Title
A Causal Model Theory of Judgment

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 33(33)

ISSN
1069-7977

Authors
Sussman, Abigail B.
Oppenheimer, Daniel M.

Publication Date
2011

Peer reviewed

A Causal Model Theory of Judgment

Abigail B. Sussman and Daniel Oppenheimer
{asussman, doppenhe}@princeton.edu
Department of Psychology
Princeton University
Princeton, NJ 08540 USA

Abstract

How do people combine cues to form judgments? Recent debate has focused on whether and when individuals use heuristics versus linear models. We propose instead that people may rely on an understanding of the causal relationships between cues to determine how much weight to place on each one. Predictions of the causal model approach match those of linear models under certain circumstances and heuristic models under others, while making unique predictions in additional cases. In two experiments, we show that, as the causal relationships among cues changes, participant judgments consistently conform to predictions of the causal model approach while matching either heuristic or linear judgments in only a limited subset of cases.

Keywords: judgment, causal reasoning, heuristics, linear models

Introduction

When making judgments about the world, we typically have access to various pieces of information, or cues, that might facilitate those judgments. Doctors might consider the weight of the patient and the severity of symptoms to determine how much medication to prescribe. Jurors might consider the number of people injured by a product and the average age of the victim when determining damages. One question that has been central in the study of judgment is how these cues are used and combined. The manner in which people combine cues impacts judgments, attitudes, and choices, and has important ramifications for welfare.

Within the field of judgment and decision making, two primary approaches have defined the debate over how people combine available information to form judgments: linear models and heuristic models. Each approach has demonstrated a high correlation between individuals' predictions and actual outcomes under certain circumstances, but both approaches also have systematic gaps in their ability to make predictions under various (and predictable) environmental situations. Since linear models excel at explaining judgment in some environments, and heuristic accounts are more effective in others, many researchers have argued that people switch between the strategies depending on the judgment task. Although strategy switching accounts have become dominant in the field, we propose that a model based upon causal reasoning may be able to subsume both linear and heuristic models to account for judgments across various environments, in a single, unified framework.

Heuristic and Linear Models of Judgment

One influential approach to judgment assumes that individuals are able to process complex information about correlations between events with a high degree of accuracy (e.g. Brunswik, 1943, 1952). According to these Brunswikian accounts, people incorporate many (or all) of the available pieces of information into their judgments and predictions by combining and weighting each cue to form an algebraic, linear model (Anderson, 1981; Brehmer, 1994; Hammond, 1996). Variations on this approach allow for simplified methods of combining cues such as inconsistency in weighting correlations (Hoffman, 1960), or equal cue weighting (Dawes & Corrigan, 1974; Einhorn & Hogarth, 1975). In many situations, linear models approximate human judgments (e.g. Hammond, 1955; Hoffman, 1960), leading researchers to propose them as a basis for understanding human cognitive processing. Indeed, in certain environments process tracing has shown information search patterns that are consistent with the predictions of linear models (e.g. Payne, Bettman, & Johnson, 1988).

Despite the positive evidence for linear models, there are reasons to doubt their descriptive validity. Questions remain about whether people have the cognitive capacity to perform the calculations necessary to compute linear models when making judgments. Even in simplified forms they regularly outperform the average decision maker (Dawes, 1979; Wainer, 1976). In some cases, reasoners' judgments have significantly deviated from linearity (e.g. Brehmer & Brehmer, 1988; Slovic, 1969; Wiggins & Hoffman, 1968). Thus, while linear models have provided insight into cognitive processes, there are a number of things that they struggle to explain.

In contrast, heuristic models assume that people engage in mental shortcuts (Gigerenzer, Todd, & the ABC Research Group, 1999; Kahneman, Slovic, & Tversky, 1982; Simon, 1957). While there is variation in the nature of heuristics that have been proposed, many of the most prominent accounts posit that people focus on a single cue at a time rather than incorporating all available information—typically the cue that is most relevant to the decision or most accessible to the decision maker (e.g. Gigerenzer & Goldstein, 1996; Shah & Oppenheimer, 2009; Tversky & Kahneman, 1974). By using only a single piece of information at a time, they are able to greatly reduce the amount of cognitive effort required (Shah & Oppenheimer, 2009).

