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“Utilizing” Signal Detection Theory

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Abstract

What do inferring what a person is thinking or feeling, judging a defendant's guilt, and navigating a dimly lit room have in common? They involve perceptual uncertainty (e.g., a scowling face might indicate anger or concentration, for which different responses are appropriate) and behavioral risk (e.g., a cost to making the wrong response). Signal detection theory describes these types of decisions. In this tutorial, we show how incorporating the economic concept of utility allows signal detection theory to serve as a model of optimal decision making, going beyond its common use as an analytic method. This utility approach to signal detection theory clarifies otherwise enigmatic influences of perceptual uncertainty on measures of decision-making performance (accuracy and optimality) and on behavior (an inverse relationship between bias magnitude and sensitivity optimizes utility). A “utilized” signal detection theory offers the possibility of expanding the phenomena that can be understood within a decision-making framework.

Keywords

signal detection theory, utility, perception, decision making

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The goal of this tutorial is to familiarize readers with aspects of signal detection theory (SDT; Green & Swets, 1966; Macmillan & Creelman, 1991) that stem from using it as a model of optimal decision making. SDT characterizes how perceivers separate meaningful information from “noise.” It is widely used to measure performance on perception, memory, and categorization tasks. In the realm of social perception, for example, when interacting with someone, it is advantageous to know whether the person is angry (and likely means you harm) or not. Signals such as the person's facial expression inform this judgment. SDT is particularly useful in situations of uncertainty and risk. *Uncertainty* is present when the alternative options are perceptually similar to one another (e.g., a scowling facial expression sometimes means that the person is angry and sometimes means that the person is merely concentrating). *Risk* is present when misclassification carries some relative cost (e.g., when failing to correctly identify someone as angry incurs punishment that would otherwise have been avoided).¹

Overview of SDT

SDT's power as an analytic tool comes from separating a perceiver's behavior into two underlying components, sensitivity and bias (see *Précis of Signal Detection Theory* in the Supplemental Material available online). *Sensitivity* is the perceiver's ability to discriminate alternatives: targets (e.g., a person who is angry) versus foils (e.g., a person who is not angry). *Response bias* is the perceiver's propensity to categorize stimuli as targets rather than foils and is described as liberal, neutral, or conservative. For example, if failing to correctly identify threat is relatively costly (resulting in, say, psychological or physical punishment), or if targets are common relative to foils, then a perceiver might treat equivocal stimuli as threatening targets rather than safe foils (a liberal bias, in which

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even mildly scowling faces are treated as angry). If, instead, incorrectly identifying a stimulus as a threat is relatively costly (resulting in, say, embarrassment arising from a misperceived need to apologize), or if targets are uncommon relative to foils, then a perceiver might treat equivocal stimuli as safe (a conservative bias, in which only strongly scowling faces are treated as angry).

SDT is applicable across a spectrum from perceptual to conceptual domains. In fact, a diverse array of nonpsychophysical “perceptions” have been treated as involving issues of signal detection. The SDT framework has been used to examine eyewitnesses’ identification of suspects (Clark, 2012), decisions to place children in foster homes (Ruscio, 1998), memory (Wixted & Stretch, 2004), cancer detection (Abbey, Eckstein, & Boone, 2009), statistical hypothesis testing (Green & Swets, 1966), and diagnostic decisions more generally (Swets, Dawes, & Monahan, 2000). Here, we use social-threat detection as an example to illustrate our points (see the Supplemental Material for additional examples across the perceptual-conceptual spectrum: interoception, social perception, jury deliberation, and navigation speed).

Despite SDT’s breadth of application, it is largely used in a descriptive way to compare sensitivity and bias across study conditions or people. For example, in a previous study, people with current depression exhibited decreased sensitivity for emotion perception, and people with remitted depression exhibited increased sensitivity and more neutral response bias for emotion perception, relative to control groups (Anderson et al., 2011). Yet SDT has much more to offer as a generative model of decision making. Combining SDT’s treatment of perceptual uncertainty with the behavioral-economic concept of utility (the net benefit expected to accrue from a series of decisions) highlights important aspects of decision making overlooked both by typical applications of SDT and by traditional models of decision making that focus on utility alone.

The Utility of Perception

According to the utility-based approach to SDT, three parameters characterize the uncertainty and risk within a specific decision environment.

- *Payoff*: Every decision has its consequences. The payoff parameter describes the value of each of four possible decision outcomes: correct detections, missed detections, false alarms, and correction rejections (see *Précis of Signal Detection Theory* in the Supplemental Material). False alarms and missed detections incur relative costs to the perceiver, whereas correct rejections and correct detections impart relative benefits to the perceiver.

In social-threat detection, for example, false alarms might lead to unnecessary apologetic disruptions of the social interaction or to unnecessary social avoidance, whereas missed detections might lead to punishment or other aversive outcomes.

