Information Processing as a Paradigm for Decision Making

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Annu. Rev. Psychol. 2015. 66:277–94

The *Annual Review of Psychology* is online at psych.annualreviews.org

This article's doi:
10.1146/annurev-psych-010814-015148

Keywords

decision making, paradigm shift, information processing, utility theory

Abstract

For decades, the dominant paradigm for studying decision making—the expected utility framework—has been burdened by an increasing number of empirical findings that question its validity as a model of human cognition and behavior. However, as Kuhn (1962) argued in his seminal discussion of paradigm shifts, an old paradigm cannot be abandoned until a new paradigm emerges to replace it. In this article, we argue that the recent shift in researcher attention toward basic cognitive processes that give rise to decision phenomena constitutes the beginning of that replacement paradigm. Models grounded in basic perceptual, attentional, memory, and aggregation processes have begun to proliferate. The development of this new approach closely aligns with Kuhn's notion of paradigm shift, suggesting that this is a particularly generative and revolutionary time to be studying decision science.

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INTRODUCTION

> *Man is a rational animal—so at least I have been told. Throughout a long life I have looked diligently for evidence in favor of this statement, but so far I have not had the good fortune to come across it.*
>
> *—Bertrand Russell*

The field of judgment and decision making (JDM) has long been dominated by an economic perspective. This approach to explaining decision making is grounded in the belief that humans are rational animals whose decisions serve to optimize utility. However, for the past several decades, psychologists have been finding empirical results that cannot be easily explained by such a framework, to the point where it is no longer surprising to observe violations of rational behavior. As holes have continued to develop in the dominant paradigm, information processing models have started to emerge as reasonable alternatives in psychology. This shifting focus of researcher attention aligns with Thomas Kuhn's (1962) notion of a paradigm change, which suggests that the field of JDM is evolving its focus, methods, and approach. This article reviews Kuhn's observations about scientific revolution, explores evidence suggesting that the field is going through a paradigm shift, and describes promising future directions during this exciting transition period.

The Evolution of Scientific Paradigms

It seems to be in the nature of fields of scientific inquiry to periodically go through an identity crisis. With the accumulated development of empirical nuance, explanatory power, and self-referential knowledge comes the ability for scientists to meaningfully probe the foundations on which their investigations rest. So argued Thomas Kuhn in his seminal work *The Structure of Scientific Revolutions* (1962), in which he established the role conceptual paradigms play in the progression of scientific inquiry.

A paradigm refers to the set of practices that defines a scientific discipline at any particular period. A paradigm provides the basis for deciding (*a*) what phenomena to study, (*b*) what kinds of questions meaningfully probe for answers, (*c*) how these questions should be structured, (*d*) how an experiment is to be conducted, and (*e*) how the results of the investigations should be interpreted. In essence, an underlying paradigm is needed to give meaning to the methodology and resultant data of an investigation.

In Kuhn's observations of the development of science throughout history, he noted several distinct stages of how problems are defined and tackled. Normal science occurs when investigators are in general consensus on the appropriate choice of methods, terminology, and kinds of experiments that will lead to further insight. This stage of normal science, in which a discipline spends the majority of its time, Kuhn dubs puzzle solving, indicating a general sense that there are answers to be pieced together in this framework.

Over time, progress in normal science may challenge original assumptions as new data are revealed. As a paradigm is stretched to its limits, anomalies—failures of the current paradigm to take into account observed phenomena—accumulate. Although many anomalies may be dismissed as errors in observation, and others may be resolved, in some cases anomalies may accumulate to the point that normal science becomes difficult owing to weaknesses in the accepted paradigm. This crisis in a discipline is often resolved within the context of normal science, but if significant efforts by normal science to explain anomalies within a paradigm fail, revolutionary science may begin. In this stage, the underlying assumptions of the field are reexamined and a new paradigm is established. This process may occur relatively quickly or over the course of decades. Once the dominance of a new paradigm has been established, the field returns to the process of normal science, albeit within the new paradigm.

Importantly, no matter how great or numerous the anomalies that persist in a given paradigm are, the practicing scientists will not, Kuhn argues, lose faith in the established paradigm until a credible alternative is available. The reason is that the existing tools are inherently inadequate for the task of deciding between conflicting theories, since they belong to the very paradigms they seek to compare.

Kuhn reviews numerous examples throughout history of the process of paradigm shifts in the sciences, but he focuses largely on perhaps the most paradigmatic of paradigm shifts: that which took place in the field of astronomy during what is now called the Copernican Revolution.

Early models of the universe, most strongly associated with Ptolemy (Lawson 2004), were geocentric in nature. These models argued that an unmoving Earth sits at the center of our universe, with the heavens moving around us in perfect circles. This model fit our naive observations well until, upon more accurate inspection, we noticed that the sun and stars did not behave as we would expect if they were traveling in perfect circular orbits around the static Earth. As observations like these began to accumulate, astronomers had to propose further nuance and complexity to the Ptolemaic system in order to correct for these anomalies. Concepts such as deferents, cycles, epicycles, and equants (essentially spheres within spheres) were attached to the original geocentric model to help explain the observed anomalies. These add-ons aided somewhat in explaining the data but made Ptolemy's theory much more unwieldy and reactive rather than elegant and predictive.

