Chapter 3
Decision-Making Under Risk: A Normative and Behavioral Perspective

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This chapter introduces the theories of decision-making under uncertainty and risk of socio-technical systems. Following the historic development of the main conceptions of rationality, we start with expected utility theories and explain the rational choice (or normative) perspective. We explain how decisions under risk can be optimized consistently within the framework of the theory, and under which conditions such analyses are particularly applicable and when they are reduced to an economic cost-benefit analysis. It is then discussed why the classic theories are sometimes misused and why the normative perspective is not suitable to describe or predict actual human behavior, perception or evaluation of decisions and their outcomes under uncertainty and risk. We then outline alternative theories of decision-making, including descriptive approaches from behavioral economics (e.g. cognitive biases) as well as ecological rationality and heuristic decision making. As is discussed in this article, the normative approach is suited for optimizing decisions in a consistent manner for relatively well defined (often technical) problems, whereas the alternative theories are more suitable to predict actual human and social evaluations and behavior and can provide improved decision making in complex situations where socio-technical system parameters as well as the decision maker's preferences are not well defined.

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The Facts

- In theories of judgment and decision making one has to distinguish between how people should make decisions (idealistic, normative approaches) and how people actually make decisions (realistic, descriptive approaches).
- Normative decision theory assumes that under certain circumstances decision makers (should) follow a certain set of rules that ensures consistency among decisions as well as optimal decision outcomes. Descriptive decision theory accounts for the fact that people do not follow these rules and for such situations in which optimal set of rules cannot be given.
- Normative decision theory is applicable to well defined and contained (often technical) problems, and can be used to optimize risk levels. A number of tools, including decision trees and graphs, exist. It can also be used to optimize the amount of information that should be collected to reduce uncertainty before making the decision.
- The utility function describes decision maker's preferences. It is an empirical function that can differ between individuals and is influenced by subjective perceptions. No mathematical form of the utility function is justified by some "universal law".
- Different from what the classical normative theory would propose, the subjective, observer-dependent perception of "objective" values and probabilities has a strong impact on human perceptions, evaluations and decisions. The normative theory therefore generally fails to accurately recognize, describe or predict actual decision making under risk and uncertainty.
- When optimization is not possible, people often make good decisions through the use of heuristics and "gut feelings".
- Most risks are embedded into socio-technical systems, thus is it advisable to be familiar with and use both normative and descriptive risk decision theories.
- There is no "fixed formula" for ideal decision making under risk and uncertainty.

1 Introduction

Decision making under conditions of uncertainty and risk is an every-day task. When deciding whether or not to take the umbrella upon leaving the house, when deciding on whether or not to wear a helmet for bicycling or when deciding whether to take the train or the airplane, you are making a decision that involves outcomes that are uncertain (Will it rain? Will you be hit by a car? Will the train or the plane be safer?) and that are associated with risks (of catching a cold; of sustaining injuries). In our every-day life, we often use intuition (also called heuristics or gut feeling—see Sect. 3) to make such decisions, which often works well. As professionals dealing with risk and uncertainty we often have to make complex and far-reaching decisions or advise the ones that make those decisions, e.g. a committee of experts in health risk that must make a recommendation on acceptable levels of air pollution, a team of engineers that must determine the optimal flood protection strategy for a city or a team of corporate manager that must weigh the economic risks against the technical risks in the introduction of new products and technologies. Even as individuals we frequently must decide between decision alternatives involving uncertainty on which we have little experience and intuition, for example as a patient between different treatment options, as we save for retirement, between different investment strategies or in private life when deciding for or against a life partner. Decision theory has been developed to describe and model the process of making such decisions and ideally supports us in identifying the best options.

Decision theory started out by assuming that the outcomes of decisions can be assessed following a set of consistent decision rules (often—and somewhat misleadingly—referred to as "rational decision making"). Based on these rules, it is then possible to mathematically identify optimal decisions under conditions of uncertainty. Today, this theory is called the *normative* decision theory, because it is useful in describing how decisions should ideally be made under some idealistic, objective and observer-independent assumptions (compare Sect. 3.2), which will be discussed in this article. When studying the behavior of decision makers, it is observed that people's assumptions and resulting actions are not consistent with the assumptions and rules of the normative decision theory. Instead, decisions made by people are influenced by a number of cognitive, motivational, affective and a number of other factors that are not addressed by the classical normative theory. Decisions associated with risk and uncertainty are often concerned with socio-technical systems of some sort, in which human, social and technical dimensions continuously interact. In order to understand, model and reduce risk in these anthropogenic systems, it is necessary to understand how people involved in the process actually perceive, evaluate and decide about risk, which is the aim of *descriptive* decision theory that concerns itself with the empirical reality of how people think and decide.

Examples for the application of the normative theory in risk management include the optimization of decisions on the optimal level of flood protection for a city based on probabilistic models of future flood events and infrastructure performance, or decisions on optimal levels of insurance and reinsurance coverage. Examples for the application of the descriptive theory arise when dealing with processes whose outcomes substantially depend on the perceptions, evaluations, decisions and interventions of humans. For example, consumers decide if genetically modified food is safe for them to buy and eat, or if nuclear energy is an acceptable form of energy technology.

As described in the above paragraphs, in this chapter we distinguish between the normative and the descriptive decision theory. Normative decision analysis uses a mathematical modeling approach based on the expected utility theory (sometimes also called normative, prescriptive, rational or economical decision analysis) and provides a framework for analyzing the optimality of decisions when knowledge of the probability and consequences involved in the decision is available or can be approximated. Descriptive or behavioral decision analysis supports risk-related decisions in complex, socio-technical systems that involve uncertainties with regard to probability and outcomes that make exact quantification difficult. Using either normative or descriptive decision theory in isolation gives an incomplete assessment of the realities of the risk situation. Risk management in socio-technical systems and situations should always consider both normative and descriptive aspects of decision analysis. Risk managers and decision makers need thus be familiar with different risk theories and perceptions.

Section 2 of this chapter presents an introduction to the normative theory while Sect. 3 introduces the descriptive theory. Finally, Sect. 4 concludes with a comparison of the main theories with regard to their assumptions, approach, decision criteria and applicability.

2 Normative Decision Making: Optimal Decision Making Based on the Expected Utility Criterion

2.1 Mathematical, Technical and Economical Perspective: The Rational Approach

In many professional situations it is desirable to select the right decision following a set of logical and reproducible rules and criteria.[1] This holds true in particular when making decisions in groups, where different verbal arguments have to be "translated" into numbers and outcomes, when probabilities and outcome can be sufficiently quantified, and when decisions affect others, as is the case in risk management of anthropogenic systems (e.g. technical systems, environmental systems or companies). When authorities prescribe an acceptable level of air pollution, society expects that the decision on the value of this level is made on a rational and consistent basis (i.e. that the decisions are perceived as legitimate), taking into account all costs and benefits; on the one hand the potential health and environmental effects and on the other hand the economic costs and benefits of setting stringent criteria. A main difficulty in making such decisions is that many of the influencing factors and future outcomes are not and cannot be known with certainty. Neither the health impact of the pollutants nor the cost of reducing them or the value derived thereof for people can be precisely quantified.

To identify optimal decisions in situations when outcomes are uncertain is the goal of classical decision analysis, which has its foundation as a scientific discipline in the publication of the book by Von Neumann and Morgenstern [49] on utility. It is worthwhile noting that although their work is entitled "Theory of games and economical behaviour", it is written by mathematicians and not by empirical scientists. Classical decision analysis is based on the premise that outcomes are uncertain

[1] We note that at least two reasons for this preference can be distinguished: (1) Rules and numbers allow for an "objective" and "true" assessment of risks, probabilities and outcomes. (2) In social interactions, the legitimacy and acceptability of decisions is increased by justifying them through the use of (sometimes just seemingly) objective and true assessment of risks, probabilities and outcomes.

but that it is possible to quantify their probabilities of occurrence. It furthermore assumes that the preferences of the decision makers follow certain rules that are considered rational, as described by utility theory introduced in Sect. 2.3. According to these rules, decisions should not be influenced by any factors that are considered irrelevant for the outcome, in particular not by the context in which gains or losses occur. Despite of (or even because of) these idealized assumptions, classical decision theory provides a useful framework for analyzing decisions involving risk in and quantifying outcomes and probabilities and in describing how decisions should be made in an ideal world. This theory makes it possible to set up consistent (i.e. reproducible and comparable) criteria for making decisions, which is often relevant when decisions need to be justified in social contexts and affect a larger group, as is commonly the case in a socioeconomically or technical context.

