

University of Nevada, Reno

**Childhood Uncertainty and Decision-Making in Adulthood: When Individual  
Differences in Information Use Reflect Adaptive Responses to the Environment**

A dissertation submitted in partial fulfillment of the  
requirements for the degree of Doctor of Philosophy in  
Social Psychology

by

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THE GRADUATE SCHOOL

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## Abstract

The ability for individuals to adapt to their local environment is a universal property of evolved organisms. As a group, humans possess a shared set of tools for overcoming recurrent adaptive challenges, but human environments are diverse and the exact characteristics of an adaptive challenge vary between individuals. Thus, the best way for individuals to overcome adaptive challenges depends on the *unique presentation* of the challenge they face. Previous research shows that an important dimension along which environments vary is *uncertainty* and that early life experiences with uncertainty can shape judgment in adulthood. When uncertainty is high, cues that predict important outcomes can be corrupted by statistical noise, leaving only a smaller subset of robust cues that remain valid predictors. Therefore, individuals seeking to make good decisions in highly uncertain environments should tend to use fewer cues when forming judgments (Hypothesis 1a), especially when stakes are high (Hypothesis 1b). Furthermore, because fewer cues remain valid in high-uncertainty environments, the preferences of people from high-uncertainty environments should be more similar than the preferences of people from low-uncertainty environments (Hypothesis 2a). Again, this relationship was expected to be stronger when stakes are high (Hypothesis 2b). To test these hypotheses, 1,035 participants were randomly assigned to complete a task designed to threaten the goal of finding a mate or a control task. Next, participants completed several trials of the mate choice task: For each trial, participants studied the descriptions of two potential mates and then indicated which individual would make a better long-term romantic partner. Results provided some support for Hypothesis 1: Women from uncertain childhood environments tended to rely on fewer cues when choosing mates, but only in

the control condition. Among men, childhood uncertainty was not associated with the number of cues used to evaluate mates in either condition. Results for Hypothesis 2 were partially supported by both men and women: When mate-seeking goals are threatened, men with uncertain backgrounds tended to express more similar preferences than men with low-uncertainty backgrounds. The same relationship was observed among women, but only in the control condition. Implications for theories proposing that the early-life environment influences adult judgment in adaptive ways are discussed.

## Dedication

To Ellie, Joey, and Bailey,  
my most cherished sources of uncertainty.

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## Chapter 1: Introduction

What does it mean for a mind to be “tuned” to its environment? One common answer is that a perfectly tuned mind (i.e., an *ideal observer*) is one with beliefs that correspond to facts about the environment (Feldman, 2013, 2017). For example, when deciding whether to bet that a six-sided die will land showing “three,” ideal observers will know fair dice show three about once every six rolls. With knowledge about the behavior of dice and the payoffs of each outcome, individuals can determine whether repeatedly accepting such bets will be profitable over time. Because a die will show a losing value five times for each win, a classic expected value framework suggests one should not accept bets unless the gain of a single win exceeds the cost of five losses.

The expected value framework was developed to understand decisions made under *risk*, whereby decision-makers possess estimates for all possible alternatives, outcomes, and probabilities. But how does this framework inform decisions about who to marry, who to befriend, and who to trust with your investment portfolio? Resolving dilemmas like these are among the most consequential challenges people face, but it is rare for people to know of all possible alternatives, outcomes, and probabilities in such situations. These types of decisions are characterized as decisions made under *uncertainty*, whereby decision-makers lack information about all alternatives, outcomes, and probabilities. When considering the contexts of everyday decisions, it is clear that even the most mundane and simple decisions are made under uncertainty. As stated by Feldman (2013):

In practice, environmental conditions are not singular, perfect, and unchanging. In

reality, probabilities vary over time, space, and context, in potentially unknown and unpredictable ways. The environment inevitably contains uncertainty, not only about the classification of items on individual trials but about the nature of the probabilistic schema itself. (p. 25)

Consider again the decision-maker who is offered a bet about the outcome of rolling a six-sided die. Assume the bet has a favorable expected value, say, that she will win \$100 if the die shows three and lose \$10 for any other outcome. Should she take the bet? Perhaps, but anyone truly facing this kind of decision would be wise to consider the possibility that some dice are intentionally constructed to be *unfair* and that encountering unfair dice is more likely in some environments. The implication is that experience with fair dice is insufficient to overcome uncertainty about *this particular die* used to resolve *this particular bet*. Instead, the decision-maker should consider a broader range of information about her environment and her particular position within that environment. *Who is offering the bet? Why is the expected value so high? Are they employed by a reputable company? Are they social scientists who might deceive me? Is anyone else eager to take the bet?* Of course, knowledge of the behavior of fair dice might be relevant, but the extent of the relevance will vary across contexts. Once these sources of uncertainty are acknowledged, it is difficult to argue that her decision to decline the bet would be irrational, *even if the die were fair*.

This scenario is intended to demonstrate that the best decision-making strategy depends on the environment and most environments are characterized by uncertainty. Furthermore, “the environment” depends heavily on the traits of decision-makers

themselves. For example, two individuals might differ on a trait (e.g., extraversion) that influences the consequences of a decision (e.g., whether to attend a party) or the availability of alternatives (e.g., whether one received multiple invitations to different parties). Because the best decision for each individual can depend heavily on that individual's characteristics, two individuals presented with identical stimuli are not necessarily in the same environment. For example, two college graduates applying for the same employment opportunity (e.g., computer programmer) are unlikely to experience the same outcome if the two graduates hold different degrees (e.g., computer science vs. business). Indeed, differences in any type of trait (e.g., personality) have the potential for creating environmental differences insofar as the trait is relevant to the decision (e.g., an extravert vs. an introvert deciding whether to attend a party). This approach to understanding the rationality of decisions is known as *ecological rationality*.

Ecological approaches to decision-making are somewhat uncommon in the field of social psychology (Brighton & Gigerenzer, 2015; Gigerenzer, 2018; Jussim, 2012; Krueger & Funder, 2004), but their value can be illustrated by examining one of the most consequential challenges that humans encounter: choosing a mate. The choice to pursue a particular mate is complicated by the fact that choosing to pursue a mate marks the initiation of a potentially decades-long process with uncertain outcomes. Successful reproduction takes time and success is a precarious state that must be maintained until offspring achieve independence. Therefore, any individual differences between decision-makers that can affect the outcomes of the reproductive process become relevant information to consider when choosing a mate. For example, one of the most important factors in choosing a mate is mutual attraction. If the decision-maker lacks traits that the

potential mate finds desirable, the choice to pursue that individual can waste valuable resources. Thus, decision-makers who are tuned to the unique aspects of their reproductive environment should exhibit individual differences in the way they judge potential mates.

### **Contribution of this Research**

Most of the literature on human mate-selection focuses on documenting species-typical mating strategies, such as the tendency to prefer mates who appear healthy and within a particular age range (Conroy-Beam & Buss, 2016). However, this research has also revealed considerable variation in mating strategies, such as differences in the tendency to prefer mates who are high in openness and extraversion (Stone et al., 2012). Furthermore, people also differ in the preferred *minimum value* (i.e., *aspiration levels*) that potential mates express on traits that are important to humans in all societies. For example, men and women show strong preferences for mates above some minimum threshold of intelligence, but the height of that threshold is greater for some individuals compared to others (Li et al., 2002). Although these examples of individual variation are not necessarily evidence of functional tuning to the environment, the causes of individual variation in mate preferences are still poorly understood and functional tuning is one plausible explanation.

An understanding of the mechanisms that give rise to individual differences complements efforts to understand species-typical mating strategies. Differences could partly result from random variation or non-functional side-effects of mechanisms unrelated to mate-selection, but the paucity of research on this topic suggests that such conclusions are premature. Some research has focused on functional differences in

mating strategies, such as research exploring why preferences for healthy-looking mates are stronger in environments characterized by high levels of exposure to pathogens (reviewed in Conroy-Beam & Buss, 2016). However, pathogen stress is only one of many potentially important environmental dimensions that might affect the performance of different mate-selection strategies. The goal of the current project is to explore the dimension of environmental uncertainty with a specific focus on how uncertainty might affect the performance of mate-selection strategies and how people might adapt to different levels of uncertainty in their environments.

The proposed research aims to demonstrate that differences in environmental uncertainty affect the strategies that people use to discriminate between potential mates. The rationale is based on research suggesting that people form implicit estimates of the uncertainty in their environments based on cues available in early-childhood and these estimates affect behavior and decision-making into adulthood. This type of functional tuning is referred to as adaptive calibration. The main reason I focus on environmental uncertainty is because there is substantial evidence demonstrating that making accurate predictions in uncertain environments requires that judges use simple strategies that ignore some of the available information. As I attempt to illustrate in the following sections, one of the crucial steps in forming an accurate inference is deciding how simple the strategy should be and which information to ignore.

## **Overview**

The remainder of this section is devoted to an overview of the proposed research followed by some important caveats to the evolutionary framework that guides my reasoning. Chapter 2 reviews the Life History framework and evidence that some

individual differences are reasonably understood as adaptive responses to the unique features of each individual's environment (Ellis et al., 2009) with a specific focus on the role of environmental uncertainty. In Chapter 3, I discuss (1) evidence that judgments under uncertainty can be improved by using simple decision-making strategies that *ignore* information, (2) the basis of this “less is more” phenomenon in statistical learning theory, and (3) why adaptive decision-making requires individuals to *match strategies to their environments*. The studies designed to test the main hypotheses and the results of those tests are presented in Chapter 4. In Chapter 5, I discuss the implications of the current project, the limitations of my approach, and how this project can be extended by future researchers focused on explaining variation in the judgment process.

### **The Current Project**

Previous research has established that human judges are skilled at discriminating between potential mates (i.e., *targets*) based on their probability of promoting the replication of the judge's genes (i.e., *mate-value*). A target's mate-value depends partly on their genetic contributions to the judge's offspring (e.g., low mutation load) as well as the target's effects on the environments inhabited by the judge's offspring (e.g., whether the target is likely to assist in child-rearing). However, long-term predictions about the outcomes of investing in a mate may be more challenging in high-uncertainty environments. Thus, the best strategy for discriminating between potential mates might differ across this dimension of environmental uncertainty. In this dissertation, I argue that people form initial estimates of environmental uncertainty based on cues available in early-childhood that correlate with environmental uncertainty (e.g., frequent relocations or changes in peer groups). In turn, estimates of environmental uncertainty enable people

to match their mate-selection strategies to the features of their local environment. Specifically, the current work focuses on differences in mate-selection strategies that present as trait-like information processing biases, such as a stronger or weaker preference for mates with a particular trait (e.g., attractiveness, income level, agreeableness, etc.).

Calibration mechanisms are responses to cues in the environment that produce some adaptive benefit, such as increasing the tendency to engage in specific behaviors. Several psychological theories focus on identifying and explaining the mechanisms that calibrate cognitive/behavioral traits, many of which are derived from the Life History framework. One of the common features of these theories is the role of sensitive periods in early-childhood wherein differences in many developmental trajectories appear to begin. For example, the robust associations between attachment styles and early-life experiences (Verhage et al., 2016) suggest that young children use cues from parents to develop strategies for maintaining relationships with others (Bowlby, 1982). One of the challenges for the field of Life History research is to model these calibration mechanisms and distinguish them from environmental influences that are either fitness-neutral or which interfere with adaptive development (e.g., fetal exposure to teratogens).

The potential value of developmental sensitivity to environmental uncertainty is based on the assumption that discriminating between potential mates depends on the ability to make accurate inferences with limited information. Information is obtained by detecting stimuli in the environment (i.e., *cues*) that correlate with mate-value. Cues can influence the identification of potential mates, estimates of mate-value, or signal the validity of other cues. Natural selection might have shaped neurological structures to

detect specific cues (e.g., facial symmetry), but humans also learn to use cues that were not available in ancestral environments (e.g., the meaning of a wedding ring). It is important to note that identifying cues that reliably predict reproductive outcomes is an inherently error-prone process. In the presence of uncertainty, individuals who observe cues preceding an important outcome are limited in their ability to determine whether those cues appeared randomly or because the cues truly tend to appear prior to the outcome. This can lead to two types of errors: Associating a cue with an outcome when the cue and outcome are independent (“false positives”), and failing to associate a cue with an outcome that it reliably predicts (“false negatives”). The extent to which each type of error reduces prediction accuracy depends on the environment, so the challenge for individuals is to develop judgment strategies that keep the total amount of error below acceptable levels. As I discuss in Chapter 3, estimates of environmental uncertainty can be used to calibrate these judgment strategies to match each individual to his or her local environment.

The complex nature of human mate-selection suggests that there is an abundance of potential mechanisms that can plausibly improve the probability of reproductive success. For example, physical characteristics like facial symmetry, skin texture, and body shape can signal traits that are robust predictors of a potential mate’s genetic contribution to offspring across most human environments (e.g., low mutation-load). However, potential mates may also possess traits that uniquely interact with specific environments (Todd et al., 2007). Is aggression a desirable trait in a potential mate? Surely aggression tends to be a liability in safe environments, but it could also mitigate risks of harm in environments characterized by high amounts of violence. What about the

presence of scars? Scars could signal disability, but scars that follow a specific pattern could signal that a potential mate occupies a position of high status in one's culture.

The examples above are intended to demonstrate that the validity of some cues to mate value are robust across environments (e.g., cues to mutation-load), whereas others are only valid in specific environments (e.g., cultural cues to status). In uncertain environments, the most reliable cues will be those based on phenomena that are relatively insensitive to differences in environments (e.g., cues to mutation-load and physical health) whereas cues that are valid in that specific environment will tend to be more difficult to distinguish from cues which randomly preceded an outcome. Conversely, in low-uncertainty environments, the same robust cues that were valid in uncertain environments remain valid, but additional cues that are uniquely valid in that specific environment become more easy to identify. For people inhabiting a highly uncertain environment, it might be adaptive to resist forming novel associations with reproductive outcomes to minimize the costs of false positives. Conversely, people in low-uncertainty environments might benefit from being relatively more willing to form novel associations with reproductive outcomes. The principal aim of this project is to test for the presence of such a mechanism in the context of choosing a long-term romantic partner.

### **Additional Considerations**

#### ***The Function of Intuition***

Part of the challenge to modeling human mate preferences is attributable to an observation about social inferences in general: People form remarkably accurate inferences based on complex sets of information while appearing to lack knowledge of the most important information. For example, after five minutes with a stranger, people

can accurately estimate all Big-five personality traits (Brown & Bernieri, 2017). That is, people can infer the long-term behavioral tendencies of others based on imperfect cues and without repeated observations of the other person's behavior (for reviews, see Ambady & Skowronski, 2008; Hall et al., 2018; Jussim, 2012; Schlegel et al., 2017). However, judgment accuracy is also domain specific. People can infer some traits better than others (e.g., Brown & Bernieri, 2017), the speed with which inferences about specific traits are formed varies across traits, and whether errors tend to be above or below objective measures (i.e., *biased*) also differs across traits (see Schaller, 2008). What explains domain-specificity in judgment accuracy and what can the study of social preferences learn from the study of social inferences?

At first, it might seem inappropriate to look to the study of inferences for guidance about understanding preferences. By definition, the accuracy of an inference can be assessed by comparison with an objective standard (e.g., estimating the number of marbles in a jar), but preferences are usually understood as judgments for which no objective standard exists (e.g., one's favorite color). However, the extent to which a psychological process models objective reality is just one of many criteria with which the process can be assessed. When a psychological process is examined in terms of *biological fitness*, the distinction between inferences and preferences as fundamentally different constructs becomes less clear. When fitness is the primary criterion, both types of judgment can be understood as processes that are shaped by natural selection to respond to cues carrying reproductively consequential information. In this way, preferences can be understood as implicit inferences about the outcomes associated with the pursuit of a specific goal (e.g., attraction to one individual over another reflecting an

inference about reproductive success, the temptation to choose chocolate cake over celery reflecting an inference about caloric density). Furthermore, an adaptationist perspective can help to explain why some interpersonal inferences tend to correspond to objective criteria more than others (Schaller, 2008) and why some social perceptions tend to be biased above or below objective criteria (e.g., perceptions of anger in faces). In addition to the unclear conceptual boundaries between preferences and inferences, there are also strong empirical arguments for believing that preferences and inferences are based on the same underlying psychological processes (e.g., Weber & Johnson, 2009).

### ***The Intuitive Statistician Metaphor***

The proposed research assumes that environmental uncertainty limits the precision of judgment and that knowledge of these limits can be used to make better judgments. A useful metaphor for understanding how cognitive processes account for uncertainty is that of humans as “intuitive statisticians” (Gigerenzer & Murray, 2015). Few contemporary psychological theories posit that the mind is literally performing statistical calculations when making a decision, but many of the underlying phenomena that shape the development of statistical models also shape mental processes. That said, statistical methods are tools developed by humans to make inferences in a way that promotes *consensus* (i.e., transparent, replicable processes), but the mind is a tool developed by natural selection that uses inference to achieve *reproduction*. Thus, the metaphor of the mind as an intuitive statistician does not imply that statistical models and cognitive processes necessarily bear any resemblance because they were shaped by different criteria through different processes. Rather, the intuitive statistician metaphor is useful for emphasizing that statistical models and cognitive processes both rely on

inference and, therefore, will sometimes exhibit similar properties. This is equivalent to the comparison of strategies for achieving flight: Birds and airplanes both achieve flight by using their wings to push air downward, but almost no modern airplanes achieve this by flapping their wings. Furthermore, some aircraft push air down by rotating their wings (i.e., helicopters) and others achieve flight without wings at all (e.g., blimps). These strategies for achieving flight are highly varied, but they all depend on the fluid properties of the atmosphere and some of these properties have universal effects on solutions to flight. For example, each of the listed methods of achieving flight are more effective in denser, colder air. The point is that researchers should expect minds and statistical models to be sensitive to the same fundamental principles that enable and limit inference, but it is not necessary to assume that processes themselves are similar.

I introduce the intuitive statistician metaphor because *uncertainty* poses a fundamental challenge to all types of inference and statistical learning theory provides well-grounded terminology for theorizing about the ways that the mind might manage uncertainty (Hirsh et al., 2012). Therefore, I will refer to decision-making strategies and judgment in general using the same language used to discuss statistical models, but this should not imply that the hypotheses tested in the current research rely on the assumption that humans are actually performing the same calculations as statistical software.

### ***Good Judgment and Well-being***

Much of the work discussed in this dissertation suggests that people are most sensitive to environmental influences during earlier periods of development and this topic often considers how individuals, especially children, adapt to conditions of deprivation and adversity (e.g., Pepper & Nettle, 2017). Due to the inconsistent use of terms like

“functionality” in the cognitive and social sciences, it is important to clarify the definition used for the purposes of the proposed research. Some researchers implicitly assume that mechanisms can be labeled “functional” or “dysfunctional” based on their effects on *well-being* and many of the outcomes of adverse childhoods are clearly detrimental to an individual’s well-being (e.g., poorer health, shorter life-span, etc.). However, what is bad for well-being is not necessarily dysfunctional (Del Giudice, 2016). The proposed research defines the functionality of a mechanism with reference to the criteria that drove the design of that mechanism. Recent progress in gene-editing notwithstanding (e.g., Gouw, 2019), humans were designed by natural selection using only one criterion: the replication of genes. Therefore, my goal is to discuss the functionality of biological, psychological, or behavioral mechanisms with a consistent reference to fitness. Like accuracy, judgments that improve well-being *can* be a good indicator of a functioning system, but accuracy is not the ultimate criterion that drives the design of evolved organisms. Thus, valenced terminology (e.g., “improved judgment”) refers to effects on fitness. That is, a “good judge” is a judge that tends to make decisions that improve her fitness even if that choice may decrease her well-being.

Despite the focus on fitness as the primary criterion that shapes the mind, criteria like accuracy compared to an objective criterion, effects on well-being, and effects on survival, can still be used to understand the adaptive features of a psychological process. For example, people tend to predict that becoming disabled will have a much more detrimental effect on well-being than researchers actually observe (e.g., Ubel et al., 2005a; Ubel, et al., 2005b). That is, people are much happier after becoming disabled than non-disabled individuals tend to expect. This bias is labeled the “disability paradox”

and is often considered to be a cognitive error. However, the ability to predict future well-being accurately is not necessarily an ability that improves fitness. Instead, a stronger argument can be made that the tendency to judge the experience of becoming disabled as permanently detrimental to well-being reflects an implicit motivation to avoid disabling experiences. It is difficult to think of scenarios in which one could become seriously disabled *without* the high risk of death or reduced fitness (e.g., infertility). Thus, the disability paradox might be best interpreted as a straightforward outcome of a functional mechanism signaling the possible effects of disabling experiences on fitness. The goal of this example is to demonstrate that accurate prediction of well-being can be a helpful criterion for probing function, but there is no justification for an a priori assumption that accuracy indicates function.

### **Organization of this Manuscript**

Adaptation to the environment can be understood across three basic time intervals: First, *proximal* adaptations reflect the moment-to-moment changes in states that organize perception and behavior in response to the local environment, such as shifts in emotions, moods, arousal, active goals, and physiological states. Second, *developmental* adaptations reflect changes that remain relatively stable, such as learned skills or knowledge (e.g., language) and shifts in tendencies, such as the tendency to experience specific emotions, pursue specific goals, seek environments, perceive cues, and perform behaviors. Third, *evolutionary* adaptations reflect changes in the genetic composition of populations based on the differential reproductive success of individuals. All three levels of adaptation are considered throughout this dissertation, but the primary focus is on how developmental adaptations give rise to individual differences in the proximal mechanisms

that mediate decision-making.

The Life History framework is used to explain how a small number of cues in the early-life environment affect many systems simultaneously and why the tuning of mate-selection strategies can be understood as part of a larger cluster of adaptive changes. In the next chapter, I review the life history framework and research related to the current project.

## Chapter 2. Life History and Strategy Development

Like many of the goals that people seek, the tendencies to identify, evaluate, and attract potential mates (i.e., *mate-selection*) are considered species-typical (Neel et al., 2016), but the exact patterns of thought and behavior expressed by an individual to accomplish these goals requires additional shaping by the environment. The current chapter reviews the Life History framework, which argues that natural selection favored individuals who were responsive to cues available in early childhood signaling important states of the environment. Research suggests that mate-selection strategies are sensitive to early-life experiences, but what information is available in early-childhood that could be used to tune mate-selection strategies and how does this information inform developmental adaptation?

Due to the countless factors that contribute to an individual's fitness and the potential changing relationships among those factors, it is informative to visualize decision-making strategies as points on a three-dimensional, infinitely large fitness landscape (Wright, 1932; see Figure 1). Individuals (or populations) adapting their decision-making strategies to the environment can be represented as agents making lateral and longitudinal movements across the fitness landscape (i.e., "adaptive walks"; Kauffman & Levin, 1987). These lateral and longitudinal movements represent changes in the values of two parameters that form part of the decision-making strategy (e.g., sensitivities to each of two cues). Changes in elevation that result from these parameter adjustments represent corresponding changes in fitness, with peaks and valleys representing local optima and pessima.

Of course, the search space with which real humans contend is comprised of too

many dimensions to visualize, but the simplification in Figure 1 can help demonstrate two important points: First, adaptive challenges are potentially complex, and organisms have limited awareness of the shape of the landscape they inhabit. The challenge is to seek or maintain elevation on the landscape with small amounts of information about the surrounding topography, as if the landscape were steeped in fog. Second, the fact that some environmental parameters are constantly changing suggests that some strategies will vary in effectiveness across time as windows of opportunity open and close, resembling the motion of a seascape (Mustonen & Lässig, 2009). Taken together, the entire fitness landscape is comprised of areas ranging from high and low visibility and areas ranging from fixed to constantly changing.

One implication is that attempts to compare individuals to “the” optimal strategy for gaining elevation might not be fruitful because there is no known way to verify optimality in uncertain environments (Feldman, 2017). Another implication is that evolved decision-making strategies are more likely to rely on “landscape-like” features that are relatively stable across time. That said, it is also possible for an individual to develop strategies that exploit short-term opportunities that are created and destroyed by changing “seascape-like” features.

With regard to the challenge of mate-selection, people likely possess evolved tools for discriminating between mates that are robust to environmental change and resistant to significant modification. However, there is also opportunity for individuals to *refine* their mate-selection strategies to exploit unique features of the local environment. Such “refinements” could be minor shifts in a single bias, but according to Life History theory some refinements are part of coordinated changes in many traits simultaneously.

Life History theory can help clarify why the specific differences in decision-making examined in the current project might be part of an overall developmental adaptation that improves fitness across the lifespan.

### **Life History Theory**

All organisms are challenged with allocating resources (e.g., time, energy) to various goals (e.g., growth, reproduction). Because many resources are limited or unevenly distributed, differences in the ways that organisms manage these resources can result in trade-offs that affect biological fitness (Ellis et al., 2009; Stearns, 1989, 1992). Life History (LH) theory was originally formulated to describe between-species differences in the management of resource trade-offs and these differences are often interpreted as adaptations to the ecological niches inhabited by each species (MacArthur & Wilson, 2001). The various resource management profiles expressed across different species are referred to as *life history strategies* and can be meaningfully described along a latent continuum ranging from *fast* to *slow* (Promislow & Harvey, 1990). Species exhibiting fast LH strategies tend to have shorter lifespans, earlier sexual maturation, reduced investment in offspring, and larger litter sizes. Conversely, slow LH strategists are characterized by the opposite traits: longer life-span, later sexual maturation, increased investment in offspring, and smaller litter sizes.

Whether a species adopts a fast or slow LH strategy depends heavily on the affordances of the environment in which the species evolved. According to LH theory, two of the fundamental dimensions along which environments vary are *harshness* and *uncertainty* (Ellis et al., 2009)<sup>1</sup>. *Harshness* refers to the rates of disability and death that

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<sup>1</sup> The life history literature often uses the term “unpredictability”, but the statistical learning literature (see Chapter 3) tends to refer to unpredictability as a type of uncertainty. Therefore, the term “uncer-

are beyond the control of individuals. *Uncertainty* refers to the extent to which resources and mortality rates vary stochastically. In general, slow strategist species tend to develop in environments that are safer and less uncertain whereas fast strategists are favored in environments that are harsher and more uncertain.

Note that environmental “uncertainty” and “harshness” both depend on the ecological niche that a species inhabits. Each dimension describes part of *the relationship* between a particular organism and its environment. For example, compare *Petauroides volans* (the “Greater Glider”) and *Pseudocheirus peregrinus* (the “Common Ringtail Possum”), two closely related marsupials who inhabit the eucalyptus forests of eastern Australia. Whereas *P. volans* subsists almost entirely on eucalyptus leaves (Menkhorst & Knight, 2001), *P. peregrinus* can digest eucalyptus *and* a much wider range of local plants (Tyndale-Biscoe, 2005). Therefore, a sudden increase in the variability of eucalyptus growth might generate a harsher and more uncertain environment for *P. volans* compared to *P. peregrinus* because *P. volans* is unable to subsist on alternative food sources. In this example, the same change in an environment may be a major threat of extinction for *P. volans* and only a minor perturbation for populations of *P. peregrinus*. Thus, to understand whether an organism inhabits a harsh or uncertain environment requires understanding how the specific traits of the organism interact with the characteristics of its environment.

### ***Within-Species Differences***

Although LH theory was developed to explain between-species differences in the allocation of resources, it has also been used to explain *within-species* differences. The

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tainty” is used throughout this manuscript with a small number of exceptions where necessary.

rationale for the extension of LH theory to individual differences follows from the fact that selection is sensitive to the *distribution* of values of environmental states that individuals will encounter. For example, many plants hydrate their leaves with a vascular system that connects roots to leaves, but the performance of each species' hydration system varies with temperature. However, a hydration system that is functional only at a specific temperature (e.g., the regional average) would not be adaptive in environments where the temperature occasionally crosses important thresholds (e.g., occasional freezing). Thus, selection pressures in plants have driven the development of hydration systems that function adequately across the *full range* of temperatures that each individual is likely to experience (Blackmore, 2018).

Natural selection can produce systems that adapt rapidly to environmental changes that occur across days and months, but some features of the environment vary more slowly or change less frequently. For example, some researchers suggest that violence between humans is lower than at any other point in human history (Pinker, 2011; Gómez et al., 2016), but the probability of any one individual experiencing violence varies considerably such that some will live entirely peaceful lives and some will be repeatedly challenged by violent encounters. Thus, it may have been adaptive for humans to develop mechanisms for mitigating the risks of violence even when large portions of a population are unlikely to need them. That said, there are costs associated with engaging defensive mechanisms when they are not needed (Sapolsky, 2004, 2005), so a mechanism for the contingent development or deployment of defensive traits can potentially improve fitness. If there are cues in the environment that *predict* variation in the utility of defensive traits over the lifespan, mechanisms that adjust the tendency to express

defensive traits become visible to selection. Insofar as such environmentally contingent traits develop, it implies that each individual's genome contains code for expressing a range of values on some traits and that the actual value expressed by an individual is determined by a calibration mechanism that is sensitive to specific environmental inputs.