Despite the observed anomalies, without a viable alternative theory, Ptolemaic theory persisted for more than 1,000 years. Eventually, Copernicus proposed that these deviations from expected stellar positions could better be explained by the fundamental assumption that the Sun, not the Earth, was at the center of the universe. A century later, research by Galileo Galilei, Johannes Kepler, and Isaac Newton demonstrated convergent evidence toward the Copernican model. Their theoretical insights significantly reduced the complexity of predictive models and solidified the paradigm shift from a geocentric model to a heliocentric model.

The Copernican Revolution in astronomy had many lasting effects on the broader scientific community. It empirically concretized the notion that difficulties in modeling an object of study may in fact arise from a fundamental misconstrual of what scientists think they are investigating.

In this article, we observe parallels between recent developments in the study of judgment and decision making and previously documented examples of scientific revolutions. We identify several current models of decision making that fundamentally deviate from classical models in their attempt to resolve anomalous observations, which suggests that the field is currently undergoing a paradigmatic transition.

A BRIEF HISTORY OF DECISION-MAKING PARADIGMS

The aim of decision theory traditionally has been to understand how agents pursue goals in the face of options (Hagen et al. 2012). Goals may include increasing wealth, health, or happiness, and corresponding options may include choosing among investment opportunities, diet plans, or which movie to watch on Saturday night.

It was not until the seventeenth century that Blaise Pascal and Pierre de Fermat began laying the foundations of what would become the science of decision making. The key insight was that agents should maximize expected value (EV), such that

$$EV = \sum p_i \cdot x_i,$$

where p_i represents the probability of receiving a given outcome and x_i represents the amount of money associated with the outcome ($i = 1, \ldots, n$) of an option.

Thus, early decision making theorists concerned themselves with the nature of an ideal decision maker under conditions of uncertainty. This approach to maximizing expected value, however, logically entailed certain gambles in which players should be willing to pay any (infinite) amount to play, a prediction that is empirically violated. For example, a casino may offer the following game (known as the St. Petersburg paradox): A fair coin is repeatedly tossed. The pot starts at $1, and for each time the coin lands heads, the pot is doubled. As soon as the coin lands tails, the game is over and the person wins whatever is in the pot. In short, the player wins 2^k dollars, where k heads are tossed before the first tail appears. What would be a fair price to pay the casino to play such a game? Inputting this game into an expected value formula, we find that the expected value of the game approaches infinity. If one considers only the expected value of change in one's wealth, one should be willing to pay any price if offered the opportunity to play the game. However, in actuality people are willing to bid well less than even $1,000 to take this gamble—an empirical violation of expected value.

To account for these kinds of anomalies, Daniel Bernoulli (1738) modified the theory, arguing that the value of an outcome should be judged not by monetary value but rather by a concave function of this value, which he called utility, reflecting the diminishing marginal benefit of money. Although the price of an item depends solely on the item itself and is equal for all, the utility of that item is dependent upon the individual circumstances of the person making the estimate. "Thus there is no doubt that a gain of one thousand ducats is more significant to a pauper than to a rich man though both gain the same amount" (Bernoulli 1738). Expected utility thus converges to a finite number, even under conditions of potentially infinite rewards.

Although the transition from raw value to subjective utility helped explain why different people ascribe different values to the same objects, it also undermined the predictive power of the model. If every individual could have a unique utility function, then what systematic predictions could be made about their behaviors? Von Neumann & Morgenstern's (1947) classic expected utility theory (EUT) was a major attempt to formulate an axiomatic foundation for representing the preferences of a rational decision maker and has largely influenced decision making theory since (Machina 1982; Savage 1954). These axioms allowed for predictions of future relationships between an individual's preferences, given the fundamental assumption that people are rational. The axioms were

1. Completeness. For any two options, the rational decision maker either prefers one to the other or is indifferent between the two.
2. Independence. If a rational decision maker prefers option A to option B, then she should not also prefer option B to option A.
3. Transitivity. If a rational decision maker prefers gamble A to gamble B, and gamble B to gamble C, then she should not prefer gamble C to gamble A.
4. Continuity. Assume a decision maker prefers \$100 to \$50 to \$0. There exists a gamble A that pays off \$100 if you win and \$0 if you lose, for which a rational decision maker is indifferent between that gamble and a sure gain of \$50.

However, anomalies continued to accumulate. For example, observations of bias in people's perceptions of probability (e.g., people do not treat a 10% chance of an event as 10 times as likely as a 1% chance) led to further modification of EUT by Leonard Savage (1954). Savage introduced further subjective elements into rational decision making theory by adding a parameter to allow for variations in the subjective probability of each outcome $P(x_i)$, defining one's expected utility as

$$\sum u(x_i) \cdot P(x_i).$$

Despite the additional flexibility in predictions afforded by Savage's additional parameter, anomalies continued to be observed and additional complexity needed to be added to utility theory to account for these anomalies. For example, Kahneman & Tversky (1979) noted that logically identical decisions led to different behaviors when they were described as losses rather than as gains.