- *Base rate*: The base-rate parameter describes the perceiver’s probability of encountering targets (e.g., a person who is angry) relative to foils (e.g., a person who is not angry).
- *Similarity*: Target and foil categories can be somewhat similar to one another, and this is the source of perceptual uncertainty. The similarity parameter models uncertainty by describing what targets and foils “look like.” For example, the physical similarity of facial expressions associated with two emotion categories can be modeled as Gaussian distributions over a continuous perceptual domain of facial expression intensity. There are two sources of perceptual uncertainty. Intrinsic sources are internal to the perceiver. They may include, for example, sensory-processing noise (e.g., Osborne, Lisberger, & Bialek, 2005), poorly learned discrimination (e.g., Lynn, 2005), and, at an abstract level, perhaps even confusion about the difference between conceptual categories. Extrinsic sources are external to the perceiver, arising from the environment or the signaler. They may include, for example, environmental noise (e.g., Wollerman & Wiley, 2002), signal attenuation (e.g., Naguib, 2003), and variation in signaler expressivity (e.g., emotional expressivity: Zaki, Bolger, & Ochsner, 2009). Research in psychophysics often emphasizes intrinsic uncertainty. Research in applied decision making (e.g., medical diagnostics) and behavioral ecology often emphasizes extrinsic uncertainty.

It is well known that payoffs and the base rate influence bias (Green & Swets, 1966; Macmillan & Creelman, 1991). Rare targets and costly false alarms promote a conservative bias (i.e., a higher threshold, or criterion, for judging that a target is present), whereas common targets and costly misses promote a liberal bias (i.e., a lower criterion for judging that a target is present; e.g., Quigley & Barrett, 1999). The perceptual similarity between targets and foils influences sensitivity (i.e., perceivers have greater sensitivity when targets and foils are less perceptually similar to one another; Green & Swets, 1966; Macmillan & Creelman, 1991). However, it is the utility-based approach to SDT (which combines uncertainty with behavioral economics) that quantifies and predicts these relationships between environmental parameters and behavior.

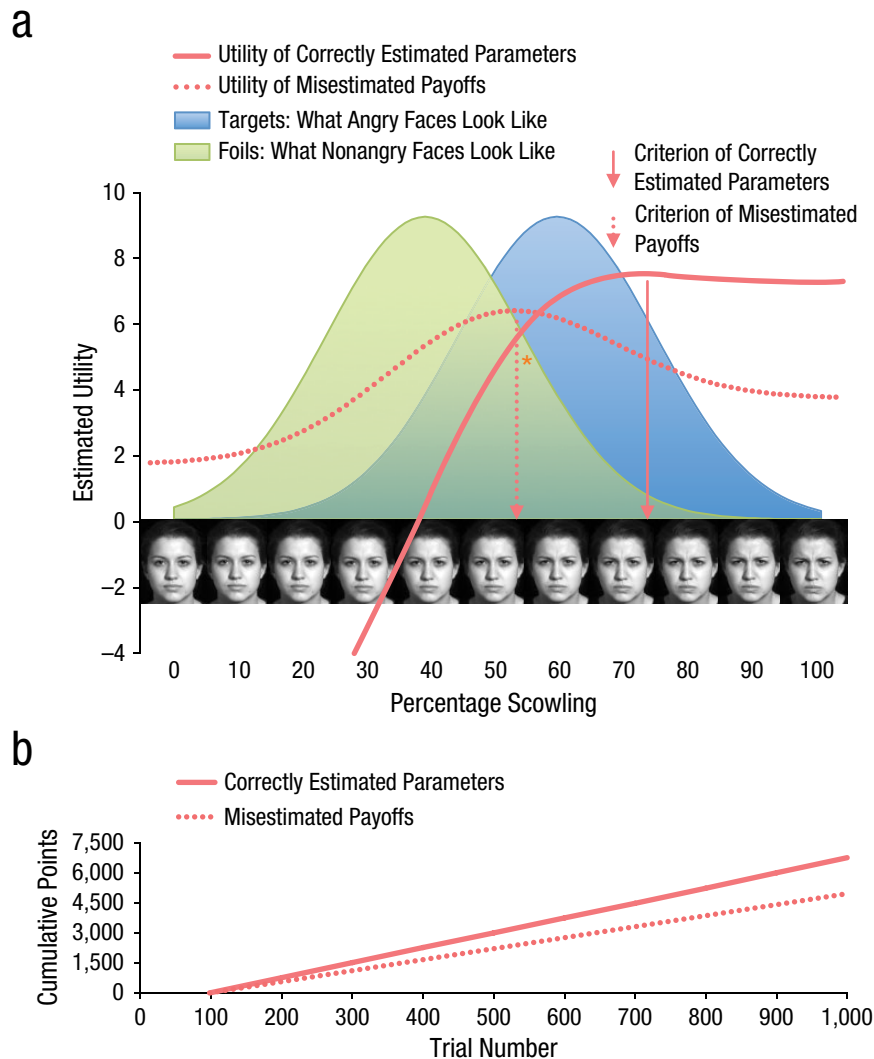


Fig. 1. Illustration of how one person (the perceiver, or decision maker) might establish the optimal criterion location in evaluating facial expressions to gauge the threat presented by another person (the sender, or signaler). The payoff, base-rate, and similarity parameters can be combined to derive a utility function for the decision environment that they characterize (a). The location in the stimulus domain (x-axis) with the highest utility is the decision criterion location that will maximize benefit over a series of decisions (the criterion of correctly estimated parameters). A simulated perceiver who misestimates payoffs (dotted utility function) may adopt a suboptimally neutral decision criterion (criterion of misestimated payoffs). This perceiver's expected utility is dictated by the intersection (denoted by the asterisk) of his or her criterion and the utility function derived from correctly estimated parameters. The y-axis for the signal distributions (probability density) is not shown. The graph in (b) shows that this perceiver's misestimate is suboptimal: The rate of utility gain (accumulation of points) over a series of trials is shallower than would have been the case if all the parameters had been estimated correctly. Parameter values for these models are provided in the Supplemental Material.

