do I like it? Do I dislike it?" If organisms avoid dangerous things because they do not like them (or are even afraid of them), then they are more likely to survive and reproduce—also because preferences can inform behavior much faster than inferences (e.g., LeDoux, 1996; Zajonc, 1998).

As we do not know whether a new, unfamiliar object or living being is potentially dangerous, *neophobia*—disliking the new—is an evolutionarily prudent strategy: Start with dislike—be cautious!—and only start liking something to the extent it has proven itself to be innocuous (e.g., Hill, 1978; Kalat & Rozin, 1973). Bornstein (1989, p. 282) argued that:

> Only after repeated exposures coupled with a consistent absence of negative reinforcement associated with the stimulus can one reliably conclude that the object is nonthreatening. A long-term memory of a stimulus with an absence of negative associations is a much more reliable index of (lack of) dangerousness than is a short-term memory trace.

The mirror image of the biological predisposition for caution when encountering novel and potentially harmful objects is the complementary preference for familiar objects (Hill, 1978; Zajonc, 1968, 1998, 2001)[3]—its rationale can be summarized with the slogan: "[A]fter all, these objects have not killed you yet!" (Smith, 2000, p. 119). The phenomenon that humans' and animals' preference for objects increases through repeated exposure is known as the *mere exposure effect* (Zajonc, 1968; Hill, 1978; for reviews see Bornstein, 1989; Zajonc, 2001) and can be seen as a form of classical conditioning where the absence of aversive events—when encountering an object—constitutes the unconditioned stimulus (Zajonc, 2001).

Next we propose a Bayesian analysis that illustrates why repeated exposure is a valid cue for danger (or lack thereof) in the reference class of objects that have not attacked or harmed us yet (see Appendix B for a more detailed treatment). We start with two sets of assumptions. First, every object has a constant probability θ of attacking or harming us in each episode; with the complimentary probability $1 - \theta$, we are "merely exposed" to the object without any experienced harm (or death). Second, we are maximally unsure about the value of this probability θ prior to the first encounter with the object. That is, any value from 0 percent to 100 percent is equally likely a priori (i.e., uniform prior distribution). Given those two assumptions, a Bayesian mean posterior estimate of θ after n harmless episodes is: $p(\text{"hit"} \mid n) = 1/(n + 2)$. Figure 12.3 shows how this "danger

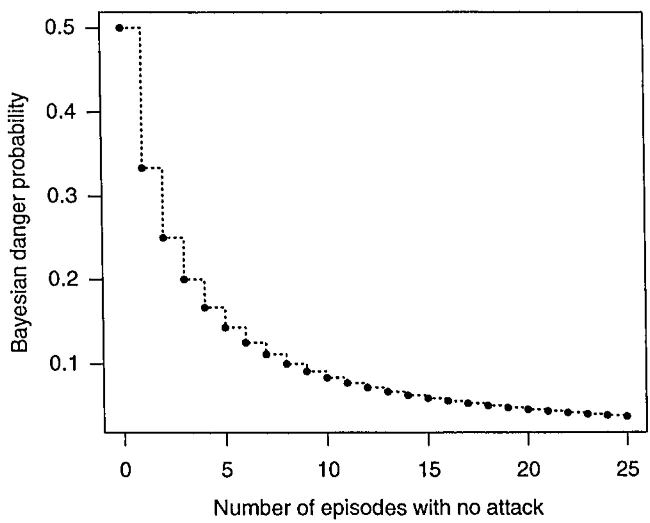

Figure 12.3 Bayesian analysis illustrating why repeated exposure is a valid cue for danger (or lack thereof) in the reference class of objects that have not attacked or harmed us yet. The figure plots the Bayesian mean posterior estimate of the probability θ with which an object attacks or harms us in any episode as a function of the number of harmless episodes so far—assuming an uniform prior distribution over θ: $p(\text{"hit"} \mid n) = 1/(n + 2)$. See main text and Appendix B for details.

probability" θ decreases as the number of harmless episodes increases: After 0, 1, 2, 3, 4 or 5 episodes, p("hit" | n) takes values of 50%, 33%, 25%, 20%, 17% and 14%, respectively. Because the decrease slows down as n increases, 10 harmless episodes can make us confident that in all likelihood the object is harmless; p("hit" | n = 10) = 8%. Although purely speculative, this marginal decrease in assessed dangerousness coincides with the observation that the mere exposure effect typically levels off after ten to 20 presentations (Bornstein, 1989), which translates into danger probabilities of 8 percent to 5 percent in our analysis.