Consider the following cases:

Case 1: Start with \$0, then offered the choice:

Option 1: 50% chance of gaining \$200, 50% chance of gaining \$0

Option 2: Sure gain \$100

Case 2: Start with \$200, then offered the choice:

Option 1: 50% chance of losing the \$200, and 50% chance of losing nothing

Option 2: Sure loss of \$100

In both cases, the decision maker has a 50% chance of ending up with \$0 and a 50% chance of ending up with \$200, compared with a sure outcome of \$100. However, many participants show preference reversals depending on whether the gamble is framed in terms of potential losses or potential gains.

To account for this, Kahneman & Tversky's (1979) prospect theory posited different utility functions for losses than gains. In particular, prospect theory suggested a function that was concave for gains and convex for losses, with steeper slope for losses than for gains. Moreover, prospect theory refined the nature of subjective probability, showing that people overweight unlikely events and underweight highly likely events.

Although prospect theory was an improvement to previous EUT models, there remained anomalies for which the theory could not account. Among them was the observation that the tendency to overweight unlikely events was much more pronounced for extreme outcomes. Prospect theory assumed that people overweight unlikely events independently of their relative outcomes. Quiggin's (1982) rank-dependent expected utility was developed around the idea that people overweight only unlikely extreme outcomes rather than all unlikely events. Further anomalies in people's perceptions of probability led to the development of cumulative prospect theory (Tversky & Kahneman 1992), which argued that cumulative probability functions, rather than probabilities themselves, are transformed.

Despite these additional parameters and assumptions, there were still observations that violated the predictions. For example, although utility theory would suggest that all money is fungible, researchers began finding evidence that people behave as though money from different sources is of differential value. Consider the house money effect (Thaler & Johnson 1990): Gamblers treat the money they bring into a casino (personal money) differently from the money they have won from the casino (known as house money). People tend to be more willing to make risky gambles with house money than with personal money. To account for this and similar findings, Thaler (1999) developed the notion of mental accounting, which suggests that decision makers have separate mental accounts for various areas of spending (e.g., an account for food and entertainment, an account for travel, an account for work-related expenses) or sources of wealth (e.g., windfalls versus earned money), each with its own utility curve. In other words, not only do different people have different utility functions, but the same person has multiple utility functions that vary depending on the source, intended purpose, and contextual features of wealth.

As complexity of the models continues to grow, so too does the number of observed anomalies that needs to be accounted for. This has led in the past half century to an expansion of decision models that can be considered modifications of EUT. Many of these theories are from a similar mold: presenting empirical deviations from the expectations of prior utility-based models and proposing modifications, extra parameters, or other forms of additional complexity to utility theory to account for these anomalies.

Birnbaum's (1972) configural weights model, Keeney and Raiffa's (1976) weighted additive model, Chew & MacCrimmon's (1979) weighted utility model, and Mellers & Biagini's (1994) contrast-weighting theory extend EUT models by toggling how weights are assigned to available options. Contrast weighting, for example, argues that small contrasts along one dimension result in greater weighting for other dimensions. Configural weighting suggests that the weight of a stimulus component depends on the relation between that component and the pattern of other stimulus components presented.

Other models attempted to refine the utility curves used in prediction [e.g., Fishburn's (1982) skew-symmetric bilinear utility model], incorporate perceived attribute differences between prospects [e.g., González-Vallejo's (2002) stochastic difference model], or add additional weighting components to utility functions [e.g., Loomes & Sugden's (1982) regret theory]. For example, in regret theory, choice is modeled as the minimizing of a function of the regret vector, defined as the difference between the outcome yielded by a given choice and the best outcome that could have been achieved in that state of nature.

A Paradigm Shift

As more anomalies accumulated and models became increasingly complex, scholars began to search for alternative paradigms for decision making. One prevalent approach was to look for domain-specific, decision making algorithms known as heuristics (e.g., Gigerenzer & Gaissmaier 2011, Tversky & Kahneman 1974). These simple decision rules (e.g., choose whichever option comes to mind most easily, or choose the option that is highest on the most important dimension) did not require calculation of optimal utility. Instead, they addressed the problem of decision making from an information processing approach—consider the specific information available to the decision maker and how that information could be used to achieve desired outcomes in a boundedly rational world.

Because heuristics are typically domain specific, or otherwise apply only to narrowly prescribed circumstances, there has been a massive proliferation of proposed heuristics. This has led to a wealth of descriptors of ostensible decision strategies, with limited predictive ability. As Dougherty et al. (1999) elegantly put it, "whereas it is sometimes possible to identify which heuristic participants use a posteriori, it is much more difficult to predict which heuristic will be used a priori."

Moreover, although there have been various attempts to unify the heuristics into an integrated theory (e.g., Gigerenzer & Gaissmaier 2011, Gigerenzer et al. 1999, Shah & Oppenheimer 2008), the bulk of heuristics remain disconnected and are only loosely based in psychological theories of information processing (c.f. Dougherty et al. 1999, Wallsten 1983). This has led researchers to start connecting decision processes to other cognitive systems and to ask whether the anomalous phenomena that heuristics were meant to explain could be modeled as emergent properties of a more integrated cognitive framework. This approach has led to a number of exciting advances in the study of decision making.