The phenomenon described above is known in the biological sciences as *plasticity* (West-Eberhard, 2003), but the idea that some *psychological* differences between humans are adaptive outcomes of a calibration mechanism has only recently started receiving greater attention from researchers. The extension of LH theory to the study of human individual differences is an attempt to understand (1) which LH traits (e.g., mate preferences) exhibit phenotypic plasticity, (2) how variation in LH traits affects fitness-relevant outcomes (e.g., reproductive success) in specific environments, and (3) how to represent the evolutionary, developmental, and proximate mechanisms that give rise to differences in LH traits with testable models.

To understand why a population might develop plastic traits, consider the following examples of how a population of prey animals might evolve over time based on the risk of predation in the environment. If predation risk is consistently high across generations, one potential response is to shape a single phenotype that is skilled at offsetting the risks of predation, such as a timid disposition. Timid individuals might thrive when risks of predation are high, but they might also incur the costs of maintaining specialized predator-avoidance mechanisms when predation is low. If predation risk is consistently low, the species may adapt toward an alternate phenotype that is skilled at exploiting, say, foraging opportunities by expressing a bold or novelty-seeking disposition. As with a timid disposition, a bold disposition could be costly when

expressed in the wrong environment (e.g., if bold individuals were more likely to place themselves in situations that make them vulnerable to predation).

If predation risk varies randomly between generations, a third phenotype might develop with moderate levels of timidity/boldness to balance predator-avoidance with foraging skills. This generalist phenotype would be able to partially exploit regularities in both high- and low-predation environments but remain unable to fully exploit either extreme. Compared to specialists in their ideal environments, generalists would perform poorly due to the costs of maintaining an unused skillset or failure to maximally exploit opportunities in the environment. However, specialist populations might suffer greatly in dissonant environments because those environments lack the features that specialist traits are narrowly designed to exploit. In environments with randomly varying predation risk, specialist populations would experience large fluctuations in the reproductive success of individual generations with the waxing and waning of predation risk. Therefore, randomly varying risks of predation might favor selection for a generalist phenotype if the specialist population is unable to consistently recover from fluctuating reproductive success. Another possibility is for a population to develop with randomly varying levels of timidity/boldness that fall within some genetically constrained range (i.e., some timid, some moderate, some bold). This heterogeneity in the population would increase the probability that a subset of the population was well-adapted to the current level of predation risk. In this case, the population itself could be considered “generalist” because it is comprised of a heterogeneous set of specialist individuals.

Yet another potential solution to uncertain levels of predation is selection for phenotypic plasticity. Such a mechanism requires that the environment contains

detectable cues that reliably signal the fitness-value of different phenotypes. With regard to predation risks, a prey animal population could develop a mechanism for *calibrating* levels of boldness based on cues that correlate with predation risks. For example, high or low levels of stress hormones in the prenatal environment could be detected by offspring early in development and used to infer the fitness value of the bold versus timid phenotype. The result is that a phenotypically plastic population would be able to rapidly adapt the traits expressed by individuals in response to a change in levels of predation without requiring genetic changes over evolutionary timescales. As long as individuals detect cues that are consistent with their environment, the specialized phenotype into which they develop is more likely to fit the environment they inhabit. Furthermore, unlike a highly specialized population with limited plasticity, the offspring of a plastic population can express phenotypes that differ considerably from the previous generation. The result is a population of individuals who are well-adapted to their current environment (e.g., high predation), but who are also capable of producing offspring who can adapt to a different environment (e.g., low predation) as they develop.

The hypothetical cases considered above illustrate possible solutions to the adaptive challenges posed by variability in the environment. However, the examples may be unrepresentative of the solutions employed by natural selection in reality. The true underlying mechanisms that enable phenotypic plasticity are likely to be sensitive to multiple cues, individual cues might simultaneously affect development of multiple traits, and the exact values expressed on plastic traits are likely to follow a variety of distributions (e.g., discrete vs. continuous, bi-modal vs. unimodal, skewed vs. symmetric, etc.). Therefore, we should expect to see a wide variety of potentially unrelated

mechanisms responsible for phenotypic plasticity, with each mechanism reflecting the adaptive challenges that shaped its design. Furthermore, phenotypic plasticity might also develop alongside the ability for individuals to *select or alter their environment to fit their traits* rather than alter their traits to fit the environment. In this case, a heterogeneous population (e.g., a mix of bold and timid individuals) could remain stable insofar as individuals actively sort themselves into the environments that fit their traits (e.g., bold individuals seeking out low-predation environments and timid individuals seeking high-predation environments). This final point is an active area of debate among LH theorists (e.g., Barbaro et al., 2017; Pepper & Nettle, 2017; Zietsch, 2016). That is, it is not clear whether certain phenotypes in a population are non-randomly distributed across environments because *development* differs across environments or because individuals seek out/alter environments to suit their traits. As with much of the work in behavioral genetics, the most likely explanation is that both phenomena are occurring simultaneously (Plomin et al., 2016).

The empirical evidence for phenotypic plasticity spans almost all of the life sciences (West-Eberhard, 2003). For example, researchers collected a sample of wild guppies (*Poecilia reticulata*) from a single population and randomly assigned them to either a high-predation or low-predation environment. Guppies reared in high-predation environments tended to grow faster, reach sexual maturity sooner, and give birth to smaller offspring in larger litters compared to guppies reared in low-predation environments (Reznick et al., 2002; Reznick, 2005). One potential benefit of faster reproduction is the reduced overall probability of predation before entering the window of reproduction. However, the value of this strategy is partly offset by the costs of

implementing it (e.g., weaker immune system, foreclosed opportunities to build energy reserves, slower recovery between reproductive cycles, etc.) and these costs will be relatively higher when the trait is expressed in a low-predation environment. In low-predation environments, guppies that mature and reproduce more slowly benefit from greater resistance to disease, bigger and stronger offspring, and the ability to build up extra energy reserves before initiating reproduction. These findings suggest that the guppy genome constrains populations to a range of species-typical values on important LH traits and that each individual has some ability to adjust its developmental trajectory toward a slightly faster or slower LH strategy depending on the environment.

### ***Individual Differences in Goals and the Timing of Life Events***

An impressive literature on phenotypic plasticity is devoted to the study of guppies and this is partly due to their success across a wide range of environments combined with the fact that they possess many traits making them convenient for researchers to study. Guppies inhabit freshwater streams in tropical climates, but the characteristics of freshwater streams are highly variable, such as changes in risk of predation, population density, food availability, water conditions, migration opportunities, and climate (Ghalambor et al., 2007). Perhaps due to prolonged environmental instability, individual guppies demonstrate an impressive ability to adapt to their local conditions. The environments that humans inhabit are also highly variable and it is unsurprising that researchers might attempt to extend such models of plasticity to the study of humans. In general, the basic LH mechanisms observed in other species appear to apply to humans, but the extension of LH theory from its roots in biology to the study of psychological differences in humans is neither straightforward nor uncontroversial. Human ecologies

are like no other species and the environmental characteristics to which humans are most sensitive are still unclear. Despite the immature state of the field, the application of LH theory to humans has been fruitful for understanding individual differences (Figueredo et al., 2005, 2006; Ellis et al., 2009). This section provides a brief review of the current state of LH research in humans, but it is important to note that some of the findings reviewed below may be challenged as the field matures.

As a species, all humans exhibit an extraordinarily slow LH strategy as indicated by a long life-span, prolonged period of juvenile dependence, high investment in offspring, and delayed sexual maturity (see reviews in Kaplan et al., 2003; Kaplan & Lancaster, 2003). However, human ecologies exhibit vast amounts of diversity with regard to important characteristics, such as climate, food sources, disease prevalence, hostility and proximity of conspecifics, and culture. Given this environmental diversity, the potential for human environments to vary in adaptive pressures is high and, therefore, the value of a relatively fast or slow LH strategy may depend on each individual's environmental and genetic circumstances.

Although there are environments that are low-uncertainty, yet harsh (e.g., prisons) and uncertain, yet physically safe (e.g., emotionally abusive households), both harshness and uncertainty appear to have independent influences on the LH strategy that an individual adopts (Ellis et al., 2009). Thus, harsh yet low-uncertainty environments and safe yet uncertain environments both seem to be associated with faster LH strategies. However, much of the LH literature conflates harshness and uncertainty (e.g., measuring both and forming a composite "childhood adversity" score), so it is not clear whether there are distinct classes of fast LH strategists or whether harshness and uncertainty each

independently influence the exact same outcomes. Another goal of contemporary LH research is to isolate the effects of harshness and uncertainty by testing the relationship between *specific* childhood experiences and *specific* adult outcomes (e.g., Barbaro & Shackelford, 2019; Simpson et al., 2012). Given space constraints, the current project will focus primarily on environmental uncertainty in favor of a more in-depth analysis rather than a broader focus on both harshness and uncertainty simultaneously.

For humans, harsh and uncertain environments are exemplified by high crime rates, exposure to violence, low socioeconomic status (SES), high pathogen stress, low life expectancy, single-parent households, frequent relocation, parental changes (e.g., entering foster care), and inconsistent use of punishment by parents. Conversely, safe and low-uncertainty environments are exemplified by low crime rates, low exposure to violence, higher SES, lower pathogen stress, longer life expectancy, two-parent households, infrequent relocation, lack of parental changes, and consistent use of punishment by parents (Ellis et al., 2009). The effects of these environments on the timing of life events is similar to effects seen in other species. For example, people with harsh or uncertain backgrounds tend to reach sexual maturity at younger ages, exhibit smaller stature, and (among women) give birth to their first child at a younger age (Walker et al. 2006; Migliano et al. 2007; Kaplan et al., 2000).

One important difference between fast and slow LH strategists is the tendency to adopt short or long time horizons. This is indicated by the fact that measures of LH speed predict the extent to which individuals seek a more generalist or specialist approach to resource allocation across their life-span, a hypothesis known as the strategic differentiation-integration effort hypothesis (Fernandes & Woodley, 2013; Figueredo et

al., 2013; Woodley & Fernandes, 2014). Slow strategists appear to allocate resources toward a wider variety of goals that take significant amounts of time to achieve (i.e., *differentiation* or *specialization*). For example, slow strategists tend to delay parenthood in favor of greater educational attainment, have fewer children, invest more resources in each child, and have longer life expectancies (Krupp, 2012; Griskevicius et al., 2011). Slow LH strategists appear to allocate more effort toward long-term investments, but the value of such long-term investments depends on the uncertainty of the environment. By definition, low-uncertainty environments are those in which associations are easier to detect (e.g., stronger correlations between cues and outcomes), easier to comprehend (e.g., simpler covariance structures), and/or easier to exploit (e.g., one is capable of the actions needed for exploitation). For example, learning to predict the migration patterns of a population of prey animals improves fitness only if one can make reliable use of those predictions over time (e.g., by establishing a food source). If migration patterns change unexpectedly (e.g., due to habitat loss), substantial costs could result from wasted time and effort put toward understanding those migration patterns and developing hunting strategies to exploit them. The environmental regularities that enable individuals to specialize are referred to as *micro-niches* (Figueredo et al., 2013).

Compared to low-uncertainty environments, those characterized by uncertainty have fewer regularities that can be successfully exploited, either because relationships are too weak to detect, too complex to comprehend, too difficult to exploit, or too likely to change. Therefore, the relative value of specialization efforts diminishes as the environment becomes uncertain. In these uncertain environments, traits that allow quickly switching between micro-niches, simultaneously investing in a wider range of

micro-niches, or investing in niches that are robust to environmental change are favored because fewer resources are lost to failed attempts at specializing in fragile niches. This process is referred to as *integration* or *generalization*.

In low-uncertainty environments, an individual who is exploiting that certainty will express traits that are a unique reflection of the micro-niches that the individual has learned to exploit. With regard to finding a mate, people pursuing a specialized mate-seeking strategy might be more likely to develop a preference for traits that are uniquely valuable in the current (low-uncertainty) environment and use them as cues to infer mate-value in others. For example, holding a four-year college degree could be a cue that an individual has the capacity and willingness to extract value from a long-term investment, but the evolutionary novelty of the “college degree” cue means that its validity as a predictor of fitness must be learned. However, the readiness to learn such associations is not necessarily always adaptive. As mentioned previously, a general readiness to associate stimuli (i.e., *credulity*) should increase the chances of discovering an exploitable niche, but it also increases the risk of forming associations between unrelated stimuli (e.g., false beliefs, illusory correlations; van Prooijen et al., 2017). Therefore, individuals seeking a specialized strategy might only benefit from the results of that strategy when inhabiting an environment with low amounts of uncertainty. As will be discussed in Chapter 3, when the environment is structured such that important outcomes are difficult to predict, *ignoring* information can be a valid strategy for improving judgment.

### ***Individual Differences in Psychological Traits***

In addition to differences in goals and the timing of life events, LH theory states

that individuals respond to the early-life environment with adaptive changes in psychological traits as well. Some of the psychological traits that appear to be sensitive to early-life experiences include stress-responsivity (Cabeza de Baca & Ellis, 2017; Ellis et al., 2017), attachment styles (Del Giudice, 2009), sociosexual orientation (Gangestad & Simpson, 2000), judgments involving risk or uncertainty (Mittal et al., 2015), HEXACO personality dimensions (Strouts et al., 2017), and big five personality dimensions (Young et al., 2017). With regard to personality, safe and low-uncertainty early life environments are associated with increased honesty, openness, conscientiousness, agreeableness, extraversion, and neuroticism (Strouts et al., 2017). Furthermore, those from safe and low-uncertainty environments tend to be perceived by others as considerate, kind, hard-working, reliable, socially awkward, insecure, and over-controlling whereas individuals from harsh or uncertain environments tend to be perceived as talkative, socially skilled, dominant, charming, unpredictable, hostile, manipulative, and impulsive (Sherman et al., 2013).

Studies of decision-making have demonstrated that harsh or uncertain backgrounds appear to have negative effects on judgment. For example, individuals with harsh or uncertain backgrounds appear to exhibit diminished behavioral control (Spears, 2011), impeded cognitive capacity (Mani et al., 2013), poorer health decisions (Katz & Hofer, 1994; DiMatteo et al., 2002), lower likelihood of keeping appointments (Karter et al., 2004; Neal et al., 2001), less productivity as employees (Kim et al., 2006), and less attentive parenting habits (McLoyd, 1998). However, some researchers have demonstrated positive effects of a harsh or uncertain background. For example, individuals with uncertain backgrounds perform worse on tasks requiring inhibition, as

would be expected based on the above research, but they perform *better* on activities requiring switching between tasks (Mittal et al., 2015). Individuals who were abused as children can identify angry faces more quickly and accurately than those without a history of abuse (Pollak, 2008; Pollak et al., 2009) and they also are better at remembering the faces of individuals with whom they had a previous negative experience (Goodman et al., 2010). Among three-year olds shown a video of a puppet show, those with insecure attachment histories (measured at 12 months old) were better at recalling negative events in the puppet show, despite showing no indication of paying more attention to those events (Belsky et al., 1996). Findings like these suggest that harsh and uncertain childhoods can adaptively shape patterns of judgment to improve decisions in these environments (for varying perspectives, see Belsky & Pluess, 2009; Ellis et al., 2009; Frankenhuis & de Weerth, 2013).

### ***Mechanisms***

The ability to adapt to one's decision-making strategies to the local environment requires that individuals possess some degree of implicit competence about the structure of the environment (e.g., how novel cues correlate with outcomes, how those correlations change over time, etc.). Part of this competence is knowing the extent to which specific outcomes can be predicted. When constructing models of environmental structures, some prior estimate of the ability to accomplish that task and the associated costs can be valuable information. If some outcomes are difficult to predict (e.g., the underlying causal structure is complex, unstable, or uncorrelated with observable cues), models that predict those outcomes will be prone to error or costly for individuals to learn (e.g., through exploration, experimentation, modification). However, if important outcomes are

easier to predict (e.g., underlying causal structure is simpler, stable, or correlated with observable cues), models shaped to predict those outcomes become less prone to error or less costly to produce. In short, to make use of models in complex environments, individuals require prior estimates of the *precision* of their predictions (Clark, 2015). Useful models account for their own limitations.

Cues are inputs to predictive models and they are associated with *probability distributions over sets of outcomes*. These distributions may take different shapes for different individuals based on their knowledge of the system, goals, and aspiration levels. For example, an individual might be unaware of some potential outcomes or consider two outcomes as equivalent if neither promotes an important goal. One way to understand the uncertainty of a model is through the characteristics of these probability distributions. For example, individuals can be judged as low in mate-value with high degrees of certainty even without speaking to that individual (e.g., too old, too young, compatible sex, wearing a wedding band). However, judging an individual to be high in mate-value before actually interacting with that individual might simply mean that this individual possesses traits *consistent* with high mate-value (e.g., attractive, single, right age, incompatible sex), but he could still be judged as low in mate-value after getting to know him (e.g., unkind, unreliable). The uncertainty around the judge's estimates of mate-value reflects how sure she can be that the individual's "true" mate-value falls within the range she desires. This is analogous to the expected performance of a regression model (e.g., R-squared) when making out-of-sample predictions.

**Internal Regulatory Variables.** To understand how early-life experiences have lasting effects on the development of individual differences in judgment, it helps to

consider the concept of *internal regulatory variables*. The function of a regulatory variable is to represent the estimated magnitude of some personal or environmental characteristic (Tooby & Cosmides, 1990, 2015) and these can serve as cues to judgment. For example, self-esteem can be considered an estimate of how positively or negatively one is perceived by others (Kavanagh, 2007; Leary, 1999; Tooby & Cosmides, 2015). When making socially relevant decisions, self-esteem can be referenced to help estimate the values of different alternative actions. If one's self-esteem is relatively low, risky decisions that could further damage one's reputation might be avoided. Over time, this could manifest as an overall tendency to withdraw from social interaction or seek alternative groups with which to interact. Self-esteem might increase or decrease over time in response to cues that one's status has changed, and such "recalibrations" could be partly mediated by emotions like pride and shame (Tooby & Cosmides, 2015). Furthermore, regulatory variables like self-esteem could also be used as inputs to developmental or physiological processes, like stress-responsivity, immune functions, and metabolic functions (Matthews et al., 2008; O'Donnell et al., 2008).

Like self-esteem, it is useful to consider the possibility that estimates of environmental uncertainty are also stored as internal regulatory variables that are referenced when making decisions or judging the uncertainty of one's mental models. Also like self-esteem, multiple estimates of environmental uncertainty could be stored to account for context specificity. However, the relationships between childhood uncertainty and outcomes in adulthood suggest that an overall estimate of environmental uncertainty might be used as an anchor (similar to a Bayesian prior) on which context specific estimates of environmental uncertainty are based. Or, alternately, an overall estimate of

the uncertainty of “the” environment could simply be a summation of multiple context-specific estimates formed when a context-independent estimate is needed (e.g., in novel environments). These questions are largely unexplored, but it is still apparent that (1) models need to account for uncertainty to be useful (Clark, 2015), (2) information about the self and the environment can be stored and used as inputs to mental models, and (3) regulatory variables can be calibrated by experience (Sznycer et al., 2017; Tooby & Cosmides, 1990, 2015).

### ***Effects of Uncertainty on Mate-Selection***

The research described so far illustrates how responses to harsh or uncertain childhood experiences that affect decision-making can be adaptive, but little research has focused on decision-making with regard to mate-selection. As slow LH strategists, humans produce relatively few offspring and each child requires substantial parental investment to survive. That said, the minimum level of investment needed to produce viable offspring is substantially higher for females compared to males, suggesting that different selection pressures are acting on each sex (Trivers, 1972). This differential-investment hypothesis helps to explain why men tend to have much more permissive attitudes regarding sex (Schmitt, 2015) such as a greater willingness to engage in extramarital mating (Wiederman, 1997), greater willingness to have sex with strangers (Clark & Hatfield, 1989), and higher quantity of sexual fantasies (Ellis & Symons, 1990). Buss and Schmitt (1993) extended Trivers’ (1972) theory by describing two dimensions of sociosexuality in an attempt to account for these differences: Short-term and long-term mating orientations. These orientations represent two basic mating goals that individuals can adopt based on the desired length of the relationship. Pursuants of the long-term

mating strategy tend to prefer extended courtships, a strong pair-bond, and heavy investment in offspring. Individuals with a short-term mating orientation tend to prefer brief sexual encounters and invest less into individual relationships or offspring.

Studies suggest that men tend to invest more effort into short-term mating goals compared to women (Schmitt, 2003), but it also shows that neither goal is always preferred by either sex. Both goals can be pursued simultaneously, and individuals appear to strategically allocate effort depending on the context (for review, see Gangestad & Simpson, 2000), a phenomenon known as strategic pluralism. Furthermore, there are also sex differences in *how* short-term and long-term mating goals are achieved. For example, men pursuing short-term mating goals tend to desire having sex with multiple partners in an apparent effort to increase the quantity and diversity of offspring whereas women pursuing short-term mating goals appear to be attempting to attract partners with high mate value (e.g., high status, low mutation-load).

Within-sex differences in short-term and long-term mating goals are also apparent. For example, men of higher status tend to spend more time pursuing short-term mating than men of lower status whereas the opposite is true among women. This pattern is thought to arise from the fact that some men (women) will be less successful at achieving short-term (long-term) mating goals and, therefore invest more in both types of mating goals to increase the probability of successfully mating even if that success results in low partner variety (quality). Furthermore, individuals adopting a fast LH strategy tend to express stronger motivations to seek short-term mating strategies and reduced motivation for long-term mating strategies (Strouts et al., 2017). The current project seeks to extend this research by testing whether the same differences in background

experiences that appear to influence mating orientation also influence the basic judgment processes used to discriminate between potential mates.

***What Information is Conveyed by the Experience of Childhood Uncertainty?***

The relevance of uncertain environments to human mate selection is based on the fact that individuals discriminate between others using cues that vary in validity. When choosing the best mate, those with the highest mate-value are those most likely to promote the survival of one's genes. This might result from mating with individuals based on their genetic contributions to offspring (e.g., low mutation load) as well as their effects on the environments inhabited by the carriers of one's genes (e.g., self, family members, offspring, etc.). A cue with high validity *can* be used to make accurate predictions of mate value, *but only if the judge believes the cue is valid*.

Individuals might believe that a cue is valid on an implicit level due to species-typical adaptations designed for detecting the cue and these potential adaptations have received much attention from evolutionary psychologists. Such cues include traits like facial symmetry, youth (for male judges), and status (for female judges). The validity of other cues and the contexts in which they are valid might require experience with the environment to discover. Again, consider a trait like aggression: A preference for aggressive mates might be costly to one's fitness when the environment is safe, but when the probability of experiencing violent conspecifics is high, the liability of an aggressive mate might be offset by his or her ability to reduce the overall risks of harm in a harsh environment (Synder, et al., 2011). In an uncertain environment, it might not be clear to judges whether aggression increases or decreases mate-value because, for example, it might not be clear whether the probability of future violent encounters is high or low.

Therefore, it might not be adaptive to discriminate between potential mates based on cues to aggression at all. Instead, the most accurate estimates of mate value in an uncertain environment might be those that rely on *fewer* cues that are less dependent on unstable features of the environment. That is, it might be best for individuals in uncertain environments to *ignore* levels of aggression as long as they are not exceedingly high or low and to rely on cues that remain valid even in changing environments.

The primary goal of the proposed research is to test the hypothesis that individuals with uncertain backgrounds adapt to their environments by relying mostly on a small set of robust cues to discriminate between potential mates. That is, environmental uncertainty diminishes one's ability to identify relationships between cues and outcomes, resulting in an overall reduction in the precision of mental models. To remain adaptive when uncertainty is high, individuals should be less willing to form evolutionarily novel associations between cues and mate-value and more willing to rely on a subset of cues that exhibit cross-environmental stability. To many, the idea that deliberately ignoring information can improve decision-making is counter-intuitive, but the plausibility of this phenomenon is well-supported by research from the study of Fast-and-Frugal heuristics and statistical learning theory. These fields are the focus of the next chapter.

### Chapter 3. Less can be More

People seem adept at identifying potential mates and producing offspring (Zahid et al., 2016), but mate-selection is neither random nor simple (Figueredo & Wolf, 2009; Robinson et al., 2017; Stulp et al., 2017; Vandenberg, 1972). The universal selectivity of mates suggests that individuals are able to reduce complex and uncertain sets of information about other individuals to discrete, binary choices. How do people manage to make such judgments when the underlying causes and relationships are intractably complex?

The current chapter discusses the tools that people use to make decisions under uncertainty and how they might be used to discriminate between potential mates. Although the overall focus is on tools for decision-making, much of the discussion focuses on the challenges that are common to all forms of decision-making in uncertain contexts. The goal of this chapter is to review evidence that simpler strategies can sometimes be better for discriminating between potential mates and the conditions under which simpler strategies are expected to work best. First, I review evidence from psychology and behavioral economics that humans make accurate decisions by using simple strategies that ignore some of the available information (i.e., *heuristics*). Then, I review one explanation for the value of simplicity by reviewing a phenomenon known as the bias-variance tradeoff. Finally, I discuss the environmental conditions that affect the performance of heuristics and why one should expect individual differences in the use of heuristics to result from individual differences in childhood experiences.

#### **Bounded Rationality**

Under classical theories of rationality, the optimal strategy for making a decision

is determined by accounting for all alternatives, outcomes, and frequencies. The performance of a decision-maker is defined as the difference between the decision-maker's strategy and the strategy of a theoretically optimal system. When decisions are made in environments for which all relevant information is available and all relationships can be calculated (i.e., *small worlds*; Savage, 1954), classical theories of rationality can provide an excellent benchmark for evaluating judgment strategies. However, researchers disagree about the extent to which the principles of classical rationality can be extended to the *large world* environments of humans, where knowledge about alternatives, outcomes, and frequencies is rarely complete (Feldman, 2013, 2017).

### ***Background***

One of the challenges that classical probability theorists faced was based on the fact that optimization techniques quickly become infeasible as environments become more complex. For example, tic-tac-toe and chess are both games with a finite number of strategies of which at least one optimal strategy exists. The optimal strategy for tic-tac-toe is already known (e.g., Crowley & Siegler, 1993), but the optimal strategy for chess will probably never be known (Fraenkel & Lichtenstein, 1981). The reason for this difference is that there are only about 250,000 possible games of tic-tac-toe and more possible games of chess than atoms in the known universe. Thus, the challenge for classical theories of rationality was to develop methods for rational decision-making when optimization is made impossible by the complexity of large-world environments.

Herbert Simon framed this as a challenge to understand the “bounded rationality” of adaptive systems and their unique relationships with their environments (Simon, 1956). Simon later described human judgment as shaped like a pair of scissors “whose

two blades are the structure of the task environments and the computational capabilities of the actor” (1990, p. 7). Whereas classical theories of rationality claimed that decision-making strategies can be evaluated in isolation using laws of logic and probability, Simon argued that understanding human judgment depends just as much on understanding the structure of the environment as the characteristics of the decision-maker. This call to extend classical theories of rationality led to the development of at least two separate research programs focused on human decision-making: the *heuristics and biases* program and the study of *fast-and-frugal heuristics*. Little of the work in these fields focuses specifically on mate selection, but both fields suggest different conclusions about the decision-making capacities of humans in general and, crucially, the value of gathering more information.

**The Heuristics and Biases Program: Optimization Under Constraints.** In social psychology, the most well-known response to Simon’s call for a new framework for understanding human judgment is the heuristics and biases program (Tversky & Kahneman, 1974). The leading researchers in this field adopted the interpretation of bounded rationality known as *optimization under constraints*. In this view, true optimization is acknowledged as unfeasible or impossible, but the *process* of optimization (i.e., collecting and processing as much information as possible) is still considered the strategy that promotes the best decisions. Because full knowledge of a system enables optimal performance and zero knowledge precludes all but random performance, it is assumed that *strategies that use as much information as possible will perform better than strategies that deliberately ignore information*.

What gives rise to the boundedly rational decision-maker is assumed to be the

strategic balance between the costs of processing more information and the benefits of increased accuracy. Therefore, boundedly rational decision-makers are those who maximize the value of collected information and/or minimize the costs of obtaining and processing the information. The relationship between the benefits and costs of information processing is often referred to as the *accuracy-effort tradeoff* and one of the important assumptions about this tradeoff is that more effort usually improves performance, *but never hinders it*.

An appealing feature of the heuristics and biases program is that the foundational assumptions are based on the formal rules of logic and probability developed in classical approaches to rationality. That is, it can be fully-grounded in mathematics. For researchers, this means that human rationality can be probed by creating contexts in which an optimal strategy *can* be objectively identified and then comparing the decisions of participants with those of the optimal strategy. Insofar as the phenomena discovered in certain, small-world environments are representative of the phenomena that characterize decision-making in uncertain, large-world environments, studies that take this form can provide insight into the decision-making strategies that people use in everyday life. This perspective led to the generation of a valuable body of literature in which people were shown to ignore relevant information when making decisions. In general, the field is often credited with providing evidence that the mind tends to make substantial sacrifices in accuracy to reduce effort by relying on simple processes known as *heuristics* and *biases*.