Because the repeated exposure to an object increases its retrieval fluency (e.g., Anderson & Schooler, 2000; Jacoby & Dallas, 1981), keeping everything else constant, high retrieval fluency signals safety. An inbuilt preference for fluent objects is thus adaptive because—according to our analysis—more fluently recognized objects tend to be less dangerous than less fluently retrieved objects. (We assume here that any negative reinforcement due to a harmful episode with an object, for example, an attack or food poisoning, can override the danger assessment based on retrieval fluency; that is, fluency's validity is conditional on not yet being attacked or harmed by an object; see also Bornstein's, 1989, quote above.)

Monkey see, monkey do? Retrieval fluency, imitation, and other people's behavior

Retrieval fluency not only predicts numerical quantities, truth and danger, but also signals social information: It is a cue to popularity because the more popular something is (e.g., a brand name, a movie, or a financial service) the more often one encounters it in everyday life (e.g., in conversations, on the streets, in newspapers, or in advertisements) and thus the higher its retrieval fluency. As a consequence, whenever a person chooses the more fluent out of two options (e.g., two brands of wine), she is likely to choose what most other people would choose—at least above chance level (see Todd & Heuvelink, 2007, for a related argument for recognition). Retrieval fluency can thus be used as a cue in social heuristics (Hertwig & Herzog, 2009), such as the *imitate-the-majority heuristic* (Boyd & Richerson, 2005; Hertwig, Hoffrage, & the ABC Research Group, 2012).

When people are unsure about what to do, they often look to what other people are doing (e.g., Bikhchandani, Hirshleifer, & Welch, 1998; Boyd & Richerson, 1985, 2005; Festinger, 1954). But why would they be interested in other people's behavior and imitate it? Let us distinguish two broad classes of domains, namely, matters of fact (e.g., which of two projects will be more successful?) and matters of taste (e.g., which of two songs is "better"?).

When it comes to *matters of fact*, imitation can improve our decisions to the extent that one can profit from the "wisdom of the crowds" (Surowiecki, 2004). For example, when we are unsure about how fast we are allowed to drive in a foreign country, we might adjust our speed so that we drive as fast (or even a bit slower) than most other drivers. Imitation is generally a good strategy whenever environments are stable (i.e., the "correct answers" do not change rapidly), individual learning is costly, and when there are original learners in the population (i.e., not everybody is copying everybody else; Bikhchandani et al., 1998; Boyd & Richerson, 1985, 2005). Under those conditions, decisions based on retrieval fluency are likely to be good because retrieval fluency tracks the wisdom of crowds.

In contrast, when it comes to *matters of taste*, there are—by definition—no agreed upon objective criteria. In many domains, whatever happens to be popular (i.e., what most people are thinking or doing) can, but does not need to, reflect objective "goodness" of the thing in question; rather, popularity *defines* a socially validated reality. For example, although a band may be (objectively) better than another in terms of technical skills, listeners may still widely disagree as to which one plays the better music. Consider the following experimental study as an illustration (Salganik, Dodds, & Watts, 2006). In an artificial music market, consumers were able to download novel songs for free and could see how often other consumers had downloaded them previously. Not surprisingly, consumers' choices were influenced by the observed behavior of other consumers. As a consequence, some songs gained momentum and increased in popularity (i.e., downloads) partly by the mere fact that they—for whatever arbitrary reason—happened to be preferred in the early stages of the evolution of the market. Salganik et al. (2006) implemented several instances of such a market. Although those "parallel universes" were identical with respect to their starting conditions, the resulting popularity rankings of the songs turned out to be markedly different because different songs initially gained popularity for partly arbitrary reasons. Consequently, popularity was only weakly predicted by the inherent "quality" of the songs, as measured by the popularity ranking from a control condition where no social information was available and participants' choices thus only reflected their taste and the songs' characteristics. In sum, imitation behavior made some songs popular and others not.