In short, the classical decision theory provides a rationale for identifying the decisions and actions that *should* be taken under conditions of uncertainty and risk. For this reason it is often termed the *normative* or *prescriptive* approach. Because it also forms the basis for classical economic theory, it is also often referred to as *economic* decision theory. Hereafter, we will generally use the term normative decision theory.

2.2 System Model, Decisions and Utility

Normative decision analysis requires a model of the relevant system and time frame, the identification of possible decision alternatives and the probabilities and outcomes as well as a measure for evaluating the optimality of the decision alternatives. For engineering problems, the relevant system is typically represented by physical, chemical and/or logical models with input and output variables, some of which are uncertain. In deference to the literature on decision analysis, we will represent the system by a vector of random variables $\boldsymbol{\Theta}$. Often, $\boldsymbol{\Theta}$ is referred to as "state of nature". As an example, consider the problem of determining the optimal flood protection for a city. Here, $\boldsymbol{\Theta}$ might represent the future maximum water height and discharge of the river, as well as the future land use in the areas at risk.

The decision alternatives can be separated into decisions on actions and decisions on gathering further information. The former, which we will denote by $\mathbf{a}$, actively change the state of the system as represented by $\boldsymbol{\Theta}$. As an example, the decision on building a dam upstream will change the probability of a flooding of the city or the decision on allowing no building close to the river will alter the damage in the case of a flood. On the other hand, decisions on gathering further information, denoted by $\mathbf{e}$, will not change the state of the system. Upon obtaining the information, our estimate of the system state may change, however. If, for example, one decides to perform an extended hydrological study, one will reduce the uncertainty on the estimate of the intensity of future flood events and obtain a more accurate estimate of maximum floods. In the following we will focus on decisions on actions $\mathbf{a}$; decisions on collecting information $\mathbf{e}$ are considered in pre-posterior decision analysis as introduced in Sect. 2.5.

Finally, we must identify the attributes of the system upon which to assess the optimality of a decision alternative. In the decision on flood protection, these attributes include safety, monetary cost of measures and damages as well as societal and environmental consequences. For optimization purposes, we translate these attributes into a unique metric that allows comparing the alternatives in a quantitative manner. This metric is termed utility u and the associated utility theory, outlined in Sect. 2.3, forms the basis of normative decision analysis

2.3 Utility Theory

The quality of an outcome of a set of decisions on an anthropogenic system is judged on the basis of a number of attributes. As an example, in a decision analysis on the management of contaminated sediments, the following attributes were identified, Kiker et al. [25]:

– monetary cost;
– size of the affected area;
– impact on human health (safety);
– impact on ecological health.

In finding an optimal decision, all attributes must be taken into account. Typically, a situation arises where one decision alternative is more optimal with respect to one attribute while another decision alternative is more optimal with respect to another attribute. Cost and safety are common attributes in risk-related problems, and in general a trade-off between the two must be made. If safety was the only attribute, then a system should be designed as safe as possible (consider the pyramids as an example of such a safe structural system). However, it is the art of engineering to design structures that are not only safe but also economical (as well as functional and aesthetical).

The motivation for utility theory is the need for a formalism that allows assessing the optimality of decision alternatives such that the preferences of the decision maker are consistently reflected. Such a formalism enables us to extrapolate from past behavior to new decision situations, both with respect to the trade-off between different attributes and the trade-off among different values of the same attribute. To this end, we define a single metric for measuring the optimality of a decision. This metric is called *utility*. Then, all attributes are transformed into utility by a suitable transformation that consistently reflects the preferences of the decision maker. It is assumed that this transformation, i.e. the weighing assigned to different attributes, is constant with time. To introduce the concept, we study the transformation of the attribute *money* into utility in the following.

First, we note that the utility function, which transforms attributes into utility, is a property of the decision maker. Different decision makers will have different utility functions. In Fig. 1, an exemplarily utility function for an individual is shown. This utility function is continuously increasing, which appears logical, since almost

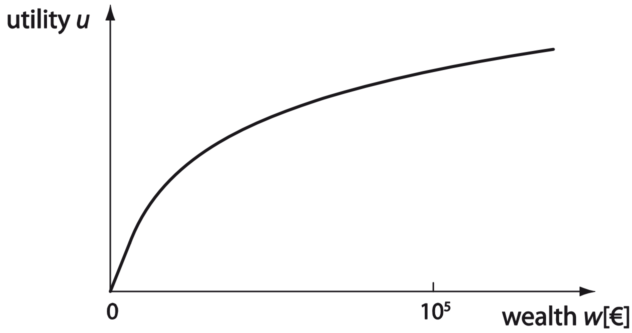

Fig. 1 Utility function for an individual decision maker, transforming monetary values into utility

everybody would prefer more over less money. However, this is not a necessary condition for the theory; in principle, the utility function can have any arbitrary shape.

Second, we note that the utility is not linear with money over the entire domain. The increase in utility associated with a small increase in wealth, i.e. $\mathrm{d}u(w)/\mathrm{d}w$, is called *marginal utility*. Most decision makers have a marginal utility that decreases with increasing wealth w. (In economics, this is sometimes referred to as the law of diminishing marginal utility.) In simple words: obtaining two million Euros is not simply two times more preferable than obtaining one million Euros.

To understand how the exact form of the utility function is derived, we consider the basic principle of utility theory developed by Von Neumann and Morgenstern [49]. This principle is that:[2]

> *Utility is assigned to the attributes in such a way that a decision* (*on which action to take*) *is preferred over another if, and only if, the expected utility of the former is larger than the expected utility of the latter.*

That is, the utility function is derived to ensure that among different set of decision alternatives, the preferable one will always result in the higher expected utility, $\mathrm{E}[U]$. Expectation is a mathematical operation, which for the case that the utility depends only on the single random variable θ, is defined as

$$\mathrm{E}[U] = \int_{-\infty}^{\infty} u(\theta) f(\theta) \mathrm{d}\theta \quad \text{or} \quad \mathrm{E}[U] = \sum_{\text{all } \theta} u(\theta) p(\theta) \tag{1}$$

where $u(\theta)$ is the utility as a function of the system state θ and $f(\theta)$ is the probability density function (PDF) of Θ if it is continuous and $p(\theta)$ is the probability mass function (PMF) of Θ if it is discrete.

A common way of determining the utility function $u(\theta)$ for monetary values is to consider a series of decisions on whether or not to accept a bet. In each bet, there

[2]For this to hold, a number of consistency requirements must be fulfilled, i.e. the preferences of the decision maker must fulfill a set of axioms, which, however, are in agreement with what is commonly considered to be consistent behaviour. As an example, one of the axioms states that the ordering of the preferences among different outcome events E_i is transitive. Formally, if $\succ$ means "preferred to" then transitivity demands that if $E_j \succ E_k$ and $E_k \succ E_l$ then it must also be $E_j \succ E_l$. For a more formal introduction and the full set of necessary axioms, consult e.g. (Luce and Raiffa [5], Sect. 2.5).

is a probability of p to win a monetary prize of x_1 and a probability of $(1 - p)$ to loose x_0. For this bet, the expected utility of the two decision alternatives are as follows:

$$\begin{aligned} &\text{Decision not to bet, } a_0: && \mathrm{E}[U \mid a_0] = u(0), \\ &\text{Decision to bet, } a_1: && \mathrm{E}[U \mid a_1] = (1-p)u(-x_0) + p \cdot u(x_1). \end{aligned}$$

$\mathrm{E}[U \mid a_0]$ stands for: the expected value of U for given decision a_0. If, for particular values of x_0, x_1 and p, the decision maker prefers the decision a_0 over the decision a_1, it must hold that $u(0) > (p-1)u(-x_0) + p \cdot u(x_1)$. If she prefers a_1 over a_0 the opposite must hold, and if she is indifferent it is $u(0) = (p-1)u(-x_0) + p \cdot u(x_1)$. By varying the values of x_0, x_1 and p, it is now possible to determine the value of the utility function for different monetary values, so that it is *consistent with the actual decisions made by the decision maker*. You may try to establish your own utility function by playing such an imaginary game.