INFORMATION PROCESSING THEORIES

As the previously dominant EUT paradigm breaks down, researchers have begun adopting a different approach: the information processing paradigm. Although the theories produced from this new paradigm differ in their specific structure, they are united in their overarching assumptions. Mainly, instead of starting from the assumption that people accurately gauge utility for various options, and thus that modeling people's choices will give insight into their utility functions, information processing models argue that decision scientists should start from basic cognitive building blocks. Decision making recruits basic processes from memory, attention, and perception, to name a few, and thus decision systems are best understood by developing models of how decision-relevant information is sampled, retrieved, and integrated (and seeing what predictions emerge from such models). Below, we review some of the most influential work to have been developed using the information processing paradigmatic approach.

Query Theory

Query theory (Johnson et al. 2007) is based on the notion that people's preferences, like all knowledge, are subject to the processes and dynamics associated with memory encoding and retrieval, and that these principles of memory and attentional processes can explain observed anomalies in evaluations of choices. The basic assumption of this approach is that when agents are faced with a decision, they naturally decompose the overall question into a series of component queries. The order of these queries is shaped by one's implicit goals in the situation, such as one's valuation of the status quo as a buyer or seller. As a result of each of these queries, various aspects of the situation are recruited from memory in a serial manner. Drawing on work on retrieval-induced forgetting (e.g., Anderson et al. 1994), query theory posits that retrieval is less successful for later queries than for earlier ones: The first few queries result in a richer, more heavily weighted set of information compared with later queries, because the retrieval of initial information interferes with the subsequent retrieval of related information.

In sum, query theory argues that decision makers undergo serial evidence sampling toward an ad hoc goal in order to make decisions rather than calculate some abstract utility or value. Since query theory was proposed, a number of experiments have tested the validity of its approach.

In a canonical study, Johnson et al. (2007) tested the notion that implicit goals frame the order of queries. Query theory was applied to the endowment effect, a phenomenon in which people who are given an item tend to value it more than do those who consider purchasing said item. The endowment effect could be considered an anomaly in an EUT paradigm; it forced models of utility to adopt steeper utility functions for losses than for gains. Johnson et al. (2007) were interested in whether this effect would emerge naturally from a model constructed from basic memory principles.

Participants were shown a mug and then were randomly split into groups of sellers and choosers. Sellers were informed that the mug was theirs to keep but that they would later be able to sell it to the experimenter for some price; choosers were informed that they would be able to choose between receiving the mug and receiving some amount of money. They were then asked to report what they were considering as they decided whether they wanted the mug or the money. The content, order, and latency of these considerations were recorded.

Those endowed with the mug considered more aspects that increased the value of the mug (positive thoughts about the mug and negative thoughts about the money), whereas those choosing between the mug and money considered more aspects that decreased the value of the mug (positive thoughts about the money and negative thoughts about the mug). In addition, sellers generated value-increasing statements earlier, whereas choosers generated value-decreasing statements earlier. Further manipulations demonstrated that changing participants' query orders eliminated the endowment effect, as well as produced an endowment effect in the absence of actual ownership. In a subsequent recall task, sellers were seen to have more accurate recall for positive features of the mug and less accurate recall for its negative features; choosers showed the reverse pattern, consistent with the idea that the first query causes interference and reduced accessibility for the second query.

These studies provide support for the notion that one's implicit goals in a situation shape the order in which aspects of an object are considered, and that the earlier considerations in a set of serial queries exert significant effects on the content and weight of later considerations. The EUT paradigm struggles to explain the endowment effect parsimoniously, because it requires a parameter that adjusts the utility value of an item based on the subjective position (buying versus selling) of an agent. Query theory, on the other hand, predicts this effect as an emergent property of basic memory and executive functions.

Subsequent studies have shown that query theory can explain a number of additional anomalies that challenge standard EUT models. Weber et al. (2007) demonstrated query order effects in asymmetric discounting in intertemporal choice: Whether one considers delayed or accelerated receipt of a gift certificate influences the order in which memory is queried, and the order of queries affects the relative number of patient versus impatient thoughts. Appelt et al. (2011) showed that query order was a causal mediator of the framing of delayed gains and losses. Hardisty et al. (2010) showed that attribute framing (e.g., labeling charges for environmental costs as either a tax or a carbon offset) can change the order in which internal queries supporting the options are posed. Khemlani & Oppenheimer (2011) implicated query theory in explanations of causal discounting, in that the search for causal evidence is likely to be biased toward the candidate causes that are recognized as present first. In addition, Ting & Wallsten (2011) explained the sunk cost bias in terms of query theory, showing that individuals generated more reasons for pursuing the invested option than for pursuing an alternative, and generated those reasons earlier. Moreover, these effects increased as the individuals made progress toward attaining the reward yielded by the invested option.