While there is a great deal of evidence for the use of heuristics, there is also evidence to suggest that simple heuristic models are incomplete descriptors of human cognition. A number of studies have shown patterns of results inconsistent with the use of single cues (e.g. Oppenheimer, 2005). Furthermore, the previously discussed evidence supporting linear models of judgment are challenging to account for if one assumes a single cue receives all or most of the weight. In other words, like linear models, heuristics can explain judgment in some cases, but leave gaps in accounting for others.

Since linear models excel at explaining judgment in some environments, and heuristic accounts are more effective in other environments, many researchers have argued for a strategy switching account. This suggests that people have a number of cognitive strategies in their repertoire and switch between them depending on the task environment. In other words, people rely on each type of model under certain circumstances (Gigerenzer, Todd, & the ABC Research Group, 1999; Hogarth & Karelaia, 2005, 2007; Newell & Shanks, 2003; Payne, Bettman, Johnson, 1988, 1993). However, while strategy switching accounts have become dominant in the field, an alternative approach would be a single strategy that mimics linear combinations under some conditions, and mimics heuristics under others—while predicting unique patterns in still others.

Using Causal Models to Reconcile Alternate Approaches

Causal models are applicable across a wide array judgments and, together with research on causal learning, can specify which cues are relevant for forming an accurate judgment and when (for reviews see Glymour, 2001; Gopnik & Shultz, 2007; Sloman, 2005). People are known to engage in spontaneous causal reasoning (Weiner, 1985). Moreover, researchers have shown that causal models play a role in how people make decisions (Hagmayer & Sloman, 2009; Sloman & Hagmayer, 2006). Specifically, Hagmayer and Sloman argue that people generate causal models of a situation and use these to determine which actions they should take (the action that causes the intended effect rather than one that is merely correlated with it). Further, causal narratives have been shown to influence jury decision making (Pennington & Hastie, 1993), and causal assumptions have been shown to affect risk assessment (Morgan, Fischhoff, Bostrom, & Atman, 2002).

While there is ample evidence that people use causal information, there has been little work to investigate whether causal models might be able to explain when people's judgments emulate heuristics vs. linear models. However, it is possible that apparent switches in strategy arise because of differences in the *causal relationships* of cues. This could account for the findings supporting both linear models and heuristics without resorting to the notion of strategy switching (and also make valid novel predictions). The studies described provide evidence that individuals determine cue weights based on the underlying causal relationships among cues being considered, and that causal models can account for patterns of data that have previously been attributed to strategy switching.

Causal Model Predictions

The present approach posits that when exposed to a set of cues, people spontaneously attempt to understand the causal relationships between those cues and the criterion of interest (c.f. Oppenheimer, 2004). Importantly, different causal relationships will lead different cues to become more or less important. Consider the following causal structures, where an arrow from A → B represents that A causes B (i.e. increasing the value of A will directly lead to an increase in the value of B), and where C represents the target of judgment.

1. A → B → C
2. C → B → A
3. A ← B → C

In these three cases, the predictions of a causal model emulate those of attribute substitution or a fast-and-frugal single cue stopping rule. While A may be correlated with C, it is not directly causally related. For the causal relationships presented in 1-3, B "screens off" A, so that once a person knows the value of B, there is no additional predictive information conveyed about C through A (Pearl, 2000; Sloman, 2005). In causal structure 1, if A causes B and B causes C, then A and C are independent, conditional on the value of B; P(C|A, B) = P(C|B). The same rationale can be used in the reverse direction in causal structure 2. A similar logic also applies in feature set 3, where knowledge of B should make knowledge of A irrelevant. As such, a causal model theory predicts that for causal structures such as those presented in 1–3, people who have access to B will use it to the exclusion of A when making judgments about C, just like non-compensatory heuristics.