When popularity socially defines—rather than just merely reflects—criteria, cues that track popularity—such as retrieval fluency—are valid cues by definition. Their validity only depends on how well they track popularity. Yet, popularity always needs to be defined relative to a reference class of people. It could, for example, pertain to the musical taste of all citizens of a nation (e.g., reflected in nationwide music charts) or of one's social class (Bourdieu, 1979/1984). Because we share with our proximate reference groups the exposure to similar objects (e.g., artifacts, events, activities, cultural products like music; Bourdieu, 1979/1984; Reber & Norenzayan, 2010), retrieval fluency will also reflect what is popular within our reference groups—in addition to what is popular in more general terms (see also Reber, Chapter 11, this volume).

When it comes to matters of taste, there are at least three reasons why going with the more fluent—and thus in all likelihood more popular—option can be advantageous. First, doing what most people do can bring coordination gains (e.g., Schelling, 1980; Todd & Heuvelink, 2007). For example, if people visit bars whose names they fluently retrieve from memory (e.g., because they have repeatedly heard other people gushing about it), then they will end up going to the same places and can enjoy the atmosphere of a busily crowded bar.

Second, doing what most people do can bring *social gains*. Humans want to belong to other people (Baumeister & Leary, 1995) and strive to be similar—but not too similar—to people from significant reference groups (Brewer, 1991; Leonardelli, Pickett, & Brewer, 2010). Whenever we want to blend in with others (e.g., with respect to food, drinks, clothing, music, or literature), choosing the more fluent of two options (e.g., two brands of beer) will help reach this goal. Indeed, when consumers feel too dissimilar from other people, they prefer popular products to unpopular products (He, Cong, Liu, & Zhou, 2010); choosing more fluent consumer products could thus be a strategy to blend in again. Furthermore, because shared exposure to the same objects increases social cohesiveness (Reber & Norenzayan, 2010), choosing popular options should thus increase social cohesion.

There is still another, third way, in which choosing the more fluent and thus more popular option can be advantageous. In many domains, people differ in their tastes, are cognizant of their preferences and therefore can implement them. For example, some people prefer and order French red wines, whereas others prefer and order Californian red wines. Some people enjoy and watch action movies, whereas others enjoy and watch documentaries about wildlife. In other domains, however, people differ in their tastes, but because they lack the relevant first-hand experiences, they may not yet know—at the time of initial choice—which option they are going to enjoy more. Take, for instance, a tourist who plans to visit the Canary Islands. But which one? After having visited, say, Tenerife and Fuerteventura the traveler could probably say whether she is more a Tenerife or a Fuerteventura "type," but she does not know it ahead of time. Thus, unless the tourist has some insightful private information about her likely preferences, her choice task amounts to inferring which type she is.

From a Bayesian perspective, as soon as one type of preference is more prevalent in the population than the other and thus represents the majority preference (e.g., most people prefer Tenerife over Fuerteventura), an agent is a priori more likely to have this preference than not—unless there is strong "private evidence" to the contrary (e.g., the tourist has already visited both islands and prefers Fuerteventura over Tenerife). This is because the posterior probability that the agent has this majority preference equals the base rate of this preference in the population in the absence of private, diagnostic evidence. And even if the agent should have some private, diagnostic evidence, the posterior probability will—through the logic of Bayes theorem (integration of private evidence with base rates)—be at least partly determined by the base rate. Because fluency tracks the popularity of options, as we have argued above, choosing the more fluent option (e.g., Tenerife) amounts to choosing the option that is more likely one's preferred option—unless one knows otherwise. Fluency is thus a helpful cue in novel domains where one lacks clear preferences and relevant experience.