Establishing the Optimal Criterion Location

In the presence of perceptual uncertainty, mistakes cannot be avoided. Consider, for example, the situation modeled in Figure 1a. A liberal criterion (identifying anger in faces with a low percentage of scowling) minimizes missed detections but increases exposure to false alarms.

A conservative criterion (identifying anger in faces only when they have a high percentage of scowling) minimizes false alarms but increases exposure to missed detections. Therefore, perceivers should seek to *optimize* their criterion location—to adopt a criterion that maximizes expected utility, producing the optimal blend of missed detections and false alarms in light of the environmental parameters.

The SDT utility function uses the payoff, base-rate, and similarity parameters to calculate the expected value (to the perceiver) of placing a decision criterion at any given location in the perceptual domain (see The Signal Utility Estimator and Receiver Operating Characteristics, in the Supplemental Material). For example, it is possible to compute the expected utility of placing a decision criterion at each facial expression along the continuum in Figure 1a. The criterion location with the highest expected utility will maximize net benefit over a series of decisions. By modeling the environmental parameters that underlie bias and sensitivity, one can mathematically predict perceivers' optimality within environments or experimental conditions of a study or empirically compare perceivers' optimality across environments or experimental conditions.

To implement these ideas within an experiment in a laboratory setting, one can create different decision environments by assigning values to the three parameters (see Lynn, Cnaani, & Papaj, 2005, for an example with nonhumans; see Lynn, Zhang, & Barrett, 2012, for an example with humans). Payoffs can be implemented behaviorally. For example, participants can earn or lose points depending on the outcome of each trial. In this way, it is possible to set unequal payoff outcomes (e.g., a missed detection and a false alarm might have different costs in a particular context). Outside the laboratory, payoffs may not be known or easily quantified, of course. In such cases, a ratio of payoffs might be used. For example, Clark (2012) explored the utility of eyewitness-lineup reforms using a 10:1 ratio of the cost of missed detections (the perpetrator goes free) to false alarms (the wrong person is identified as the perpetrator). Base rate can be implemented as the proportion of targets to foils shown. The base rate can model, for example, the fact that some people with whom a perceiver interacts may be angry more often than other people. The similarity parameter can be implemented with targets and foils randomly drawn from their respective distributions imposed on a continuum of stimuli.

Because criterion location is a function of the three environmental parameters, suboptimal bias or sensitivity in a perceiver can be understood as a perceiver's "misestimate" of one or more parameters, which can result in suboptimal decisions (Fig. 1b). Individual differences, alone or in interaction with the decision environment, may influence parameter estimates (see Estimating Perceivers' Parameter Values in the Supplemental Material; Lynn et al., 2012).

The application of utility to SDT is not new—it was part of the theory's initial development in psychophysics (Green & Swets, 1966; Tanner & Swets, 1954). Nonetheless, a "utilized" SDT—which incorporates the notion that perceivers attempt to maximize net benefit while operating under perceptual uncertainty²—generates a number of

unexpected but important theoretical observations that have yet to be widely explored in the psychological literature. One surprising observation is that there are contexts in which maximizing accuracy conflicts with maximizing utility, so that there are common situations in which accuracy should be sacrificed to achieve effective decision making. This conflict has implications for the use of accuracy as a measure of performance. A second surprising observation is that there is a functional relationship between bias and sensitivity: Within a perceiver, the optimal criterion location is not independent of sensitivity. Probably the most widely appreciated insight of SDT is its separation of sensitivity and bias as factors explaining behavior (Swets, Tanner, & Birdsall, 1961), and many users believe that these two parameters are orthogonal, or independent of one another. This relationship between sensitivity and bias has implications for interpreting differences in sensitivity and bias among perceivers or different contexts.

Measuring Behavior: Optimal Is Better Than Accurate

One clear tenet of SDT is that estimates of accuracy (i.e., the proportion of trials garnering correct response) should be abandoned in favor of estimates of bias and sensitivity as measures of performance when feasible (Macmillan & Creelman, 1991). There are two reasons to avoid accuracy. First, accuracy does not account for two aspects of decision making under uncertainty and risk that are important for a full understanding of the perceiver's behavior: Accuracy confounds the effects of sensitivity and bias on performance, and this is true whether one applies a utility framework to SDT or not. Second, the inadequacy of accuracy is compounded under economic risk, when payoffs should optimally bias behavior, because accuracy is the simple tally of correct and incorrect decisions without regard to their actual benefits and costs.