Contrast those causal structures with the following:

4. A → C ← B
5. A ← C → B
6. A → C → B

A causal model for these relationships emulates the predictions of a linear model. Both A and B are directly and independently causally related to C. As such, both A and B would be useful predictors of C in some combination. Just as linear models would typically weight cues based on the magnitude of the correlation between cues, causal models would weight cues based on the strength and the structure of the perceived causal relationship (Griffiths & Tenenbaum, 2005). Stronger causal relationships lead to higher correlations. As such, a causal model theory predicts that for causal structures such as those presented in 4-6, people will use a weighted combination of A and B, just like linear models.

Importantly, while a causal model theory can, in a single unifying framework, subsume both heuristic and linear modeling approaches to judgment, it can also make unique predictions for certain causal structures. Consider:

7. C → B ← A

In feature set 7, reliance on the causal model would lead to a unique pattern of cue use. As in 1-3, , there is no direct causal relationship between A and C. However unlike in 1-3, the utility of the cue B in judging C is conditional on the value of A. That is, in scenario 7, a high value of B could be explained by *either* a high value of C or A (or both). Thus, while A does not directly impact judgments of C, it changes the amount of weight placed on cue B. In the causal reasoning literature, this is known as explaining away or discounting (for a review, see Khemlani & Oppenheimer, 2010). And in fact, this pattern of results has been found in several studies of judgment (e.g. Oppenheimer, 2004; 2005; Oppenheimer & Monin, 2009).

Importantly, this pattern of results could not arise from either heuristic models or linear models. Heuristic models would predict that reasoners would rely on a single cue (B) for their judgment because it is the most highly correlated with C. Linear models would factor in both A and B, but since A is uncorrelated with C, the weight would likely be near zero and the predictions would align with those of heuristic models. In other words, causal model theory can account for the successful predictions of both heuristic models and linear models, as well as other findings in the literature that previous models have been unable to explain. The ensuing experiments compare the accuracy of predictions of causal models to those made by using representative linear or heuristic models.

Experiment 1

The primary predictions of the causal model approach are that qualitatively different cue weighting patterns will arise depending on the causal relationships between the cues. In particular, cue weighting will mimic the predictions of heuristic approaches for certain causal structures (e.g. the Causal Chain: A → B → C), will mimic the predictions of linear models for other causal structures (e.g. the Common Cause: A → C ← B), and will show patterns that differ from both heuristic and linear models for still other causal structures (e.g. the Common Effect: C → B ← A). This prediction was directly tested here.

Method

Participants. 32 participants were recruited through an online platform hosted through Amazon.com, in exchange for monetary compensation. The population was 66% female, with a mean age of 35.

Design and Procedure. Participants were randomly assigned to one of three conditions (Chain, Common Cause, or Common Effect as specified above) in a between-subjects design. Participants were then introduced to a novel (blank predicate) domain involving a set of mechanical parts and how they relate to each other; the causal relationship between the parts varied by condition. For example, in the Chain condition, participants saw:

When pressure in the Blanden Pipe increases, it causes water flow through the Morton Spout to increase. And, when water flow through the Morton Spout increases, it causes the Nurbert Clamp to tighten.

In the Common Cause condition, the relationship described was:

When the Nurbert Clamp tightens, it causes water flow through the Morton Spout to increase. And, when the Nurbert Clamp tightens, it also causes the pressure on the Blanden Pipe to increase.

And, in the Common Effect condition, the relationship described was instead:

When the Nurbert Clamp tightens, it causes water flow through the Morton Spout to increase. And when pressure in the Blanden Pipe increases, it also causes water flow through the Morton Spout to increase.

In each trial, participants were given values for two of the parts (amount of pressure in the Blanden Pipe and level of water flow through the Morton Spout) and their task was to estimate the value for the third part (tightness of the Nurbert Clamp). They responded by marking their judgment on a 10 point scale that ranged from "very loose" to "very tight". Participants completed 10 trials during which the cue values of the Blanden Pipe and Morton Spout were systematically varied. However, these values were held consistent across conditions – the only thing that varied between conditions was the causal relationship between the cues.