Conclusion

Although we know a lot about how and when fluency influences our judgments and decisions (see e.g., Oppenheimer, 2008; Schwarz, 2004), we are only starting to understand when it is an ecologically valid cue for the world that we live in. As we have reviewed in this chapter, fluency can help us navigate an uncertain world because it reflects the statistical structure of our environment and thus connects our minds to the world. We can then use this ecological connection between fluency and the world to inform our judgments and decisions. For example, retrieval fluency—the speed with which we retrieve objects from memory—reflects numerical quantities of importance, the truth of statements, the danger of objects and social information about what other people are doing. But there is certainly more to be learned. We hope we have been able to persuade other fluency researchers to open the next chapter in the investigation of fluency: the descriptive and normative chapter delineating those environmental and social conditions that turn fluency into an ecologically valid cue and those that rob it of its validity.

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Notes

1 Because of skewness and thick tails in the data, we used robust statistics (e.g., Erceg-Hurn & Mirosevich, 2008) to summarize the data within a domain, as well as across domains. We used the 20%-trimmed mean as a robust measure of central tendency (abbreviated as "M_R"); it is a better estimator of the population mean than the sample mean when the data are not normally distributed (Wilcox & Keselman, 2003).

2 We have conceptualized retrieval fluency as the speed with which a word is recognized (Hertwig et al., 2008; Schooler & Hertwig, 2005). Others, however, adopted a broader conception of retrieval fluency that, next to quantitative differences in recognition speed, also uses the distinction between a "recognized" and a "not recognized" judgment as a qualitative difference in retrieval fluency (e.g., Newell & Fernandez, 2006; but see Schooler & Hertwig, 2005). The ecological validity of recognition is defined as the proportion of correct decisions that a person would make if she always inferred that the recognized object has the larger criterion value than the unrecognized object among all possible pairings of objects in the environment where one object is recognized and the other is not (see Goldstein & Gigerenzer's, 2002, *recognition validity*). Ecological validity of retrieval fluency and recognition both thrive on the same environmental frequencies mediating between the criterion and memory (see Figure 12.1). Therefore, studies showing that reliance on recognition results in relatively accurate inferences in a domain by extension also indicate that retrieval fluency would be a valid cue in those domains (for overviews on the ecological validity of recognition, see Gigerenzer & Goldstein, 2011; Herzog & Hertwig, 2011; Pachur, Todd, et al., 2012). The recognition validity, however, will inevitably be larger than the respective fluency validity within the same domain because recognized and unrecognized objects differ, on average, more

in their activation strengths (and thus environmental frequencies) than two recognized objects (see Hertwig et al., 2008, p. 1203). The validity of such a more inclusive conception of retrieval fluency (including the qualitative difference between recognized and not recognized) would thus lie between that of retrieval fluency proper and that of recognition.

3 The preference for familiar stimuli seems to contradict the notion that humans and animals often show a behavioral preference for novelty (e.g., a rat's preference for a new, unfamiliar compartment; e.g., Bardo, Bowling, Robinet, Rowlett, Lacy, & Mattingly, 1993). This seeming contradiction can be resolved, however, by noting that evaluative and behavioral preferences are not the same. Zajonc (1968, p. 21) argued that "orienting toward a novel stimulus in preference to a familiar one may indicate that it is less liked rather than it is better liked. Ordinarily, when confronted with a novel stimulus the animal's orienting response enables it to discover if the novel stimulus constitutes a source of danger. It need not explore familiar stimuli in this respect."

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Appendix A

Our literature search was conducted as follows. We constructed search terms by combining "fluency," "ease," "meta-cognitive experience," "meta-cognitive experiences," "experience," or "experiences" with "validity" or "accuracy" to form strings (e.g., "fluency validity" or "accuracy of meta-cognitive experiences") and then searched PsycInfo and GoogleScholar on November 4, 2010. On PsycInfo, we found a total of 40 hits, but most articles concerned reading and mathematical skills. Our searches turned up more hits on GoogleScholar, but suffered from a very low specificity. In our experience, the most informative search query was ["fluency validity" OR "fluency * validity" OR "validity of fluency"], which yielded 82 hits on GoogleScholar.