The sampling process account posited by query theory may not be limited to memory retrieval. Krajbich et al. (2012) highlighted the role of visual attention and sampling in their attentional drift diffusion model, wherein fixation patterns have been shown to influence binary and ternary choice (Krajbich & Rangel 2011, Krajbich et al. 2010). That is, the basic approach of examining the effect of goals on query order, and the consequent effects on cue weighting and eventual decision making, has the potential to extend considerably more broadly than has yet to be explored.

Decision Field Theory

Decision field theory (DFT) was put forth by Busemeyer & Townsend (1993) as a dynamic process account of decision making, based in cognitive fundamentals rather than economic principles. The inspiration for this theory came from an earlier approach-avoidance conflict model—field theory (Lewin et al. 1935).

DFT is grounded in the notion that preferences change during deliberation and that the amount of time spent making a decision influences the final choice. The deliberation process involves an accumulation of information about the consequences of a decision through repeated sampling of decision-relevant information. This deliberation process is manifested by indecisiveness, vacillation, and inconsistency (Janis & Mann 1977, Svenson 1992). The amount of attention allocated to the various consequences changes over the course of deliberation time, a process that can be conceptualized as a random walk (Busemeyer et al. 2006a). For a decision to be made, many consequences may be considered, and these anticipated consequences are retrieved from a rich and complex associative memory process. As various features of the decision set are brought to mind, the relative benefits and drawbacks of the available options provide evidence for and against those options. Evidence slowly accumulates but no action is taken until the preference for one action reaches a motivation threshold, causing the decision maker to act.

DFT integrates a strong connectionist base—drawing upon basic neural and cognitive universals—with lateral inhibition. That is, as with neural behavior in the visual cortex, activation of one concept inhibits activation of similar concepts. As such, and in contrast to classic utility models, DFT posits that basic neural and cognitive processes lead to emergent choices. DFT is distinguished from previous mathematical approaches in that it is probabilistic (rather than deterministic) and dynamic (rather than static). DFT has been successfully applied across a broad range of cognitive tasks, including sensory detection, perceptual discrimination, memory recognition, conceptual categorization, and preferential choice (Busemeyer & Diederich 2002, Lee et al. 2008). In this sense, DFT is based on domain-general sampling processes. EUT treats decision making as a special, insulated domain, independent of other psychological research. In contrast, DFT assumes basic cognitive primitives as a process for understanding perception, memory, and concepts, and in this manner accounts for choice.

Since its introduction in the early 1990s, DFT has accumulated an impressive amount of supportive evidence. Much of the evidence involves the dynamic elements incorporated into the model. Decisions take time to make. Whereas EUT suggests that the same choice will be made regardless of deliberation time, and that deliberation time effects are anomalies, DFT capitalizes on this aspect of decision making as a main strength. DFT predicts a number of preference changes over time.

Empirical research on decision making under time pressure has demonstrated that the difference in choice probabilities, $\Pr[A|\{A, B\}] - \Pr[B|\{A, B\}]$, can change sign as deliberation time increases (see Diederich 1997, Svenson & Edland 1987). These preference reversals tend to occur when the most important dimension (e.g., cost) weakly favors one option and the less important dimension (e.g., quality) strongly favors the alternative option (Busemeyer & Diederich 2002).

According to multiattribute DFT (MDFT), attention is focused initially on the most important attribute, and during this time the drift rate drives the preference toward one option. Under short time pressure, the action threshold is set to a low magnitude, allowing time only for the first attribute to be processed, which causes the probability of choosing that option to exceed 0.50. Under little or no time pressure, the threshold is set to a higher magnitude, allowing more processing time for the second attribute. During the time that the second attribute is processed, the drift rate drives the preference toward the alternative option. This causes the probability of choosing that option to exceed 0.50, thus reversing the choice probabilities for longer time intervals.

Further evidence for DFT can be found in studies on context effects and preference reversals. Three particularly vexing anomalies for EUT are the similarity effect (Tversky 1972), attraction effect (Huber et al. 1982), and compromise effect (Simonson 1989). Consider a choice set in which an agent is indifferent between two options {A and B}. If a third option, S, is introduced, such that S and A are similar on relevant dimensions, then the market share of B increases (similarity effect). If instead a third option (A′) is introduced that is dominated by A, but not by B, then the market share of A increases (attraction effect). Meanwhile, options that serve as compromises between two extreme values generally gain more of the market share—therefore adding an option C_A that makes A look like a compromise between C_A and B will increase the market share of A, and adding an option C_B that makes B look like a compromise between A and C_B will increase the market share of B (compromise effect). Note that for all these cases nothing about either option has changed aside from the presence of a third choice; according to the axioms of rational choice, there should be no change in preference between A and B with the addition of C.

DFT can account for all three of these anomalies. For example, for the similarity effect, as attention stochastically shifts toward dimensions that favor A and S, those two options split the activation (and, through lateral inhibition, undermine positive evidence accumulation). Meanwhile, when attention shifts toward dimensions that favor B, it gains evidence unimpeded. The result is that B gathers more evidence more quickly, and DFT accurately predicts the similarity effect. Moreover, studies have shown that these context effects take time to emerge (Pettibone 2012), providing further evidence for information accumulation models such as DFT.