(We note that a linear transformation of the utility function does not alter the ordering of preferences, i.e. with $u_1(X) = c + b \cdot u(X)$ and b and c being constants, if $\mathrm{E}[u(X) \mid a_0] > \mathrm{E}[u(X) \mid a_1]$ it must also hold that $\mathrm{E}[u_1(X) \mid a_0] > \mathrm{E}[u_1(X) \mid a_1]$. For this reason, any linear transformation of the utility function is allowed, which implies that two points of the utility function can be freely selected.)

2.3.1 Probability

Decision making based on the expected utility theory requires one to assess the probability of all relevant system outcomes. In practice, these probabilities must often be estimated by the decision maker on the basis of limited or no data. The probabilities represent the knowledge of the decision maker at the time of making the decision, and are therefore subjective values. The problem of assessing these probabilities in real situation is further addressed in Sect. 3.1 and in Chap. 12, [42].

2.3.2 Risk

In the context of utility theory and normative decision analysis, we will use the following definition of risk:

> Risk is the expected change in utility associated with uncertain, undesirable outcomes.

Following utility theory, decisions are not made based on risk, but on the basis of the expected utility (of which risk is a part). The optimal decision is the one that leads to the highest expected utility. It follows that the risk that should optimally be taken is the risk associated with this decision.

2.3.3 Risk-Aversion

Utility functions are often concave, like the one of Fig. 1, corresponding to diminishing marginal utility. When considering losses, this can be explained by the fact

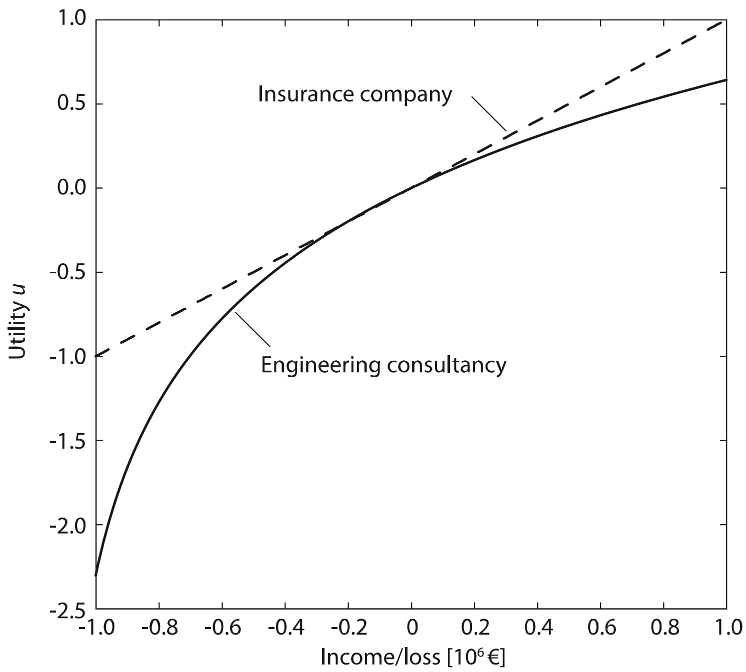

Fig. 2 The utility function for a small engineering consultancy versus the utility function for a large insurance company

that substantial losses can have consequences that go beyond the direct losses, and which therefore cannot be compensated by gains elsewhere. As an example, for a company the loss of 10,000€ is likely to be twice as bad as the loss of 5,000€, but the loss of 2 Million € can be disproportionally worse than the loss of 1 Million € if such a loss threatens the liquidity of the company.

Typically, the utility function is linear (or almost linear) within a range that is small compared to the working capital of the decision maker. This "size effect" is illustrated in Fig. 2, showing the difference in the utility function of a small versus a large company. In the considered range, the utility function is linear for the large company (these sums are "peanuts" for the insurance company), whereas it is concave for the small company where the loss of one million is a critical event.

A consequence of the concave shape of the utility function is that decision makers tend to avoid risks. Consider an event A, causing a loss of 10^5€, and an event B, with associated loss 10^6€. Assume that the probabilities of these events are $p_A = 0.1$ and $p_B = 0.01$. The expected monetary loss of both events is $p \cdot Loss = -10^4$€. Assume that the decision maker is the engineering consultancy whose utility function is shown in Fig. 2. The utility associated with the losses are $u(-10^5€) = -0.09$ and $u(-10^6€) = -2.3$, respectively. The expected utility associated with events A and B (the risks) are $\mathrm{E}[U_A] = 0.1 \cdot (-0.09) = -0.009$ and $\mathrm{E}[U_B] = 0.01 \cdot (-2.3) = -0.023$. Therefore, although the expected monetary loss is the same, the risks associated with event B are higher. This effect is commonly referred to as *risk aversion*.

Illustration 1 (Why Risk Aversion Motivates Insurance) This illustration is taken from Straub [6]. Consider the engineering consultancy whose preference is represented by the utility function in Fig. 2:

$$u(x) = \ln\left(\frac{0.9}{10^6}x + 1\right), \quad [x \text{ in } €].$$

This company is managing a project that involves considerable risk because of a penalty in case of a delay. It is estimated that the probability of the event "project delayed" is $p = 5\ \%$, and the penalty associated with that event is 800,000€. The company is now offered an insurance that, in the event of a delay, covers the penalty minus a deductible of 80,000€. The premium is 50,000€.

For the engineering consultancy, the expected utility of action a_0, not to buy insurance, is

$$\mathrm{E}[U \mid a_0] = p \cdot u(-800{,}000\,€) = 0.05 \cdot \ln\left[\frac{0.9}{10^6}(-800{,}000\,€) + 1\right] = -0.064.$$

The expected utility of action a_1, to buy insurance, is

$$\begin{aligned}\mathrm{E}[U \mid a_1] &= p \cdot u(-130{,}000€) + (1-p) \cdot u(-50{,}000€)\\ &= 0.05 \cdot \ln\left[\frac{0.9}{10^6}(-130{,}000\,€) + 1\right] + 0.95 \cdot \left[\frac{0.9}{10^6}(-50{,}000\,€) + 1\right]\\ &= -0.050.\end{aligned}$$

Since it is $\mathrm{E}[U \mid a_1] > \mathrm{E}[U \mid a_0]$, the optimal decision for the consultancy is to buy the insurance.

On the other hand, for the insurance company (whose utility function is $u_1(x) = x/10^6$) the optimal action is to sell the insurance, since $\mathrm{E}[U_1 \mid a_0] = 0$ and $\mathrm{E}[U_1 \mid a_1] = p \cdot u_1(-670{,}000€) + (1-p) \cdot u_1(50{,}000€) = 0.008$.

It is important to realize that insurance only makes sense if the insured party has a different utility function than the insurer. If the engineering company had a linear utility function, it should not buy the insurance, since the expected utility associated with that decision would be lower. (It corresponds to computing expected monetary values.) This linearity holds approximately when losses are small. (You can verify this yourself by repeating the above calculations for the case where all costs are reduced by a factor of 10, i.e. when the penalty cost is 80,000€, the premium is 5,000€, and the deductible is 8,000€. You will find that in this case, insurance is not an optimal strategy for the consultancy.)

The above example illustrates the effect of *risk-averse* behaviour. A decision maker is said to be risk-averse whenever his utility function is concave; mathematically this corresponds the utility function having a negative second derivative: $\mathrm{d}^2u(w)/\mathrm{d}w^2 < 0$. This decision maker tries to avert risks, even though this reduces his expected monetary gains, because it maximizes his expected utility.