Accuracy confounds sensitivity and bias

Accuracy is not a good indicator of what people are doing; it does not describe their behavior. This is because accuracy is blind to the separate contributions of sensitivity and bias to decision making. Although this fact is well known, it is less appreciated that multiple combinations of sensitivity and bias values produce the same accuracy (Fig. 2). The overt behaviors that yield a given accuracy level may encompass dramatic extremes of liberal and conservative bias. Consequently, the researcher analyzing accuracy rather than optimality will pool participants

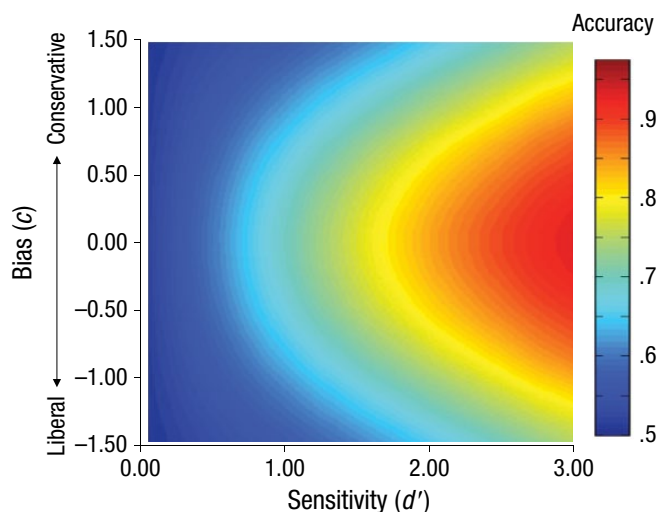


Fig. 2. Illustration showing that multiple combinations of sensitivity and response bias produce the same accuracy. For example, the iso-accuracy gradients in this simulated neutral-bias environment show that at moderate sensitivity ($d' = 2$), both liberal bias ($c = -0.5$) and conservative bias ($c = 0.5$) can produce accuracy near .8. Parameter values for this model are provided in the Supplemental Material.

who are potentially behaving quite differently from one another (Lynn, Hoge, Fischer, Barrett, & Simon, 2014).

Accuracy is blind to payoffs but not base rate

When benefits and costs differ, accuracy is not a good indicator of how well people are doing; it is an inadequate measure of their performance. Accuracy is blind to the influences of benefits and costs on decision making

(Egan, 1975; Maddox & Bohil, 2005) because it is determined without regard to the value the perceiver accrues for those decisions. This means that maximizing accuracy and maximizing utility can be at odds with one another in environments in which bias is due to payoffs. However, because accuracy is derived from the proportions of correct and incorrect responses, it is congruent with utility in environments in which bias is due to the base rate.

A comparison of simulated environments with different sources of bias exemplifies these points (Table 1). When payoffs alone bias behavior (the payoff environment, in which false alarms are relatively costly but the base rate is balanced at .5), accuracy is highest when bias equals 0 (neutral bias). Nevertheless, utility is maximized when bias equals 0.4 (i.e., a somewhat conservative bias). Utility at the criterion that maximizes accuracy is 7.1 points, less than the maximum utility possible, 7.5 points. Accuracy at the criterion that maximizes utility is .82, less than the maximum accuracy possible, .84. Perceivers with bias of 0 will achieve lower maximum utility over a series of decisions than will those with bias of 0.4, despite exhibiting higher accuracy. When the base rate alone biases behavior (the base-rate environment, in which benefits and costs cancel each other out but the base rate is .3), the amount of bias that maximizes accuracy also maximizes utility (again at bias = 0.4). For comparison, Table 1 also contains results for neutral and base-rate-and-payoff environments. When benefits and costs differ, then, optimally biased decision making will yield lower accuracy than unbiased decision making, despite its greater utility. Consequently, accuracy cannot properly describe performance in environments in which there is risk due to payoffs.

Table 1. Expected Accuracy, Criterion Locations, Bias, and Utility in Four Simulated Decision Environments

Measure	Type of decision environment			
	Neutral	Base rate	Base rate and payoff	Payoff
Maximum accuracy	.84	.86	.86	.84
Criterion location that maximizes accuracy	50.0	50.4	50.4	50.0
Bias that maximizes accuracy	0.0	0.4	0.4	0.0
Utility at the criterion location that maximizes accuracy	6.8	7.2	7.7	7.1
Maximum utility	6.8	7.2	8.0	7.5
Criterion location that maximizes utility	50.0	50.4	50.8	50.4
Bias that maximizes utility	0.0	0.4	0.8	0.4
Accuracy at the criterion location that maximizes utility	.84	.86	.85	.82

Note: Values for expected accuracy, criterion location (percentage of range), bias (c), and utility (points accrued) were derived by applying each environment's parameters to the utility function in signal detection theory. The parameter values for the neutral environment are as follows: correct detections and correct rejections = 10 points; missed detections and false alarms = -10 points; base rate = .5; and means of target and foil signal distributions = 60% and 40% of the perceptual domain's range, respectively, with standard deviation = 10% for both distributions. The base-rate environment is identical to the neutral environment except that the base rate is reduced to .3. The payoff environment is identical to the neutral environment except that false alarms are more costly (-15 points) and missed detections less costly (-1 point). The base-rate-and-payoff environment combines the base rate and payoffs from the base-rate and payoff environments, respectively; the similarity parameter values are the same as in the neutral environment.