There have been a number of extensions of DFT since it was initially proposed. Diederich (1997) extended DFT to account for binary choices with multiple attributes. Roe et al. (2001) proposed a multialternative DFT model that was conceptualized as a connectionist network (for further surveys of DFT models, see Busemeyer & Diederich 2002). In summary, DFT has evolved from a one-dimensional binary choice model, to a multiattribute binary choice model, and finally to a multiattribute and multichoice model (Huang et al. 2012).

Although DFT is the most prominent model of its class, other researchers have developed competing models based on similar foundations and assumptions. For example, the multiattribute linear ballistic accumulation (MLBA) model (Trueblood et al. 2014) also is based on the idea that the decision maker accumulates evidence in favor of each choice and makes a decision as soon as the evidence for any choice reaches a threshold. Unlike MDFT, the MLBA model has an analytical solution, making it easier to fit to experimental data, though its linear and deterministic foundations may limit its generalizability to real-world scenarios.

Another approach based on evidence accumulation is Bhatia's (2013) associative accumulation model (AAM). Formulated within a connectionist network, AAM embeds the associative relationship between choice task and attribute accessibility within a stochastic, sequential accumulation framework commonly used to model dynamic cognitive processes (Bogacz et al. 2007, Busemeyer & Johnson 2004, Busemeyer & Townsend 1993, Diederich 1997, Johnson & Busemeyer 2005, Krajbich et al. 2010, Milosavljevic et al. 2010, Rangel & Hare 2010, Roe et al. 2001, Usher & McClelland 2004). The model can be instantiated in a three-layer neural network corresponding to task representation, potentially relevant attribute listing, and preference states. AAM assumes that the associations between an attribute and an available alternative affect the attribute's accessibility. In this sense, AAM can be seen as a hybrid between query theory and DFT: The model relies on repeated stochastic sampling of attributes, but the current states and goals of the agent exert effects on the likelihood that certain attributes will be sampled over others. This model provides predictive explanations for many of the major context effects (e.g., similarity effect, attraction effect, and compromise effect), as well as alignability effects (i.e., putting more weight on attributes of a choice that are easy to compare, even if they are less important) and less-is-more effects (i.e., improved decision making when the decision maker has less information upon which to base her choice).

Leaky, Competing Accumulator Model

Inspired by models of visual perception (e.g., Mazurek et al. 2003), Usher & McClelland's (2001) leaky, competing accumulator (LCA) model is based on basic cognitive notions of diffusion, modeling decision making as an error-prone (i.e., leaky) buildup of information over the deliberation process. Like DFT, LCA relies on stochastic alternation of attention and collection of information during the input-processing stage. However, LCA adds fundamental assumptions about imperfections and decay of memory during the deliberation process, which are taken into account during a leaky integration process, in which evidence degrades over time (Usher & McClelland 2004). The model also includes an inhibition parameter, which represents the lateral competition between alternatives (analogous to that seen in the visual system). That is, when two options in a choice set are similar along a particular attribute (e.g., two cars with similar gas mileage), activation of one of the options inhibits activation of the other.

Thus, like DFT, LCA is based on the fact that decision making in humans is not a perfect integration of available and relevant information, but instead is subject to many context-dependent factors such as attention, memory of previous experiences, and memory decay. As a result, LCA allows context effects to emerge naturally as predictions of the theory, not as anomalies.

LCA, however, differs from MDFT in two crucial respects. First, in LCA the strength of the lateral inhibition interactions is independent of the psychological distance between options (Usher & McClelland 2004). Second, LCA does not make use of negative activation. Instead, LCA assumes loss aversion (cf. Tversky & Kahneman 1992). An asymmetric value function transforms the evidence before transmitting it to the leaky integration process.[1] LCA has successfully captured a number of features of human decision making, including lexical decision making (Dufau et al. 2012), perceptual decision making (Bogacz et al. 2007; Gao et al. 2011; Usher & McClelland 2001, 2004), and psychophysiological testing of dynamic multialternative choice (Tsetsos et al. 2011).[2]

Decision by Sampling

One research program that has explicitly rejected the notion of utility is the decision by sampling (DbS) approach (Stewart et al. 2006). Motivated by psychophysical evidence that people are considerably more effective at comparing the magnitude of two stimuli than at estimating absolute magnitude, DbS suggests that decision makers do not mentally represent utility at all. Instead, decision makers are presumed to make binary, ordinal comparisons between the present option and alternatives drawn from memory and the current environment, and to track frequencies of how often a particular option wins. As such, the perceived value of an option will be a function of the nature of other values in the immediate context and those drawn from memory. Even though DbS does not incorporate the concept of utility, it can account for and predict the shape of the most prominent utility functions, including a concave function for gains, a convex function for loss, a

[1] Usher & McClelland (2004) criticize the MDFT model because negative activation, though allowing a closed-form mathematical formula, contradicts the biological characteristics of a neural connectionist model. Yet by being restricted to positive neural activation, the attraction effect can only be explained by integrating a loss-aversion function into LCA (Busemeyer et al. 2005).