Measures for risk aversion have been proposed by economists. The most well known measure is the coefficient of *absolute risk aversion* (*ARA*), introduced by Arrow and Pratt [32], defined as

$$ARA(w) = -\frac{u''(w)}{u'(w)} \tag{2}$$

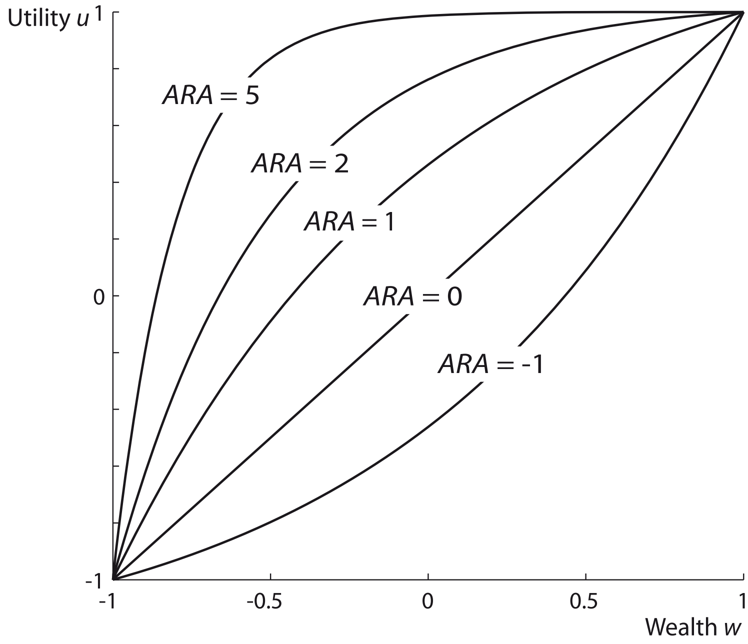

Fig. 3 Utility functions with different absolute risk aversion (*ARA*). All utility functions have been scaled to give $u(-1) = -1$ and $u(1) = 1$

where $u'(w) = \mathrm{d}u(w)/\mathrm{d}w$ is the first derivative and $u''(w) = \mathrm{d}^2u(w)/\mathrm{d}w^2$ the second derivative of the utility function with respect to wealth w. Figure 3 shows several utility functions with varying *ARA*. These are of the form

$$u(w) = 1 - \exp(-cw). \tag{3}$$

This utility function results in an $ARA(w) = c$ that is constant for all values of w (you can verify this claim by inserting the utility function in Eq. (2)). For a negative *ARA*, the decision maker is said to be risk seeking. This corresponds to a convex utility function, as exemplified in Fig. 3 by the utility function with $ARA = -1$.

Alternative measures of risk aversion exist, e.g. the Arrow-Pratt coefficient of relative risk aversion (*RRA*):

$$RRA(w) = -w\frac{u''(w)}{u'(w)}. \tag{4}$$

There is a vast body of literature available investigating these and other measures of risk aversion (e.g. Menezes and Hanson [30]; Binswanger [11]), most of which is rather technical. It is, however, important to realize that the utility function is an empirical function and there is no mathematical form of the utility function that is justified by some "universal law". In fact, Rabin [33] shows that already relatively weak assumptions on the form of the utility function, namely the assumption of diminishing marginal utility for all levels of wealth w, can lead to absurd predictions when extrapolating from decisions involving small sums to decisions with large consequences. The reason behind this is that people do not generally behave consistently according to the expected utility theory, as discussed later in Sect. 3. This observation does not invalidate the use of expected utility theory, but it points to the fact that extrapolation of the utility function assuming some underlying mathematical form (like the one of Eq. (3)) should not be performed. If this is taken into consideration, then utility theory (and the measures of risk aversion) provides rules for optimizing decisions under uncertainty and risk.

2.3.4 Expected Utility Theory vs. Economic Cost-Benefit Analysis

Many decisions involve events with consequences that are small compared to the "working capital" of the decision maker. This is particularly true if the decision maker is society or a representative of society, e.g. a governmental body such as the federal transportation administration. In this case, the utility function will be linear with respect to monetary values. As we have seen earlier, the ordering of the expected utility of different decision alternatives is not altered by a linear transformation of the utility function; we can thus set the utility function equal to monetary values when all consequences are in the linear range of the utility function. In this case, the decision problem can be reduced to an economic cost-benefit analysis (Chap. 11, [36]).

Because monetary values are commonly used in society and economics for exchanging and comparing the value of different goods and units, decisions are often assessed based on expected monetary values. However, it is important to be aware that such an approach is only valid under the conditions stated above (i.e., a linear utility function in the relevant range of consequences). For example, if the engineering consultancy in the example above would make its decision based on expected monetary values, it would decide not to buy the insurance, which would not be optimal according to the company's preferences expressed by the non-linear utility function.

2.4 Multi-attribute Decision Making

So far we have seen utility functions of a single attribute (wealth), yet in most real-life problems involving risks, consequences are associated with several attributes (e.g. economical cost and safety). When multiple attributes are relevant, it becomes necessary to define joint utility functions of the different attributes. Multi-attribute utility theory (MAUT) as presented in Keeney and Raiffa [3] is concerned with decision problems involving multiple attributes.

As an example, consider a decision problem with two attributes X_1 and X_2. A possible joint utility function is constructed from the marginal utility functions $u_1(X_1)$ and $u_2(X_2)$ by

$$u(X_1, X_2) = c_1 u_1(X_1) + c_2 u_2(X_2) + c_{12} u_1(X_1) u_2(X_2). \tag{5}$$

In this case, the two attributes X_1 and X_2 are said to be utility independent. Often, it is $c_{12} = 0$ and the joint utility function reduces to

$$u(X_1, X_2) = c_1 u_1(X_1) + c_2 u_2(X_2). \tag{6}$$

In this case, the two attributes X_1 and X_2 are said to be additive utility independent.

Once the joint utility function u is established, decision analysis proceeds as in the case of the single attribute: the optimal decision is identified as the one that leads to the highest value of the expected utility.

We do not go further into the details of MAUT, but we note that whenever multiple attributes are present (and they are so in most decision problems), a joint utility function is necessary to make consistent decisions. It is important to be aware of this, because it is sometimes argued that it is unethical to assess attributes such as the health of humans or ecological values by the same metric as monetary values (in particular if that metric happens to be the monetary value itself). These arguments are generally misleading, however. In the end, a decision is made, which always implies a trade-off between individual attributes. If two designs for a new roadway are possible, one with lower costs and one with lower environmental impacts, then the final decision made will imply a preference that weights these two attributes, if only implicitly. In fact, it is possible to deduce an implicit trade-off from past decisions. Viscusi and Aldy [48] present an overview on research aimed at estimating the "value of a statistical life" based on societal decisions and choices, and Lentz [28] demonstrates how such deduced trade-offs can be used to assess the acceptability of engineering decisions. The problem with not making these trade-offs explicit is the possibility for making decisions that reflect an inconstant assessment of society's preferences and which lead to an inefficient use of resources. An example of such inconsistent decision making is given by Tengs [44], who compares 185 potential life-saving measures that are or could be implemented in the United States. She finds that with current policies, around 600,000 life years are saved by these measures at a cost of 21 Billion US$ (the numbers are valid for the 1990s). By optimizing the implemented measures using cost-effectiveness criteria, she concludes that with the same amount around 1,200,000 life years could be saved. It follows that the inefficient use of resources here leads to a loss of around 600,000 life years (corresponding to around 15,000 pre-mature deaths each year that could be avoided at no additional cost).[3]

The above argument does not discard the benefits of communicating the values of individual attributes for different decision alternatives. In particular for important and complex decisions it is strongly advocated that decision makers and stakeholders should be given the information on the effect of their decisions on all the relevant attributes.

[3]We note that, in principle, such a cost-effectiveness analysis does not require us to assign our preferences, i.e. it is not necessary to make the trade-off between money and safety explicit. Theoretically it would be sufficient to list the measures according to their effectiveness, as done by Tengs [44], and then starting from the top of the list select all measures that are affordable. In practice, however, such an approach is not possible, because these measures are implemented by different governmental agencies and other actors, who do not make a joint planning. By assigning an explicit trade-off between safety and cost (i.e. by putting a monetary value to human life), however, it can be ensured that money is spent optimally even without performing a joint optimization. Each decision can be tested individually against the criteria set by decision analysis, based on the joint utility function of life-savings and money (see also Lentz [28]).