Behavioral data also indicate that accuracy sometimes reflects the optimality of decision making and sometimes does not, depending on the environment. For example, in one study, participants who were engaged in an emotion-perception experiment of the sort described in Figure 1a attempted to maximize points earned over 178 trials (see Lynn et al., 2012, for methodological details). Additional analyses (not reported in Lynn et al.) showed that accuracy did not reflect the optimality of decision making when bias was caused by payoffs (as illustrated in Table 1). For participants in a condition that implemented a liberal environmental bias via relatively costly missed detections (all else being equal), more liberal response bias was associated with lower accuracy, $\rho = .50$ (all ρ s are one-tailed partial correlations controlling for sensitivity, d'), $p < .001$, $n = 67$. Additionally, more liberal response bias was associated with more points earned, $\rho = -.82$, $p < .001$, whereas higher accuracy was marginally associated with fewer points earned, $\rho = -.17$, $p > .086$.

In contrast, accuracy did reflect the optimality of decision making when bias was caused by the base rate of targets (as illustrated in Table 1). For participants in a condition that implemented a conservative environmental bias via a relatively low base rate (i.e., targets were less common than foils), more conservative response bias was associated with higher accuracy, $\rho = .91$, $p < .001$, $n = 75$. Additionally, more conservative response bias and higher accuracy were associated with more points earned—bias: $\rho = .50$, $p < .001$; accuracy: $\rho = .58$, $p < .001$.

Humans appear to more easily adapt their response bias to the base rate than to payoffs (Bohil & Maddox, 2001). This discrepancy leads to an observed response bias that maximizes accuracy at the expense of optimality (Maddox & Bohil, 2005). When payoffs matter, perceivers maximizing accuracy over optimality will accrue less benefit than could otherwise be the case. By ignoring the differences between benefits and costs, such perceivers are unable to tune their bias to balance those differences. Moreover, when the payoff matrix and base rate demand bias in opposing directions (i.e., liberal- vs. conservative-going bias), perceivers who neglect payoffs could exhibit bias in the wrong direction relative to what is optimal for the environment.

Many studies are blind to the difference between optimality and accuracy as a consequence of not assigning separate payoff values to correct detections and correct rejections, or to false alarms and missed detections. Emphasizing accuracy instead of optimality corresponds to a misalignment of behavior with the contingencies of the decision because those contingencies are ignored. In social-threat perception, for example, emphasizing accuracy over a series of judgments could correspond to considering the costs of false alarms and missed detections to

be of equal value, and the benefits of correct detections and correct rejections to be of equal value. It may be appropriate for participants to assume balanced payoffs in most laboratory experiments of emotion perception, but the use of balanced payoffs reduces the experiments' ecological validity because it seems unlikely for payoffs to be balanced outside the laboratory. Outside the laboratory, decisions involve benefits and costs, and maximizing net benefit, not accuracy, is what matters. Testing perceivers under conditions that demand a nonneutral bias and measuring performance as accumulated payoff, or optimality of bias, rather than accuracy, better reflects decisions made outside the laboratory.

Interaction of Uncertainty and Risk: The Relationship Between Sensitivity and Bias

Perceivers maximizing utility experience a functional relationship between bias and sensitivity predicted by the SDT utility function. This relationship dictates that, given some nonneutral response bias required by the environment (determined by base rate, payoffs, or both), to maximize their utility, perceivers with low sensitivity should be more biased than perceivers with high sensitivity.

To get an intuitive feel for this relationship, consider walking through an obstacle-strewn room as a signal detection issue (this example is further developed in the Supplemental Material). Why do people navigate space more cautiously in conditions of poor visibility than in conditions of good visibility? A missed detection (say, stepping barefoot on an object) is costly (it is painful to the perceiver and may break the object). When the room is well lit, a person can walk quickly through the room. When the room is dimly lit, the person walks more cautiously, reducing the frequency of missed detections that would otherwise occur. This increased caution corresponds to a change in bias. What about the environment has changed to cause this change in bias? The benefits and costs of correct and incorrect judgments about the presence or absence of obstacles in the person's path have not changed, nor has the base rate of encountering obstacles. Only the perceptual similarity between targets and foils has changed: Obstacles and clear space look more similar in the dark, which reduces the person's sensitivity to discriminate obstacles against the background. In this example, a decrease in sensitivity leads to a more liberal bias, which produces a change in response: Decreased walking speed results in fewer missed detections and more false alarms.