One of the results of the popularity of the heuristics and biases program is the proliferation of the belief that humans are exceptionally resistant to employing their

cognitive resources when making decisions. Instead, the mind is described in terms of errors and illusions that result as the side-effects of evolved processes that procure some benefit to the decision-maker without being costly to employ. From this assumption, it follows that human decision-making can be improved by altering the environment to encourage people to expend more effort considering as much information as possible (e.g., Kahneman, 2011). However, the relationship between effort and accuracy is not consistently positive in uncertain environments, meaning that gathering and processing more information can sometimes *worsen* accuracy (see below, “Testing the accuracy-effort tradeoff with computational models”). Thus, the costs to judges who expend too much effort in an uncertain environment include both wasted resources (e.g., time) *and* reduced accuracy. If humans encounter environments where the accuracy-effort tradeoff does not hold, approaches that assume the truth of the accuracy-effort tradeoff *a priori* can lead to erroneous conclusions about the way humans make decisions. Indeed, one of the major criticisms of research in the heuristics and biases program is that it rarely provides evidence that the accuracy-effort tradeoff is a justified assumption.

Classical theories of rationality were developed as a method for making decisions in small worlds wherein all alternatives, outcomes, and frequencies are known. By calculating all of the relevant model parameters from perfect information about the environment, optimization can reveal choices with the highest expected value with certainty. The observation that more information leads to better decisions in small worlds led to the reasonable hypothesis that more information also leads to better decisions in the uncertain context of large worlds. However, very few studies in the heuristics and biases literature focus on testing whether the superiority of optimization in small worlds actually

extends to large world contexts. In other words, the veracity of the assumption that more information always improves decisions in an uncertain environment lacks convincing empirical support, yet this assumption remains foundational to the descriptions of human decision-making provided by the heuristics and biases program. If people frequently encounter contexts in which *less* information can lead to better decisions, a different framework is needed for understanding human rationality. The next section reviews one such alternative known as the study of fast-and-frugal heuristics.

**Ecological Rationality and the Study of Fast-and-Frugal Heuristics.** The study of fast-and-frugal heuristics differs most from the heuristics and biases program in that it does not assume optimizing methods (i.e., processes that incorporate as much information as possible) are always superior to methods that intentionally ignore information. Instead, the relative performance of decision-making strategies remains an open, empirical question. This approach defines *heuristics* as strategies “[...] that ignore part of the information, with the goal of making decisions more quickly, frugally, and/or accurately than more complex methods” and *bias* as a label for the tendency for predictive models to make a particular type of error (Gigerenzer & Gaissmaier, 2011, p. 452; see below). In general, the study of fast-and-frugal heuristics seeks to answer three types of research questions (Gigerenzer et al., 2008):

First, *what heuristics do organisms use?* This first question promotes documenting and modeling the heuristics that organisms use, their building blocks, and the environmental factors that shaped them. These heuristics range from those coded in DNA for solving specific problems that recurred throughout evolutionary development (e.g., peahens favoring mates with the largest number of tail spots; Petrie & Halliday,

1994) to those constructed through experience to overcome novel challenges (e.g., through social learning). Many of the heuristics used by humans are assumed to be partly based on evolved building blocks that are modified by experience to overcome unique challenges. For example, *imitate-your-peers* (Gigerenzer, 2010) is a heuristic where individuals copy the decisions of their peers and its near universality suggests that it has evolutionary origins. However, the widespread application of the imitation heuristic to solve evolutionarily novel problems suggests that learning processes enable people to use imitate-your-peers flexibly for many types of decisions. This ties into the second type of research question pursued in this field.

Second, *what are the environmental structures in which a heuristic performs well?* As implied above, people may use the same heuristic for a variety of decisions, or they may modify a heuristic to broaden the class of problems to which the heuristic is suited to solve. The primacy of this particular research question is what distinguishes the study of fast-and-frugal heuristics from much of the work in the heuristics and biases program. Whereas the heuristics and biases program assumes that optimization techniques are best across all environments, the study of fast-and-frugal heuristics treats the relative performance of different decision-making strategies as an empirical question, whether or not the strategy in question is heuristic or optimizing. Furthermore, it is informative to create controlled environments that evoke the use of a heuristic, but these demonstrations are insufficient for forming conclusions about how people make the same kind of judgment in their natural environments.

Third, *how can the study of fast-and-frugal heuristics be used to improve decisions?* The final aim of the study of fast-and-frugal heuristics is applying what is

learned about human decision-making to improving real world decisions. This includes recommendations for presenting information in a format that lay individuals understand intuitively (e.g., using natural frequencies instead of conditional probabilities; McDowell et al., 2018) and developing easily learned heuristics to improve the accuracy of treatment decisions in a health care setting (e.g., a three-step decision tree for prescribing statins to prevent heart disease; Hozo et al., 2015).

In summary, since Simon introduced the concept of bounded rationality, at least two research programs developed with different interpretations of the concept. In the heuristics and biases program, bounded rationality was understood as optimization under constraints. Researchers in this field usually define or estimate what is rational *a priori*, then describe human judgment based on observed differences between decision-makers and the predefined criteria. Conversely, the study of fast-and-frugal heuristics interprets bounded rationality as the fit between a decision-making strategy and the structure of the environment such that the rationality of a strategy is treated as an open, empirical question by default. Note that the second and third types of research questions can be adopted for both descriptive and prescriptive research and that there is no inherent need for researchers to explore the fitness-enhancing properties of a heuristic. That is, the study of fast-and-frugal heuristics is useful for researchers seeking functional descriptions of decision-making mechanisms as well as researchers intending to *co-opt* decision-making mechanisms to achieve goals like promoting well-being (e.g., in health care settings) or increasing profit for a company.

**Testing the Accuracy-Effort Tradeoff with Computational Models.** As discussed above, many theories of judgment and decision-making are based on the

assumption that more information improves performance. However, few theories describe decision-making strategies with enough detail to enable researchers to test their performance. This highlights another defining feature of the study of fast-and-frugal heuristics: the production of *computational models*. For example, *weighting-and-summing* is a class of strategies in which the decision-maker weighs the evidence provided by several cues and sums all of the weights to form an inference about the value of the criterion (e.g., whether it will rain tomorrow). Ordinary Least-Squares (OLS) regression is an example of a computational model of a weighting-and-summing strategy that can be tested with unambiguous results.

The value of computational models in the study of decision-making is that they enable clear tests of performance. By removing all ambiguity about the definition of the strategy, computational models enable researchers to compare models based on how well they approximate the processes that people actually use (the first class of research questions discussed above) as well as their ability to predict the intended criterion (the second class of research questions). A shortcoming of the heuristics and biases program is that the lack of computational models precludes research into the strengths and weaknesses of the heuristic as a tool for decision-making. For example, the representativeness heuristic is often described as a measure of similarity, but without linking this label to a testable model (e.g., Euclidean distance), it is not clear what evidence would confirm its use among people or quantify its performance as a strategy. The examples below illustrate how research that compares computational models can generate insight into the heuristics that they are intended to approximate. The results of these studies demonstrate the existence of ordinary decision-making contexts in which

the accuracy-effort assumption does not appear to hold.

**Hiatus.** Commercial retailers intending to distinguish between customers who will and will not make future purchases (i.e., *active vs. inactive*) can rely on carefully constructed statistical models such as the Pareto/NBD model (Schmittlein & Peterson 1994), but most managers choose to rely on their intuitions (Parikh, 1994). Wübben and Wangenheim (2008) reported that the most experienced managers classify customers as inactive after a specified number of months had passed since each customer's most recent purchase. In two tests, this *hiatus heuristic* correctly predicted the active status of more customers than the Pareto/NBD model (83% vs. 75% and 77% vs 74%) and the two models performed equally in a third test (77%).

**1/N.** The 1/N rule or the *equity heuristic* states that one should allocate resources evenly across all alternatives. When studied as a guide for allocating wealth in an investment portfolio, 1/N outperformed all 14 competing portfolio allocation policies, each of which was optimized using 10 years of US stock data (DeMiguel et al., 2006). This heuristic is so effective (and efficient) that there is evidence that human and non-human parents rely on this heuristic for deciding how to distribute time and resources among offspring (see review in Hertwig et al., 2002). Note that this heuristic has no free parameters and, therefore, no prior experience is needed to implement it effectively.

**Take-the-Best.** Take-the-best is used to infer which alternatives are higher on some criterion (e.g., physical strength) based on cues that correlate with the criterion (e.g., height, build). First, the decision-maker compares the alternatives based *only* on the value of the cue with the highest validity. If the cue values differ (e.g., one alternative is taller) then one should infer that the alternatives also differ accordingly on the criterion

(e.g., the taller one is probably stronger). If the difference between values is trivial (e.g., one is only *slightly* taller), then compare the alternatives on the cue with the second-highest validity (e.g., muscular build). If alternatives are also equal on the second cue, repeat this process until no more valid cues are available.

The performance of take-the-best in uncertain environments is well established. In one of the earliest demonstrations, a list of cities was created and each city was linked to the values of several cues (e.g., whether the city had a major league soccer team). Next, take-the-best and several optimizing competitors were trained on the data to predict which of two cities had a larger population using the available cues. The inferences generated by take-the-best were most accurate, *regardless of the sample size of the training set* (Gigerenzer & Goldstein, 1996). Combined with replications of this study (Gigerenzer & Brighton, 2009; Brighton, 2006), take-the-best has been shown to outperform multiple regression, tallying, classification and regression trees, three-layer feed-forward connectionist networks, exemplar-based models, and the C4.5 decision tree induction algorithm.

The decision-making strategies reviewed in this section suggest that the accuracy-effort tradeoff assumption is violated in many uncertain environments. In other words, decision-making is not always improved by attempts to gather more information or process information more deeply. Instead, sometimes the best way to make a decision in an uncertain environment is to ignore some of the available information. The next section discusses how the idea that less information can improve decisions in uncertain environments is grounded in statistical learning theory.

### *Why is Less Sometimes More?*

The performance of a predictive model can be summarized by the total error, with smaller values indicating increased accuracy. Total error can be divided into two components, as shown in the equation below:

$$\text{Total error} = (\text{bias})^2 + \text{variance}$$

Biased models tend to make predictions that deviate from the true value in a consistent direction. For example, Figures 2, 3, and 4 depict the error distributions for three different hypothetical models. The predictions of the model depicted in Figure 2 demonstrate high amounts of error because they are consistently below the true value (dashed vertical line). The model suffers from high amounts of bias (i.e., *under-fitting*). Figure 3 depicts an unbiased model with low variance. Errors are not consistently above or below the true value and their overall distance from the true value tends to be relatively short (i.e., *balanced*). Figure 4 depicts an unbiased model that suffers from high variance (i.e., *over-fitting*). This model suffers from high amounts of error because the predictions from this model tend to fall far from the true value, but there is no tendency for predictions to fall consistently above or below the true value.

As shown in Figures 2, 3, and 4, a good predictive model is one that minimizes bias and variance. However, bias and variance are not independent (Geman et al., 1992). The relationship between bias and variance as different components of prediction error was explored in the field of statistical learning beginning in the late 1970s. The motivation for understanding this relationship was based on the realization that complex

predictive models tended to underperform when used to make out-of-sample predictions. That is, researchers would carefully construct models to account for the relationships observed in their datasets (e.g., by maximizing R-Squared), but when they tried to use those models to predict *new* data, they tended to make far more errors than one would expect based on how well the models described the data on which they were trained. Makridakis and Hibon (1979) reported one of the first rigorous demonstrations of this pattern: Using 111 time series datasets from business and economics, the performance of 22 forecasting models was compared. The controversial result reported by Makridakis and Hibon was that the best performing strategy across all 111 series was one of the simplest models tested. In response to skepticism of these findings, Makridakis and colleagues hosted the first “M-competition” in which experts were invited to submit predictive models to a formal and open test of their performance. The results of the first M-competition again showed that the best performance was achieved with simple models using fewer free parameters (Makridakis et al. 1982). Makridakis has since hosted three more M-competitions, all of which replicated the original findings (Makridakis et al., 1993; Makridakis & Hibon, 2000; Makridakis et al., 2018): Models that ignored information tended to outperform models that used as much information as possible. The reason is because complex models are prone to inflation in the variance component of the error term.

It is well known that the simplest models tend to suffer from high amounts of bias because they fail to account for true relationships in the environment (Figure 2). For example, a model predicting performance in graduate school using only GPA might consistently underestimate individuals with moderate GPAs *and* very high GRE scores.

As parameters are added to a biased model, the center of the error distribution begins to shift toward zero (Figure 3) and overall accuracy increases (e.g., a model predicting graduate school performance using both GPA and GRE scores together). However, as more and more parameters are added to the model, the probability of including information that is unrelated to the outcome increases and the variance term begins to inflate (Figure 4). For example, a model predicting graduate school performance using GPA, GRE scores, and hair color might successfully reduce bias, but the inclusion of a useless predictor would *arbitrarily penalize or reward* individuals for reasons completely unrelated to graduate school performance. The result of adding more and more parameters to make finer and finer adjustments to the model begins to flatten the error distribution and harms performance.

Figure 5 depicts a typical relationship between model complexity and model accuracy in uncertain environments. Empirically estimated parameters are added to the model in decreasing order of validity. The first two parameters dramatically increase accuracy when making out-of-sample predictions, but it still suffers from high error due to bias as in Figure 2. After the third parameter is added gains in performance begin to lessen as more parameters are added to the model. For models with three to seven parameters in Figure 5, the distribution of errors look more like the distribution in Figure 3. Eventually, bias is no longer reduced by adding more parameters and the overall performance of the model starts to decline because additional parameters are more likely to reflect statistical noise rather than true relationships. With ever increasing complexity, the distribution of errors widens as illustrated by Figure 4.

In sum, simpler models sometimes outperform more complex models because

they reduce overall error by balancing bias and variance. Several methods have been developed in statistical learning theory for helping statisticians balance bias and variance (i.e., *model regularization*), but there is no universal method for reaching a balance for all types of models in all environments. For example, reasonable levels of complexity for a model generated using procedures like logistic regression might differ significantly from a reasonable level of complexity using random forests. There is no “optimal” model in uncertain environments, but some models perform better than others and the only way to rank models is by comparing performance making out-of-sample predictions. Heuristics are also predictive models, and like balanced statistical models, they tend to rely on a subset of the available information. Therefore, it is reasonable to expect that heuristics outperform complex statistical models for the same reason that simpler statistical models tend to outperform complex statistical models: by reducing the variance component of the error term.

This goal of this section was to demonstrate that simple heuristics often outperform complex optimization techniques in ordinary (but uncertain) decision-making contexts, that penalizing complexity when generating statistical models can increase the accuracy of out-of-sample predictions, and that both of these observations can be explained by the same phenomenon documented in statistical learning theory: The bias-variance tradeoff. It follows that, when considering performance in uncertain environments, the question should not be about whether committing extra resources and increasing complexity is worth the gains in accuracy, but *when* that extra processing will begin to harm accuracy. The next section discusses the environmental structures that determine when to expect relatively simple models to outperform relatively complex

models.

### ***The Context Specificity of Heuristics***

A complete understanding of a heuristic requires documenting its relative performance across environments. If, for example, Heuristic A performs better at discriminating between mates in some environments and Heuristic B is superior in other environments, then observing individuals switching between these heuristics based on the environment could be evidence of attempts to match heuristics to their environments. This is one of the underlying assumptions of the current project: That people are capable of strategically matching heuristics to the environments that they believe they are encountering. In this section, I consider the environmental characteristics that affect the performance of heuristics as well as evidence that people are sensitive to these characteristics when making decisions.

**Cue Redundancy.** Redundant cues are cues that carry overlapping information, often quantified as the extent to which two cues are correlated with each other (i.e., *collinearity*). In redundant environments, the first cue considered can explain a major proportion of variation in the criterion, but the value of additional cues diminishes rapidly. Many cues of mate-value might be considered redundant because they are correlated with each other. For example, body-symmetry and intelligence are moderately correlated ( $r = .39$ ; Prokosch et al., 2005) and both traits are highly desired in mates (Jones et al., 2001; Li et al., 2002). As correlated indicators of mate-value, the information gained when moving from zero knowledge to having knowledge of one trait is larger than the gain of adding the second trait. The two traits together are worth less than the combined value of each trait alone. When cues are independent (e.g., age and

intelligence), the value of learning one does not depend on whether a judge already knows the other. There are many traits shown to be related to attractiveness and the extent to which all of these traits are correlated varies considerably (for review, see Geher & Miller, 2008). Thus, whether the mate-selection environment is considered redundant or not depends heavily on which traits are available to the judge and the judge's understanding of the relationships between those traits.

**Distribution of Cue Validities.** The distribution of cue validities refers to the extent to which each cue correlates with the criterion. It is likely that variation in the contexts that elicit mate-value judgments is such that multiple distributions are relevant. In some cases, one cue is so important that it is sufficient to discriminate between alternatives even if all other cues disagree. These environments are considered *non-compensatory* and they may be common in the initial stages of the mate-selection process. Before making a decision to pursue a mate, individuals form *consideration sets*: the set of individuals a decision-maker considers as potential mates. Miller and Todd (1998) outline this sequential nature of mate-selection by pointing out that judges first assess whether alternatives meet basic thresholds using easily measured cues, such as age, sex, attractiveness, availability, and the presence of competition. Many cues are used to exclude individuals from a consideration set (“deal-breakers”) such as genetic relatedness (e.g., sibling status), extreme youth or old age, and (among heterosexual individuals) same-sex status. The current project focuses on mate-selection within a judge's consideration set and refers to these contexts unless otherwise noted.

In general, people appear to believe that the context of mate-selection is *compensatory* when large amounts of relevant information are available (Li et al., 2002).

That is, people appear sensitive to trade-offs between traits such that high values on some traits (e.g., mutual attraction) can “compensate” for low values on other traits (e.g., physical attractiveness), and the value on no single trait provides enough information to ignore the other traits (e.g., Stone et al., 2012). However, this assumes that judges actually have access to the values of many important traits. When placed in environments in which decisions must be made quickly (e.g., speed dating) or with small amounts of information (e.g., a photo), individuals are far more likely to behave as if the environment were non-compensatory. In short, there is no known distribution of cues to mate-value that reasonably describes a “typical” mate-selection context. Instead, individuals are likely to experience several different distributions of cue validities in contexts that activate judgments of mate-value. The current research focuses on situations which are not rushed (i.e., individuals can take as much time as they want to make a decision) and which are rich in potentially relevant information (i.e., many valid cues are available simultaneously). Considering the fact that many modern humans have access to large amounts of information about potential mates through technology like social media, an un-rushed, information-rich environment seems appropriate for attempting to increase understanding of how a non-trivial number of these decisions are made in reality.

#### **Empirical Demonstrations of Heuristic Performance in Different Contexts.**

Although a variety of heuristics have been studied, one of the most extensively studied is take-the-best. In one study, take-the-best and competing models were tested at predicting a criterion in a set of simulated environments that varied in cue redundancy (Dieckmann & Rieskamp, 2007). In high-redundancy environments, take-the-best outperformed or tied with optimizing strategies at predicting the criterion, but when redundancy was low

(i.e., when cues were independent) optimizing strategies outperformed take-the-best.

Hogarth and Karelaia (2007) report an extensive examination of the performance for four heuristic decision models and a fifth optimizing strategy (i.e., linear regression).

Environments varied in redundancy, distribution of cue validities, and random statistical noise. For each environment, model performance was recorded for each of nine simulated levels of noise ranging from nearly random information to perfect information. Several results are worth noting:

- Regression performed poorly compared to all heuristic strategies in nearly all environments. In short, the precise weights estimated by OLS regression only improved accuracy in environments with almost no random noise added to the system (i.e., near-perfect information).
- The performance of all strategies deteriorated in high-redundancy environments.
- The best performing heuristic varied considerably across environments (i.e., across levels of redundancy, different distributions of cue validities, and amount of noise).
- The overall best performing heuristic was take-the-best, which was neither the simplest nor the most complex.
- For each heuristic there was at least one environment in which the model's performance was superior to all others.

The findings reported by Hogarth and Karelaia (2007) are an important

demonstration of the varying performance of heuristics across different environmental structures. However, it is important to note that conclusions drawn from studies of simulated environments are, at best, tentative in the absence of data about decision-making strategies used in real decision-making environments. The current project takes a similar approach by comparing the performance of various decision-making strategies at predicting the criterion, but the criterion under examination is the behavior of real participants.

**Empirical Demonstrations of Heuristics as Models of Decision-making.** In the first study by Dieckmann and Rieskamp (2007) discussed above, take-the-best was shown to outperform optimizing strategies in a simulated environment when cue redundancy was high, but not low. In their second study, participants were placed into the same simulated environment with which the heuristic models were tested and asked to use the same cues to make inferences about the same criterion. When the strategies tested in the first study were used to predict participants' decisions in the second study, take-the-best was again shown to outperform all other models in high-redundancy environments, with accuracy diminishing again in low-redundancy environments. Because participants were given the same instructions in both environments, these results suggest that participants were adapting their decision-making strategies to the structure of the task. Furthermore, the results also showed that take-the-best was a reasonable approximation of the strategy that many participants were using in high-redundancy environments. Thus, take-the-best performed well as a predictive model of the criterion itself as well as a descriptive model of the tool that humans were using to make decisions. This pattern of adaptive use of heuristics has been demonstrated in a variety of contexts with both

humans (Martignon & Hoffrage, 2002; Bröder, 2003, Bröder 2000, Newell & Shanks, 2003, Rieskamp & Hoffrage, 2007; Bröder & Schiffer, 2006; Rieskamp & Otto, 2006) and non-humans (for review, see Hutchinson & Gigerenzer, 2005).

### **What is an Environment?**

The evidence that organisms select and apply heuristics in adaptive ways goes deeper than the average differences between groups exposed to different experimental conditions. The considerable within-group variation in nearly all social psychological experiments suggests that, in many cases, the average person's response to an environment or stimulus is only partly described by summaries of experimental groups and the environments to which they were exposed. People perceive and interpret the environments differently and these differences can affect the goals that people adopt and the strategies people use to achieve them. Therefore, characteristics of "the environment" (e.g., cue redundancy and the distribution of cue validities) are not necessarily objective properties of an external structure, but properties of the mind-environment system (Todd & Gigerenzer, 2011). Human mate-selection illustrates this point well because individuals competing for a potential mate are not equally likely to succeed at attracting that mate. For two decision-makers with different characteristics, the same cue exhibited by a potential mate (e.g., physical attractiveness) may signal higher mate-value to one judge and lower mate-value to the other judge. It is possible for these judges to disagree about the mate-value of the same target *and* both conclusions might be considered perfectly valid.

The fact that individuals can inhabit the same physical environment but experience different ecologies suggests that researchers can create settings with uniform

starting conditions for all participants, but researchers cannot eliminate the need for participants to make assumptions about that environment. Even if researchers are willing to reveal the details about how the environment was constructed to participants, the trustworthiness of a researcher's description of the environment is itself an assumption about the environment on which participants could disagree. In many of the studies discussed above, environments were intentionally constructed to minimize individual differences in perceptions of the environment, such as asking participants to form predictions about novel or meaningless stimuli. However, the topic of the current research (mate-selection) was chosen for its potential to promote the expression of individual differences with the goal of assessing their adaptive significance.

### **Regularization**

Demonstrations of the accurate performance of heuristics show that accurate predictions in uncertain environments depend on ignoring some available information. However, for some decisions, people may rely on multiple heuristics in sequence, tally the predictions of multiple heuristics, or create new heuristics from experience. These possibilities make the computational modeling of heuristics far from obvious or straightforward. Thus, the use of flexible and “information-greedy” models like OLS regression remain invaluable tools for researchers attempting to discover new heuristics or account for variation in decision-making processes using “as-if” models (Gigerenzer & Murray, 2015). That is, the structures that mediate decision-making in humans are unlikely to rely on optimization, but discovering these structures can still be aided by optimizing techniques that form flexible descriptions of the data collected by researchers. These statistical processes can be made more useful when researchers use regularization

techniques that penalize complexity to avoid over-fitting (James et al., 2013; Hastie et al., 2017). Although optimizing procedures themselves do not make plausible models of cognition in large-world contexts, they can help to reveal the complexity of the underlying decision-processes that individuals are using.

Several studies provide insight into the ways that people manage the bias-variance trade-off without needing to explicitly model the underlying heuristics. Regularization is the processes of calibrating a model based on a parameter that determines how closely any learning process should adhere to its training data. If one holds a prior belief and subsequently encounters new information, this parameter determines how much weight to assign to the new data. Too much weight risks over-fitting and too little weight prevents adaptation. Briscoe and Feldman (2011) demonstrated that, in the simplest environments, people were far more likely to learn to trust all of the available data and the result was that participants learned to make highly accurate predictions. However, as environments became more complex and uncertain, people's decision-making strategies reflected simpler, heuristic-like processes that ignored information. This effect was also shown in a different context by Smith (2014). Brandstätter, Gigerenzer, and Hertwig (2006) found that the priority heuristic (a derivative of take-the-best) was the most accurate model of participants' preferences when discriminability was low (alternatives had comparable expected values) and that more complex techniques based on expected utility theory were most accurate when discriminability was high (expected values differed by large amounts). Taken together, these studies extend findings that show people use different heuristics based on the structure of the environment and as the environment becomes more complex and uncertain, people begin to ignore information and rely on *simpler*

strategies.

### ***The Regularized Ideal Observer***

Feldman (2013) refers to “regularized ideal observers” as individuals who successfully adapt to uncertain environments by restricting the extent to which information gathered from experience is used to update mental models. The proposed research assumes that the most adaptive level of restrictiveness depends on each individual’s unique environmental circumstances and that individual differences in levels of restrictiveness (i.e., differences in the chosen value of the *regularization parameter*) should manifest as individual differences in decision-making.

Assuming that people begin life with non-random prior beliefs about cues that indicate mate-value (e.g., preferences for symmetrical faces), individuals who update those beliefs or incorporate evolutionarily novel cues (e.g., the unique value of a personality trait for accumulating resources in the local environment; the meaning of a wedding ring) are *not* guaranteed to make better judgments. If the environment is relatively uncertain, updating prior beliefs entails a higher probability of making a mistake when those beliefs are later used to form estimates of mate value. Thus, individuals in uncertain environments should tend to express mate-selection strategies that only use the most reliable and robust cues to mate-value in order to minimize the costs associated with overfitting one’s strategies to the environment (i.e., inflated variance).

When the environment is low in uncertainty, updating prior beliefs to tune one’s mate-selection strategy should entail a lower probability of making mistakes when evaluating potential mates in the future. The result is that the potential costs of updating

prior beliefs are lower because the data used to make these updates is more likely to reflect true relationships in the environment. Thus, individuals from low-uncertainty backgrounds should tend to express mate-selection strategies that incorporate more evolutionarily novel cues than their counterparts with uncertain backgrounds. This reduces errors associated with underfitting one's strategies to the environment (i.e., inflated bias) without increasing the risks of overfitting.

The concept of evolved organisms as regularized ideal observers forms the foundation of the hypotheses tested in the proposed research. Despite the success of this perspective in fields like perception (Feldman, 2009, 2012), neuroscience (Clark, 2015; Engel et al., 2015), evolutionary biology (West-Eberhard, 2003), and statistical learning (Hastie et al., 2017; James et al., 2013), its utility for understanding the study of social preferences remains mostly untested. Next, I review the main hypotheses of the current project and present the studies conducted to test them.

## Chapter 4: Current Project

### Hypothesis 1

Environmental uncertainty can be an indicator of how well a judgment strategy will perform at different levels of complexity. In highly unstable or uncertain environments, the predictive models that tend to perform best are those that rely on fewer parameters to generate predictions. Conversely, in stable or low-uncertainty environments, complex models can perform better than simpler models because they are less likely to overfit the data on which they are trained. Thus, an estimate of environmental uncertainty can help people identify a judgment strategy that is neither too complex nor too simple for their local environment. Hypothesis 1 predicts the pattern of results that would emerge if such a mechanism was active while participants were forming judgments about potential mates:

H1a. Individuals from uncertain childhood environments will tend to rely on fewer cues to discriminate between potential mates.

Several studies suggest that the effects of the early-childhood environment on judgment in adulthood are most pronounced when individuals perceive threats to their goals. Across four studies, Griskevicius et al. (2011) found that people from low SES households wanted to have children sooner than people from high SES households, but only after reading that the world was expected to become more dangerous in the future. Differences in preferences among participants who read a non-threatening vignette were either much smaller or undetectable. In a similar set of studies, lower childhood SES

predicted increased temporal-discounting and greater risk-taking among threatened participants, but not among control participants (Griskevicius et al., 2013; Griskevicius et al., 2011). Finally, Mittal and Griskevicius (2014) demonstrated that participants' sense of control in threatening conditions depended on the SES of the household in which they developed. Specifically, threat decreased sense of control among individuals from low SES households and increased sense of control among individuals from high SES households. This research suggests that the relationship between the early-childhood environment and judgment in adulthood can be conditioned on the perception of relevant threats. Therefore, the relationships between childhood uncertainty and mate choice explored in the current study might only appear when participants feel threatened:

H1b. There will be an interaction between experimental condition and childhood uncertainty. Specifically, the effect described in H1a will be stronger in the threat (vs. control) condition.