Results and Discussion

For one of the 10 trials, the values of both cues were the same; this question was included as a manipulation check. Regardless of how they chose to combine the cues, anyone who read this question carefully and understood the task should have responded to the missing value with the same value that had been provided for the other two devices. Prior to analyzing the data, responses from 7 participants were discarded for failing the manipulation check. Results are similar if data from these participants is included.

Data from each of the remaining participants were examined to determine how participants were integrating known information into their final judgment. β weights were calculated for each participant using a linear regression to determine the weight given to the values of cue A (Blanden Pipe) and cue B (Morton Spout) in participant estimations of cue C (Nurbert Clamp). This method of estimation of participants' weighting policy is common in both the Brunswikian tradition of linear modeling (Cooksey, 1996) and in heuristic approaches to attribute substitution.

While heuristic models would predict that participants should weight one cue substantially more heavily than the other, and linear models would predict that weights should be split more evenly between the cues, they both predict that weights should look equivalent across conditions. Because the judgment environment was held constant across conditions (e.g. no cognitive load or time pressure, identical cue values, etc.) there is no a priori reason to expect strategy switching. The causal model, however, predicts qualitative differences in the weights placed on cues depending on the causal structure that the participants were presented with.

In Table 1 below, weights predicted by the causal model hypothesis are shown beside actual weights generated by participant data. Each of the hypothesized beta weights were generated by using a regression approach where we entered the expected responses for each of the 10 trials shown to participants, based on the anticipated weight given to each cue. Specifically, predicted weights for the Chain condition (β_A = 0; β_B = 1) were determined as a result of screening off; B receives the full weight of the judgment while A remains unused. Predicted weights for the Common Cause condition (β_A = .63; β_B = .55) are a result of the both A and B having an independent causal impact on the value of C (the predictions are not β_A = .5; β_B = .5 because we created these weights using the cue values actually shown to participants, which were somewhat arbitrarily chosen and therefore not perfectly balanced around the midpoint of the scale). In the case of the Common Effect condition, predictions may vary depending on the amount of causal discounting that takes place, as described in the theoretical background above. However, the most straightforward prediction (β_A = -0.64; β_B = 1.07), is based on the assumption that A takes on the average value of B and C, and is included in Table 1.

Table 1: Actual and predicted cue weights in estimating missing cue values in Experiment 1.

	Causal Model Prediction		Participant Responses	
Condition	β_A	β_B	β_A	β_B
Chain	0.00	1.00	0.02	0.73
Common Cause	0.63	0.55	0.50	0.45
Common Effect	-0.64	1.07	0.03	0.84

While heuristic and linear models would predict similar weights across conditions, the pattern of data suggests that this is not what is occurring. Instead, the pattern matches the qualitative predictions of a causal model.

Although it appears at first glance that predictions are off in the case of the Common Effect condition, this may be due to individual differences in discounting. The averaged values shown in the table above hide individual level judgments: no individual placed the majority of her judgment on cue B alone. Instead, approximately half of responses for the Common Effect condition suggested negative beta weights for cue A while the other half of responses implied positive beta weights for cue A. These averaged to zero, making it appear as if no weight was given to cue A when looking across the whole sample. While a bimodal distribution could be explained by individual differences in discounting, this is admittedly a post-hoc explanation. Research supports the possibility that there are individual differences in discounting; differences in working memory capacity impact susceptibility to a cognitive load manipulation (Cokely, Kelley, Gilchrist, 2006) and cognitive load influences discounting (Oppenheimer & Monin, 2009). Importantly, the overall data pattern seems to support the key prediction of qualitative differences in weighting by condition.

To determine if the differences between conditions were statistically reliable, a one-way ANOVA was run. Results revealed a main effect of condition on the difference between weights participants placed on A and B in their judgments ($F(2, 22) = 9.27$, $p = .001$, $\eta^2 = .46$). Consistent with the causal model hypothesis, post-hoc tests indicated that the mean difference in weights for the Chain condition (M = .87) was marginally greater than for the Common Cause condition (M =.05, $p = .070$) and significantly greater than for the Common Effect condition (M = -.96, $p < .001$). The difference in weights for the Common Cause condition was also marginally greater than for the Common Effect condition ($p = .056$). Not only was the difference in weights lowest in the case of the Common Effect condition, but the sign was actually reversed, indicating a distinct pattern of evaluation.