In short, decreased sensitivity makes errors more likely. Perceivers can mitigate this increased risk to some extent by adopting a more extreme bias. The consequence of this functional relationship is that more

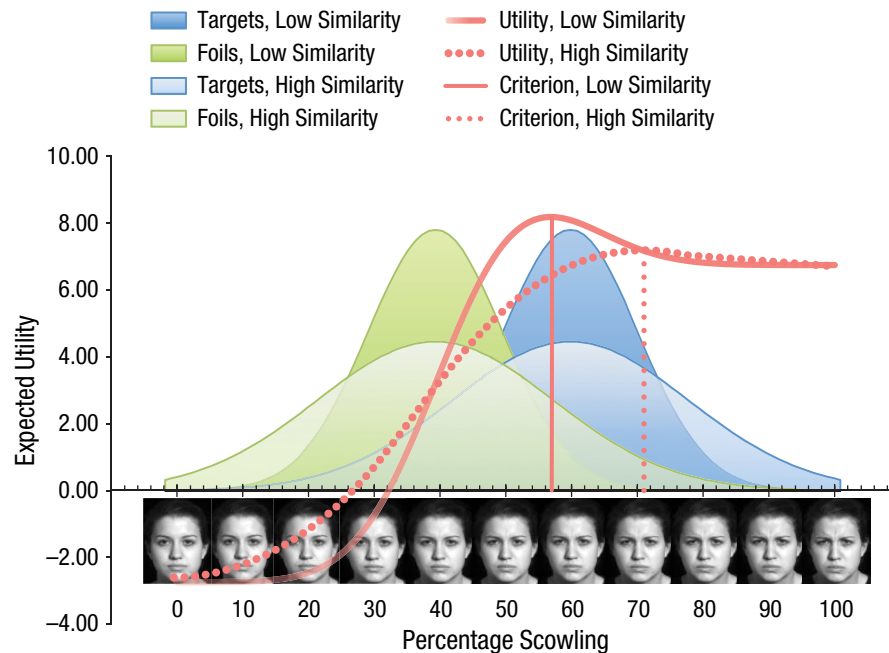


Fig. 3. Optimizing performance in a biased environment. As illustrated by these two models for environments with low and high similarity of targets and foils, to offset the decrement in performance (lower utility) caused by high similarity (low sensitivity), perceivers should adopt a more extreme bias (depicted by the rightward shift of the criterion for the high-similarity utility function). In these models, the maximum sensitivity (d') is 2.0 for the low-similarity environment and 1.1 for the high-similarity environment. Given these levels of sensitivity, the amount of bias (c) that will optimize a perceiver's decisions is 0.7 for the low-similarity environment and 1.2 for the high-similarity environment. Note that bias as measured by the ratio of target to foil likelihood at the criterion (β) is 4.0 in both models and does not explicitly reflect the difference in behavior. Parameter values for these models are provided in the Supplemental Material.

extreme behavior is associated with greater uncertainty (see Fig. 3 and also Receiver Operating Characteristics in the Supplemental Material).

The line of optimal response

A line of optimal response (LOR; Fig. 4; Lynn et al., 2012) depicts the functional relationship between bias and sensitivity. Any unique set of environmental base-rate and payoff values has a unique LOR. The LOR can be derived from the equation relating the likelihood ratio of the signal distributions at a given criterion (a measure of bias called *beta*, β ; see Précis of Signal Detection Theory in the Supplemental Material) to the criterion or center measure of bias, c , and sensitivity, measured as d' (Macmillan & Creelman, 1991, Equation 2.10):

$$\beta = e^{(cd')} \quad (1)$$

Providing the environment's optimal beta value and solving for c (i.e., $\log(\beta)/d'$) over a range of d' values yields the LOR. The environment's optimal beta value can

be calculated from the base rate and payoffs (Tanner & Swets, 1954, Equation 2; see also Wiley, 1994):

$$\beta_{\text{optimal}} = (1 - \alpha) / (\alpha) \times (j - a) / (b - m), \quad (2)$$

where α is the base rate and j , a , b , and m are the payoffs for correct rejections, false alarms, correct detections, and missed detections, respectively (see The Signal Utility Estimator in the Supplemental Material).

The value of β_{optimal} is constant for all sensitivity values; it is set by the environmental payoffs and base rate, and is not a function of sensitivity. By Equation 1, which defines beta in terms of c and d' , c must change with sensitivity if beta is constant. Although there is a literature examining beta (e.g., Snodgrass & Corwin, 1988; Wood, 1976), we have chosen to focus on how c changes with sensitivity (Stretch & Wixted, 1998). Focusing on the lability of c , rather than the stability of beta, emphasizes how perceivers' behavior—which stimuli they categorize as targets and which as foils—should differ between environments that differ in target-foil similarity or among individuals who differ in sensitivity (e.g., in the high- and

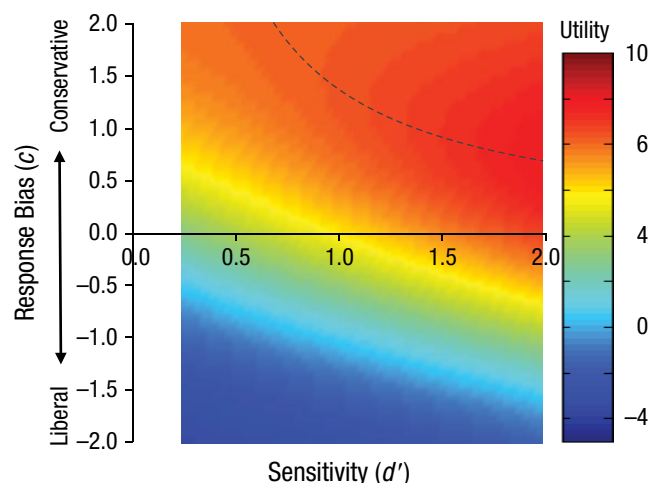


Fig. 4. Illustration of the relationship between bias and sensitivity according to the utility approach to signal detection theory. Mathematical modeling shows that for the utility of perceptual decisions to be maximized, a perceiver's sensitivity and response-bias magnitude should be inversely related. A line of optimal response (LOR; dashed line) is defined by the bias that yields maximum utility for any given level of sensitivity, for constant base-rate and payoff values. The non-zero slope of the LOR indicates that the decrease in utility that results from reduced sensitivity can be mitigated by increased magnitude of bias (here, a more conservative-going bias). Parameter values for this model are provided in the Supplemental Material.