2.5 Modeling and Optimizing Decisions with Decision Trees and Influence Diagrams

Utility theory prescribes that the optimal set of decisions is the one maximizing the expected utility. Therefore, normative decision analysis essentially corresponds to computing the expected utility for a given set of decisions $\mathbf{a}$, $\mathrm{E}[u(\mathbf{a}, \boldsymbol{\Theta}) \mid \mathbf{a}]$, and then solving the optimization problem:

$$\mathbf{a}_{opt} = \arg\max_{\mathbf{a}} \mathrm{E}\big[u(\mathbf{a}, \boldsymbol{\Theta}) \mid \mathbf{a}\big]. \tag{7}$$

The operator $\arg\max_{\mathbf{a}}$ reads: the value of the argument that maximizes the expression on the right hand side. The expectation E[ ] is with respect to the random variables describing the uncertain system state $\boldsymbol{\Theta} = [\Theta_1; \ldots; \Theta_n]$. It is defined as

$$\mathrm{E}\big[u(\mathbf{a}, \boldsymbol{\Theta}) \mid \mathbf{a}\big] = \int_{\Theta 1} \cdots \int_{\Theta n} u(\mathbf{a}, \boldsymbol{\theta}) f_{\boldsymbol{\Theta}}(\boldsymbol{\theta}) \mathrm{d}\theta_1 \cdots \mathrm{d}\theta_n. \tag{8}$$

This is a generalization of Eq. (1) to the case of multiple random variables. Equation (8) applies to the case where all uncertain quantities $\boldsymbol{\Theta} = [\Theta_1; \ldots; \Theta_n]$ are described by random variables with joint probability density function $f_{\boldsymbol{\Theta}}(\boldsymbol{\theta})$. If all or some of the random variables are discrete, the corresponding integration operations in Eq. (8) must be replaced with summation operations.

To represent and model the decisions $\mathbf{a}$ and their effect on (expected) utility, *decision trees* and *influence diagrams* have emerged as useful tools. The presentation in this section is limited to decision problems with given information, i.e. for problems in which all uncertain quantities are described by known probability distributions and it is not possible to gather further information. The possibility to collect further information will be introduced in Sect. 2.6.

2.5.1 Decision Trees

In a decision tree, all decisions $\mathbf{a}$ as well as random vectors $\boldsymbol{\Theta}$ describing the states of the system are modeled sequentially from left to right. Each decision alternative is shown as a branch in the tree, as is each possible outcome of the random variables. A generic decision tree is shown in Fig. 4, with only one random variable Θ with m outcome states $\theta_1, \ldots, \theta_m$. The tree is characterized by the different decision alternatives a, the system outcomes Θ described by a probability distribution conditional on a, and the utility u as a function of a and Θ. The decision alternatives as well as the system outcomes can be defined either in a discrete space, a continuous space or a combination thereof.

The analysis proceeds from left to right: for each decision alternative a_i, the expected value of the utility is computed following Eq. (8) and the optimal decision is found according to Eq. (7).

Illustration 2 (Pile Selection) This example, which involves only discrete random variables and decision alternatives, is due to Benjamin and Cornell [10]. A construction engineer has to select the length of steel piles at a site where the depth to the

Table 1 Utility function

State of nature	Actions	
	a_1: Drive 15 m piles	a_2: Drive 20 m piles
θ_1: Depth to bedrock is 15 m	No loss	5 m of the pile must be cut off, 100 unit loss
θ_2: Depth to bedrock is 20 m	Piles must be spliced and welded and construction is delayed, 400 unit loss	No loss

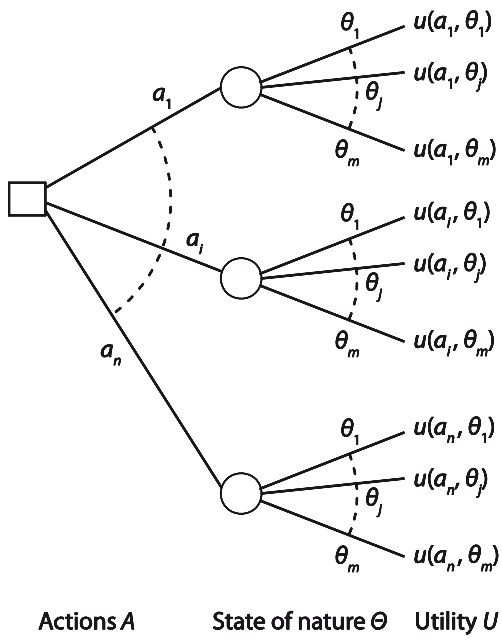

Fig. 4 Generic decision tree for the analysis with given information

bed-rock is uncertain. The engineer has the choice between 15 m and 20 m piles and the possible states of nature are a 15 m or 20 m depth to the bedrock. The consequences (utility) associated with each combination of decision and system state is summarized in Table 1.

The probabilities of the different outcomes are $p(\theta_1) = 0.7$ and $p(\theta_2) = 0.3$. The full decision tree for this problem is shown in Fig. 5. The expected utilities for decisions a_1 and a_2 are obtained as $\mathrm{E}[U \mid a_1] = 0.7 \cdot 0 + 0.3 \cdot (-400) = -120$ and $\mathrm{E}[U \mid a_2] = 0.7 \cdot (-100) + 0.3 \cdot 0 = -70$. Obviously, the optimal decision is to order the larger piles.

The decision tree grows exponentially with the number of decisions and random variables considered, due to the necessary ordering of decisions and random variables (each decision must be made conditional on the decisions and random variables to its left, and each random variable is described by a probability distribution conditional on the decisions and random variables to its left). The decision tree is thus not convenient for representing decision problems involving more than just a few parameters. A more efficient and flexible alternative are influence diagrams, introduced in the following section.

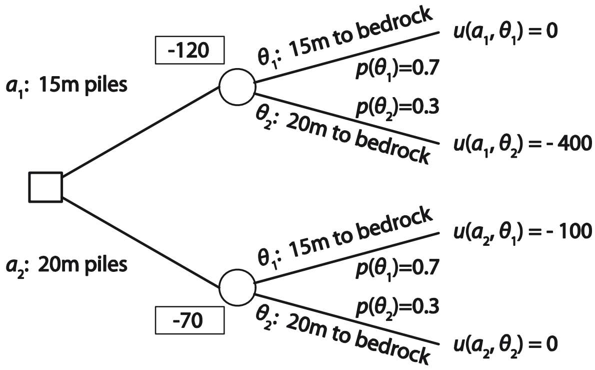

Fig. 5 Decision tree for the pile selection problem with given information

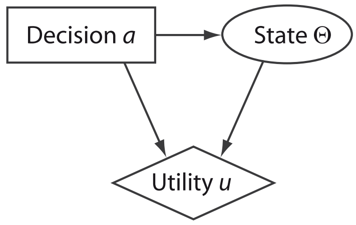

Fig. 6 Influence diagram for a basic decision problem corresponding to the decision tree in Fig. 4

2.5.2 Influence Diagrams

As an alternative to decision trees, decision problems can be represented by influence diagrams. These are more concise representations of the problem, and they are particularly useful in problems where several decisions have to be considered. They were first proposed by Howard and Matheson [21].

Influence diagrams are acyclic directed graphs, whose nodes represent random variables (round nodes), decisions (squared nodes) and utility functions (diamond-shaped nodes). Directed arrows among the nodes represent the dependence structure of the problem. Figure 6 shows a generic influence diagram with one decision a and one random variable Θ. Here it is assumed that Θ depends on the decision a and the utility is a function of both a and Θ.

To understand the semantics of the influence diagrams, it is useful to interpret them as extensions of Bayesian networks (BN) (Jensen and Nielsen [2]). The rules for dependence among the variables follow directly from the BN, with only a few additions: in influence diagrams, links have the additional meaning of representing the flow of information. When making a decision a, the state of the variables that have links going to the node a are known, as are all the ancestors of those variables. Consider the example of Fig. 7, which is different from the one in Fig. 6 only in the direction of the link between a and Θ. This graph implies a completely different decision problem: because the state of Θ is known at the time of making the decision, this represents a decision problem under certainty. A second important rule in influence diagrams is that for the case of several utility nodes, it is assumed that the utility functions are additive independent, Eq. (6).