Experiments 2a-d

In addition to the study described above, we have conducted four variations that extend results to all seven proposed causal models, as well as a control condition where no model is specified. Because these variations are similar to one another, for the purposes of brevity and space constraints, we will describe them briefly below and combine results in subsequent analysis.

Methods

Participants. All participants (numbers specified below) were recruited online, through an online platform hosted by Amazon.com, and completed the experiment for monetary compensation. The population was 61% female, with a mean age of 35.

Experiment 2a: 110 participants were randomly assigned to one of eight conditions in a between subjects design. The conditions corresponded to each of the seven causal models specified above as well as an additional condition where no model was specified (used as a control). Apart from the additional conditions, the central procedure was the same as described in the Experiment 1 above. However, after the 10 trials were complete, participants were presented with a new page with the names of each of the three parts and asked to draw arrows connecting them. This procedure was included to determine whether the participants understood the underlying causal model intended by each experimental condition, and to allow for additional analysis based on participants' causal models, regardless of their condition.

Experiment 2b: One concern stemming from Experiment 2a was that participants may not understand the basic causal relationships being described. This could be a result of lack of attention rather than a true underlying cognitive process. To address this, the remaining experiments used a Star Trek theme to engage participants. Specifically, 95 participants were told that their crew was on a mission to rescue human hostages from the Romulans on a faraway planet. Their ship had been facing a string of mechanical problems and the participants needed to incorporate known information about mechanical parts to identifying key issues to fix the ship and make it there in time! Pages with encouragement from Star Trek characters were interspersed throughout the experiment to keep participants engaged in the task. Apart from the theme, study 2b was identical to 2a.

Experiment 2c: This study varied by changing from named mechanical parts to colored gears spinning to ensure that (84) participants were not overlaying any prior knowledge of the relationships between mechanical parts into the causal descriptions presented to them. Additionally, it changed the method of testing participants' causal models to multiple choice questions asking what each gear directly causes to avoid any difficulty with the causal drawing task. Otherwise, this study was identical to 2b.

Experiment 2d: This study incorporated the changes in Experiment 2c, and also allowed (81) participants to intervene on the system to visualize the relationship between gears (including stochastic elements), thus aiding their learning of the causal relationships. After reading through the introduction participants were show a diagram with a separate vertical bar representing the speed of each of the three gears. They were able to change and set the speed of one gear at a time and watch as the speed of the other gears changed. The remainder of the experiment was identical to Experiment 2c. Responses to the (multiple choice) questions regarding causal relationships at the end of the experiment revealed that this learning phase did help participants grasp the intended models.

Results and Discussion

195 participants reported causal models (collected at the end of the experiment) that did not match the model intended by the condition they were randomly assigned to. Two analyses were done, one including these participants and one excluding them. The results, as well as underlying demographic characteristics, were qualitatively the same. Due to page constraints, only the latter analysis (subjects who passed the manipulation check) will be reported here.

Table 2: Actual and predicted cue weights in estimating missing cue values in Experiment 2a-d.

Condition (Predicted Model Match)	Causal Model Prediction		Participant Responses	
	β_A	β_B	β_A	β_B
1-3 (Heuristic Model)	0.00	1.00	0.12	0.69
4-6 (Linear Model)	0.63	0.55	0.56	0.54
7 (Causal Model Only)	-0.64	1.07	-0.33	0.82
8 (No Model)	—	—	0.24	0.23

To conserve space and to simplify analysis for reporting, we will pool data across experimental variations as well as group conditions based on the predictions made about their weights. Thus, conditions 1-3, which all share predictions of the heuristic model, and conditions 4-6, which all share predictions of the linear model, will be grouped together. In the analysis that follows, all predictions are generated based on the reasoning described in the data analysis for Experiment 1. As shown in Table 2, differences across groups were consistent with the causal model hypothesis.