## **Hypothesis 2**

Strategic differentiation and strategic integration are phenomena that tend to emerge in low-uncertainty and high-uncertainty environments respectively. Strategic differentiation is part of a slow life history strategy characterized by cognitive and behavioral specialization. The benefit of this tendency in low-uncertainty environments is that it enables individuals to learn to exploit regularities that are unique to a particular environment, such as gaining expertise in a small number of uncommon skills. Therefore, the traits expressed in a population of specialists should appear relatively heterogeneous.

In high-uncertainty environments, the regularities that enable specialization are less common or more costly to exploit. In these environments, strategic integration is more likely to emerge as part of a fast life history strategy characterized by cognitive and behavioral generalization. The benefit of integration is that it reduces the costs of switching between unstable ecological niches, a need that is more likely in a high-uncertainty environment.

It is possible that the effects of strategic differentiation and integration extend to judgment and decision-making in the context of mate selection and that the adoption of these strategies is guided by perceptions of environmental uncertainty. Among people with uncertain backgrounds, mate preferences should appear somewhat similar because only the most robust cues to mate value remain valid in highly uncertain environments. In low-uncertainty environments, cues which signal mate value in that particular environment should be learned more easily and remain stable over time. Thus, people with low-uncertainty childhoods should have a more specialized set of preferences and, therefore, their preferences should be less similar. As with Hypothesis 1, this effect is expected to be magnified when participants feel threatened:

H2a. Preferences will be more similar among individuals from uncertain childhood environments.

H2b. There will be an interaction between experimental condition and childhood uncertainty. Specifically, the difference in preference similarity between people with low and high childhood uncertainty will be greater in the experimental

condition.

### **Overview of Current Project**

The goal of the main study was to measure and account for individual differences in the number of cues that people use when discriminating between potential mates. These differences were measured by obtaining a description of each participant's ideal mate based on 14 traits (e.g., personality, demographic, etc.) and using that description to “train” multiple decision models of each participant. A total of 14 models were trained for each participant differing only in the number of traits (i.e., cues) used to generate a decision. Next, participants were asked to complete multiple trials of a mate-choice task requiring that they identify which of two alternatives would make a better mate. Finally, the models from the first step were used to predict the participant's choices in the mate-choice task and the accuracy of each model was recorded by comparing these predictions to the actual responses of the participant. Once the most accurate model for a participant was identified, the number of cues that model used to generate predictions was recorded as the dependent measure. The main assumption on which this approach relies is that people who base their decisions on a larger number of cues will be most accurately represented by models that also rely on a larger number of cues. Therefore, one method for estimating the number of cues that an individual uses to make decisions is to identify the number of cues used by the model that best describes her. In this section, I describe the process of developing the method for the Main Study using the results of three pilot studies and end with a description of the method for the Main Study.

Pilot 1 was designed to help select *which* cues participants in the Main Study

would use to describe their ideal mates and for discriminating between potential mates. The value of this study is ensuring that the traits describing ideal mates and potential mates are relevant to participants' decision-making. Pilots 2 and 3 were designed to guide the process for generating the descriptions of potential mates used in the Mate Choice Task. Results from these studies were used to ensure that there would be sufficient variability in the choices participants make when completing the Mate Choice Task in the Main Study.

### **Pilot 1**

Recall that cue validities vary in robustness such that some maintain their validity across diverse environments and others remain valid only in a subset of environments. By presenting participants with a set of cues to mate value that vary in robustness, differences in the tendency to rely on additional, context specific cues can be measured. The goal of Pilot 1 was to guide the selection of the traits shown to participants in the Main Study to ensure that the set of traits represents a mix of robust and context-specific cues.

### ***Participants***

Participants were recruited from Amazon's Mechanical Turk (M-Turk;  $n = 237$ ) to complete an online survey about preferences and personality. Most individuals in the sample were women (64.1%), college educated (63.7%), white (76.8%), and currently in a romantic relationship (66.7%). The average age was 33 years and the distribution of ages was positively skewed, indicating that the older half of participants spanned a much wider age range (32-71 years) compared to the younger half (18-31 years).

### ***Materials and Procedure***

A set of 31 traits was created (See Table 1) with the intention of eliciting variable responses in perceptions of importance to mate value. Some traits are well-established as important cues to mate-selection for most people and across cultures (e.g., attractiveness, kindness) whereas other traits were selected based on the assumption that they would only guide mate-selection for a subset of individuals in a stable environment (e.g., religiosity, creativity).

Participants were informed that the intent of the study was to learn more about what information people would want to know when choosing a good long-term romantic partner. Next, each participant was shown a list of statements, such as “When looking for a long-term romantic partner, knowing if someone is open-minded or closed-minded would be \_\_\_\_\_ to me.” Participants were instructed to fill in the blank portion of the statement by selecting one of seven response options on a scale ranging from 1 (*not important at all*) to 7 (*extremely important*). To avoid fatigue, the first 74 participants were initially required to provide ratings for 10 randomly selected traits. However, completion times were shorter than expected and observations 75 through 237 were required to rate all 31 traits. After providing ratings for each trait, participants completed a demographic questionnaire, were thanked for their participation, and debriefed.

### ***Results and Discussion***

Traits qualified for inclusion in the Main Study if they received high mean importance ratings ( $M > 5.00$ ) or high standard deviation of importance ratings ( $SD > 1.50$ ). Of the 31 traits tested, 29 qualified for inclusion on the ideal mate scale (see Table 1). I chose thirteen traits for inclusion on the ideal mate scale with a goal of creating a diverse list of traits, some of which most people find important to judging potential mates

(e.g., Dependability) and some of which importance varied substantially between individuals (e.g., Religiosity). *Dominance* was considered for inclusion as the 14<sup>th</sup> trait on the ideal mate scale, but it was ultimately excluded due to concerns that participants might conflate dominance with aggression. Instead, the closely-related trait *assertiveness* was chosen as the 14<sup>th</sup> trait on the ideal mate scale.

## **Pilot 2**

Pilot 2 was designed to test the Ideal Mate Scale for use in the Main Study and to guide the creation of the profiles used to describe potential mates in the Mate Choice Task for the Main Study.

### ***Participants***

Participants were recruited from M-Turk ( $n = 533$ ) to complete an online survey about preferences and personality. Most individuals in the sample were women (62.8%), college educated (69.2%), white (73.4%), and currently in a romantic relationship (67.5%). The average age was 34 years and the distribution of ages was positively skewed, indicating that the older half of participants spanned a much wider age range (33-73 years) compared to the younger half (18-32 years).

### ***Materials and Procedure***

After agreeing to participate in the study, participants were asked to complete the Ideal Mate Scale. The scale itself was comprised of a list of the 14 traits chosen using the results of Pilot 1. Participants were instructed to “design your ideal long-term romantic partner” by going through each trait and indicating the ideal value that his or her ideal mate would express using an 11-point scale. Response options for each trait ranged from 0 (*Extremely Low*) to 5 (*Average*) to 10 (*Extremely High*). After completing the ideal mate

task, participants completed a demographic questionnaire, were thanked for their participation, and debriefed.

### ***Results and Discussion***

Responses to each item on the Ideal Mate Scale are summarized in Table 2. The first step of the analysis was to test for the presence of gender differences in the ideal values for each trait. Of the 14 traits on the scale, significant gender differences were observed for 9 (64%). Given the large gender differences, separate sets of profiles for use in the Mate Choice Task were generated for men and women.

Before generating profiles for use in the Mate Choice Task, two “standard” profiles were created in which the values for each trait was defined as the average ideal value for men’s ideal mate (first column of Table 2) and for women’s ideal mate (third column of Table 2). To create a single profile, random noise was added to each of the 14 ideal values in the standard profile. This process was repeated 100,000 times to create a set of potential female mates based on the standard created from male participants. Another 100,000 profiles were created to form the set of potential male mates using the standard generated by female participants. The result of this process is a large simulated population of potential mates with traits that are distributed around the average ideal values. The purpose of generating profiles with this method was to avoid the high proportion of undesirable profiles that would result from assigning values to profiles at random. For example, about 50% of potential mates would express above-average levels of aggression if trait values were assigned at random whereas only 5% of profiles created using the process described above expressed above-average aggression. Thus, the pool of profiles that participants would evaluate in the Main Study tended against expressing trait

values that were extreme deviations from the average ideal.

Pairs of profiles were created by randomly selecting two profiles from within the larger sets of profiles, formatted using the Flextable package for R, and saved as PNG image files (e.g., see Figure 6). These images depicted a table with the description of one profile shown to the left (Person A) and one profile shown to the right (Person B). A total of 1,000 profile pairs were created using the data from women and another 1,000 was created using data from men.<sup>2</sup>

### **Pilot 3**

The results of Pilot 2 were used to generate two large sets of profiles that generally tended to express desirable values for each trait. However, the random pairing of profiles did not prevent the possibility that some pairs of profiles were inappropriate for testing the hypotheses explored in this project. Pilot 3 was designed to identify and exclude profile-pairs in which responses from participants exhibited low variability to eliminate potential ceiling or floor effects produced by specific pairs of profiles (e.g., one potential mate is overwhelmingly preferred by most participants). Thus, Pilot 3 was necessary to calibrate the set of stimuli used in the Mate Choice Task to maximize *differences* in the ways that individuals respond to those stimuli. Of the 2,000 profile pairs prepared using the results from Pilot 2, 60 were randomly selected for testing in Pilot 3 (30 male targets and 30 female targets).

### ***Participants***

Participants were recruited from M-Turk ( $n = 274$ ) to complete an online survey

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2 The large number of stimuli prepared was intended to ensure that the process of simulating profiles would not need to be repeated if specific pairs of profiles needed to be excluded in future steps of the project.

about preferences and personality. By design, nearly equal numbers of heterosexual men ( $n = 138$ ; 50.4%) and women ( $n = 136$ ; 49.6%) were recruited. Most of the sample was college educated (68.6%), white (70.1%), and currently in a romantic relationship (65.7%). The average age was 34 years and the distribution of ages was positively skewed, indicating that the older half of participants spanned a much wider age range (32-68 years) compared to the younger half (18-31 years).

### ***Materials and Procedure***

After agreeing to participate in the study, all participants completed a demographic questionnaire, followed by multiple trials of the Mate Choice Task. The task was designed to elicit judgments from participants when presented with a complex set of information. The goal for participants was to decide which of two potential mates would make the best long-term romantic partner (i.e., *mates*) by comparing them on the same 14 traits used in the Ideal Mate Scale (e.g., see Figure 6). As in the Ideal Mate Scale, values for each trait could range between 0 (*extremely low*) and 10 (*extremely high*). One potential mate was labeled “Person A” and the other labeled “Person B”. Participants were instructed to study each profile, then answer the following question: “Who do you think would make a better long-term romantic partner?” Response-options ranged from -4 (*Definitely Person A*) to 0 (*About the same*) to +4 (*Definitely Person B*). To avoid fatigue, participants were only asked to rate six randomly selected profile-pairs and data collection continued until each profile pair was rated by at least 20 participants. After completing six trials, participants were thanked for their participation and debriefed.

### ***Results and Discussion***

The main criterion for evaluating each profile pair was the standard deviation of

preferences for the item asking participants to indicate which of the two profiles would make a better long-term romantic partner. Specifically, if the standard deviation of responses to a particular profile pair was below 2.00, that pair was excluded from use in the main study. Using this criterion, 40 profile-pairs qualified for the main study and 36 were randomly selected for use (18 male pairs, 18 female pairs).

### **Main Study**

The goal of the current study is to gain insight into individual differences in the number of cues that people use when discriminating between two potential mates. The study was conducted as an online survey and a screening survey was used to identify heterosexual individuals who were not currently in a romantic relationship. Data collection began on November 7, 2019 and ceased January 7, 2020 after the target sample size ( $n > 1,000$ ) was reached.

### ***Participants***

Participants were recruited to complete a survey about their preferences and personality through M-Turk. Participants were informed that they would all receive a small monetary award for completing the demographic questionnaire, but that some individuals would be invited to complete the main study for an additional monetary award. Only heterosexual participants who indicated that they were not currently in a relationship received the invitation to complete the main study. Data collection continued until at least 500 men and 500 women completed the main study.

A total of 6,598 M-Turk workers completed the demographic questionnaire and 1,739 qualified to participate in the main study. Of those who qualified, 609 (35.0%) declined to participate, 20 (1.2%) agreed to participate and dropped out before

completion, and the remaining 1,110 (63.8%) completed the entire study. After removing 75 (6.8%) observations for poor-quality data (see “Exclusion Criteria” below), the final sample size rests at 1,035 observations (50.7% men, 49.3% women; see Table 3).

### ***Procedure***

Participants first completed a demographic questionnaire in exchange for a small monetary payment. After completing the demographic questionnaire, heterosexual participants who indicated that their relationship status was “single” were invited to participate in the main study for an additional monetary payment. Next, participants were randomly assigned to one of two conditions in the threat induction task. One condition was designed to induce the perception that finding a compatible mate would be difficult; the other condition was designed to serve as a neutral control. After completing the threat induction task participants completed the manipulation check, followed by the ideal mate scale, mate choice task, ranked trait importance scale, and childhood uncertainty scale.

**Demographics.** The demographic questionnaire consisted of 13 items measuring age, gender, political conservatism, political affiliation, race, income, household class during childhood, education level, sexual orientation, whether the participant has ever been divorced, current relationship status, number of children, and the participant’s age when his or her first child was born.

**Threat Induction Task.** To test for the conditional effect of childhood uncertainty, participants were randomly assigned to one of two experimental groups (threat vs. control). In the threatening condition, a prompt stated that researchers were alarmed over evidence that people were having greater difficulty finding relationship partners. The end of the prompt instructed participants to provide a typed response

describing how they would feel if they were never able to find a compatible relationship partner. The control prompt instructed participants to describe their use of electronic entertainment. All participants were required to type at least 400 characters (~100 words) before advancing to the next page of the survey.

**Manipulation Check.** Participants indicated the extent to which they felt each of eight emotions (afraid, uncertain, nervous, worried, bored, happy, driven, confident) on a five-point scale ranging from 1 (*not at all*) to 5 (*extremely*). The mean response to four items was calculated as a composite measure of perceived threat: afraid, uncertain, worried, nervous ( $\alpha = .888$ ).

**Ideal Mate Scale.** The Ideal Mate Scale is identical to the scale used in Pilot 2. The scale lists 14 traits and participants are instructed to indicate the value their ideal mate would hold on each trait using an 11-point scale ranging from 0 (*extremely low*) to 5 (*average*) to 10 (*extremely high*).

**Mate Choice Task.** After completing the ideal mate scale, participants were required to complete six trials of the Mate Choice Task. The procedures for the Mate Choice Task were nearly identical to those used in Pilot 3. The only change in procedures is that profiles shown to participants in the Main Study were randomly selected from the pool of 18 opposite-sex profile pairs (36 total) that qualified based on the results of Pilot 3.

**Ranked Trait Importance Scale.** Next, participants completed the ranked trait importance scale. Completing this scale required participants to rank each of the 14 traits in the Mate Choice Task based on their importance for judging potential mates. The scale consisted of 13 multiple-choice items, each displayed on separate pages of the survey.

The first question instructs participants to “Imagine that you had to pick a long-term romantic partner from a list of options. What is the FIRST thing you’d want to know about your different options?” Fourteen response options were provided, each corresponding to the 14 traits on the ideal mate scale (e.g., “how attractive/unattractive each person was”). After completing the first item, participants were directed to the next page and shown the second item. The second item was identical to the first item with two exceptions: First, the response option chosen on the previous page was omitted, leaving only 13 response options. Second, participants were asked to indicate the *second* thing they would want to know about potential long-term romantic partners. After completing the second item, participants were directed to the next page and shown the third item. Again, the third item was identical to the second item, but differed only in that it excluded all previously chosen response options and participants were instructed to consider the *third* thing they would want to know about potential long-term romantic partners. This pattern repeated for the remaining items.

**Childhood Uncertainty.** Childhood uncertainty was assessed using ten items. Six statements were taken from the Family Unpredictability Scale (Ross and Hill, 2000) and reworded for retrospective reporting on one’s early-life environment (see Ross and McDuff, 2008). These items described perceptions of the early-life environment (e.g., “Things were chaotic growing up”) and participants were asked to indicate the extent to which they agreed with each statement on a scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*).

An additional four statements were created based on the research conducted by Simpson et al. (2012) using data from the Minnesota Longitudinal Study of Risk and

Adaptation (MLSRA; Sroufe, Egeland, Carlson, & Collins, 2005). Using a longitudinal design, Simpson and colleagues used records of the number of times each child in the study experienced events that signaled environmental uncertainty. Specifically, they showed that individuals who experienced more changes in parental employment, moves to a new residence, and changes in cohabitation (e.g., individuals moving into or out of the current residence) between the ages of 0 and 5 tended to exhibit higher rates of risky behavior at age 23. Given that direct recordings of these events are not possible for the current study, participants were asked to recall how frequently they experienced these events during early childhood following the same approach by Barbaro and Shackelford (2019). Participants were shown four statements describing events associated with uncertain childhood environments (e.g., “I switched schools”) and participants were asked to indicate how frequently they experienced each event on a scale ranging from 1 (*much less than normal*) to 5 (*much more than normal*). All items were averaged to form a composite measure of childhood uncertainty ( $\alpha = .787$ ).

### ***Results***

**Exclusion Criteria.** As mentioned previously (see above, “Participants”), 1,110 participants completed the main study and 75 (6.8%) were excluded from analysis for one of several reasons. Twenty-three were removed for failure to follow instructions on the threat induction task (e.g., inserting nonsense strings until the 400-character limit was reached), 16 were removed for providing the exact same response to all items on the childhood uncertainty scale (e.g., selecting “strongly agree” to all items), eight were removed for providing the exact same response to all trials of the mate-choice task<sup>3</sup>, three

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<sup>3</sup> These participants were removed because the analyses testing Hypothesis 1a and 1b cannot be performed on sets of responses with zero variation.

were removed for indicating they had their first child before 11-years old, and 25 were removed for taking more than 45 minutes to complete the study. After removing disqualified participants, the final sample size was 1,035.

**Manipulation Check.** Perceived threat was subjected to a 2 (threat, no threat)  $\times$  2 (men, women) between-subjects ANOVA. Results revealed a significant main effect of threat ( $F(1,977) = 34.40, p < .001, \eta^2 = .034$ ), a non-significant main effect of gender ( $F(1,977) = 2.83, p = .093, \eta^2 = .003$ ), and a non-significant interaction term ( $F(1,977) = 0.18, p = .669, \eta^2 < .001$ , see Figure 7). These results suggest that the threat manipulation successfully induces perceived threat and that the magnitude of this response is roughly the same for men and women.

**Hypothesis 1.** The main hypothesis of the current study is that, when threatened, people from uncertain childhood environments will tend to use fewer cues when judging potential mates compared to people with low-uncertainty backgrounds. To test this hypothesis, models predicting the responses of participants were developed with varying levels of complexity. Then, the accuracy of each model was tested for each participant and the level of complexity for the most accurate model was recorded. This process is detailed below.

Recall that participants reported the value that an ideal mate would express on each of 14 traits in the ideal mate scale. Presumably, participants will prefer potential mates insofar as they express levels of each trait that closely match each participant's ideal value. As demonstrated by Conroy-Beam and Buss (2017), mate preferences can be accurately predicted based on the Euclidean distance between all 14 traits expressed by a

potential mate and the ideal values reported by each individual participant. However, it is unlikely that all 14 traits contribute equally to judgments of a potential mate for all participants. Therefore, models relying on all 14 traits to predict decisions are prone to overfitting. For example, a participant might consider deviations from the ideal value for intelligence to be far less desirable than equally large deviations from the ideal value for creativity. Thus, a model that incorporates a potential mate's creativity when predicting judgments might be less accurate than a simpler, regularized model that ignores creativity entirely.

Similar to Conroy-Beam and Buss (2017), preferences in the mate-choice task were predicted by calculating the Euclidean distance between the values indicated in the ideal mate scale and the observed values for each potential mate in the mate choice task. The most complex model calculated Euclidean distances using all 14 traits from the ideal mate scale ( $c = 14$ ). However, regularized models ( $c = 1$  to 13) were also tested by dropping traits based on how participants responded to the ranked trait importance scale. The trait each participant identified as least important to him/herself was dropped first to create the model with the second-highest complexity ( $c = 13$ ) and the two least important traits were dropped to create a yet simpler model ( $c = 12$ ). The simplest model ( $c = 1$ ) predicted preferences using only deviations from the ideal value of the single most important trait. In sum, 14 models were created for each participant based on the descriptions they provided for their ideal mates and the ranked importance of each trait.

The mate-choice task required participants to indicate which of two potential mates would make a better long-term romantic partner on a nine-point scale ranging from -4 (*definitely person A*) to +4 (*definitely Person B*). Six profile pairs were shown to each

participant, yielding six judgments per participant. For each judgment, the 14 models generated previously were used to estimate the mate values (MVs) of both profiles based on the Euclidean distance from the participants' ideal. Then, a difference score between the two MVs was calculated with negative values indicating that Person A had a higher MV, positive values indicating Person B had a higher MV, and values near zero indicating indifference.

To assess the relationship between model complexity and model accuracy, predictions from each model were regressed onto each participant's judgments and the corresponding coefficients of determination (R-square) were recorded. The average performance of models at each level of complexity is plotted in Figure 8, revealing at least three noteworthy patterns: First, models generally tended to predict women's preferences more accurately than men's preferences and this divergence is most pronounced at higher levels of complexity. Second, although the simplest models ( $c = 1$ ) were usually the least accurate, the greatest gains in accuracy were made when the second-most important trait was added to the model ( $c = 1$  vs.  $c = 2$ ). As model complexity increased ( $c > 2$ ), gains in accuracy diminished and eventually leveled off for all participants as a group. Third, the benefits of increasing complexity leveled off sooner for men ( $c = 2$ ) than for women, ( $c = 3$  to  $7$ ), suggesting that women's judgments relied on a larger number of traits than men's judgments.

In addition to the differences in overall model performance, there are some similarities and differences between men and women with regard to what information they considered most important in judging potential mates. As shown in Figure 9, traits differed in their tendency to appear in women's top three most important traits. For

example, dependability appeared most frequently as one of the most important traits that women used for judging potential mates whereas almost no women reported that assertiveness was one of their most important traits. Figure 10 summarizes the most important traits that men used for judging potential mates. Although dependability was also reported as one of the most important traits, attractiveness tended to be the single-most important trait for men. As with women, assertiveness was rarely selected as one of the top three most important traits that men used to judge potential mates. Finally, Figure 11 shows the differences in the most important traits men and women use. Compared to men, women were relatively more likely to choose aggression and dependability as one of the three most important traits whereas men were relatively more likely to select attractiveness and intelligence.

The main hypothesis of the current project is that the most accurate model for each individual depends partly on his or her childhood experiences with environmental uncertainty. To test this, for each participant ( $i$ ), the model with the greatest R-square value was identified and the corresponding level of complexity ( $c_i$ ) was recorded as the score for that participant on the dependent measure. In the event that two models produced identical R-square values, the simpler of the two models was recorded as the most accurate. For example, if  $c_i$  for a participant equals “4” it indicates that the participant’s preferences were most accurately predicted by the Euclidean model using that participant’s four most important traits.

Because men and women viewed unique sets of profile pairs in the mate-choice task, gender differences and interactions with gender are potentially confounded by the differences in stimuli shown to each group. Therefore, results for the following analyses

will be discussed separately for men and women.

Scores on the childhood uncertainty scale, experimental condition, and their interaction were regressed onto  $c_i$  using ordinary least-squares regression. For men, the interaction between childhood uncertainty and experimental condition failed to reach significance ( $b_{\text{Int}} = 0.344$ ,  $se = 0.578$ ,  $t = 0.596$ ,  $p = 0.552$ ), so the interaction term was dropped from the model. After excluding the interaction term, there was no evidence of an effect of experimental condition ( $b_{\text{Threat}} = 0.315$ ,  $se = 0.380$ ,  $t = 0.831$ ,  $p = 0.407$ ) or childhood uncertainty ( $b_{\text{ChildUncert}} = 0.258$ ,  $se = 0.287$ ,  $t = 0.900$ ,  $p = 0.369$ ).

The same analysis was repeated for women, but the interaction between childhood uncertainty and experimental condition reached significance ( $b_{\text{Int}} = 1.410$ ,  $se = 0.545$ ,  $t = 2.588$ ,  $p = 0.010$ , see Figure 12). To probe this interaction, the relationship between childhood uncertainty and  $c_i$  was examined separately for the experimental and control conditions. In the control condition, there was a significant negative relationship between childhood uncertainty and decreasing model complexity ( $b_{\text{ChildUncert}} = -0.727$ ,  $se = 0.356$ ,  $t = -2.043$ ,  $p = 0.042$ ). However, the relationship between childhood uncertainty and model complexity was not significant in the threat condition ( $b_{\text{ChildUncert}} = 0.684$ ,  $se = 0.415$ ,  $t = 1.646$ ,  $p = 0.101$ ).

**Discussion.** Taken together, the results reviewed above provide some support for Hypothesis 1a and no support for Hypothesis 1b. Among men, there did not appear to be a relationship between childhood uncertainty and  $c_i$  across conditions, nor was there evidence that the relationship differed between experimental conditions. Thus, responses

from the men in the current study do not provide any support for Hypothesis 1a or 1b. Among women, there was a conditional relationship between childhood uncertainty and  $c_i$ . In the control condition, higher childhood uncertainty scores were associated with the use of fewer cues when judging mates. However, this relationship fell below the threshold of significance in the threat condition. This provides qualified support for Hypothesis 1a and no support for Hypothesis 1b. That is, the negative relationship between childhood uncertainty and the number of cues used in the mate-selection task was only present in one of the four subgroups tested in the current study: Women in the control condition. Although Hypothesis 1b stated that there would be an interaction between childhood uncertainty and experimental condition, the observed interaction effect was in the opposite direction of predictions. Instead of perceived threat causing the relationship between childhood uncertainty and  $c_i$  to become more strongly negative, the threat manipulation caused the significant negative relationship to diminish to an undetectable size among women. Thus, it does appear that the threat manipulation altered the judgment processes of women, but the observed pattern is antithetical to Hypothesis 1b.

**Hypothesis 2.** To test whether people with high uncertainty childhoods tend to express more similar preferences compared to people with low uncertainty childhoods, participants were first sorted by their scores on the childhood uncertainty scale. Next, participants were assigned to a same-sex, same-experimental condition cohort consisting of their ten nearest-ranked neighbors: five ranked immediately above the participant and five ranked below. Thus, a participant with the  $j^{\text{th}}$  rank was assigned a cohort consisting

of the following participants: ( $j-5$ ), ( $j-4$ ), ( $j-3$ ), ( $j-2$ ), ( $j-1$ ), ( $j+1$ ), ( $j+2$ ), ( $j+3$ ), ( $j+4$ ), and ( $j+5$ ). Once assigned to a cohort, each participant received a score indicating how similar he or she was to the members of their cohort.

The similarity score was quantified as the average Euclidean distance between responses to the 14 items comprising the ideal mate scale. For each member of a participant's cohort, the distance between that member's responses and the responses of the participant was calculated and recorded. Once a participant's distance from each member of his or her cohort was recorded, the average of all ten distances was recorded as that participant's similarity score. Finally, all similarity scores were z-scored and inverted such that higher values indicated greater similarity. In summary, the similarity score assigned to each participant reflects how similar his or her responses were to other participants of the same sex, same experimental condition, and nearby ranking on the childhood uncertainty scale.

Childhood uncertainty, experimental condition, and their interaction were regressed onto similarity scores using OLS regression. As with tests for Hypotheses 1a and 1b, men and women were analyzed separately.

Among men, the interaction between childhood uncertainty and experimental condition was significant ( $b_{\text{Int}} = 0.483$ ,  $se = 0.146$ ,  $t = 3.317$ ,  $p = 0.001$ ). To probe this interaction, the relationship between childhood uncertainty and preference similarity was examined separately for each experimental condition. In the control condition, there was no evidence that childhood uncertainty was associated with preference similarity ( $b_{\text{ChildUncert}} = -0.123$ ,  $se = 0.091$ ,  $t = -1.344$ ,  $p = 0.180$ ). However, in the threat condition,

there was a significant positive relationship between childhood uncertainty and preference similarity ( $b_{\text{ChildUncert}} = 0.361, se = 0.115, t = 3.143, p = 0.002$ ; see Figure 13).