[2] LCA is not the only model premised on memory decay. For example, Dougherty et al.'s (1999) Minerva-DM model assumes that people have access to thousands of memory traces, built up over a lifetime, in varying states of decay (cf. Hintzman 1984). According to Minerva-DM, people use their current goals/hypotheses, the data available to them, and the environmental context to probe their memory for similarity to the current conditions. Minerva-DM is an elegant and influential model but has been applied mostly to judgment rather than decision phenomena and thus is outside the scope of this review.

steeper slope for losses than for gains, and the prospect theory risk function (i.e., overweighting small probabilities and underweighting large probabilities).

Moreover, evidence that supports the predictions of DbS has begun to accumulate. For example, short-term exposure to lower or higher supermarket prices changes the environment of sampling for dollar values. Whereas classic EUT models would not expect incidental exposure to choice-irrelevant stimuli to influence people's ostensibly rather stable utility curve, DbS predicts that people exposed to different supermarket prices would demonstrate different preferences for lotteries (Ungemach et al. 2011). Similarly, people's sensitivity to the number of people killed in a natural disaster and their willingness to endorse policy positions that risk human lives closely aligned with the predictions of DbS (Olivola & Sagara 2009).

Importantly, DbS is based in psychophysics and entirely neglects the notion of utility. In fact, the model argues that utility has no meaning outside of a particular context and that people do not process utility, instead having access only to ordinal comparisons of magnitudes. Nonetheless, DbS subsumes utility models by predicting both the behavioral patterns that utility-based theories had been successful at describing and the anomalies that have confounded utility-based theories.

It is worth noting that DbS differs from query theory, DFT, and LCA in that it does not sample attributes or features of a decision (e.g., quality, cost, or gas mileage for car purchasing decisions). Rather, it focuses on sampling of the universe of possible options and determining an ordinal rank for present options (e.g., Toyotas, Hondas, and Buicks). Obviously these two approaches are not mutually exclusive—one must compare the attributes of the options in order to compare the options themselves. As such, one potentially fruitful avenue for future work in the information processing paradigm would be to juxtapose these two approaches.

Voting Agent Model of Preferences

Another approach to explaining decision anomalies as emergent properties of basic cognitive and neural processes can be found in the voting agent model of preferences (VAMP) (Schneider et al. 2007). VAMP argues that many of the observed anomalies can be explained as a by-product of aggregation of differential preferences of neural systems within an individual.

VAMP draws inspiration from the fact that certain neurons and neural systems are sensitized to different features. For example, some neurons in early visual cortex are responsive to visual stimuli of particular shapes or orientations. VAMP extends this notion to higher-order decision making, suggesting that within a single individual, different neural systems might have different preferences—some might prefer to minimize risk, others to maximize possible outcomes, and still others may respond to ad hoc goals. The preference of the individual as a whole is a result of the aggregation of the preferences of the neural systems.

Applying voting geometry (Saari 1994) to decision sets, Schneider et al. (2007) demonstrated that a number of decision anomalies were an inevitable result of aggregation (across nearly all methods of aggregation). For example, consider attraction effects (Huber et al. 1982) in which the addition of a dominated option {A′} to a choice set {A,B} increases the choice share of the option that dominates it {A}. If A′ is dominated by A, but not by B, then all agents will prefer A to A′, but some agents (those that care about the dimensions upon which A and A′ are stronger than B) will prefer A′ to B. In other words, A′ steals second-place votes from B.

As with DFT, LCA, and DbS, phenomena that were considered anomalous within the EUT paradigm emerge naturally from VAMP and are evidence for the model rather than problems. Crucially, instead of viewing decision making as a separate and insulated system, VAMP assumes that it is based on cognitive building blocks similar to the rest of cognition. Indeed, there are a number of multiagent models in cognitive science, ranging from language development (Freedman

& Foster 1985) to vision (Poggio et al. 1988). VAMP applies the logic of aggregation to decision making and demonstrates that the anomalies are not anomalous when decision making is viewed through the lens of cognitive and neural primitives rather than choice axioms.

Constraint Satisfaction

Another approach that has gained traction in recent years is based on constraint satisfaction and Thagard's (1989) explanatory coherence (ECHO) cognitive architecture. This approach posits an associative network between each item in the choice set and the attributes upon which they vary. The system seeks to achieve coherence in which related concepts have similar levels of activation. Crucially, the links are presumed to be bidirectional; that is, not only do the attributes influence preferences for various options, but also these preferences influence perceptions of the attributes. Activation spreads through the network in multiple iterations until the network stabilizes.

ECHO-based models reject a central tenet of utility models, wherein the attributes/features of the options are presumed to have stable value and the value of an option can be considered a weighted sum of its attributes/features. Instead, ECHO imagines a more fluid dynamic wherein the value of the different attributes/features changes depending on the relationships to and values of the other attributes. As such, the primary evidence for constraint satisfaction can be found in the fact that the favorability of the attributes varies over the decision-making process (Simon et al. 2004a). For example, people deciding between jobs that varied on commute time, salary, vacation time, and office quality tended to discount the attributes that gave evidence against a superior option. That is, subjects who were led to believe that a particular job with a poor salary and limited vacation time was the better job began to care less about vacation and salary (rather than factor those features into their preferences for the job; Simon et al. 2004a). Similar patterns have emerged in legal decisions (Simon et al. 2004b).