Specifically, a one-way ANOVA revealed that the main effect of condition on the difference between weights participants placed on A and B in their judgments was significant ($F(3, 162) = 20.38$, $p < .001$, $\eta^2 = .28$). Consistent with the causal model hypothesis, post-hoc tests indicated that the mean difference in weights for the combined conditions 1-3 ($M = .57$) was significantly greater than for that of conditions 4-6 (M =-.02, p = < .001) and condition 8 ($M = .01$, p =.002). At the same time, the differences between weights given to cues A and B in conditions 1-3 were significantly lower than in condition 7 ($M = 1.15$, $p < .001$), as predicted.

General Discussion

In this paper, we have proposed a causal model theory of judgment; namely, that people rely on their understanding of the causal relationships among events to determine how to weight various cues when forming judgments. Across two studies with several variations, we have shown that predictions of the causal model approach consistently meet or exceed the accuracy of predictions of human judgment made by either linear or heuristic models. Furthermore, the causal model theory can specify when predictions of linear versus heuristic models will be more accurate, and make unique predictions in other situations.

These results suggest that, while linear and heuristic models may be able to make predictions about cue weights that match those of human judgments under certain circumstances, these models may not be accurate descriptions of the underlying cognitive process. Although a strategy-switching approach may map onto actual judgments more closely than either heuristic or linear models do independently, this possibility adds unnecessary complexity. Furthermore, without the ability to make a priori specifications about which strategies would be used under which circumstances, a strategy-switching approach becomes unfalsifiable. In contrast, the causal model theory makes clear predictions that parsimoniously explain observed changes in the weights placed on various cues.

Absent specific prompts used in this paper to differentiate causal relationships, situational factors may also change perceived causal models, even when the underlying relationship among events remains unchanged. This would allow for judgments based on causal relationships to follow patterns previously found by strategy switching in other contexts. For example, putting people under time pressure or cognitive load may lead them to develop simplified causal models (e.g. Oppenheimer & Monin, 2009). This underlying change would lead to judgments that mimic those described by a shift from a linear model to a heuristic strategy. While we acknowledge that causal models may be used to inform strategy switching rather than supplant it, it will be worthwhile to investigate both the strong (causal models supplant strategy switching) and weak (causal models inform strategy use) versions of the hypothesis.

The experiments reported here support the hypothesis that the presumed combination of heuristics and linear models is actually describing specific instantiations of reliance on causal models in judgment. While this paper has begun to build a case for the causal model hypothesis, future studies should aim to provide converging evidence as well as to improve understanding of when and how a particular causal model would be used.

Acknowledgements

We are grateful to Steven Sloman and members of the Opplab for useful comments and suggestions.

References

Anderson, N. H. (1981). *Foundations of information integration theory.* New York: Academic Press.

Brehmer, A., & Brehmer, B. (1988). What has been learned about human judgment from thirty years of policy capturing? In B. Brehmer & C.R.B. Joyce (Eds.), *Human judgment: The SJT view*. Amsterdam: North-Holland, Elsevier.

Brehmer, B. (1994). The psychology of linear judgment models. *Acta Psychologica* , *87*, 137–154.

Brunswik, E. (1943). Organismic achievement and environmental probability. *The Psychological Review, 50,* 255-272.

Brunswik, E. (1952). *Conceptual framework of psychology*. Chicago, IL: University of Chicago Press.

Cokely, E.T., Kelley, C.M., & Gilchrist, A.L. (2006). Sources of individual differences in working memory: Contributions of strategy to capacity. *Psychonomic Bulletin and Review, 13,* 991-997.

Cooksey, R.W. (1996). *Judgment analysis: Theory, methods, and applications.* San Diego, CA: Academic Press, Inc.

Dawes, R.M., & Corrigan, B. (1974). Linear models in decision making. *Psychological Bulletin, 81,* 95-106.

Dawes, R. M. (1979). The robust beauty of improper linear models in decision making. *American Psychologist, 34,* 571-582.

Einhorn, H.J. & Hogarth, R.M. (1975). Unit weighting schemes for decision making. *Organizational Behavior and Human Performance, 13,* 171-192.

Gigerenzer, G., & Goldstein, D.G. (1996). Reasoning the fast and frugal way: Models of bounded rationality. *Psychological Review*, *103*, 650–669.