Among women, the interaction between childhood uncertainty and experimental condition was also significant, but the interaction effect was in the opposite direction compared to men ( $b_{\text{Int}} = -0.272, se = 0.135, t = -2.017, p = 0.044$ ). To probe this interaction, the relationship between childhood uncertainty and preference similarity was examined separately for each experimental condition. In the control condition, there was strong evidence that childhood uncertainty was positively associated with preference similarity ( $b_{\text{ChildUncert}} = 0.410, se = 0.098, t = 4.163, p < 0.001$ ). However, the relationship between childhood uncertainty and preference similarity failed to reach significance in the threat condition ( $b_{\text{ChildUncert}} = 0.138, se = 0.091, t = 1.508, p = 0.133$ ; see Figure 14).

**Discussion.** Hypothesis 2 predicted (a) a positive relationship between childhood uncertainty and preference similarity and (b) that this relationship would be amplified under conditions of threat. The data from male participants provide support for both parts of Hypothesis 2. The significant interaction between childhood uncertainty and experimental condition indicates that the relationship between childhood uncertainty and preference similarity depends on perceived threat. Whereas similarity scores were unrelated to childhood uncertainty in the control condition, a positive relationship emerged among threatened men. This is evidence that when men with uncertain childhood environments are threatened by the possibility that they might not find a long-

term romantic partner, their descriptions of ideal mates become more similar.

The data for women provides partial support for Hypothesis 2a and no support for Hypothesis 2b. As with men, the relationship between childhood uncertainty and preference similarity was conditional: Childhood uncertainty was positively associated with similarity scores in the control condition, but that relationship was suppressed in the experimental condition. In sum, whereas higher childhood uncertainty scores were associated with preference similarity only among threatened men, the same relationship only emerged in non-threatened women. This is partial support for Hypothesis 2a, but the suppressing effect of the threat induction task is in the opposite direction than predicted by Hypothesis 2b. As with Hypothesis 1b, the threat induction task indeed appeared to moderate the judgment processes of women in the current study, but the opposite direction than expected.

## Chapter 5: General Discussion

The current project built on life history theory, statistical learning theory, and ecological rationality to develop and test hypotheses about decision-making under threat. Research from life history theory suggests that people adapt to their environment based on cues available in early childhood and that some of the most influential features of the early-life environment are indicators of uncertainty. Given the role of uncertainty in developing predictive models used by statisticians, the current study sought to test if uncertainty during early-childhood might have similar effects on the mental models people use to form judgments in adulthood. The rationale is that in environments characterized by high amounts of uncertainty, valid cues that can be used to make predictions are corrupted by random noise. As demonstrated by progress in the field of statistical learning theory, models developed in uncertain environments (e.g., high amounts of random noise, missing data, sparse data) are prone to overfitting insofar as those models attempt to utilize as much information as possible. This field has shown that one of the best strategies to avoid overfitting is to develop models that only rely on a subset of the most reliable cues, a process known as regularization. In humans, the observation that people tend to rely on a small number of cues to form judgments is often assumed to be evidence of an evolutionary trade-off between judgment quality and efficiency, a phenomenon labeled the “accuracy-effort tradeoff”. Ignoring information surely reduces the computational load of making a decision, but many studies show that the tendency for people to ignore some information improves the accuracy of their judgments in various contexts. Thus, rather than needing to balance accuracy and effort, it appears that a crucial step in learning to make accurate inferences is determining *how*

*much information to ignore*, whether the inferences are generated by a statistical model or an evolved organism.

The primary goal of this dissertation is to test the hypothesis that individual differences in the amount of information used to form judgments arise from differences in early-life experiences of environmental uncertainty. This assumes that people implicitly rely on estimates of environmental uncertainty to decide how much information to ignore while forming a judgment. Thus, people from uncertain childhood environments should tend to ignore more information when forming judgments compared to people from stable, low-uncertainty environments (H1a). Hypothesis 1a received some support: There was no overall relationship between childhood uncertainty and the number of cues men used to discriminate between potential mates, nor was there evidence that the relationship was contingent on experimental condition. Thus, data from men in the current study provide no support for Hypothesis 1. However, childhood uncertainty did predict the use of fewer cues among women, but only in the control condition. This finding supports Hypothesis 1a, but the suppression of the relationship by the threat induction task suggests complex interactions between perceptions of threat and judgments of mate-value that the current study was not designed to explore.

The secondary goal of this dissertation was to test the extent to which people from uncertain childhood environments tended to express similar mate preferences. This is based on the assumption that cues differ in the extent to which their validity for predicting a criterion varies with the environment. Robust cues are indicators of high mate value regardless of the environment whereas the validity of other cues will vary more considerably across environments. Most people appear to rely on a similar set of

robust cues to mate value, but in a low-uncertainty environment there is greater opportunity to learn to associate novel cues with mate value as well. Therefore, two individuals with low-uncertainty childhoods should tend to provide more unique descriptions of their ideal mates compared to two individuals with high-uncertainty childhoods.

The data from the current project provides some support for this hypothesis. Among men, there was no relationship between childhood uncertainty and preference similarity in the control condition. However, a positive relationship emerged in the threat condition. This indicates that the ideal mates described by men with uncertain childhoods were more similar to each other than those described by men with low-uncertainty childhoods. Childhood uncertainty was also associated with preference similarity among women, but, unlike with men, the relationship only emerged in the control condition.

### **Implications**

The results of the current project lend qualified support for Hypothesis 1: Women with uncertain childhood environments tend to rely on fewer cues when judging potential mates in adulthood, but not under threatening conditions. I expected to see that the relationship was significant for both men and women in the non-threatening condition and that the relationship would be magnified when participants' mate-seeking goals are threatened. However, the only evidence for an interaction was among women and the direction of the interaction opposed predictions. Rather than threat amplifying the relationship between childhood uncertainty and the number of cues used to judge potential mates, the threat induction task *suppressed* the relationship among women and failed to generate any relationship among men.

Results for Hypothesis 1 suggest that the mechanism linking childhood uncertainty to the number of cues that women use to discriminate between mates may be active by default and that this mechanism is deactivated or altered when mate-seeking goals are threatened. This pattern could be the result of several alternative explanations. For example, threatening conditions might lead men to shift from a long-term to short-term mating orientation, thereby increasing the costs of reproduction for women. If women anticipate this shift in men, women with highly uncertain childhoods might hedge against the risks of short-term mating by adopting a relatively *more* complex decision-making strategy. If the number of men with more long-term mating orientations is relatively small, scrutinizing men on a greater number of traits might increase the chances of identifying one who women consider suitable as long-term mates. This is consistent with the pattern of results in Figure 12 where the biggest effects of threat are seen among women with uncertain childhoods.

Another alternative explanation is that the threat-induction task might have suppressed the mechanisms responsible for accurate judgments of mates as a side effect of activating other mechanisms. Because the threat induction task was designed to induce the perception that attempts to find a mate would result in low success rates, it is possible that the motivation to judge potential mates accurately was displaced by, say, the motivation to improve one's own mate value. Therefore, men and women in the threat condition might have been more concerned about successfully competing with other same-sex individuals rather than devoting attention to carefully choosing among two highly desirable mates.

One way to test the hypothesis that unintended goals were activated in the current

study would be to repeat the study with a third experimental condition designed to prime mating *opportunities* in addition to the threat condition. By persuading participants to believe that they will be relatively more likely to find long-term mates in the future, the challenge may shift from managing the risks of never reproducing (threat) to managing the risks of failing to identify the best potential mates among alternatives (opportunity). There is some evidence for this alternative explanation. For example, Griskevicius and his colleagues (2012) showed that when men perceive desirable women to be scarce, they engage in behaviors apparently intended to elevate their own mate-values, such as spending more money during courtship and paying higher prices for engagement rings. Furthermore, manipulating the perceived availability of women led men to report stronger feelings of competitiveness with other men. Although Griskevicius et al (2012) did not report results for the effects of sex-ratios on women's competitiveness, there is some evidence to suggest that similar patterns emerge among women (see Schmitt, 2016 for review).

The other important set of findings focuses on the similarity of preferences observed among participants with approximately equal childhood uncertainty scores. Overall, I found some evidence that individuals with high childhood uncertainty scores tended to be more similar to each other than those with low childhood uncertainty scores (Hypothesis 2). Among men, this relationship was only present when men had first completed the threat induction task whereas the relationship among women only appeared in the control condition. These results provide qualified support for the strategic differentiation-integration hypothesis, which states that people following a fast life history trajectory tend to develop sets of traits that are more strongly correlated with each

other.

By integrating one's traits, the sensitivity of any one trait to features of the environment is relatively restrained and, consequently, the costs of overly-extreme adjustments to the environment are avoided. The result is that integrated individuals maintain a greater ability to exploit a broader range of micro-niches in the environment or switch between micro-niches more frequently. The value of integrating one's mate preferences is likely to emerge from the fact that an individual's mate-value varies with the environment he or she inhabits. For example, aggression might be a valuable trait only in the subset of environments characterized by high levels of violence between conspecifics. However, when the environment is uncertain (e.g., violence varies unpredictably over time), it becomes more risky to form strong beliefs about the value of a relevant trait using experience. For example, an individual who grew up in a relatively safe environment might learn to strongly prefer mates with low aggression, but if the environment suddenly became violent in adulthood that individual might experience a costly mismatch between her preferences and the environment. Trait integration can reduce the risks of mismatching in uncertain environments by decreasing the tendency to form evolutionarily novel preferences or to adjust preferences away from species-typical values. The resulting phenotype is one in which people from uncertain childhood environments will tend to appear more similar to each other compared to those with low-uncertainty childhoods.

The results from the current study are also relevant for work related to the contingent activation of life history traits (Griskevicius et al., 2013; Griskevicius, et al., 2011; Mittal & Griskevicius, 2014). The presence of a relationship between childhood

uncertainty and preference similarity among threatened men suggest that the preferences of men with uncertain childhoods become more similar in a threatening context.

However, the same positive relationship only emerged in the control condition for women. Thus, it appears that the mechanism responsible for the relationship between childhood uncertainty and preference similarity is active by default among women and that the mechanism is deactivated or displaced by the effects of perceived threat. As with the pattern of results for Hypothesis 1, the suppression effect in women could be explained as a displacement effect in which the threat induction task activated an unintended goal that shifted attention away from forming accurate inferences about potential mates. Repeating this study with a task designed to signal mating opportunities could also provide insight into the interactions between contexts and traits.

#### ***Sex Differences in Euclidean Model Accuracy.***

As illustrated in Figure 8, there are clear sex differences in overall performance of the Euclidean models used to predict responses to the Mate-Choice Task. This is also what Conroy-Beam and Buss (2017) found using similar methods. The main difference is that the current study was using Euclidean models to predict preferences among alternatives whereas Conroy-Beam and Buss predicted levels of attraction to individual profiles. Another difference between these two studies is the fact that the current study used a different, but overlapping set of preferences. Of the 14 traits included in the current study, eight are also present among the 23 used in the Conroy-Beam and Buss study. Despite these methodological differences, the two studies still share important features, such as the numeric presentation of traits in the mate profiles shown to participants. For that reason, it is not clear the sex differences that emerged in the current

study reflect the fact that the Euclidean model is a closer representation of how women (vs. men) tend to judge potential mates.

One possible explanation for the observed sex differences is the fact that men and women in the current study were shown different pairs of profiles, so the differences in accuracy could be an artifact of the different parameters used for generating the profile pairs for men and women. Another possibility is that the set of traits used in both studies are more relevant, more easily interpreted by, or otherwise more valuable to women compared to men. This suggests that the sex differences observed in the current study are merely the result of chosen method for presenting potential mates to participants. For example, the effects of attractiveness on men's judgments may have been underestimated in the current study because attractiveness presented in numerical format. If differences in attractiveness between profiles was displayed using images, it is possible that predictions of men's decision-making would have been more accurate. This possibility can be tested by observing the accuracy of Euclidean models while varying the channel through which information about potential mates is communicated as well as the content communicated.

For example, Oosterhof and Todorov (2008) generated a database of images of human faces, asked participants to rate the faces on nine personality dimensions (e.g., attractiveness, trustworthiness, etc.), and made these materials publicly available for researchers. The current study could be repeated, but instead of showing participants numeric representations of potential mates, faces from the Oosterhof and Todorov (2008) image database could be shown instead. Using the empirically derived estimates of the traits associated with each image, a Euclidean model could be used to predict participant's preferences and sex differences in model accuracy could be examined. If the

Euclidean model remained more accurate for women, it would suggest that the Euclidean model is not an equally valid representation of men and women's judgment processes when discriminating between potential mates. Conversely, data based on images could also show that the Euclidean model is more accurate at predicting men's preferences compared to women. This would suggest that sex differences in the performance of the Euclidean model is more a result of how the information is presented rather than a stable sex difference in the predictive validity of Euclidean models.

### ***Value of Regularizing Models of Decision-making***

As illustrated in Figure 8, the most complex models predicting mate selection perform no better than simpler models that exclude less important cues. Indeed, models based on the three most important variables ( $c = 3$ ) performed nearly as well as the most accurate models. Overall, the best models tended to make predictions based on fewer than half of the available traits ( $M_{c_i} = 6.28$ ,  $SD = 4.43$ ) and the most accurate model for over 90% of the sample was one which ignored at least one piece of information ( $c_i < 14$ ). Thus, the current study found strong evidence that the accuracy of relatively complex Euclidean models predicting human mate preferences can be matched or surpassed by simpler versions that ignore some of the traits that individuals find less important. One caveat of this finding is that the chosen regularization method required directly asking participants to indicate the most important traits to retain in simplified models. Obtaining this information may come at a non-trivial cost to researchers considering the use of similar methods (e.g., increasing survey length), especially if predictive accuracy is not an important goal.

## **Limitations**

### ***Ideal Mate Scale***

The ideal mate scale captured participants' point estimates for the value that an ideal mate would take on each trait, but it is likely that each participant varies in the extent to which an ideal mate could express a *range* of trait values. For example, two individuals who prefer a high level of extraversion might differ in the amount of weight placed on a deviation from the high-scoring ideal. Whereas one individual might still be willing to date people with moderate or low extraversion levels, the other could perceive anything but a small deviation to be undesirable. If the mate choice task were modified to allow participants to provide a range of values that an ideal mate could express, the Euclidean algorithm could be adjusted such that only values falling outside the ideal range would penalize MV estimates. This would improve measurement of participants' preferences by providing participants with a procedure that inherently includes information about the weights of each trait. For example, participants could provide a range that covers the entire scale to indicate complete indifference or a very narrow range to indicate high preference specificity. Wide ranges would imply that no potential mate is penalized for their value on that trait whereas narrow ranges would imply that potential mates are penalized for even the smallest deviations from the ideal.

### ***Number of Available Cues***

Another limitation is the possibility that the number of cues used in the mate-choice task restricted the range of  $c_i$  scores. This is evident from the distribution of  $c_i$  demonstrating one mode at each extreme ( $c = 1$  and  $c = 14$ ; see Figure 15). The mode at

$c_i = 14$  suggests that an unrestricted distribution would have a longer right tail extending into higher values of  $c$ , something easily tested by increasing the number of traits.

Researchers should include enough cues in similar studies to avoid this apparent range restriction.

### ***The Euclidean Model of Mate Preferences***

One of the important assumptions on which Hypothesis 1 is based is that the Euclidean algorithm is an adequate representation of the process(es) that people use to estimate mate-value. Several studies show that predictions based on Euclidean distance are reasonably accurate compared to other algorithms (Conroy-Beam, 2018; Conroy-Beam & Buss, 2016, 2017), but it is possible that future research reveals improved models of how people discriminate between potential mates. For example, instead of regularizing the Euclidean model by dropping individual traits entirely, weights could be applied to traits such that deviations from ideal values of the most important traits penalize mate values much more than deviations from ideal values of the least important traits. In addition to future work focused on identifying models that accurately predict human judgments, researchers should also focus on their plausibility as explanatory models of human cognition. Although the Euclidean algorithm makes reasonably accurate predictions, accurate predictions are not necessarily equivalent to accurate explanations. Insofar as the mind does calculate something like Euclidean distances when forming judgments, it will also be important to identify the conditions under which such calculations are made. For example, the mind might estimate mate-value by calculating Euclidean distances only when a relationship has continued long enough to learn more details about a potential mate, but rely on one-reason-heuristics when quickly deciding if

a stranger should be considered a potential mate at all.

### ***Self-Reported Preferences***

One limitation of the current study is that the ideal mate scale and the ranked trait importance scale both relied on the assumption that participants have conscious access to their mate preferences *and* that they are willing to report them honestly. For example, participants who were most influenced by a potential mate's attractiveness or income might have been hesitant to report the primacy of one of these traits due to perceptions that such preferences are socially undesirable. One way to address this question would be to adopt procedures that could enable researchers to infer participants' preferences based on actual decisions (i.e., revealed preferences). This could be accomplished by revising the mate-choice task such that participants are required to judge potential mates based on values for only two traits at a time. By varying which traits are shown across trials and the extent to which trait values deviate from ideal values, a ranking of trait importance can be inferred from the choices of participants.

Despite the likelihood that responses to the ideal mate scale and the ranked trait importance scale are noisy or misleading, perfect accuracy is not necessary for these measures to be used in a valid test of the main hypotheses. The most important characteristic of these measures is that they are an improvement over random values or values that were intentionally misleading (e.g., ranking items in *reverse* order of importance) and that the current study had enough power to detect that improvement.

Figure 16 is a recreation of Figure 8 in that it shows the overall performance of models across each of the 14 levels of complexity. Whereas Figure 8 shows results split by gender, each line in Figure 16 includes data from all participants. The different lines in

Figure 16 show how models perform with three different regularization strategies. The dashed line reflects a random regularization process whereby the traits included at each level of complexity are chosen randomly. The solid line shows performance with the regularization strategy used in the current study (i.e., *informed*). When  $c = 1$ , the informed model makes predictions based only on the single most important trait and, when  $c = 13$ , the informed model makes predictions based on all but the least important trait. Finally, the dotted line shows performance when traits are included in *reverse* ranked order. This method is labeled “stupid” because it results in models that perform worse than models regularized using the random regularization strategy (Krakauer, 2015). Thus, when  $c = 1$ , the stupid model makes predictions using only the *least* important trait and the most important trait is only added when  $c = 14$ .

Figure 16 is intended to demonstrate that the responses provided by participants to the ranked trait importance scale provide valid information for guiding the regularization process. The random method is the pattern one might expect if participants had no insight into their own preferences and the stupid method was included to illustrate participants who provided reliably misleading responses. Thus, although it is unlikely that participants were highly accurate or perfectly truthful in their responses, the information contained in their responses is useful for guiding the regularization of Euclidean models.

### ***Characteristics of the Mate Choice Task***

Generating profile-pairs with an appropriate distribution of traits proved to be challenging for several reasons and the chosen solution is not without its limitations. The profile-pairs chosen for use in the mate-choice task were selected based on the amount of variability they generated among participants deciding which profile would make a better

long-term mate (Pilot 2b). The intent was to present participants with somewhat difficult decisions, but this process of generating profile-pairs might have affected the results in ways that sacrificed external validity. For example, few profile-pairs depicted individuals with high levels of aggression and both men and women tended to rank aggression as moderately important for assessing potential mates ( $M = 8.54$  and  $M = 6.72$  respectively). By restricting the range of aggression levels in potential mates, differences in aggression between profiles might have been too small to affect perceptions of mate-value. Therefore, the models of people who ranked aggression as highly important might have performed poorly because aggression would have remained in all but the most simple models. Of course, the simplest model for individuals who ranked aggression as the single most important trait (4.6% of men and 9.0% of women) would have predicted all choices based on differences in aggression. If differences in aggression level were too small in the current study, these models would have performed quite poorly for participants who ranked aggression as the most important trait.

The decision to have participants complete the ranked trait importance scale after the mate choice task was intended to mitigate the concerns described above. The goal was to encourage participants to reflect on the decisions they just made when considering the importance of each trait. Insofar as that goal was achieved, the concerns described above about range restriction in the traits of potential mates might not apply because participants would have adjusted their trait importance rankings to reflect the features of the task (e.g., ranking aggression low because potential mates in the task all expressed tolerable levels of aggression). One way to test the success of this decision would be to repeat the study and randomly assign participants to complete the ranked trait importance

scale before or after the mate choice task. If the average rank of traits differed significantly based on the order in which tasks were completed or models performed better when the ranked trait importance scale followed the mate choice task, it would suggest that the chosen method for mitigating the effects of range restriction in profile traits was effective.

Another limitation of the mate choice task is the extent to which each profile represented a realistic set of traits. The traits that real people express are correlated. For example, the correlation between education level and income in the current sample of M-Turk workers was moderate ( $r = 0.304, p < .001$ ), but there was no correlation between education level and income among the profile pairs generated for the mate-choice task ( $r = 0.003, p = 0.853$ ). Thus, it is possible that some of the profile-pairs failed to produce a context that participants might plausibly encounter in the real world.

The ideal solution to the problems above would be to base the profiles used in the mate-selection task on a random sample of data describing real people who participants would consider as potential mates. For example, a pilot study could recruit participants to complete personality scales (e.g., NEO-PI or HEXACO) and another pilot study could be used to screen personality profiles for some minimum level of desirability. Then, these real profiles could be randomly paired and used as stimuli in the mate-choice task.

### ***Sensitivity to Childhood Uncertainty***

Another limitation of the current study is the possibility that mate preferences are somewhat insensitive to childhood uncertainty. It is plausible that the effects of childhood uncertainty on judgments are most consequential in novel contexts and that effects diminish as one becomes more experienced with a specific type of judgment. Two

individuals might differ in the tendency to rely on simpler decision-making strategies when initially exposed to a novel context, but converge on strategies of similar complexity as both individuals become experts at the task. Insofar as the effects of childhood uncertainty diminish with experience, then evidence for Hypothesis 1 might be stronger among participants with the least experience judging potential mates. Using the current paradigm, this could be tested by repeating the study with a much younger sample. This can also be tested by having participants provide judgments for topics on which they have little experience, such as comparing profiles describing the traits and skills of potential job applicants in an occupation unfamiliar to participants.

### ***Mediating Regulatory Variable***

Although there are several constructs that could plausibly represent a stable estimate of environment uncertainty (e.g., causal uncertainty, self-efficacy, etc.), exploring mediators was beyond the scope of the current study. An important step for future researchers will be to examine the extent to which people develop a singular estimate of overall environmental uncertainty on which many forms of judgment rely, multiple estimates of environmental uncertainty that are unique to specific forms of judgment, or a combination of context-independent and context-specific estimates of environmental uncertainty.

### ***Genetic Confounding***

Perhaps the most overlooked limitation of any adaptive-calibration hypothesis is the potential for genetic confounding. Barbaro et al (2017) attempted to bring this subject to the attention of Life History researchers by examining one of the more well-studied relationships in life history theory: father absence and age at menarche. One of the

dominant theories about the correlation between father absence and age at menarche ( $r_s = 0.11$  to  $0.14$ ) is that father absence is a reliable cue that the environment is harsh and uncertain. This is believed to trigger a shift toward developing a fast life history strategy and, consequently, earlier onset of menarche. However, few studies focusing on this topic have accounted for the genetic correlations with both father absence and age at menarche. Given estimates of the heritability of father absence and age at menarche from the behavioral genetics literature, Barbaro et al showed that the relationship between father absence and age at menarche could be completely explained by genetic factors if a few reasonable assumptions are met.

Although Barbaro et al (2017) were focused on father absence and age at menarche, their results demonstrate the importance of accounting for genetics when attempting to explain associations between phenotypes and environments. Insofar as the correlation between childhood uncertainty and judgment in adulthood is due to a shared genetic cause, the form of the current adaptive calibration hypothesis becomes an implausible mechanism. The alternative mechanism would not necessarily prevent the emergence of patterns predicted by Hypotheses 1 and 2, but it would require major revisions to the theories used to explain these patterns. For example, features of environments might correlate with the traits of the people who inhabit them because people who inherit those traits also inherit the tendency to seek out particular environments. Insofar as such patterns are adaptive from an evolutionary perspective, it would imply a completely different type of adaptive calibration. Instead of individuals altering their own traits to match their environment, they alter their environments to match their traits.

## **Future Directions**

The implications and limitations discussed above suggest several possible extensions of the current research. One direction is to explore the extent to which the current findings generalize to other judgment domains, such as interpersonal inferences about the stable personality traits of others or how individuals choose among alternatives when making decisions with high financial impact (e.g., purchasing vehicles or homes). Another extension is to focus on how the medium over which information is conveyed can influence decisions. As discussed above, people do not usually obtain all information about the traits of potential mates simultaneously in a numerical format and it is possible that decision-making differs substantially when the information is obtained sequentially through typical channels (e.g., assessing attractiveness visually). Finally, it will be important for future research to explore the possible mechanisms that mediate the link between childhood experiences and outcomes in adulthood. For example, experiencing uncertainty in early-childhood could lead people to adopt a constellation of beliefs about the extent to which the world can be understood and whether the future can be predicted. Ross and Hill (2002) describe such sets of beliefs as an “unpredictability schema” and it is possible that such beliefs mediate the relationship between childhood uncertainty and adult judgment observed in the current study.

## **Conclusion**

This manuscript opened with a thought experiment intended to demonstrate how there is no universal criterion for determining the rationality of a decision in the presence of uncertainty. The implication is that the responses of two individuals to the same set of stimuli can be both different and rational. This apparent paradox is partly due to the fact

that judges possess unique sets of traits and those traits alter and interact with the environment. Thus, we (as researchers) often lack full descriptions of the environments we create for participants. Full descriptions are probably unnecessary for many research goals, but ignoring what participants contribute to research settings can result in incomplete conclusions about the inferences we draw from participants' behaviors. For example, Milgram's famous obedience experiments are often framed as demonstrations of the power of the situation, but recall that 35% of participants in Milgram's most well-known study *defied* experimenters (Milgram, 1963) . Furthermore, participants' reactions to the pressure ranged from nervous laughter to "a seizure so violently convulsive that it was necessary to call a halt to the experiment". Given the amount of individual variation in Milgram's studies, a strong case can be made for the extraordinary power of individual differences, but understanding that power requires a focus on how the traits of individuals interact with the contexts we create as researchers.

The goal of this project was to explore the role of individual differences in the basic strategy that people use to discriminate between potential mates, but the rationale for these arguments extend beyond the mating context. The claim that perceptions of environmental uncertainty can improve inferences by regulating the complexity of one's judgments can, in principle, be applied to any judgments made under uncertainty.

Although the results from the current project are somewhat equivocal, they can provide a point of departure for future researchers interested in how people form inferences using complex sets of information and why individuals might differ in the amount of information they use.

## References

- Ambady, N., & Skowronski, J. J. (Eds.). (2008). *First impressions*. Guilford Press.
- Barbaro, N., Boutwell, B. B., Barnes, J. C., & Shackelford, T. K. (2017). Genetic confounding of the relationship between father absence and age at menarche. *Evolution and Human Behavior, 38*(3), 357–365.  
<https://doi.org/10.1016/j.evolhumbehav.2016.11.007>
- Barbaro, N., & Shackelford, T. K. (2019). Environmental unpredictability in childhood is associated with anxious romantic attachment and intimate partner violence perpetration. *Journal of Interpersonal Violence, 34*(2), 240–269.  
<https://doi.org/10.1177/0886260516640548>
- Belsky, J., & Pluess, M. (2009). Beyond diathesis stress: Differential susceptibility to environmental influences. *Psychological Bulletin, 135*(6), 885–908.  
<https://doi.org/10.1037/a0017376>
- Belsky, J., Spritz, B., & Crnic, K. (1996). Infant attachment security and affective-cognitive information processing at age 3. *Psychological Science, 7*(2), 111–114.  
<https://doi.org/10.1111/j.1467-9280.1996.tb00339.x>
- Blackmore, S. (2018). *How plants work: Form, diversity, survival*. Princeton University Press.
- Bowlby, J. (1982). *Attachment* (2nd ed.). Basic Books.