low-similarity environments of Fig. 3, β does not change, but c does).

We interpret the distance from the point defined by a perceiver's observed sensitivity and bias (d' , c) to the LOR as a measure of how well the perceiver is able to adjust his or her bias to optimally accommodate his or her level of sensitivity. We have elected to measure distance to the LOR as euclidean distance rather than vertical distance, as a means of accounting for the unknown bivariate error distribution in the estimates of sensitivity and bias (Lynn et al., 2012).

Sensitivity as a source of bias

Surprisingly, this functional relationship means that low sensitivity can prompt extreme bias, just as the payoff and base-rate parameters can. As a consequence, bias can change solely from a difference in the perceived similarity of targets and foils, without any changes in the parameters commonly understood to drive bias (i.e., base rate and payoffs).³ In studies that have found response bias (c) to be inversely associated with perceptual sensitivity (d'), the associations have sometimes been explained as methodological or measurement artifact (e.g., See, Warm, Dember, & Howe, 1997; Snodgrass & Corwin, 1988). However, when sensitivity and bias magnitude (measured as either c or the criterion's location in the perceptual domain) vary inversely between

conditions, low sensitivity should be considered as a possible explanation for extreme bias.

Recognizing a functional relationship between sensitivity and bias is critical because it has the potential to reverse researchers' conclusions about differences in bias that are observed whenever signal detection issues occur (i.e., decisions involving category uncertainty and costly miscategorization). For example, under the assumption that bias is functionally independent of sensitivity, perceivers exhibiting poor sensitivity combined with extreme bias (relative to a control group) would be considered to exhibit two separate impairments in decision making: poor sensitivity and extreme bias. For decision making to be optimal, however, bias magnitude *should* vary inversely with sensitivity, particularly at low sensitivity. According to the utility-based account, therefore, more extreme bias may reflect not an impairment but a normal adaptive mechanism that offsets the single impairment, poor sensitivity. Conversely, under the independence assumption, perceivers exhibiting poor sensitivity with no difference in bias (relative to more sensitive individuals) would be considered to exhibit a single impairment, in sensitivity. In fact, such individuals may have a dual impairment: poor sensitivity coupled with failure to calibrate their bias to their poor sensitivity.

In the study by Lynn et al. (2012), perceivers exhibited wide variation in their ability to optimally adjust their bias to their sensitivity, but an inverse relationship between bias magnitude and sensitivity did function to maximize utility (Fig. 5; results not reported in Lynn et al.). As predicted by the utility approach to SDT, perceivers with poor sensitivity (d') exhibited more extreme bias (c) than did perceivers with better sensitivity, both in an environment using payoffs to induce a liberal bias, $r = .26$, $p < .023$, $n = 67$, and in an environment using the base rate to induce a conservative bias, $r = -.48$, $p < .001$, $n = 75$. Furthermore, as predicted, perceivers with more optimal bias (shorter distance from the LOR) earned more points over the series of trials (liberal payoff environment: $\rho = -.81$, $p < .001$; conservative base-rate environment: $\rho = -.50$, $p < .001$). Thus, perceivers who adopted a more extreme bias that reflected their reduced sensitivity made more optimal perceptual decisions.

Conclusions

SDT is a well-established analytic tool for describing decision-making performance in a wide variety of domains, ranging from the perceptual to the conceptual. A utilized SDT goes farther—it provides a theoretical framework to predict or explain behavior. The SDT utility function (Swets et al., 1961) makes SDT a predictive tool by modeling the perceptual uncertainty and behavioral risk that are inherent to many decisions both inside and