We do not go further into the details of the influence diagrams here, but note that they can often be constructed from intuition. However, care is needed in ensuring that the relations among the nodes are consistent with causality and with

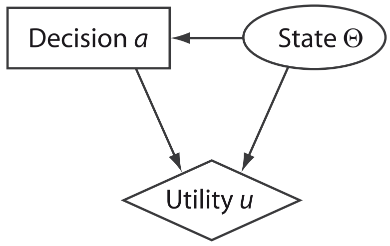

Fig. 7 Alternative influence diagram for a basic decision problem. Here, the uncertain state of the system Θ is known at the time of making the decision a: this is a decision problem under certainty

the assumptions regarding independence among variables. Examples for the construction of such models are given e.g. in Jensen and Nielsen [2], Straub [6]. Free software that allows the construction and computation of influence diagrams (and Bayesian networks) is available, e.g. the Genie/Smile code that can be downloaded from http://genie.sis.pitt.edu/.

2.6 Preposterior Decision Analysis (How to Optimize Decisions on Collecting Information?)

Previously, we have assumed that all information is available at the time of making the decision and that it is not possible to obtain additional information on the uncertain state of nature $\boldsymbol{\Theta}$. However, in most cases when decisions must be made under conditions of uncertainty, it is possible to gather additional information to reduce the uncertainty prior to making the decisions $\mathbf{a}$. As an example, in the decision on flood protection, it might be possible to perform additional detailed studies to reduce the uncertainty in estimating damages for given levels of flood. The question that must be answered is: is it efficient to collect additional information before deciding $\mathbf{a}$? Or in other words: is the value of the information higher than the cost of obtaining it?

Preposterior decision analysis aims at optimizing decisions on gathering additional information $\mathbf{e}$, together with decisions on actions $\mathbf{a}$ (the letter $\mathbf{e}$ is derived from the word experiment). Typical applications of preposterior decision analysis are:

– Optimization of monitoring systems and inspection schedules
– Decision on the appropriate level of detailing in an engineering model
– Development of quality control procedures
– Design of experiments

It is important to realize that collecting and analyzing information does not alter the system. (Exceptions are destructive tests, which sometimes worsen the state of the system.) For this reason, decisions on gathering information $\mathbf{e}$ do not directly lead to a change in the risk, unlike decisions on actions $\mathbf{a}$. The benefit of $\mathbf{e}$ is the reduction in uncertainty on the system state $\boldsymbol{\Theta}$, which in turn facilitates the selection of optimal actions $\mathbf{a}$. Preposterior decision analysis allows quantifying this benefit, the so-called *value of information*. (The word preposterior derives from the fact that we calculate in advance (pre-) the effect of information on the model, i.e. the updating of the prior model with the information to the posterior model.)

The quality of the information obtained by performing $\mathbf{e}$ is described by a likelihood function $L(\boldsymbol{\theta} \mid \mathbf{z}) \propto \Pr(\mathbf{Z} = \mathbf{z} \mid \boldsymbol{\theta})$, which is well known from classical statistics. The change in the probability distribution of the system state $\boldsymbol{\Theta}$ with information $\mathbf{z}$ is obtained via Bayes' rule as

$$f_{\boldsymbol{\Theta}|\mathbf{Z}}(\boldsymbol{\theta} \mid \mathbf{z}) \propto L(\boldsymbol{\theta} \mid \mathbf{z}) f_{\boldsymbol{\Theta}}(\boldsymbol{\theta}). \tag{9}$$

Once the information $\mathbf{z}$ is obtained (posterior case), the optimal decisions $\mathbf{a}_{opt}$ are found according to the procedure described in the previous section, whereby $f_{\boldsymbol{\Theta}}(\boldsymbol{\theta})$ is replaced with $f_{\boldsymbol{\Theta}|Z}(\boldsymbol{\theta} \mid \mathbf{z})$. Prior to obtaining the information, however, it is necessary to consider all possible outcomes $\mathbf{Z}$ to assess the benefit of collecting the information in the first place.

In preposterior analysis, we jointly optimize the decisions $\mathbf{e}$ and $\mathbf{a}$. If additional information is obtained through $\mathbf{e}$, then the decision on $\mathbf{a}$ will be based on that information. Therefore, it is not reasonable to determine the optimal action $\mathbf{a}$ a-priori. In contrast, it is possible to optimize so-called *decision rules* d, which determine which actions $\mathbf{a}$ to take based on the type of experiment performed $\mathbf{e}$ and the outcomes of the experiment $\mathbf{Z}$, i.e., $\mathbf{a} = d(\mathbf{e}, \mathbf{z})$. For example, a decision rule in the case of a medical test would be to subscribe a treatment if the test results in a positive indication and do nothing if the test result is negative. The optimization problem in preposterior analysis can thus be written as

$$[\mathbf{e}_{opt}, d_{opt}] = \arg\max_{e,d} \mathrm{E}\big[u\big(\mathbf{e}, \mathbf{Z}, d(\mathbf{e}, \mathbf{Z}), \boldsymbol{\Theta}\big) \mid \mathbf{e}, d\big] \tag{10}$$

where the utility is now a function of the selected experiments $\mathbf{e}$, the outcome of the experiments $\mathbf{Z}$, the state of the system $\boldsymbol{\Theta}$ and the final actions $\mathbf{a}$, $u(\mathbf{e}, \mathbf{z}, \mathbf{a}, \boldsymbol{\theta})$, and the expectation is with respect to the system state $\boldsymbol{\Theta}$ and the experiment outcomes $\mathbf{Z}$.

Details on how to compute the above expectations, as well as on modeling the information, can be found in the literature, in particular in the classical reference of Raiffa and Schlaifer [35] and in Straub [43]. Here, we restrict ourselves to presenting the computations by means of an illustrative example in the following.

Illustration (Pile Selection) We reconsider the pile selection problem introduced earlier. The engineer is now considering whether or not she should use a simple sonic test to obtain a better estimate of the depth to the bedrock. A sound wave created at the surface is reflected at the bedrock and the time between the hammer blow and reception at the surface is utilized to estimate the depth. The test has three possible outcomes, namely estimates of 15 m depth, 17.5 m depth and 20 m depth. The corresponding test likelihoods $L(\theta_i \mid z_i) = \Pr(Z = z_i \mid \Theta = \theta_i)$ are summarized in Table 2.

The sonic test e_1 comes at a cost, corresponding to the deployment of the test equipment and the analysis of the test results. This cost is 20 utility units, i.e. $u_e(e_1, z) = -20$. (The utility associated with different combinations of bedrock depth and pile lengths are given in Table 1.)

To determine whether the sonic test should be carried out or not, the engineer carries out a preposterior decision analysis. She summarizes the problem in the form of a influence diagram, Fig. 8.

Table 2 *Test likelihoods* $L(\theta_j \mid z_i) = \Pr(Z = z_i \mid \Theta = \theta_j)$

Test result	State of nature	
	θ_1: Depth is 15 m	θ_2: Depth is 20 m
z_1: 15 m indication	0.6	0.1
z_2: 17.5 m indication	0.3	0.2
z_3: 20 m indication	0.1	0.7

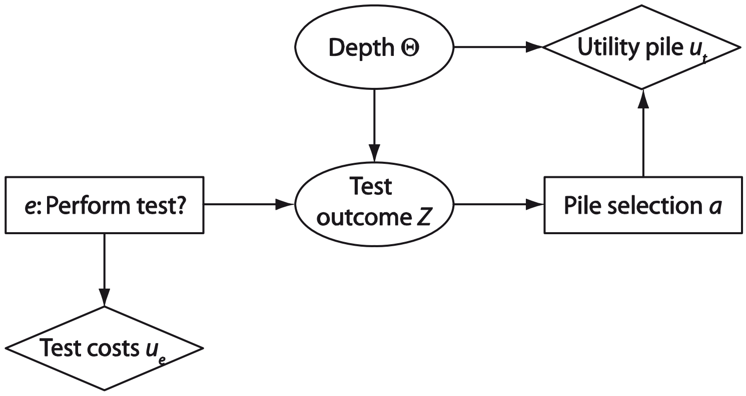

Fig. 8 Influence diagram for the pile selection preposterior analysis

The influence diagram can be implemented in software, since all the relevant information is provided earlier in the text. For this small example, calculations can also be performed manually, as illustrated in Straub [6]. The decision not to inspect leads to an expected utility of −70, as was calculated earlier. The decision to inspect leads to an expected utility of −60, and is therefore optimal. The reason for this higher utility is that the test might indicate a lower depth and the smaller pile can be chosen in this case. Even though this indication is not completely reliable (there is a probability $\Pr(\Theta = \theta_2 \mid Z = z_1) = 0.07$ that the depth is 20 m despite an indication of 15 m), it is sufficiently accurate to provide a higher expected utility.