- Brandstätter, E., Gigerenzer, G., & Hertwig, R. (2006). The priority heuristic: Making choices without trade-offs. *Psychological Review*, *113*(2), 409–432.  
<https://doi.org/10.1037/0033-295X.113.2.409>
- Brighton, H. (2006). In *Between a rock and a hard place: Cognitive science principles meet AI-hard problems: Papers from the AAAI Spring Symposium* (pp. 17-22). AAAI Press.
- Brighton, H., & Gigerenzer, G. (2015). The bias bias. *Journal of Business Research*, *68*(8), 1772–1784. <https://doi.org/10.1016/j.jbusres.2015.01.061>
- Briscoe, E., & Feldman, J. (2011). Conceptual complexity and the bias/variance tradeoff. *Cognition*, *118*(1), 2–16. <https://doi.org/10.1016/j.cognition.2010.10.004>
- Bröder, A. (2000). Assessing the empirical validity of the “Take-the-best” heuristic as a model of human probabilistic inference. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *26*(5), 1332–1346.  
<https://doi.org/10.1037//0278-7393.26.5.1332>
- Bröder, A. (2003). Decision making with the “adaptive toolbox”: Influence of environmental structure, intelligence, and working memory load. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *29*(4), 611–625.  
<https://doi.org/10.1037/0278-7393.29.4.611>

- Bröder, A., & Schiffer, S. (2003). Bayesian strategy assessment in multi-attribute decision making: Strategy Assessment in Decision Making. *Journal of Behavioral Decision Making, 16*(3), 193–213. <https://doi.org/10.1002/bdm.442>
- Brown, J. A., & Bernieri, F. (2017). Trait perception accuracy and acquaintance within groups: Tracking accuracy development. *Personality and Social Psychology Bulletin, 43*(5), 716–728. <https://doi.org/10.1177/0146167217695557>
- Buss, D. M., & Schmitt, D. P. (1993). Sexual strategies theory: an evolutionary perspective on human mating. *Psychological Review, 100*(2), 204-232.
- Cabeza de Baca, T., & Ellis, B. J. (2017). Early stress, parental motivation, and reproductive decision-making: applications of life history theory to parental behavior. *Current Opinion in Psychology, 15*, 1–6.  
<https://doi.org/10.1016/j.copsyc.2017.02.005>
- Clark, A. (2015). *Surfing uncertainty: Prediction, action, and the embodied mind*. Oxford University Press.
- Clark, R. D., & Hatfield, E. (1989). Gender differences in receptivity to sexual offers. *Journal of Psychology & Human Sexuality, 2*(1), 39–55.
- Conroy-Beam, D. (2018). Euclidean mate value and power of choice on the mating market. *Personality and Social Psychology Bulletin, 44*(2), 252–264.  
<https://doi.org/10.1177/0146167217739262>

- Conroy-Beam, D., & Buss, D. M. (2016). Mate preferences. In V. Weekes-Shackelford, T. K. Shackelford, & V. A. Weekes-Shackelford (Eds.), *Encyclopedia of evolutionary psychological science* (pp. 1–11). Springer.  
[https://doi.org/10.1007/978-3-319-16999-6\\_1-1](https://doi.org/10.1007/978-3-319-16999-6_1-1)
- Conroy-Beam, D., & Buss, D. M. (2017). Euclidean distances discriminatively predict short-term and long-term attraction to potential mates. *Evolution and Human Behavior*, 38(4), 442–450. <https://doi.org/10.1016/j.evolhumbehav.2017.04.004>
- Crowley, K., & Siegler, R. S. (1993). Flexible strategy use in young children's Tic-Tac-Toe. *Cognitive Science*, 17(4), 531–561.  
[https://doi.org/10.1207/s15516709cog1704\\_3](https://doi.org/10.1207/s15516709cog1704_3)
- Del Giudice, M. (2009a). Human reproductive strategies: An emerging synthesis? *Behavioral and Brain Sciences*, 32(01), 45–67.  
<https://doi.org/10.1017/S0140525X09000272>
- Del Giudice, M. (2009b). Sex, attachment, and the development of reproductive strategies. *Behavioral and Brain Sciences*, 32(1), 1–21.  
<https://doi.org/10.1017/S0140525X09000016>
- Del Giudice, M. (2016). The evolutionary future of psychopathology. *Current Opinion in Psychology*, 7, 44–50. <https://doi.org/10.1016/j.copsyc.2015.07.010>

- DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, 22(5), 1915–1953. <https://doi.org/10.1093/rfs/hhm075>
- Dieckmann, A., & Rieskamp, J. (2007). The influence of information redundancy on probabilistic inferences. *Memory and Cognition*, 35(7), 1801–1813. <https://doi.org/10.3758/BF03193511>
- DiMatteo, M. R., Giordani, P. J., Lepper, H. S., & Croghan, T. W. (2002). Patient adherence and medical treatment outcomes: A meta-analysis. *Medical Care*, 40(9), 794–811. <https://doi.org/10.1097/00005650-200209000-00009>
- Ellis, B. J., Figueredo, A. J., Brumbach, B. H., & Schlomer, G. L. (2009). *Fundamental dimensions of environmental risk: The impact of harsh versus unpredictable environments on the evolution and development of life history strategies* (Vol. 20). <https://doi.org/10.1007/s12110-009-9063-7>
- Ellis, B. J., Oldehinkel, A. J., & Nederhof, E. (2017). The adaptive calibration model of stress responsivity: An empirical test in the Tracking Adolescents' Individual Lives Survey study. *Development and Psychopathology*, 29(03), 1001–1021. <https://doi.org/10.1017/S0954579416000985>
- Ellis, B. J., & Symons, D. (1990). Sex differences in sexual fantasy: An evolutionary psychological approach. *Journal of Sex Research*, 27(4), 527–555.

- Engel, A. K., Friston, K. J., & Kragic, D. (Eds.). (2015). *The pragmatic turn: toward action-oriented views in cognitive science*. The MIT Press.
- Feldman, J. (2009). Bayes and the simplicity principle in perception. *Psychological Review*, *116*(4), 875–887. <https://doi.org/10.1037/a0017144>
- Feldman, J. (2012). Symbolic representation of probabilistic worlds. *Cognition*, *123*(1), 61–83. <https://doi.org/10.1016/j.cognition.2011.12.008>
- Feldman, J. (2013). Tuning your priors to the world. *Topics in Cognitive Science*, *5*(1), 13–34. <https://doi.org/10.1111/tops.12003>
- Feldman, J. (2017). What are the “true” statistics of the environment? *Cognitive Science*, *41*(7), 1871–1903. <https://doi.org/10.1111/cogs.12444>
- Fernandes, H. B. F., & Woodley, M. A. (2013). Strategic differentiation and integration among the 50 states of the USA. *Personality and Individual Differences*, *55*(8), 1000–1002. <https://doi.org/10.1016/j.paid.2013.07.463>
- Figueredo, A. J., Vásquez, G., Brumbach, B. H., Schneider, S. M. R., Sefcek, J. A., Tal, I. R., Jacobs, W. J. (2006). Consilience and Life History Theory: From genes to brain to reproductive strategy. *Developmental Review*, *26*(2), 243–275. <https://doi.org/10.1016/j.dr.2006.02.002>
- Figueredo, A. J., Vasquez, G., Brumbach, B. H., Sefcek, J. A., Kirsner, B. R., & Jacobs, W. J. (2005). The K-factor: Individual differences in life history strategy.

*Personality and Individual Differences*, 39(8), 1349–1360.

<https://doi.org/10.1016/j.paid.2005.06.009>

Figueredo, A. J., & Wolf, P. S. A. (2009). Assortative pairing and life history strategy.

*Human Nature*, 20(3), 317–330. <https://doi.org/10.1007/s12110-009-9068-2>

Figueredo, A. J., Woodley, M. A., Brown, S. D., & Ross, K. C. (2013). Multiple

successful tests of the Strategic Differentiation-Integration Effort (SD-IE)

hypothesis. *Journal of Social, Evolutionary, and Cultural Psychology*, 7(4), 361–

383. <https://doi.org/10.1037/h0099182>

Fraenkel, A. S., & Lichtenstein, D. (1981, July). Computing a perfect strategy for  $n \times n$

chess requires time exponential in  $n$ . In *International Colloquium on Automata,*

*Languages, and Programming* (pp. 278-293). Springer, Berlin, Heidelberg.

Frankenhuis, W. E., & de Weerth, C. (2013). Does early-life exposure to stress shape or

impair cognition? *Current Directions in Psychological Science*, 22(5), 407–412.

<https://doi.org/10.1177/0963721413484324>

Gangestad, S. W., & Simpson, J. A. (2000). The evolution of human mating: Trade-offs

and strategic pluralism. *Behavioral and Brain Sciences*, 23(4), 573–587.

<https://doi.org/10.1017/S0140525X0000337X>

Geher, G., & Miller, G. (Eds.). (2008). *Mating intelligence: Sex, relationships, and the*

*mind's reproductive system*. Erlbaum.

Geman, S., Bienenstock, E., & Doursat, R. (1992). Neural networks and the bias/variance dilemma. *Neural Computation*, 4(1), 1–58.

<https://doi.org/10.1162/neco.1992.4.1.1>

Ghalambor, C. K., McKAY, J. K., Carroll, S. P., & Reznick, D. N. (2007). Adaptive versus non-adaptive phenotypic plasticity and the potential for contemporary adaptation in new environments. *Functional Ecology*, 21(3), 394–407.

<https://doi.org/10.1111/j.1365-2435.2007.01283.x>

Gigerenzer, G. (2010). Moral satisficing: Rethinking moral behavior as bounded rationality. *Topics in Cognitive Science*, 2(3), 528–554.

<https://doi.org/10.1111/j.1756-8765.2010.01094.x>

Gigerenzer, G. (2018). The bias bias in behavioral economics. *Review of Behavioral Economics*, 5(3–4), 303–336. <https://doi.org/10.1561/105.00000092>

Gigerenzer, G., & Brighton, H. (2009). Homo Heuristicus: Why biased minds make better inferences. *Topics in Cognitive Science*, 1(1), 107–143.

<https://doi.org/10.1111/j.1756-8765.2008.01006.x>

Gigerenzer, G., & Gaissmaier, W. (2011). Heuristic decision making. *Annual Review of Psychology*, 62(1), 451–482. [https://doi.org/10.1146/annurev-psych-120709-](https://doi.org/10.1146/annurev-psych-120709-145346)

145346

- Gigerenzer, G., & Goldstein, D. G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*(4), 650–669.  
<https://doi.org/10.1037/0033-295X.103.4.650>
- Gigerenzer, G., Hoffrage, U., & Goldstein, D. G. (2008). Fast and frugal heuristics are plausible models of cognition: Reply to Dougherty, Franco-Watkins, and Thomas (2008). *Psychological Review*, *115*(1), 230–239. <https://doi.org/10.1037/0033-295X.115.1.230>
- Gigerenzer, G., & Murray, D. J. (2015). *Cognition as intuitive statistics*. Psychology Press.
- Goetz, C. D., & Meyer, K. B. (2017). Mate value Discrepancies, the Dark Triad and Relationship Satisfaction: a Euclidean distances Approach. *Evolutionary Psychological Science*, (2016). <https://doi.org/10.1007/s40806-017-0122-8>
- Gómez, J. M., Verdú, M., González-Megías, A., & Méndez, M. (2016). The phylogenetic roots of human lethal violence. *Nature*, *538*(7624), 233–237.  
<https://doi.org/10.1038/nature19758>
- Goodman, G. S., Quas, J. A., & Ogle, C. M. (2010). Child maltreatment and memory. *Annual Review of Psychology*, *61*(1), 325–351.  
<https://doi.org/10.1146/annurev.psych.093008.100403>
- Gouw, A. (2019). The CRISPR advent of Lulu and Nana. *Theology and Science*, *17*(1), 9–12. <https://doi.org/10.1080/14746700.2018.1557378>

- Griskevicius, V., Ackerman, J. M., Cantú, S. M., Delton, A. W., Robertson, T. E., Simpson, J. A., Thompson, M. E., & Tybur, J. M. (2013). When the economy falters, do people spend or save? Responses to resource scarcity depend on childhood environments. *Psychological Science, 24*(2), 197–205. <https://doi.org/10.1177/0956797612451471>
- Griskevicius, V., Delton, A. W., Robertson, T. E., & Tybur, J. M. (2011). Environmental contingency in life history strategies: The influence of mortality and socioeconomic status on reproductive timing. *Journal of Personality and Social Psychology, 100*(2), 241–254. <https://doi.org/10.1037/a0021082>
- Griskevicius, V., Tybur, J. M., Ackerman, J. M., Delton, A. W., Robertson, T. E., & White, A. E. (2012). The financial consequences of too many men: Sex ratio effects on saving, borrowing, and spending. *Journal of Personality and Social Psychology, 102*(1), 69–80. <https://doi.org/10.1037/a0024761>
- Griskevicius, V., Tybur, J. M., Sundie, J. M., Cialdini, R. B., Miller, G. F., & Kenrick, D. T. (2007). Blatant benevolence and conspicuous consumption: When romantic motives elicit strategic costly signals. *Journal of Personality and Social Psychology, 93*(1), 85–102. <https://doi.org/10.1037/0022-3514.93.1.85>
- Hall, J. A., Mast, M. S., & West, T. V. (2018). *The social psychology of perceiving others accurately*.
- Hastie, T., Tibshirani, R., & Friedman, Jerome. (2017). *The elements of statistical learning: Data mining, inference, and prediction* (Vol. 2). Publisher.

- Hertwig, R., Davis, J. N., & Sulloway, F. J. (2002). Parental investment: How an equity motive can produce inequality. *Psychological Bulletin*, *128*(5), 728–745.  
<https://doi.org/10.1037//0033-2909.128.5.728>
- Hirsh, J. B., Mar, R. A., & Peterson, J. B. (2012). Psychological entropy: A framework for understanding uncertainty-related anxiety. *Psychological Review*, *119*(2), 304–320. <https://doi.org/10.1037/a0026767>
- Hogarth, R. M., & Karelaia, N. (2007). Heuristic and linear models of judgment: Matching rules and environments. *Psychological Review*, *114*(3), 733–758.  
<https://doi.org/10.1037/0033-295X.114.3.733>
- Hozo, I., Djulbegovic, B., Luan, S., Tsalatsanis, A., & Gigerenzer, G. (2017). Towards theory integration: Threshold model as a link between signal detection theory, fast-and-frugal trees and evidence accumulation theory. *Journal of Evaluation in Clinical Practice*, *23*(1), 49–65. <https://doi.org/10.1111/jep.12490>
- Hutchinson, J. M. C., & Gigerenzer, G. (2005). Simple heuristics and rules of thumb: Where psychologists and behavioural biologists might meet. *Behavioural Processes*, *69*(2), 97–124. <https://doi.org/10.1016/j.beproc.2005.02.019>
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (Eds.). (2013). *An introduction to statistical learning: with applications in R*. New York: Springer.
- Jones, B. C., Little, A. C., Penton-Voak, I. S., Tiddeman, B. P., Burt, D. M., & Perrett, D. I. (2001). Facial symmetry and judgements of apparent health support for a

“good genes” explanation of the attractiveness–symmetry relationship.  
*Evolution and Human Behavior*, 22(6), 417-429.

Jussim, L. (2012). *Social perception and social reality: Why accuracy dominates bias and self-fulfilling prophecy*. OUP USA.

Kahneman, D. (2011). *Thinking, fast and slow*. <https://doi.org/10.1007/s13398-014-0173-7.2>

Kaplan, H., Hill, K., Lancaster, J., & Hurtado, A. M. (2000). A theory of human life history evolution: Diet, intelligence, and longevity. *Evolutionary Anthropology: Issues, News, and Reviews*, 9(4), 156–185.

Kaplan, H., Lancaster, J., & Robson, A. (2003). Embodied capital and the evolutionary economics of the human life span. *Population and Development Review*, 29, 152-182.

Kaplan, H. S., & Lancaster, J. B. (2003). An evolutionary and ecological analysis of human fertility, mating patterns, and parental investment. In *Offspring: Human fertility behavior in biodemographic perspective*, National Academies Press.

Karter, A. J., Parker, M. M., Moffet, H. H., Ahmed, A. T., Ferrara, A., Liu, J. Y., & Selby, J. V. (2004). Missed appointments and poor glycemic control: An opportunity to identify high-risk diabetic patients. *Medical Care*, 42(2), 110–115.

- Katz, S. J., & Hofer, T. P. (1994). Socioeconomic disparities in preventive care persist despite universal coverage: Breast and cervical cancer screening in Ontario and the United States. *Jama*, *272*(7), 530–534.
- Kauffman, S., & Levin, S. (1987). Towards a general theory of adaptive walks on rugged landscapes. *Journal of Theoretical Biology*, *128*(1), 11–45.  
[https://doi.org/10.1016/S0022-5193\(87\)80029-2](https://doi.org/10.1016/S0022-5193(87)80029-2)
- Kavanagh, P. S. (2007). *Social exclusion, self-esteem, & mating relationships: Testing a domain-specific variant of sociometer theory*. Retrieved from  
<http://hdl.handle.net/10092/4084>
- Kim, J., Sorhaindo, B., & Garman, E. T. (2006). Relationship between financial stress and workplace absenteeism of credit counseling clients. *Journal of Family and Economic Issues*, *27*(3), 458–478. <https://doi.org/10.1007/s10834-006-9024-9>
- Krakauer, D. (April, 2015). The systems theorist explains what's wrong with standard models of intelligence. <http://nautil.us/issue/23/dominoes/ingenious-david-krakauer>
- Krueger, J. I., & Funder, D. C. (2004). Towards a balanced social psychology: Causes, consequences, and cures for the problem-seeking approach to social behavior and cognition. *Behavioral and Brain Sciences*, *27*(03), 313–327.  
<https://doi.org/10.1017/S0140525X04000081>

- Krupp, D. B. (2012). Marital, reproductive, and educational behaviors covary with life expectancy. *Archives of Sexual Behavior, 41*(6), 1409–1414.  
<https://doi.org/10.1007/s10508-012-9949-z>
- Leary, M. R. (1999). Making sense of self-esteem. *Current Directions in Psychological Science, 8*(1), 32–35. <https://doi.org/10.1111/1467-8721.00008>
- Li, N. P., Kenrick, D. T., Bailey, J. M., & Linsenmeier, J. A. W. (2002). The necessities and luxuries of mate preferences: Testing the tradeoffs. *Journal of Personality and Social Psychology, 82*(6), 947–955. <https://doi.org/10.1037//0022-3514.82.6.947>
- Li, N. P., Valentine, K. A., & Patel, L. (2011). Mate preferences in the US and Singapore: A cross-cultural test of the mate preference priority model. *Personality and Individual Differences, 50*(2), 291–294.  
<https://doi.org/10.1016/j.paid.2010.10.005>
- MacArthur, R. H., & Wilson, E. O. (2001). *The theory of island biogeography*. Princeton University Press.
- Makridakis, S., Andersen, A., Carbone, R., Fildes, R., Hibon, M., Lewandowski, R., Winkler, R. (1982). The accuracy of extrapolation (time series) methods: Results of a forecasting competition. *Journal of Forecasting, 1*(2), 111–153.  
<https://doi.org/10.1002/for.3980010202>

- Makridakis, S. (1993). Accuracy measures: theoretical and practical concerns. *International Journal of Forecasting*, 9(4), 527–529.
- Makridakis, S., & Hibon, M. (2000). The M3-Competition: Results, conclusions and implications. *International Journal of Forecasting*, 16(4), 451–476.  
[https://doi.org/10.1016/S0169-2070\(00\)00057-1](https://doi.org/10.1016/S0169-2070(00)00057-1)
- Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). The M4 Competition: Results, findings, conclusion and way forward. *International Journal of Forecasting*, 34(4), 802–808. <https://doi.org/10.1016/j.ijforecast.2018.06.001>
- Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013a). Poverty impedes cognitive function. *Science*, 341(6149), 976–980. <https://doi.org/10.1126/science.1238041>
- Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013b). Response to comment on “Poverty impedes cognitive function.” *Science*, 342(6163), 1169–1169.  
<https://doi.org/10.1126/science.1246799>
- Martignon, L., & Hoffrage, U. (2011). *Fast, frugal, and fit: Simple heuristics for paired comparison*. <https://doi.org/10.1093/acprof:oso/9780199744282.001.0001>
- Matthews, K. A., Räikkönen, K., Gallo, L., & Kuller, L. H. (2008). Association between socioeconomic status and metabolic syndrome in women: Testing the reserve capacity model. *Health Psychology*, 27(5), 576–583.  
<https://doi.org/10.1037/0278-6133.27.5.576>

- McDowell, M., Galesic, M., & Gigerenzer, G. (2018). Natural frequencies do foster public understanding of medical tests: Comment on Pighin, Gonzalez, Savadori, and Girotto (2016). *Medical Decision Making*, *38*(3), 390–399. <https://doi.org/10.1177/0272989X18754508>
- McLoyd, V. C. (1998). Socioeconomic disadvantage and child development. *American Psychologist*, *20*.
- Menkhorst, P., & Knight, F. (2001). *A field guide to the mammals of Australia*. Retrieved from <http://agris.fao.org/agris-search/search.do?recordID=US201300067572>
- Migliano, A. B., Vinicius, L., & Lahr, M. M. (2007). Life history trade-offs explain the evolution of human pygmies. *Proceedings of the National Academy of Sciences*, *104*(51), 20216–20219.
- Miller, G. F., & Todd, P. M. (1998). Mate choice turns cognitive. *Trends in Cognitive Sciences*, *2*(5), 190–198. [https://doi.org/10.1016/S1364-6613\(98\)01169-3](https://doi.org/10.1016/S1364-6613(98)01169-3)
- Mittal, C., Griskevicius, V., Simpson, J. A., Sung, S., & Young, E. S. (2015). Cognitive adaptations to stressful environments: When childhood adversity enhances adult executive function. *Journal of Personality and Social Psychology*, *109*(4), 604–621. <https://doi.org/10.1037/pspi0000028>
- Mustonen, V., & Lässig, M. (2009). From fitness landscapes to seascapes: Non-equilibrium dynamics of selection and adaptation. *Trends in Genetics*, *25*(3), 111–119. <https://doi.org/10.1016/j.tig.2009.01.002>

- Neal, R. D., Lawlor, D. A., Allgar, V., Colledge, M., Ali, S., Hassey, A., & Wilson, A. (2001). Missed appointments in general practice: Retrospective data analysis from four practices. *British Journal of General Practice*, 3. Coordinates?
- Neel, R., Kenrick, D. T., White, A. E., & Neuberg, S. L. (2016). Individual differences in fundamental social motives. *Journal of Personality and Social Psychology*, 110(6), 887–907. <https://doi.org/10.1037/pspp0000068>
- Newell, B. R., & Shanks, D. R. (2003). Take the best or look at the rest? Factors influencing “one-reason” decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 29(1), 53–65. <https://doi.org/10.1037/0278-7393.29.1.53>
- O’Donnell, K., Brydon, L., Wright, C. E., & Steptoe, A. (2008). Self-esteem levels and cardiovascular and inflammatory responses to acute stress. *Brain, Behavior, and Immunity*, 22(8), 1241–1247. <https://doi.org/10.1016/j.bbi.2008.06.012>
- Penke, L., Denissen, J. J., & Miller, G. F. (2007). The evolutionary genetics of personality. *European Journal of Personality: Published for the European Association of Personality Psychology*, 21(5), 549-587.
- Penke, L., & Jokela, M. (2016). The evolutionary genetics of personality revisited. *Current Opinion in Psychology*, 7, 104–109. <https://doi.org/10.1016/j.copsyc.2015.08.021>

- Pepper, G. V., & Nettle, D. (2017). The behavioural constellation of deprivation: Causes and consequences. *Behavioral and Brain Sciences*. ??  
<https://doi.org/10.1017/S0140525X1600234X>
- Petrie, M., & Halliday, T. (1994). Experimental and natural changes in the peacock's (*Pavo cristatus*) train can affect mating success. *Behavioral Ecology and Sociobiology*, *35*(3), 213–217. <https://doi.org/10.1007/BF00167962>
- Pinker, S. (2011). *The better angels of our nature: Why violence has declined*. Penguin Books.
- Plomin, R., DeFries, J. C., Knopik, V. S., & Neiderhiser, J. M. (2016). Top 10 replicated findings from behavioral genetics. *Perspectives on Psychological Science*, *11*(1), 3–23. <https://doi.org/10.1177/1745691615617439>
- Pollak, S. D. (2008). Mechanisms linking early experience and the emergence of emotions: Illustrations from the study of maltreated children. *Current Directions in Psychological Science*, *17*(6), 370–375. <https://doi.org/10.1111/j.1467-8721.2008.00608.x>
- Pollak, S. D., Messner, M., Kistler, D. J., & Cohn, J. F. (2009). Development of perceptual expertise in emotion recognition. *Cognition*, *110*(2), 242–247. <https://doi.org/10.1016/j.cognition.2008.10.010>
- Prokosch, M. D., Yeo, R. A., & Miller, G. F. (2005). Intelligence tests with higher g-loadings show higher correlations with body symmetry: Evidence for a general

fitness factor mediated by developmental stability. *Intelligence*, 33(2), 203–213.  
<https://doi.org/10.1016/j.intell.2004.07.007>

Promislow, D. E. L., & Harvey, P. H. (1990). Living fast and dying young: A comparative analysis of life-history variation among mammals. *Journal of Zoology*, 220(3), 417–437. <https://doi.org/10.1111/j.1469-7998.1990.tb04316.x>

Reznick, D., Bryant, M. J., & Bashey, F. (2002). r-and K-selection revisited: The role of population regulation in life-history evolution. *Ecology*, 83(6), 1509-1520.

Reznick, D. N. (2005). Selection in nature: Experimental manipulations of natural populations. *Integrative and Comparative Biology*, 45(3), 456–462.  
<https://doi.org/10.1093/icb/45.3.456>

Rieskamp, J., & Otto, P. E. (2006). SSL: A theory of how people learn to select strategies. *Journal of Experimental Psychology: General*, 135(2), 207–236.  
<https://doi.org/10.1037/0096-3445.135.2.207>

Robinson, M. R., Kleinman, A., Graff, M., Vinkhuyzen, A. A., Couper, D., Miller, M. B., & van Vliet-Ostapchouk, J. V. (2017). Genetic evidence of assortative mating in humans. *Nature Human Behaviour*, 1(1), 1-13.

Ross, L. T., & Hill, E. M. (2000). The family unpredictability scale: Reliability and validity. *Journal of Marriage and Family*, 62(2), 549-562.

Ross, L. T., & Hill, E. M. (2002). Childhood unpredictability, schemas for unpredictability, and risk taking. *Social Behavior and Personality*, 30(5), 453-473.

- Ross, L. T., & McDuff, J. A. (2008). The retrospective family unpredictability scale: Reliability and validity. *Journal of Child and Family Studies, 17*(1), 13-27.
- Sapolsky, R. M. (2004). *Why zebras don't get ulcers: The acclaimed guide to stress, stress-related diseases, and coping-now revised and updated*. Holt Paperbacks.
- Sapolsky, R. M. (2005). The Influence of social hierarchy on primate health. *Science, 308*(5722), 648–652. <https://doi.org/10.1126/science.1106477>
- Schaller, M. (2008). Evolutionary bases of first impressions. In *First Impressions* (pp. 15–35). Guilford Press.
- Schlegel, K., Boone, R. T., & Hall, J. A. (2017). Individual differences in interpersonal accuracy: A multi-level meta-analysis to assess whether judging other people is one skill or many. *Journal of Nonverbal Behavior, 41*(2), 103–137. <https://doi.org/10.1007/s10919-017-0249-0>
- Schmitt, D. P. (2003a). Are men universally more dismissing than women? Gender differences in romantic attachment across 62 cultural regions. *Personal Relationships, 10*(3), 307–331.
- Schmitt, D. P. (2003b). Universal sex differences in the desire for sexual variety: Tests from 52 nations, 6 continents, and 13 islands. *Journal of Personality and Social Psychology, 85*(1), 85-104.
- Schmitt, D. P. (2015). The evolution of culturally-variable sex differences: Men and women are not always different, but when they are...it appears not to result from

patriarchy or sex role socialization. In T. K. Shackelford & R. D. Hansen (Eds.), *The Evolution of sexuality* (pp. 221–256). Springer. [https://doi.org/10.1007/978-3-319-09384-0\\_11](https://doi.org/10.1007/978-3-319-09384-0_11)

Schmittlein, D. C., & Peterson, R. A. (1994). Customer base analysis: An industrial purchase process application. *Marketing Science*, *13*(1), 41–67. <https://doi.org/10.1287/mksc.13.1.41>

Sherman, R. A., Figueredo, A. J., & Funder, D. C. (2013). The behavioral correlates of overall and distinctive life history strategy. *Journal of Personality and Social Psychology*, *105*(5), 873–888. <https://doi.org/10.1037/a0033772>

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological review*, *63*(2), 129.

Simon, H. (1990). *Reason in Human Affairs*. Stanford University Press.