We further performed a citation pearl search by inspecting the cited and citing references of the following papers: Alter and Oppenheimer (2006, 2009), Hertwig et al. (2008), Oppenheimer (2008), Reber and Unkelbach (2010), Schooler and Hertwig (2005), Unkelbach (2006, 2009), and Unkelbach and Stahl (2009). We also contacted several key researchers and asked them to name, in their view, potentially relevant articles concerned with the ecological validity of fluency.

We identified the following references as relevant: Alter and Oppenheimer (2006), Green and Jame (2011), Hertwig et al. (2005, 2008), Hilbig (2010), Hilbig, Erdfelder, and Pohl (2011), Hilbig and Pohl (2009), Marewski and Schooler (2011), Pachur and Hertwig (2006), Schooler and Hertwig (2005), Unkelbach and Stahl (2009); as well as unpublished data from Herzog, Hertwig, and Steinmann (2011), Hilbig, Erdfelder, and Pohl (2010), and Pachur, Rieskamp, and Hertwig (2012). The raw data from Newell and Fernandez (2006, Study 2) were not available in a form amenable to re-analysis. Gaissmaier (2007, Chapter 3) discusses how retrieval fluency can inform the cue search order of knowledge-based strategies; we will not discuss this approach in this chapter.

Appendix B

In what follows, we develop the Bayesian answer to the question: What is the probability that an object will attack me in the next episode given that it has not yet attacked me in n (e.g., 5) previous episodes?

We start with two sets of assumptions. First, every object has a constant probability θ of attacking or harming us in each episode; with the complementary probability $1 - \theta$, we are "merely exposed" to the object without any experienced harm (or death). Second, we are maximally unsure about the value of this probability θ prior to the first encounter with the object. That is, any value from 0 percent to 100 percent is equally likely *a priori* (i.e., uniform prior distribution).

The Bayesian mean posterior probability of getting a "hit" (i.e., an attack) in the next trial after observing m "hits" (i.e., attacks) in n previous trials (i.e., episodes) and assuming a uniform prior distribution is (see, e.g., Kruschke, 2011, p. 84): $p(\text{"hit"} \mid n, m) = (m + 1)/(n + 2)$. In our analysis, there are by definition no hits (i.e., no attacks, that is, $m = 0$) and thus the formula simplifies to p("hit" | n, $m = 0$) = $1/(n + 2)$. The Bayesian mean posterior estimate of the probability that an object will attack me in the next episode given that it has not yet attacked me in n episodes is thus: p("hit" | n) = $1/(n + 2)$. One can, of course, assume other prior distributions. For instance, more "pessimistic" priors put more weight on *high* values of θ a priori, and will squeeze the curve in Figure 12.3 upwards; more "optimistic" priors put more weight on *low* values of θ a priori and will squeeze the curve downwards.

Our analysis can be seen as the reversal of Laplace's *rule of succession* (Keynes, 1921, pp. 367–383) and could thus be called the *rule of non-succession.* Let us briefly illustrate the rule of succession. We assume an event x (e.g., the rising of the sun in the morning) that has been successively observed n times (e.g., for 1,000 mornings). Prior to the first observation, one was completely uncertain about the value of the probability that this event x will happen (i.e., we assume an uniform prior). Then, the Bayesian mean posterior probability of the hypothesis H that x will happen in the observation period $n + 1$ is $p(H \mid n) = (n + 1)/(n + 2)$. For the example above, this probability is thus (1,000 + 1)/(1,000 + 2) = 99.9%. Whereas in our Bayesian mere-exposure analysis the number of "hits" m equals zero (by definition), in the rule of succession m equals the number of trials n (by definition). When plotting $p(H \mid n)$ as a function of n, one will obtain a mirror curve of the one shown in Figure 12.3 (i.e., imagine mirroring the curve at a horizontal line at .5); as the number of successive observations increase, so does $p(H \mid n)$.