The value of information of the test can be computed by comparing the expected utility with and without the test and subtracting the cost of the test itself. For the considered sonic test, the value of information is $-60 - (-70) - (-20) = 30$.

3 Descriptive Decision Making: Decision Making Based on Empirical Observation

3.1 Challenges and Limitations of Normative Decision Theory

> "When the map and the territory don't agree,
> always believe the territory"
> Gause and Weinberg [17]—describing Swedish Army Training

Normative decision theory is widely used in economics, mathematics and engineering, and in many other decision-related sciences. Its strength lies in the quantification of probabilities and outcomes, and thus of translating verbal arguments into a common (mathematical) language making different risks directly comparable. Yet, this strength of the theory is also the source of its weaknesses. Normative decision theory struggles when quantification cannot be easily accurately achieved, which is particularly the case when dealing with many of the more complex challenges and problems involving risk. In particular those, that involve human and social systems and their the interaction with technical systems. Moreover, empirical research has repeatedly demonstrated that by using normative decision theory one cannot accurately predict how people will decide in a given situation.

The following anecdote reported by Gigerenzer [20, p. 62] illustrates how these two points of criticism often limit the practical usefulness of normative decision theory in guiding our decision-making. He describes how

> *A decision theorist from Columbia University struggled with the decision on whether to accept an alternative offer from another university or whether he should stay at his current university. His colleague allegedly gave him the following advice: "Just maximize your expected utility—you always write about doing this". To which the decision theorist replied. "Come on, this is serious".*

It sheds a light on the dispute between the different branches of decision theory that the decision theorist in question, Howard Raiffa, never actually said this, but on the contrary did decide to move to Harvard using a formal decision analysis to guide his decision, as he recalls in [34].

Broadly, the limitations of normative decision theory can be divided into the following two categories:

People Decide Based on Their Subjective and Observer-Dependent Perceptions and Observations A main assumption of normative decision theory is that peoples' evaluations and decisions are guided by "objective" and "observer-independent" criteria. However, empirical research has repeatedly shown us that the same objective characteristics of a situation can be assessed completely differently by different people (cf. Welpe et al. [50]). Someone might, for example, think that the probability of 80 % of failing with their entrepreneurial start-up is too high a risk for them to take, whereas someone else in the same situation might find a 10 % probability of success to be "a good chance" and "well worth the risk". In other words, normative decision theory does not take into account that economic and social evaluations and decision are subjectively perceived and thus observer-dependent. Thus, different utility functions can lead to different "best or optimized decisions" by different individuals in the same situation or with the same information. Whenever people are part of the decision-making, there is no universal objective reality that can be quantified and calculated. What does this mean for the empirical study of risk and uncertainty?

Probabilities and Outcomes Often Cannot be Quantified in Risk Decisions Economists have in the past studied risk by looking at rather simple economic risk games ("gambles"), such as the centipede game. This enhances our understanding of decision-making in situations where probabilities and outcomes are well-known in advance. It does, however, help us little in understanding the real-life decisions of entrepreneurs or politicians, as they are typically not faced with decision situations in which all different outcomes along with their probabilities are known in advance. In many situations, decision-makers (regardless of which decision theory is used) are unable to rigorously determine probabilities and outcome values of all risk-related events in advance (Sect. 2.3.1). Risk managers, entrepreneurs, decision-makers typically encounter situations that are not entirely mathematically resolvable, unlike when betting on a number in the Roulette game, where the probabilities of winning and losing as well as the potential pay offs are known in advance to all players (i.e. decision-makers). This is rarely the case in complex socio-technical risk problems. This might call into question the usefulness of economic risk experiments that use gambles to understand risk decision making (Stanton and Welpe [41]).

Whenever accurate predictions are necessary (e.g. when important issues are at stake) but impossible, it is advisable better to realize and accept these limitations instead of falsely relying on alleged and delusive certainty. For some problems, the issues can be addressed by making a decision analysis and forecast based on the best available estimates followed by sensitivity analyses. For all problems that are not sufficiently well understood and the interrelations of the parameters are not well known, in particular with social and economic systems that are inherently complex, self-emergent and variable, it is often impossible to accurately predict the future of such systems. It is advisable to employ several alternative approaches for risk assessment and risk decisions in order to harvest the strengths of multiple approaches and compensate for their respective limitations.

3.2 Examining the Underlying Assumptions of Normative Decision Theory

The assumptions of normative decision theory closely resemble and are based on the well-known (some people think: infamous) "Homo Oeconomicus". Homo Oeconomicus is an artificial model of human perception and decision-making, who is self-oriented, has preferences that are stable over time and is able to process information fully and rationally. Following Kirchgässner [26], "Homo Oeconomicus" lives in an unrealistic world in which all information including probabilities and outcome values of all choice options are known and freely available without any transaction costs, which also include the time and energy necessary to search, evaluate, contract, and control information and information providers (e.g. Kirchgässner [26]). The model of "Homo Oeconomicus" makes a number of additional assumptions among which are *optimality*, *universality* and *omniscience* (Kurz-Milcke and Gigerenzer [27]). Here, *optimality* means that individuals strive for the best possible solution instead of a solution which is good-enough. *Omniscience* implies that individuals have complete information about positive and negative consequences of a decision. Kurz-Milcke and Gigerenzer [27] further argue: (1) that *universality* is an expression of the idea that a common currency or calculus exists which underlies all decisions, (2) that normative decision theory assumes that humans are always both willing and cognitively capable of identifying the optimal decision, which would be one that maximizes according to a certain criterion (e.g. money, happiness), (3) that individuals (as well as organizations) are fully aware of all existing decision possibilities and their associated costs, benefits and probabilities in the present and future. Of course, these assumptions are a "mathematical idealization" of reality, and are not adequate to completely describe the current evaluations, decisions and behaviors of people, let alone predict their future utilities and actions. The question to ask is whether a completely accurate description is necessary, use- or helpful for any given risk management problem.

Previous research has repeatedly shown that the formal conceptualization of rational decision-makers and the empirically observed human behavior differ substantially (e.g. Tversky and Kahneman [47]; Kahneman and Tversky [23]). Since 1970, Akerlof [8] has argued that information is typically unevenly shared between any two transaction partners, resulting in ubiquitous "information asymmetry" as the rule not the exception. Having full information during a decision process is in reality impossible. Furthermore, transaction costs exist in virtually all transactions (Coase [13]). Even if such a world ever existed in which all information is known and freely available, Simon [38] was one of the first scholars to point out that the limited cognitive ability of individuals limits the identification of any best option from several alternatives. People are simply unable to process and evaluate every alternative in an acceptable time frame.

Ford et al. [16] review 45 studies that investigate the outcomes of decision-making and shows that humans often use heuristics instead of weighing pros and cons as normative decision theory would predict. They conclude with the statement that "*the results conclusively demonstrate that non-compensatory*[4] *strategies were the dominant mode used by decision makers. Compensatory strategies* (i.e. trading off good and bad aspects of two competing alternatives—parentheses added by Straub and Welpe) *were typically used only when the number of alternatives and dimensions were small or after a number of alternatives have been eliminated from consideration*".

3.3 Behavioral Decision-Making Theories

The following section introduces two theories in decision making that address the limitations of the classical theory for descriptive decision analysis, namely, (a) prospect theory that emphasizes the limitations, cognitive and affective biases of human decision making and (b) the approach of ecological rationality that emphasizes the human ability to make correct decisions under limited time and information through the use of heuristics and "gut feeling". The goal of this section is

[4]Heuristics are an example of a non-compensatory strategy.

to illustrate that human decision-making is inevitably influenced by a great number of biases, emotional and cognitive influencing factors which are difficult to foresee and quantify and which sometimes benefit and sometimes deteriorate the outcomes of human decisions.