Simpson, J. A., Griskevicius, V., Kuo, S. I.-C., Sung, S., & Collins, W. A. (2012). Evolution, stress, and sensitive periods: The influence of unpredictability in early versus late childhood on sex and risky behavior. *Developmental Psychology*, *48*(3), 674–686. <https://doi.org/10.1037/a0027293>

Smith, J. D. (2014). Prototypes, exemplars, and the natural history of categorization. *Psychonomic Bulletin & Review*, *21*(2), 312–331. <https://doi.org/10.3758/s13423-013-0506-0>

- Spears, D. (2011). Economic decision-making in poverty depletes behavioral control. *The B.E. Journal of Economic Analysis & Policy*, *11*(1). <https://doi.org/10.2202/1935-1682.2973>
- Stearns, S. C. (1989). Trade-offs in life-history evolution. *Functional Ecology*, *3*(3), 259. <https://doi.org/10.2307/2389364>
- Stearns, S. C. (1992). *The evolution of life histories*. Oxford University Press.
- Stone, E. A., Shackelford, T. K., & Buss, D. M. (2012). Is variability in mate choice similar for intelligence and personality traits? Testing a hypothesis about the evolutionary genetics of personality. *Intelligence*, *40*(1), 33–37. <https://doi.org/10.1016/j.intell.2011.10.003>
- Strouts, P. H., Brase, G. L., & Dillon, H. M. (2017). Personality and evolutionary strategies: The relationships between HEXACO traits, mate value, life history strategy, and sociosexuality. *Personality and Individual Differences*, *115*, 128–132. <https://doi.org/10.1016/j.paid.2016.03.047>
- Stulp, G., Simons, M. J. P., Grasman, S., & Pollet, T. V. (2017). Assortative mating for human height: A meta-analysis. *American Journal of Human Biology*, *29*(1), e22917. <https://doi.org/10.1002/ajhb.22917>
- Sznycer, D., Cosmides, L., & Tooby, J. (2017). Adaptationism carves emotions at their functional joints. *Psychological Inquiry*, *28*(1), 56–62. <https://doi.org/10.1080/1047840X.2017.1256132>

- Todd, P. M., Penke, L., Fasolo, B., & Lenton, A. P. (2007). Different cognitive processes underlie human mate choices and mate preferences. *Proceedings of the National Academy of Sciences, 104*(38), 15011–15016. <https://doi.org/10.1073/pnas.0705290104>
- Todd, P. M., & Gigerenzer, G. (2011). What is ecological rationality? In *Ecological Rationality: Intelligence in the World*. Oxford University Press.
- Tooby, J., & Cosmides, L. (1990). The past explains the present. *Ethology and Sociobiology, 11*(4–5), 375–424. [https://doi.org/10.1016/0162-3095\(90\)90017-Z](https://doi.org/10.1016/0162-3095(90)90017-Z)
- Tooby, J., & Cosmides, L. (2015). The theoretical foundations of evolutionary psychology. In *The Handbook of Evolutionary Psychology: I. Foundations (2nd ed., pp. 3-87)*. Wiley.
- Trivers, R. (1972). Parental investment and sexual selection. In *Sexual selection & the descent of man* (136–179). Transaction Publishers.
- Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124–1131. <https://doi.org/10.1126/science.185.4157.1124>
- Tyndale-Biscoe, C. H. (2005). *Life of marsupials*. Csiro Publishing.
- Ubel, P. A., Loewenstein, G., & Jepson, C. (2005). Disability and sunshine: Can hedonic predictions be improved by drawing attention to focusing illusions or emotional adaptation? *Journal of Experimental Psychology: Applied, 11*(2), 111–123. <https://doi.org/10.1037/1076-898X.11.2.111>

- Ubel, P. A., Loewenstein, G., Schwarz, N., & Smith, D. (2005). Misimagining the unimaginable: The disability paradox and health care decision making. *Health Psychology, 24*(4S), S57–S62. <https://doi.org/10.1037/0278-6133.24.4.S57>
- van Prooijen, J. W., Douglas, K. M., & De Inocencio, C. (2018). Connecting the dots: Illusory pattern perception predicts belief in conspiracies and the supernatural. *European Journal of Social Psychology, 48*(3), 320-335. <https://doi.org/10.1002/ejsp.2331>
- Vandenberg, S. G. (1972). Assortative mating, or who marries whom? *Behavior Genetics, 2*(2–3), 127–157. <https://doi.org/10.1007/BF01065686>
- Verhage, M. L., Schuengel, C., Madigan, S., Fearon, R. M. P., Oosterman, M., Cassibba, R., van IJzendoorn, M. H. (2016). Narrowing the transmission gap: A synthesis of three decades of research on intergenerational transmission of attachment. *Psychological Bulletin, 142*(4), 337–366. <https://doi.org/10.1037/bul0000038>
- Weber, E. U., & Johnson, E. J. (2009). Mindful judgment and decision making. *Annual Review of Psychology, 60*(1), 53–85. <https://doi.org/10.1146/annurev.psych.60.110707.163633>
- West-Eberhard, M. J. (2003). *Developmental plasticity and evolution*. Oxford University Press.
- Wiederman, M. W. (1997). Extramarital sex: Prevalence and correlates in a national survey. *Journal of Sex Research, 34*(2), 167–174.

- Woodley, M. A., & Fernandes, H. B. F. (2014). Strategic and cognitive differentiation-integration effort in a study of 76 countries. *Personality and Individual Differences, 57*, 3–7. <https://doi.org/10.1016/j.paid.2013.09.010>
- Wright, S. (1932). The roles of mutation, inbreeding, crossbreeding, and selection in evolution. *Proceedings of the Sixth International Congress on Genetics, 1*(8), 355–366.
- Wübben, M., & Wangenheim, Florian. (2008). Instant customer base analysis: Managerial heuristics often “get it right.” *Journal of Marketing, 72*, 13-xx.
- Young, E. S. (2017). Can an unpredictable childhood environment enhance working memory? Testing the sensitized-specialization hypothesis. [Unpublished master’s thesis]. University of Minnesota
- Young, E. S., Simpson, J. A., Giskevicius, V., Huelsnitz, C. O., & Fleck, C. (2017). Childhood attachment and adult personality: A life history perspective. *Self and Identity, 8868*(July), 1–17. <https://doi.org/10.1080/15298868.2017.1353540>
- Zahid, H. J., Robinson, E., & Kelly, R. L. (2016). Agriculture, population growth, and statistical analysis of the radiocarbon record. *Proceedings of the National Academy of Sciences, 113*(4), 931–935. <https://doi.org/10.1073/pnas.1517650112>
- Zietsch, B. P. (2016). Individual differences as the output of evolved calibration mechanisms: Does the theory make sense in view of empirical observations? *Current Opinion in Psychology, 7*, 71–75.

<https://doi.org/10.1016/j.copsyc.2015.08.014>

**Tables**

Table 1  
*Summary of Trait Importance Ratings (Pilot 1)*

Trait	<i>N</i>	<i>M</i>	<i>SD</i>
Qualified and Included			
Dependability	168	6.46	0.82
Openness	169	6.11	1.04
Intelligence	76 <sup>a</sup>	6.04	1.04
Patience	168	5.91	1.10
Aggression	169	5.60	1.65
Desire for Children	169	5.58	1.74
Attractiveness	169	5.05	1.33
Education Level	169	4.85	1.51
Political Beliefs	169	4.79	1.74
Introversion	169	4.49	1.60
Religiosity	169	4.47	2.09
Creativity	168	4.38	1.57
Income	168	3.83	1.57
Qualified and Excluded			
Trustworthiness	168	6.68	0.68
Mutual Attraction	169	6.50	0.76
Kindness	168	6.38	0.85
Honesty	169	6.36	0.88
Sense of Humor	169	6.20	1.12
Neuroticism	168	6.15	1.19
Greediness	168	5.80	1.41
Ambition	169	5.47	1.21
Healthiness	169	5.19	1.35
Confidence	169	5.17	1.37
Dominance	169	4.56	1.65
Unusual Talents	168	3.74	1.59
Formidability	169	3.58	1.60
Number of Sexual Partners	168	3.53	1.85
Height	169	3.08	1.57
Social Status	169	2.88	1.57
Not Qualified			
Exciting Personality	169	4.93	1.47
Age	168	4.70	1.47

<sup>a</sup> Intelligence was added to the list of traits after data collection began.

Table 2  
*Summary of Trait Values of Ideal Mates (Pilot 2)*

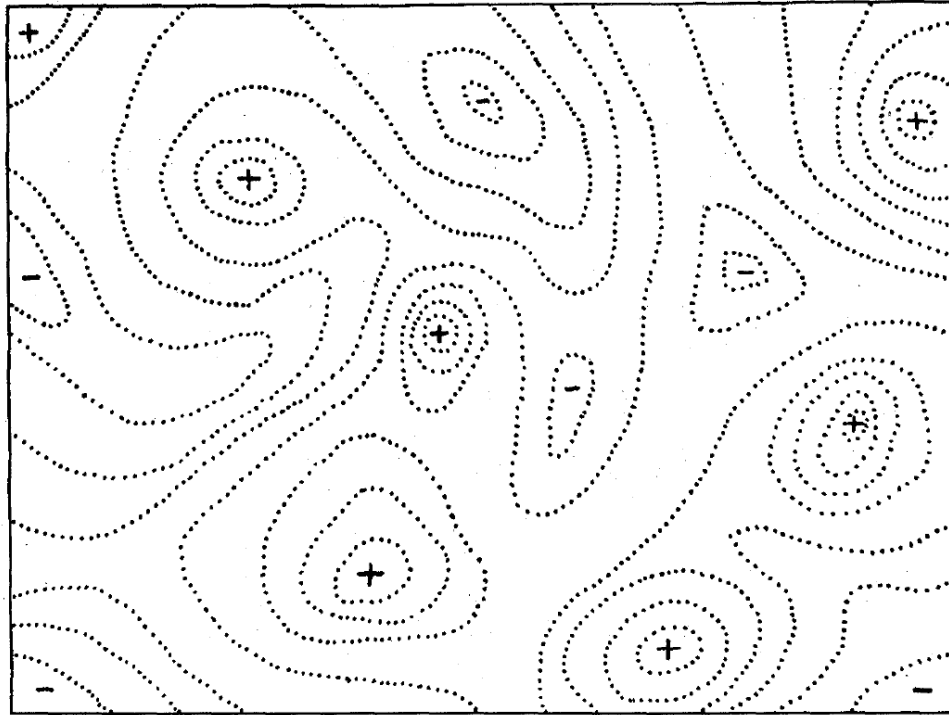
	Men		Women		<i>t</i>	<i>p</i>	<i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>			
Income	4.833	2.451	6.186	1.928	7.304	<0.001	0.635
Dependability	8.046	2.044	8.901	1.679	5.411	<0.001	0.470
Similar Political Beliefs	5.574	2.739	6.754	2.606	5.125	<0.001	0.445
Patience	7.570	1.660	8.223	1.532	3.477	0.001	0.414
Attractiveness	7.300	1.945	6.616	1.819	-4.225	<0.001	-0.367
Aggression	2.140	1.861	1.560	1.824	-2.660	0.008	-0.317
Desire for Children	4.569	3.252	5.586	3.580	3.388	0.001	0.294
Creativity	6.991	2.012	6.457	2.243	-2.083	0.038	-0.248
Religiosity	2.929	3.004	3.607	3.478	2.361	0.019	0.205
Intelligence	7.949	1.580	8.195	1.509	1.847	0.065	0.160
Education	6.533	2.002	6.811	2.015	1.168	0.244	0.139
Assertiveness	5.919	1.894	6.153	1.910	1.420	0.156	0.123
Openness	7.904	1.806	8.027	1.850	0.776	0.438	0.068
Extraversion	4.919	2.342	5.054	2.101	0.711	0.477	0.062

Table 3

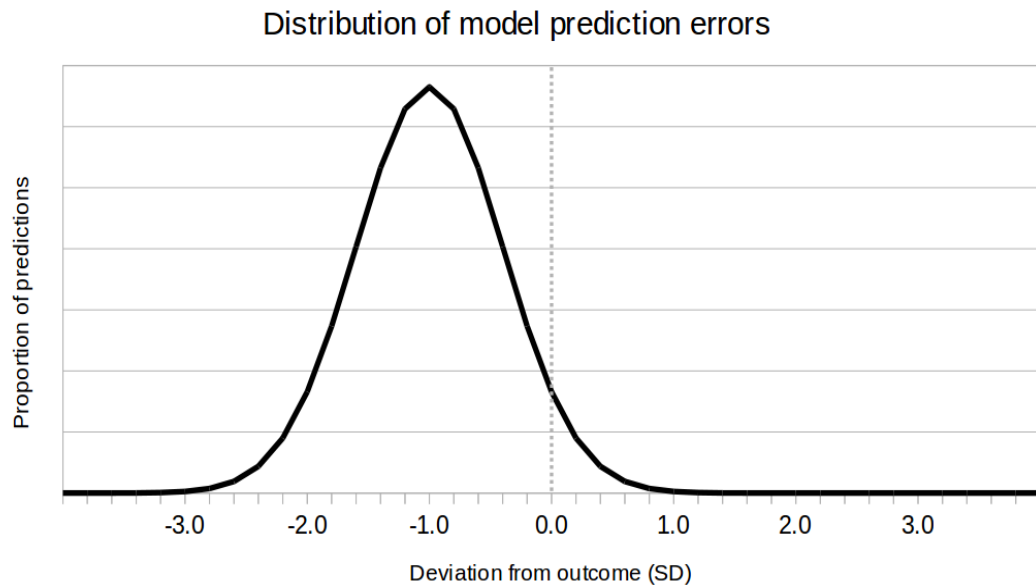
*Sample Characteristics for Main Study*

	Men	Women	All
<i>n</i>	525	520	1035
Mean Age ( <i>SD</i> )	35.8 (12.1)	41.3 (14.9)	38.5 (13.8)
% White	67.6	69.6	68.6
% With College Degree	50.7	49.8	50.2

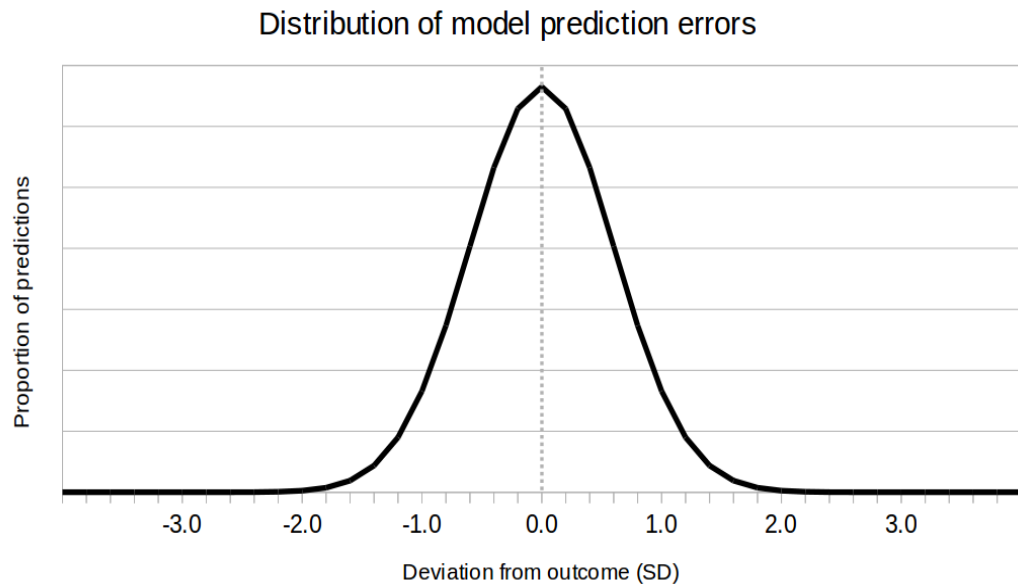
## Figures



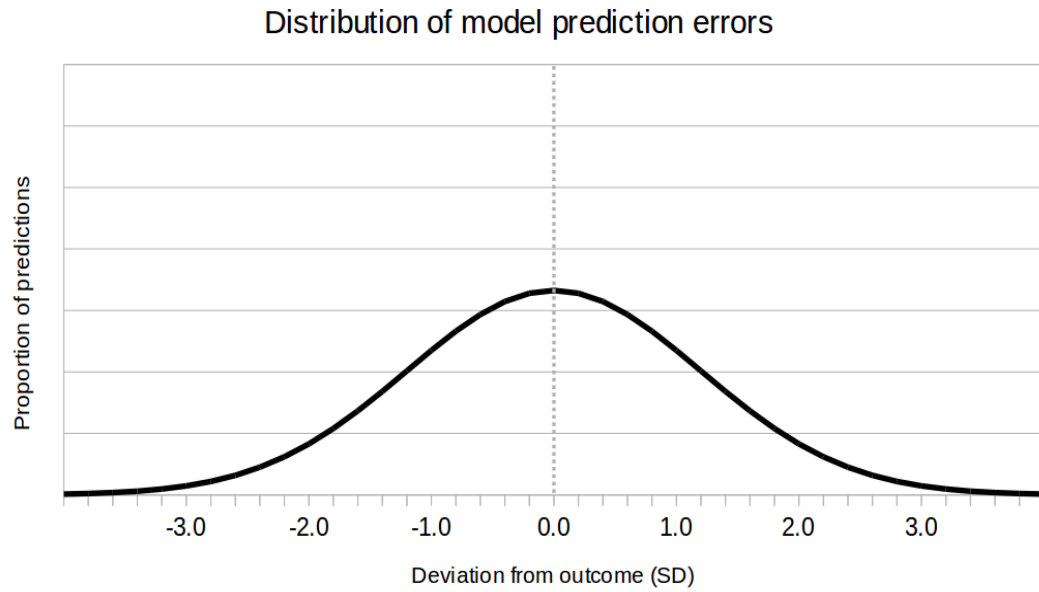
*Figure 1.* This image (Wright, 1932) illustrates how different agents or populations can use decision strategies that are both different and adaptive. The horizontal and vertical axes represent different values for a two-parameter decision strategy and the contours represent differences in adaptiveness. The crosses represent adaptive “peaks” (highly adaptive combinations of parameters).



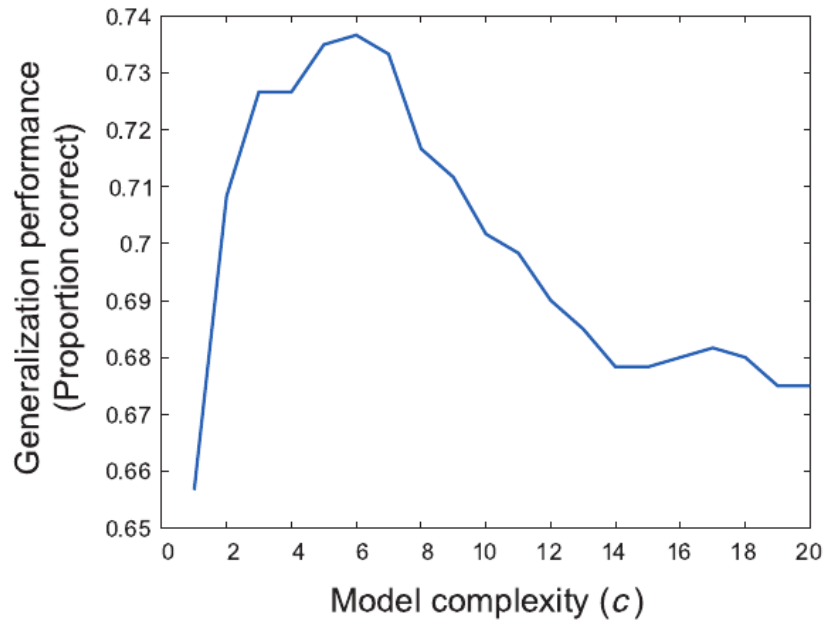
*Figure 2.* This is a biased model. It suffers from high error primarily due to systematic deviations from the outcome (dashed vertical line). Biased models tend to be oversimplified representations of the true relationships in the environment. The errors of biased models tend to result from a failure to account for true relationships in the environment.



*Figure 3.* A low-bias, low-variance model. As parameters reflecting true relationships are added to a biased model (e.g., Figure 2), the central tendency of the error distribution shifts toward zero and overall accuracy increases. This model accounts for more true relationships than the one depicted in Figure 2 and fewer spurious relationships than the model depicted in Figure 4.



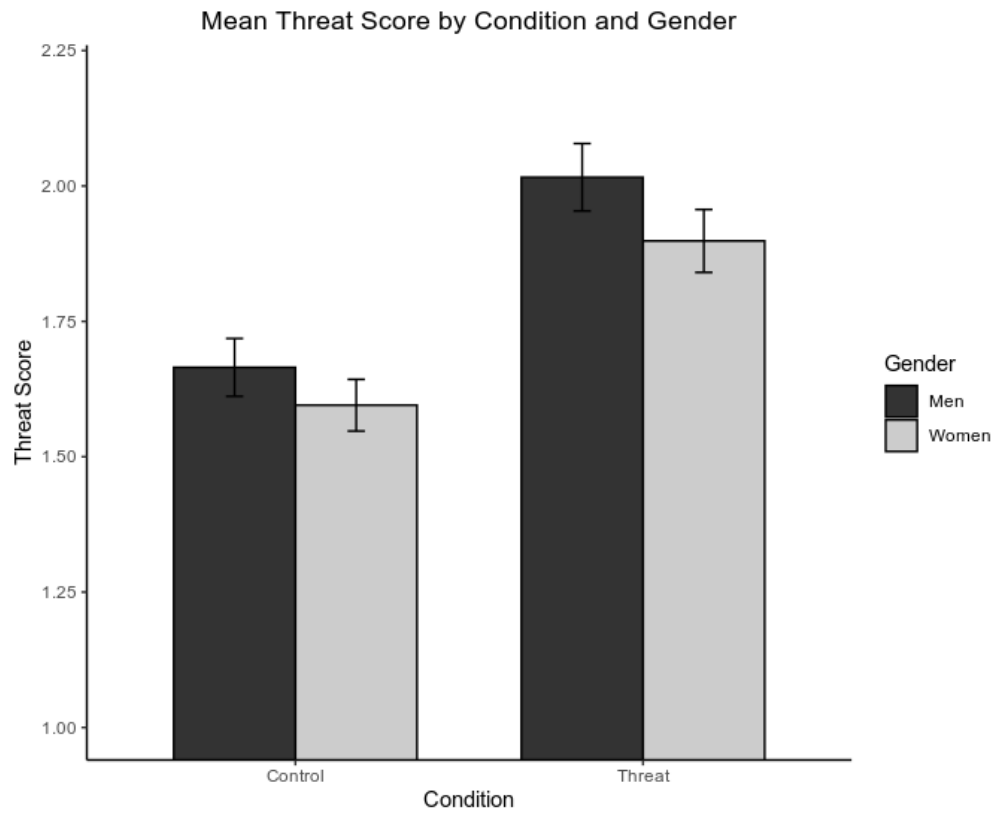
*Figure 4.* This model is unbiased, but it suffers from high variance. It accounts for the same true relationships as the model in Figure 3, but it also accounts for spurious relationships that were present in the training data. It is considered overly-complex.



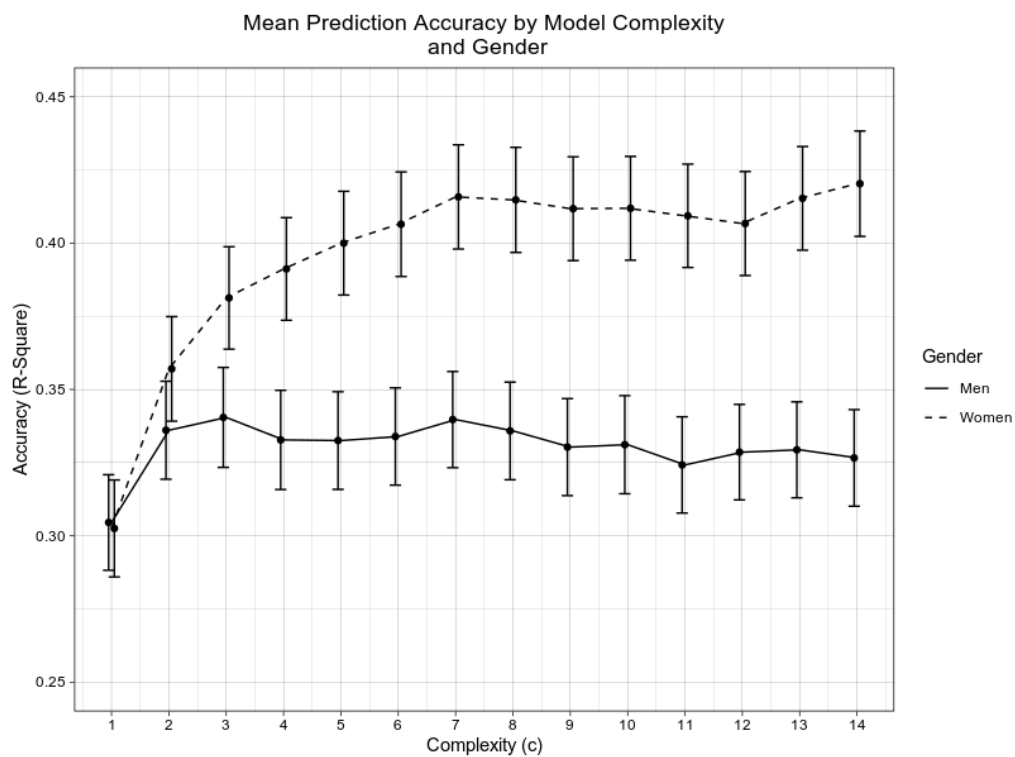
*Figure 5.* An example of the relationship between model complexity and accuracy in uncertain environments (Briscoe & Feldman, 2011). The peak of this curve for any given model depends on the structure of the environment in which it is used to make predictions, the information available to the perceiver (i.e., the training data), and how the model was trained.

Person A	Trait	Person B
5.3	Assertiveness	5.8
7.2	Patience	8.4
3.7	Extraversion	6.3
3.7	Creativity	7.8
7.9	Open-Mindedness	8.2
6.5	Similar Political Beliefs	9.5
5.9	Intelligence	5.7
7.8	Education Level	6.2
5.2	Desire for Children	0.4
6.8	Income	6.8
4.4	Aggression	1.7
4.4	Religiosity	9.7
7.4	Dependability	4.9
8.9	Attractiveness	4.4
Pair ID: 033707		

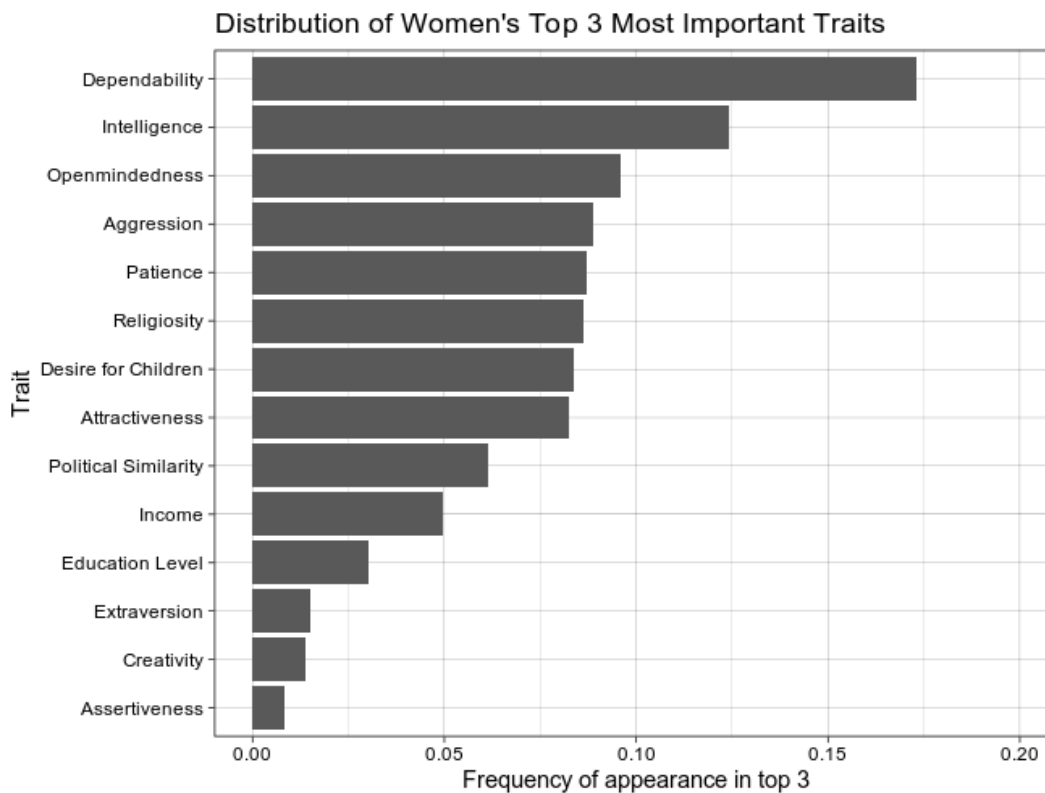
*Figure 6.* An example of a pair of potential mates shown to participants during the mate choice task.