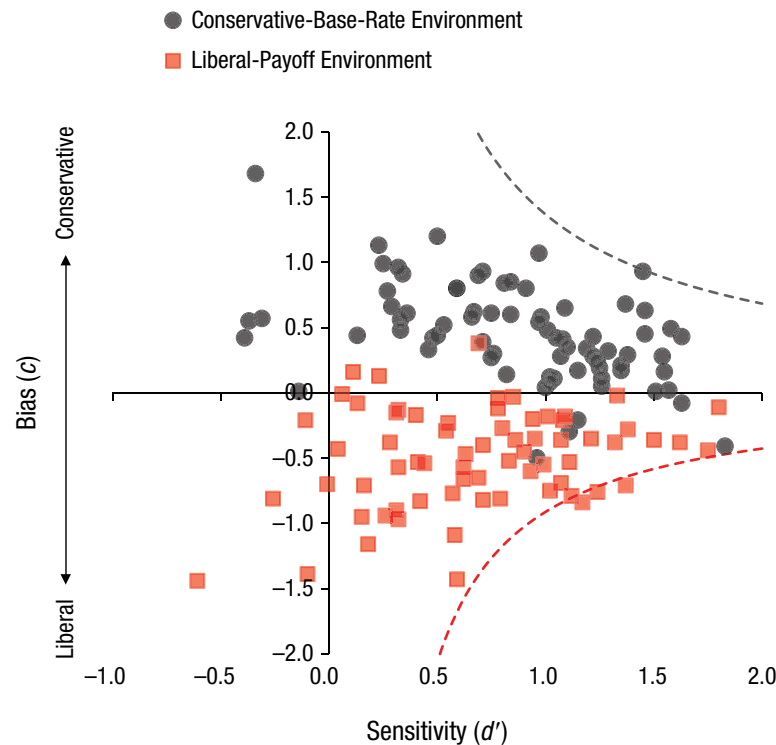


Fig. 5. Illustration of the inverse relationship between bias magnitude and sensitivity in conservatively and liberally biased decision environments (data from Lynn, Zhang, & Barrett, 2012). Participants in both environments showed more extreme bias as their sensitivity decreased, as predicted by the lines of optimal response (LORs; dashed lines) for the environments' parameter values. Perceivers closer to their environment's LOR earned significantly more points than those farther away, which indicates that the inverse relationship is driven by utility maximization.

outside the laboratory. The model can be used to generate novel experimental questions about computational processes underlying bias and sensitivity and functional decision making (e.g., see Affective Calibration in Mental Illness in the Supplemental Material).

Understanding decision making and criterion placement as dependent on perceivers' subjective estimates of parameters that characterize the environment has exciting ramifications. First, designing experiments to manipulate the payoff, base-rate, and similarity parameters, and measuring the optimality of decision making, will provide a more mechanistic approach to understanding the factors that underlie perceivers' bias and sensitivity. Examining how perceivers make decisions in biased conditions will yield better understanding of decision making because biased environments are more realistic than those that are typically implemented in cognitive and perceptual experiments, in which payoffs are unspecified and the base rate is balanced across alternatives.

Second, adopting SDT as a theoretical model of decision making offers a path by which behavioral-economic and neuroeconomic studies of judgment and

decision making can investigate the influence of uncertainty. Examining perceivers operating under uncertainty would reflect decision making in more realistic environments than are typically employed in judgment and decision-making tasks that manipulate economic risk—variation in payoffs—but ignore signal-borne risk—variation in what options look like.

Sensitivity to the three signal parameters is taxonomically widespread, exhibited by vertebrates and arthropods (e.g., Lynn, 2010). Model-driven approaches (Glimcher & Rustichini, 2004; Gold & Shadlen, 2007; Redish, 2004; Redish, Jensen, & Johnson, 2008) in which these three parameters are systematically manipulated may thus permit a broadly comparative investigation of how decision making is accomplished across levels of biological organization and complexity.

Author Contributions

S. K. Lynn developed the tutorial and drafted the manuscript. L. F. Barrett provided critical revisions. Both authors approved the final version of the manuscript for submission.

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The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at <http://pss.sagepub.com/content/by/supplemental-data>

Notes

1. These definitions of uncertainty and risk differ somewhat from those used in the literature on economic decision making, where commonly risk is defined as knowable variation in the value (payoff) of a decision's outcome and uncertainty as unknowable variation in that value (e.g., see the review by Volz & Gigerenzer, 2012).
2. It is perceptual uncertainty, modeled by the similarity parameter, that distinguishes SDT from other models of decision making. Other models of decision making attempt to account for how decisions are influenced by variability in benefits and costs accrued from correct or incorrect decisions, by variability in the probability of alternative choices or events, and by variability in factors internal to the decision maker that affect risk sensitivity, singly or in combination (e.g., see reviews in Krebs & Kacelnik, 1991; McNamara, Houston, & Collins, 2001). Game-theoretic approaches to decision making additionally account for the effect of other individuals' responses on the decision maker's own behavior (e.g., Grafen, 1991). Yet these models ignore that a perceiver's expectations of the payoff to be accrued, the probabilities of alternative choices, the responses of others, and even the perceiver's own body state (e.g., homeostatic and metabolic response) are based on signals emitted by the resources, game partners, body, and so forth. SDT posits that these signals themselves have variation.
3. Sensitivity and bias independently characterize decision making: A perceiver's ability to distinguish targets from foils is conceptually separate from his or her estimate of the payoffs and base rate. Additionally, the measures d' and c are estimated with statistical independence from one another (Dusoir, 1975; Macmillan & Creelman, 1990; See, Warm, Dember, & Howe, 1997; Snodgrass & Corwin, 1988). Nonetheless, these notions

of conceptual and statistical independence have inadvertently influenced assumptions about functional independence, such that there exists a misconception that a perceiver's observed bias should be independent of his or her observed sensitivity. The utility approach to SDT shows instead that a perceiver's observed bias and sensitivity are functionally related by the goal of maximizing utility.

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