Some of the classic anomalies from the EUT paradigm also have been investigated through the lens of constraint satisfaction. For example, Guo et al. (2002) have shown that both the attraction effect and the similarity effect can arise from an appropriately constructed ECHO model. Meanwhile, other researchers have begun juxtaposing this kind of modeling with dual process frameworks (e.g., Glöckner & Betsch 2008) and, as with DFT, have yielded different predictions over different time spans. Crucially, ECHO models do not need to posit a utility function in order to predict or explain decision making. Instead, decision making emerges from basic, core, information processing primitives.

Other Notable Models

Although the models above are some of the most prominent and promising, the burgeoning information processing paradigm has spawned a number of other high-quality models worth mentioning. For example, Soltani et al. (2012) developed the range normalization model in the hopes of building a model of decision making that fits into the physiological limits of the basic units of cognition—neurons. They argue that the rate of neural firing is central to the brain's representation of values and options and that there is an upper and lower boundary to these values. As such, in order for the neural system to represent many distinct kinds of values, the neural system dynamically adjusts itself to distinguishably represent the required information while maintaining the relative magnitudes of that information. This argument leads to many interesting predictions, but it remains unknown the extent to which those predictions will bear out.

In a different vein, Hagmayer & Sloman (2009) have proposed that decision making could be viewed through the lens of causal reasoning, noting that people think of their choices as interventions on causal systems. They argue that decision making can be modeled using causal Bayes networks (Pearl 2000) and have provided evidence that people's choices are driven to a large extent by the underlying causal structure of the decision options. Although this approach has not been explored as fully as some of the other models described above, Bayesian theories of cognition have recently been gaining traction and popularity across cognitive science (cf. Griffiths et al. 2008), suggesting that theories of decision making grounded in causal models have considerable potential to provide insight (see also Lee 2006).

Finally, we would be remiss if we did not mention the novel approach found in Busemeyer and colleagues' (2006c) quantum dynamic model. This model rests on the idea that the underlying mathematical structures derived from quantum theory provide a much better account of human thinking than traditional models do. Choice and preference probability states are assumed to exist in a dynamic superposition, and only when a preference is revealed does the state collapse into a particular partial order.

Although it remains to be seen how much traction quantum decision theories will gain over other models, researchers have successfully used quantum probability theory to address concrete and long-standing paradoxical problems in decision and cognition research (Busemeyer & Wang 2010, Busemeyer et al. 2006b; for a review, see Busemeyer & Bruza 2012). However, note that quantum dynamic models are not grounded in information processing and thus represent a competing paradigm rather than a model within the emerging paradigm that we have reviewed herein.

CONCLUSION

For the past several decades, researchers have repeatedly observed patterns of behavior for which utility theory cannot easily account. Indeed, it has become the norm to use EUT as a foil for modern theories of human behavior, to the point where the incremental value of identifying additional anomalies has become rather limited. Kuhn argued that researchers cannot shift from one paradigm until there exists a viable alternative paradigm. This article points to information processing frameworks as such an alternative in decision science.

Looking at decision making through the lens of information processing involves questions of how decisions emerge from basic cognitive processing, such as attention, memory, and causal reasoning. Human decision makers are conceptualized as inherently constrained by bounded rationality, and decisions are a function of the manner in which sampled evidence is accumulated and integrated. Accordingly, understanding decision making requires conceptual grounding in other cognitive primitives. Decision science has long considered itself a field related to but separate from the rest of cognitive science, but it has become increasingly clear that models of cognition in areas not specifically related to decision making will have relevance to decision processes. It is time for the field of JDM to become more integrated with general cognition.

Although this shift in researcher attention may not come as a surprise to decision scientists, the gradual adoption of the new paradigm has not been reflected in the way that decision making is taught to undergraduate and graduate students across psychology. A quick survey of textbooks for introductory psychology, social psychology, and cognitive psychology classes reveals that not one of the information processing models discussed in this article has made its way into the teaching cannon. This serves as evidence that the paradigm shift is still under way and that the field is still undergoing what Kuhn would call revolutionary science.

That is not to say that information processing is the only fruitful approach to studying decisions. Affective science has provided tremendous insight into decision processes, as have investigations into social and contextual factors influencing decisions and analysis of the decision-making profiles of those with various psychological disorders. The new paradigm is still in its infancy, and it remains to be seen how it will evolve and what it will include. That said, the emergence of the information processing paradigm provides a viable alternative to the classic utility framework, making this an exciting time to be in decision research.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

Although Oppenheimer is listed as first author as per *Annual Review of Psychology* policy, the authors wish to note that Kelso's contribution was equal to Oppenheimer's, and for journals that did not specify author ordering, he would be considered first author.

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