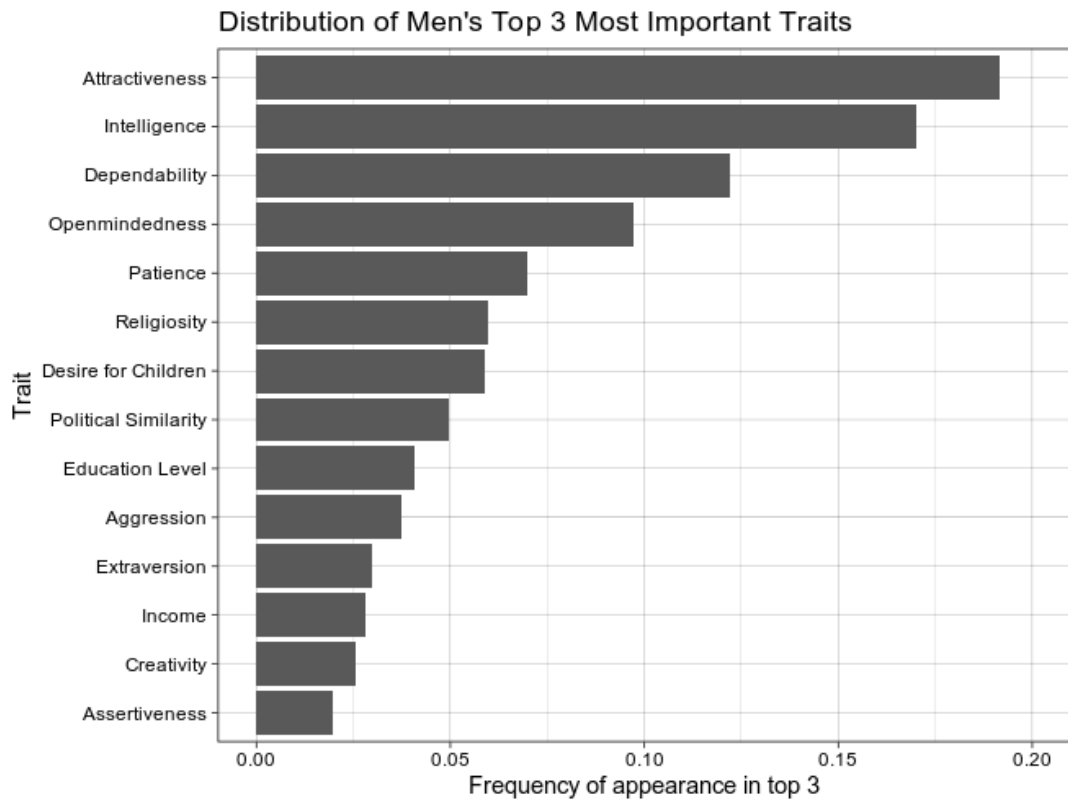
*Figure 7.* Results for the manipulation check. Participants in the threat condition reported significantly higher threat scores than those in the control condition. This effect was not moderated by gender. Error bars represent one standard error above and below the mean.



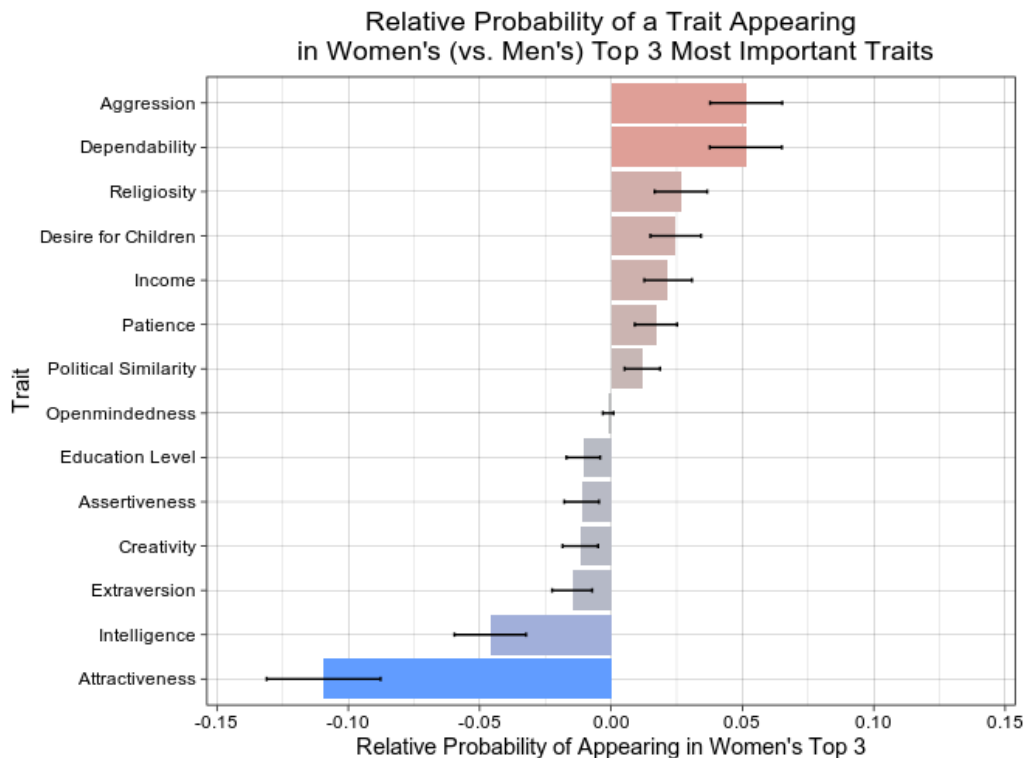
*Figure 8.* For each participant, a Euclidean model was built to predict their preferences based on their responses to the ideal mate scale. The average accuracy of Euclidean models at each level of complexity is shown above. For example, the R-square value for models using the three most important traits ( $c = 3$ ) is about 0.38 for women and 0.34 for men.



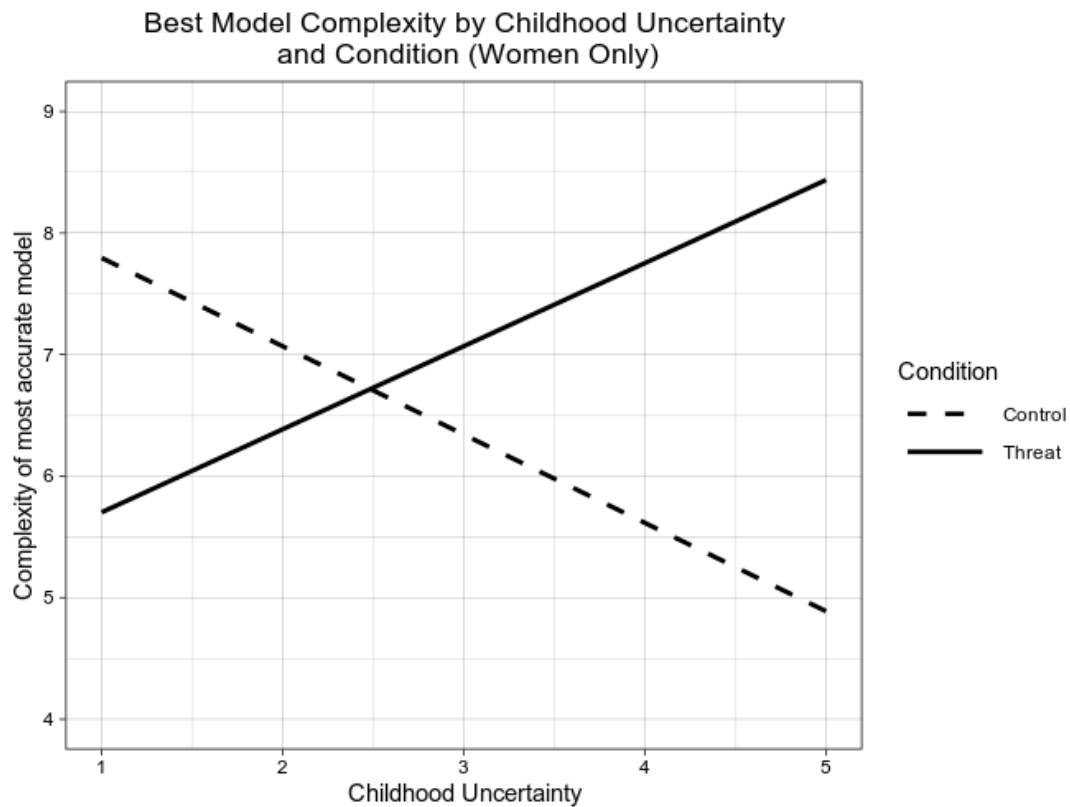
*Figure 9.* Summary of the frequency with which each trait appeared in one of the top three most important traits women reported using when judging potential mates collapsed across both experimental conditions. For example, about 17.5% of women chose dependability as either their first, second, or third most important trait when judging potential mates.



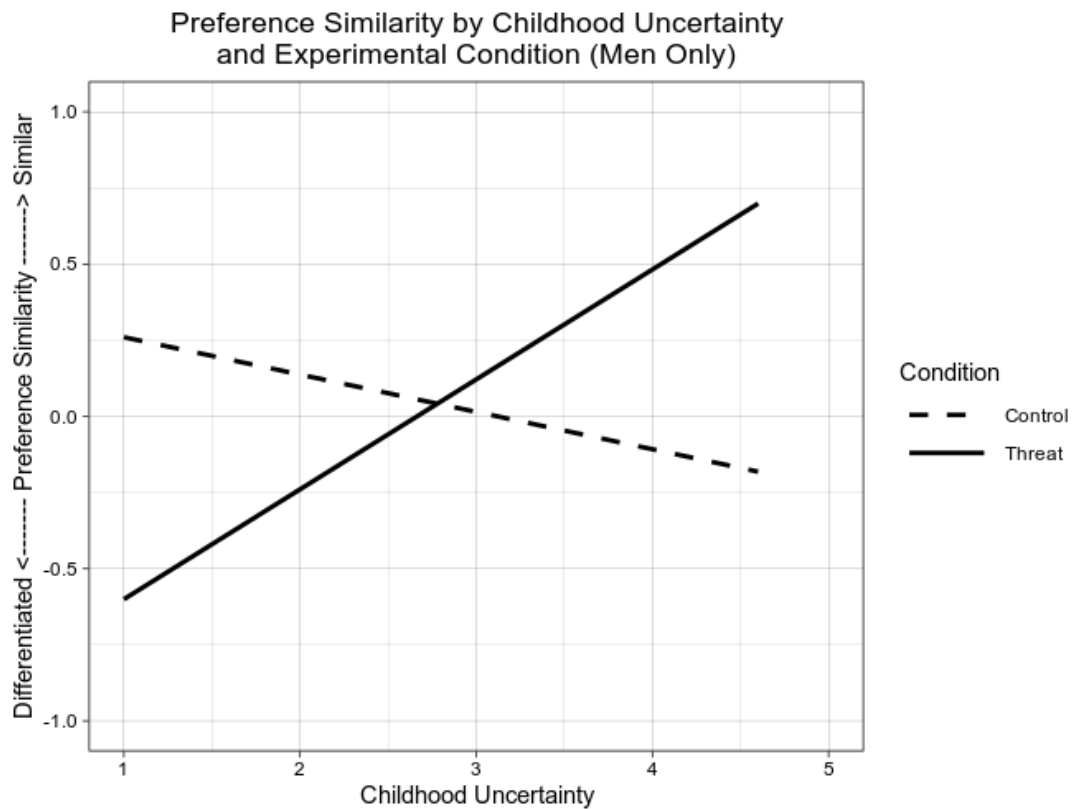
*Figure 10.* Summary of the frequency with which each trait appeared in one of the top three most important traits men reported using when judging potential mates collapsed across both experimental conditions. For example, about 19% of men chose attractiveness as either their first, second, or third most important trait when judging potential mates.



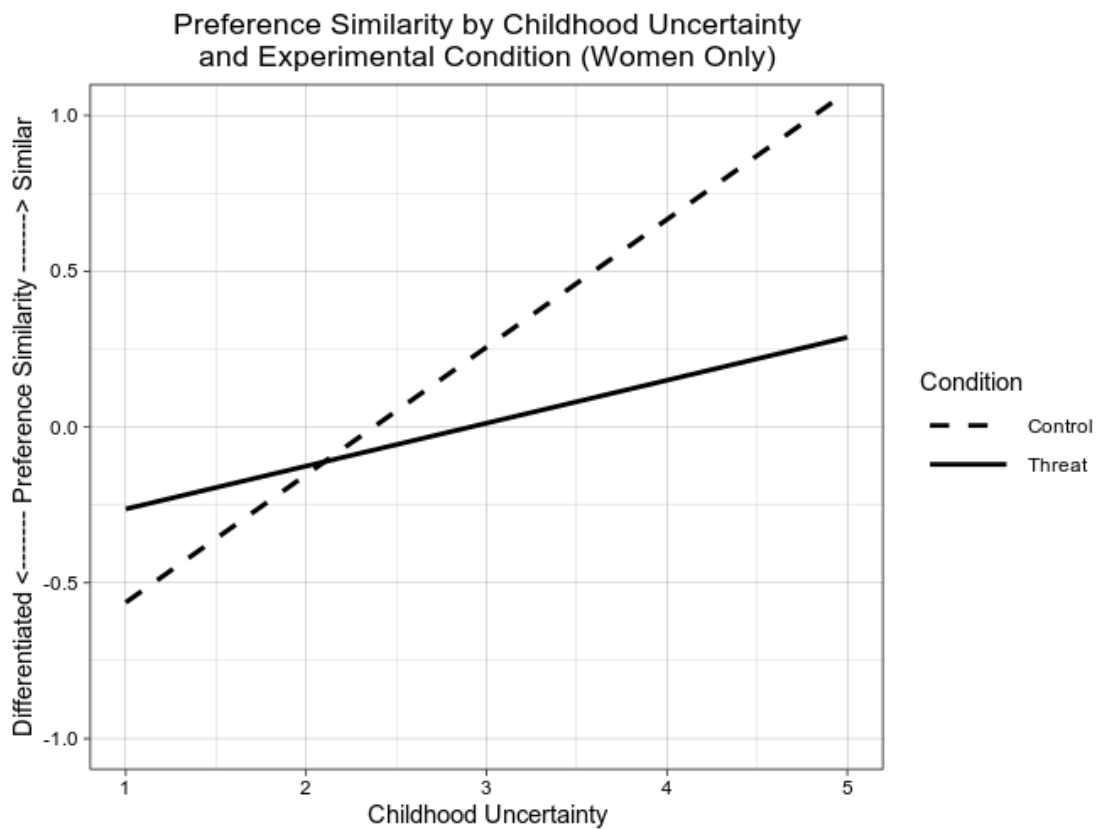
*Figure 11.* Summary of the *relative* frequency with which each trait appeared in one of the top three most important traits men and women reported using when judging potential mates. For example, Figure 14 shows that women chose aggression as one of the top three most important traits about 8% of the time whereas Figure 15 shows that men chose aggression about 3% of the time. That 5% difference in the probability of selecting a trait is summarized in this chart. One interpretation is that the pink-shaded bars near the top of the figure are more “female-typical” and the blue-shaded bars near the bottom are more “male-typical”. The grey-shaded bars near the middle (e.g., political similarity, openmindedness, education level) were no more likely to be selected by either gender.



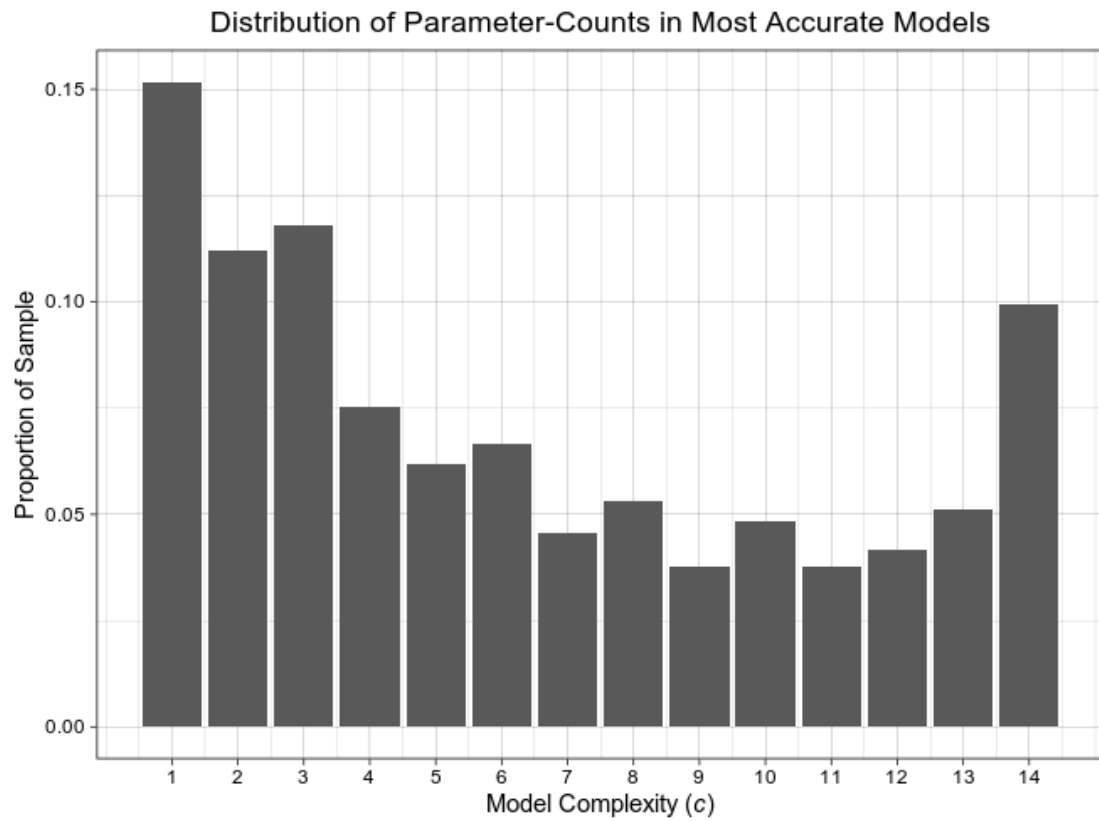
*Figure 12.* Relationship between childhood uncertainty and the complexity of the most accurate model predicting participants' preferences split by experimental condition. This chart only shows results for women.



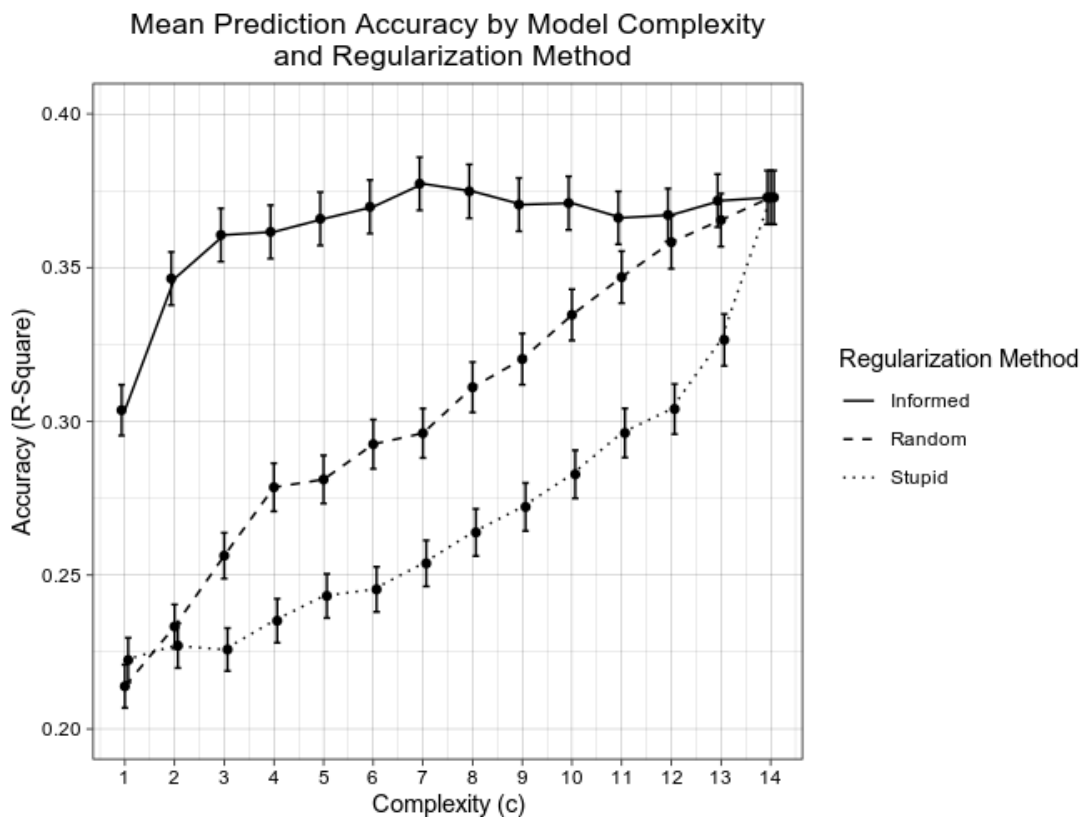
*Figure 13.* Relationship between childhood uncertainty and preference similarity split by experimental condition. This chart only shows results for men.



*Figure 14.* Relationship between childhood uncertainty and preference similarity split by experimental condition. This chart only shows results for women.



*Figure 15.* The distribution of  $c_i$  is clearly bimodal, suggesting that the range of model complexity was restricted in the current study. This suggests that the same study repeated with a greater number of traits would produce a highly skewed distribution resembling a decreasing exponential function.



*Figure 16.* Demonstration of the validity of the regularization method used in the current study. The solid line represents the performance of models when the variables added to the model are added based on the importance indicated by participants in the ranked trait importance scale. The dashed line represents the average performance when traits are added in a random order. The dotted line represents the average performance when traits are added in reverse order of importance. This suggests that although participants might not have perfect insight into their preferences, their self-reported preferences were at least somewhat accurate.

## Appendix: Copy of Survey

### Demographic Questionnaire

- 1 What is your age?
  - 17 years or younger
  - 18
  - [...]
  - 74
  - 75 years or older
  
- 2 What is your gender?
  - Male
  - Female
  
- 3 How do you identify politically?
  - Very liberal
  - 
  - 
  - 
  - Neither liberal nor conservative
  - 
  - 
  - 
  - Very conservative
  
- 4 Please tell us if you identify with any of the political parties listed below:
  - Republican
  - Democrat
  - Libertarian
  - Green Party
  - Independent
  - I do not identify with any political party
  
- 5 Which of the following best describes your race?
  - White or European American
  - Hispanic
  - Black or African American
  - Native American
  - Asian
  - Other, please specify: \_\_\_\_\_
  
- 6 What is your approximate income?
  - \$0 - \$24,999
  - \$25,000 - \$49,999

- \$50,000 - \$74,999
  - \$75,000 - \$99,999
  - \$100,000 or More
  - Do Not Know
- 7 How would you describe the household in which **you spent most of your childhood**?
- Upper class (super rich)
  - Upper middle class (highly educated, wealthy)
  - Middle class (educated, above average income)
  - Lower middle class (some education, average income)
  - Working class (less educated, below average income)
  - Poor (below poverty line)
- 8 What is the highest level of education that you have obtained?
- Some High School
  - High School Graduate
  - Some College, but no degree
  - Associates Degree
  - Bachelor's Degree
  - Graduate Degree (Master's/Doctorate/etc)
- 9 What is your sexual orientation?
- Heterosexual
  - Homosexual
  - Bisexual
  - Other
- 10 Have you ever been divorced?
- Yes
  - No
- 11 What is your current relationship status?
- Single
  - In a relationship (not cohabiting)
  - In a relationship (cohabiting)
  - Married
- 12 How many children do you have?
- None
  - 1
  - 2
  - 3
  - 4 or more

13 How old were you when your **first child** was born?

- 17 years or younger
- 18
- [...]
- 59
- 60 years or older

## **Threat Induction Prompts**

### ***Threat Condition***

Researchers have recently started expressing alarm over the fact that people are having much more difficulty finding relationship partners. Studies show that young men and women are:

- Having fewer relationships
- Reporting lower relationship satisfaction
- Reporting lower sexual satisfaction
- Generally pessimistic when it comes to relationships and sex

We are trying to learn how these trends might be affecting people. Please use the space below to tell us how you would feel if you were never able to find a compatible relationship partner.

### ***Control Condition***

Please describe your use of electronic entertainment. This includes watching television (Netflix, Hulu, etc.), using the internet, and playing video games. If you do not use electronics for entertainment, please tell us why.

### ***Note Shown to All Participants***

Make sure you write at least 400 characters (about 100 words)!

**Manipulation Check**

We'd like to know a little more about your current mood. Below is a list of words and phrases that describe different feelings and emotions. Please indicate the extent to which you feel this way right now.

- 1 Afraid
  - not at all
  - a little
  - moderately
  - a lot
  - extremely
  
- 2 uncertain
  - not at all
  - a little
  - moderately
  - a lot
  - extremely
  
- 3 bored
  - not at all
  - a little
  - moderately
  - a lot
  - extremely
  
- 4 happy
  - not at all
  - a little
  - moderately
  - a lot
  - extremely
  
- 5 nervous
  - not at all
  - a little
  - moderately
  - a lot
  - extremely
  
- 6 worried
  - not at all
  - a little
  - moderately

- a lot
- extremely

7 driven

- not at all
- a little
- moderately
- a lot
- extremely

8 confident

- not at all
- a little
- moderately
- a lot
- extremely

## **Ideal Mate Scale**

**INSTRUCTIONS:** Please design your ideal long-term romantic partner (e.g., for marriage). For each of the traits listed below, use your mouse to drag the slider-bar to the left or right. Keep in mind:

- If you place the bar at 0 on a trait, your mate will be extremely low on that trait.
- If you place the bar at 5 on a trait, your mate will be average on that trait.
- If you place the bar at 10 on a trait, your mate will be extremely high on that trait.

Example 1: Someone who scores 2 on "Income" makes much less money compared to the average person.

Example 2: Someone who scores 9 on "Similar Political Beliefs" is very similar to YOU politically compared to the average person.

### Mate Choice Task

The table below describes two men/women on a variety of traits. Please study each man/woman before answering the questions below.

- Scores near 0 mean the person is far below average on that trait.
- Scores near 5 mean the person is about average on that trait.
- Scores near 10 mean the person is far above average on that trait.

Example 1: Someone who scores 2 on "Income" makes much less money compared to the average person.

Example 2: Someone who scores 9 on "Similar Political Beliefs" is very similar to YOU politically compared to the average person.

[ Profile Pair Displayed Here ]

Who do you think would make a better long-term romantic partner?

*Definitely Person A*

*About the Same*

*Definitely Person B*

○ ○ ○ ○ ○ ○ ○ ○ ○ ○

### Ranked Trait Importance Scale

Imagine that you had to pick a long-term romantic partner from a list of options. What is the FIRST thing you'd want to know about your different options?

- how Attractive / Unattractive each person was
- how Intelligent / Unintelligent each person was
- how Dependable / Undependable each person was
- how Open-Minded / Closed-Minded each person was
- whether each person's Income was High or Low
- how Assertive / Unassertive each person was
- how Extraverted / Introverted each person was
- how Politically Similar / Different to me
- whether each person's Desire for Children was High or Low
- how Religious / Non-Religious each person was
- how Educated / Uneducated each person was
- how Patient / Impatient each person was
- how Creative / Uncreative each person was
- how Aggressive / Non-aggressive each person was

## Childhood Uncertainty

Try to remember what it was like growing up with your parent(s).

("parent" refers to the person or people who you consider to be your "true" parent(s). These can be biological parents, adoptive parents, grandparents, etc.)

- 1 My parent(s) use of punishment was consistent.
  - Strongly disagree
  - Disagree
  - Neither agree nor disagree
  - Agree
  - Strongly agree
- 2 My parent(s) use of punishment was fair.
  - Strongly disagree
  - Disagree
  - Neither agree nor disagree
  - Agree
  - Strongly agree
- 3 One (or both) of my parents sometimes lashed out for no reason.
  - Strongly disagree
  - Disagree
  - Neither agree nor disagree
  - Agree
  - Strongly agree
- 4 I always ate healthy food growing up.
  - Strongly disagree
  - Disagree
  - Neither agree nor disagree
  - Agree
  - Strongly agree
- 5 I was never worried about whether I had enough to eat.
  - Strongly disagree
  - Disagree
  - Neither agree nor disagree
  - Agree
  - Strongly agree
- 6 Things were chaotic growing up.
  - Strongly disagree
  - Disagree

- Neither agree nor disagree
- Agree
- Strongly agree

Compared to the average person, how frequently did the following events occur in your childhood?

- 1 My parents changed jobs
  - Much less than normal
  - Less than normal
  - About normal
  - More than normal
  - Much more than normal
  
- 2 I switched schools
  - Much less than normal
  - Less than normal
  - About normal
  - More than normal
  - Much more than normal
  
- 3 We moved to a new house or apartment
  - Much less than normal
  - Less than normal
  - About normal
  - More than normal
  - Much more than normal
  
- 4 Someone moved into or out of my house (e.g., because of a divorce)
  - Much less than normal
  - Less than normal
  - About normal
  - More than normal
  - Much more than normal