

Rational Decision Making, Dual Processes, and Framing: Current Thoughts and Perspectives

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INTRODUCTION

Decisions, decisions, decisions, we are constantly faced with them everyday. Should I get out of bed or sleep 10 more minutes? Should I hit the delete key or save as a new document? Should I take the dishes to the sink or wait and see if my spouse will do it? Inherent in most decisions is the tradeoff between some benefit and decrement we may face along with an element of risk. The course of action that we choose to take has always been of interest to scholars. Fitting the principles of decision-making into an *a priori* developed plan to choose which alternative is “best” is, by and large, what most consider to be rationality.

Because the decisions that we make have so much influence in our life, their importance cannot and should not be underestimated. While we cannot always know which decision will eventually hold the greatest benefit, it is an aspect of human nature to gamble on the best option, but only when the gamble seems warranted. Determining what is the “rational” choice allows us to at least rest easy in the assumption that the decisions that we have made are the right ones. Interestingly, as time immortal has shown, making the right or “rational” decision does not always provide the most favorable outcome.

THEORETICAL APPROACHES

Two Approaches: The “Should” and the “Do”

At the core of decision making research, there are two essential ways that researchers approach rational decision-making, the prescriptive and the descriptive approach. The prescriptive approach centers on explaining how we “should” make decisions and choose between alternatives. This approach offers a guide for choosing the optimal choice when faced with varying

alternatives. It gives us an *a priori* set of rules that we can follow for making the best decision.

On the other hand, the descriptive approach refers to describing how people actually “do” make decisions. This approach focuses on recounting normative data and is generally thought of as less applied than its counterpart. In this approach, participants are presented with decision problems set in predetermined parameters and the choices that they make are captured by later statistical descriptions. By and large, most theoretical models attempting to understand rational decision making are descriptive in their intent. That is to say, they seek to explain how it is that people make decisions rather than how people should make decisions.

Expected Value and Utility Theories

One theory of rational decision making that does offer a means for determining how people should make rational decisions is expected utility theory. The tenets of expected utility theory and its predecessor expected value have been used as a means for determining not only what choice a decision maker “should” make but also to provide a framework for better understanding and describing what is a rational choice. While there are a number of approaches that fall under the heading of expected utility theory, most people associate this approach with work by Von Neumann & Morgenstern (1947). Because the general approach discussed in this article is consistent across the foundations of expected utility as well as its later developments, we shall refer to the original Von Neumann & Morgenstern as our guide.

Expected Value Approach

According to expected value theory, individuals should always choose the alternative that offers the greatest expected value. Expected value is determined by weighting the value of a target (e.g., winning a luxury

vacation) by its probability of success. For example, consider a situation where there are two possible options:

- a. A 40% chance to win 2000 dollars
- b. A 70% chance to win 1000 dollars

In this example the expected value of each option can be determined by multiplying the probability of winning by the amount of money. The expected value for option (a) would be $.40(2000) = 800$ and the expected value for option (b) would be $.70(1000) = 700$. Therefore, according to an expected value analysis, the decision maker should choose option “a.”

This type of analysis is straightforward and allows for a numerical comparison that can be easily contrasted yielding a clearly preferable option. However, the problem that arises with this type of approach is that people are not always objective numerical calculators, assigning increasing amounts of value to proportionally increasing amounts of the object that is at stake. For example, the personal value (utility) that we would feel from suddenly receiving a gift of \$100 would be more than one hundred times that of receiving \$1. On the other hand, the personal value (utility) of receiving \$9,000,000 would probably not differ from that of suddenly receiving \$8,000,000. As a result of this and other discrepancies in human value-processing, Von Neumann & Morgenstern (1947) developed what is known as expected utility theory.

Expected Utility Theory Approach

Expected utility theory (e.g., Von Neumann & Morgenstern, 1947; Savage, 1954) asserts that individuals have a desire to maximize their expected utility in light of the risky options that they are faced with. Utility is determined by determining the amount of satisfaction that an individual will derive from each option. Further, it is postulated that individuals intend to maximize their expected outcome that is available in the possible alternatives and they will choose the option with the highest expected payoff. The formula for determining expected utility is similar to that of expected value. Specifically, expected utility is determined by weighting the utilities (e.g., utility of dollar amounts) of each potential outcome by the respective probabilities. Decision makers should then choose the option that has the greatest potential or weighted sum.

Take for example a person who is in a financially bad situation and he needs 2,000 dollars to catch up on his bills and to avoid eviction. This person decides to go to Las Vegas and is confronted with an individual who presents him with the following situation.

- a. 40% chance to win 2,000 dollars, or
- b. 90% chance to win 1,000 dollars

What will this person do? According to expected utility theory, we can predict what a person both will do as well as what they should do. By assigning numerical utilities for the amounts of money contained within the alternatives, the utility for each alternative can be calculated and comparison across the alternatives should occur. In this particular situation, we can assign a utility of 100 for the \$2000 and a utility of 10 for the \$1,000. Using this information, we can then calculate this person’s rational course of action:

- a. A 40% chance to win $U(100) = (.4)(100)$ or 40
- b. A 90% chance to win $U(10) = (.9)(10)$ or 9

Therefore, according to expected utility theory the rational course should be to choose option “a.” It should be noted that this choice differs from that of an expected value approach where the person should choose option “b” with an expected value of \$900 over option “a” with an expected value of \$800. Maximization of expected utility has become the most common decision rule in decision-making research.

Later research investigating and expanding the findings of expected utility theory has identified several extensions and modifications to the set of axioms first presented by Von Neumann & Morgenstern (e.g., Pratt, Raiffa, & Schlaifer, 1965; Edwards, 1954). This research has expanded the basic assumptions of utility theory, demonstrating that not only do people want to maximize their outcome, they also have a general aversion to risk (e.g., Arrow, 1971; Slovic & Lichtenstein, 1968) resulting in a general preference for risk-averse choices. Further, research has also shown that decision-makers have both a utility function and subjective function that is based on personal probabilities. The general findings of this research show that subjective probabilities often relate non-linearly to objective probabilities. And at the extremes, people tend to overestimate low probabilities and underestimate high probabilities. Such

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