Gigerenzer, G., Todd, P.M., & the ABC Research Group (Eds.) (1999). *Simple heuristics that make us smart*. New York: Oxford University Press.

Glymour, C. (2001). *The mind's arrows: Bayes nets and graphical causal models in psychology*. Cambridge, MA: MIT Press.

Gopnik, A. & Shulz, L. (Eds.) (2007). *Causal learning: Psychology, philosophy, and Computation*. New York: Oxford University Press.

Griffiths, T.L. & Tenenbaum, J.B. (2005). Structure and strength in causal induction. *Cognitive Psychology, 51,* 334-384.

Hagmayer, Y., & Sloman, S. A. (2009). Decision makers conceive of themselves as interveners, not observers. *Journal of Experimental Psychology: General, 138,* 22-38.

Hammond, K.R. (1955). Probabilistic functionalism and the clinical method. *Psychological Review*, *62*, 255–262.

Hammond, K.R. (1996). *Human judgment and social policy: Irreducible uncertainty, inevitable error, unavoidable injustice*. New York: Oxford University Press.

Hogarth, R.M., & Karelaia, N. (2005). Ignoring information in binary choice with continuous variables: When is less "more"? *Journal of Mathematical Psychology, 49,* 115-124.

Hogarth, R. M., & Karelaia, N. (2007). Heuristic and linear models of judgment: Matching rules and environments. *Psychological Review, 114,* 733–758.

Hoffman, P.J. (1960). The paramorphic representation of clinical judgment. *Psychological Bulletin, 57,* 116–131.

Kahneman, D., Slovic,P. & Tversky, A. (Eds.) (1982). *Judgment Under Uncertainty: Heuristics and Biases.* New York: Cambridge University Press.

Khemlani, S., & Oppenheimer, D.M. (2010). A levels of analysis framework of causal discounting.

Morgan, M. G., Fischoff, B., Bostrom, A., & Atman, C. J. (2001). *Risk communication. A mental model approach.* New York: Cambridge University Press.

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,* 53–65.

Oppenheimer, D. M. (2004). Spontaneous discounting of availability in frequency judgment tasks. *Psychological Science, 15*(2), 100-105.

Oppenheimer, D. M. (2005). Consequences of erudite vernacular utilized irrespective of necessity: Problems with using long words needlessly. *Applied Cognitive Psychology, 20*(2), 139-156.

Oppenheimer, D. M., & Monin, B. (2009). The retrospective gambler's fallacy: Unlikely events, constructing the past, and multiple universes. *Judgment and Decision Making, 4,* 326–334.

Payne, J.W., Bettman, J.R., & Johnson, E.J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14,* 534-552.

Payne, J.W., Bettman, J.R., & Johnson, E.J. (1993). *The adaptive decision maker.* New York: Cambridge University Press.

Pearl, J. (2000). *Causality.* New York: Cambridge University Press.

Pennington, N., & Hastie, R. (1993). Reasoning in explanation-based decision making. *Cognition, 49,* 123–163.

Shah, A.K. & Oppenheimer, D.M. (2009). The path of least resistance: Using easy-to-access information. *Current Directions in Psychological Science, 18,* 232-236.

Simon, H. (1957). *Models of man*. New York: Wiley.

Sloman, S.A. (2005). *Causal models: How people think about the world and its alternatives*. New York: Oxford University Press.

Sloman, S.A. & Hagmayer, Y. (2006). The causal psycho-logic of choice. *Trends in Cognitive Sciences, 10,* 407-412.

Slovic, P. (1969). Analyzing the expert judge: A descriptive study of a stockbroker's decision processes. *Journal of Applied Psychology, 53,* 255-263.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185,* 1124–1131.

Wainer, H. (1976). Estimating coefficients in linear models: It don't make no nevermind. *Psychological Bulletin, 83,* 213-217.

Weiner, B. (1985). Spontaneous causal thinking. Psychological Bulletin, 97, 74-84.

Wiggins, N. & Hoffman, P.J. (1968). Three models of clinical judgment. Journal of Abnormal Psychology, 73, 70-77.