3.3.1 Prospect Theory

Prospect theory was introduced by Kahneman and Tversky [23]. They were awarded the Nobel Prize in Economic Sciences in 2002 "*for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty*" (Royal Swedish Academy of Sciences [46, p. 1]). Their work integrates normative decision theory with insights from behavioral sciences and cognitive psychology. Furthermore, they introduced experiments as an innovative methodology for economics in their research. These developments have laid the foundation for a new field of research called behavioral economics, which has been the starting point of a paradigmatic shift in the study of human decision-making under risk. In contrast to expected utility theory, which is considered to be a *prescriptive and normative* theory, prospect theory is a *descriptive* theory of human behavior in decision making under risk constituting an extension of the normative expected utility theory.

One of the main contributions of prospect theory is in its explicit consideration and inclusion of the observer-dependent *perceptions* of utility and in the subjective weighting of outcome probabilities. An important aspect economists have previously overlooked (some continue to overlook it) is that human preferences with regard to seemingly "objective facts" are highly context-dependent and can consequently show a great deal of inter-individual differences. To illustrate this further: a glass of water can be worth a few pennies if you are sitting at home and are not thirsty and it can be worth a million dollars if you are alone in the desert, close to dying of thirst. This seemingly trivial example illustrates a central point. Standard economic theory uses normative decision theory, which has not found a way yet to incorporate how individuals perceive, evaluate, weigh and judge objective probabilities, risks, outcomes, costs and benefits depending on the context and their subjective mental states. Even though these observations and deliberations are hardly surprising to social scientists, especially psychologists, and probably also to the average lay person, they had a great impact on economists and economic theory, for reasons outlines in Sects. 3.1 and 3.2.

Kahneman, Tversky and colleagues empirically investigate the value function of individuals, in which the loss curve has a steeper decline than the gain curve based on the person's respective reference point or status quo. A main finding of prospect theory (e.g. [23]) shows that people react more sensitively to any losses (i.e. changes below their individual status quo on the value function) than to gains (i.e. changes above the individual status quo), even when the resulting value of the outcome is the same (so that normative decision theory predicts the same utility).

Furthermore, this line of research has consistently shown that the subjective perceptions of objectively equal risk alternatives can vary because of different wording and phrasing of the decision alternatives. The most basic example of this kind would be to describe a glass, which only contains half of its content as 50 % empty versus 50 % filled. Scholars (e.g. Tversky and Kahneman [7]; Levin and Chapman [29]) have repeatedly demonstrated in numerous experiments that individuals' preferences change simply due to a different wording, the so called "framing" alone.

Illustration (The Framing Effect in an Example by Messick and Bazerman [31, p. 13])

Situation 1: *A large car manufacturer has recently been hit with a number of economic difficulties. It appears that it needs to close three plants and lay off 6,000 employees. The vice president of production, who has been exploring alternative ways to avoid the crisis, has developed two plans:*

Plan A: *Will save one of three plants and 2,000 jobs*
Plan B: *Has a one-third probability of saving all three plants and all 6,000 jobs, but has a two-thirds probability of saving no plants and no jobs*

Situation 2: *Same situation as in situation 1, but two different plans*

Plan C: *Will result in the loss of two plants and 4,000 jobs*
Plan D: *Has a two-thirds probability of resulting in the loss of all three plants and all 6,000 jobs, but has a one-third probability of losing no plants and no jobs*

Empirical studies show that most executives choose plan A in situation 1, but plan D in situation 2, despite of Plan A and C being equivalent and Plan B and D being equivalent. This example shows: when the glass is described as half-full it is more attractive than when it is described as half-empty. Messick and Bazerman [31] explain this result by the fact that the reference point of the decision-makers is a different one: in the first case, the reference point is the good situation where all plants are OK; in the second case, the reference point is the bad situation, namely the one where all plants must be shut-down. The typical pattern of responses is consistent with the general tendency to be risk averse with gains and risk seeking with losses. If the problem is framed in terms of saving jobs and plants (plans A and B) executives tend to avoid the risk and take the sure plan. If the problem is framed in terms of losing jobs and plants (plans C and D) executives tend to seek the risk and not to take the sure plan.

Kahneman, Knetsch, and Thaler [24] argue that loss aversion described in prospect theory influences decision processes in that humans are generally more negative about potential losses (risks) than they are positive about possible gains (opportunities). Related to prospect theory, Kahneman et al. [24] have identified a number of additional cognitive biases and so-called irrational "anomalies" with regard to human decision-making. For instance, the *status quo bias* or the *endowment bias* (Samuelson and Zeckhauser [37], Kahneman et al. [24]).

The *endowment bias* effect is closely associated with loss aversion (Thaler [45]) and is salient when a loss of any asset weighs much higher in the decision-making than a win of an asset with the same size and value would. The decisive aspect with the endowment effect stems from the ownership of an object. Research on the endowment effect shows that assets are valued more highly when they are in the possession of the decision-maker than when they are not. Again, this finding confirms that subjective perceptions of seemingly objective characteristics are more important when describing and predicting human decision-making. In a similar way, the *status quo bias* describes the tendency of individuals to prefer the status quo over taking chances and risks in decision making (Samuelson and Zeckhauser [37], Fernandez and Rodrik [14]).

According to *status quo bias theory*, consumer choices depend on which option is framed as the default (i.e. status quo) option. Kahneman et al. [24] have suggested that the status quo bias is the result of a combination of loss aversion and the endowment effect. For politicians, management executives and anyone managing risk-related challenges, the status quo bias means that thinking about what will constitute the "default" in the organization or decision processes will greatly influence which decisions will be taken. An example for a risk-related default would be an organizational rule such as "safety first—when in doubt do what is best for the safety of our products and not what is best from an economic perceptive".

3.4 Ecological Rationality and Heuristic Decision Making

The previous sections have dealt with the abilities and inabilities of humans to optimize decisions and make full use of all information available. More often than not, individuals have to make decisions under limited time and information, which rules out the application of any analytic decision making procedure to determine an "optimal" decision. How do people decide in situations like this? To illustrate this, we first consider an example.

Gigerenzer [20] gives an example that mirrors the different theories and approaches of decision making humans can use: the problem of catching a ball flying in the air in baseball. One could approach this problem by calculating all the probabilities and utilities or one could use a simple heuristic to catch the ball. It is impossible for humans to know all necessary parameters of the flight of the ball to correctly calculate the "parabolic trajectories", i.e. the "ball's initial distance, velocity, wind strength and projection angle" necessary to catch the ball. All of these parameters would need to be assessed and calculated in the short time while the ball is in the air. As the calculation of these parameters is impossible, Gigerenzer [20] suggests, the use of so-called "heuristics", in this case the gaze heuristics to accomplish the task of catching the ball. The gaze heuristic works in the following way: a player fixates the ball and starts running and adjusts his or her speed of running in an extent that allows him or her to keep the angle of his or her gaze constant. The player will probably be unable to know or "calculate" where exactly the ball will touch the ground, but more importantly, keeping the angle between his or her eyes and the ball constant the player will be at the spot where the ball lands. The gaze heuristic is a well-known example of a fast and frugal heuristic. It is called fast, because the heuristic can address problems within matters of seconds, and it is called frugal because it requires little information to work accurately.

Descriptive (and behavioral) decision theory generally agrees that the human information processing capacity is limited, for example through cognitive and affective biases, which make human decision making in general—including heuristic decision making—sub-optimal. In contract, the heuristics approach as pointed out by Gigerenzer and colleagues takes an evolutionary perspective—and argues that such "fast and frugal heuristics" have emerged as a result of human evolution in order to facilitate good decision-making under limited information and time.

Gigerenzer [18, 19] and colleagues are also critical of behavioral economics for a number of points. First, with regard to biases (see Sect. 3.3) they argue that these are "first-best solutions" and "environmental adjustments" of human decision making resulting from long evolutionary processes. In contrast to behavioral economists, he does not categorize heuristic decision making or so called "irrationalities" in decision making in any negative way as "errors" or "second best solutions". They argue that calculating probabilities is much more difficult to accomplish for humans than understanding frequencies (Gigerenzer [18]). Their basic argument is that bounded rationality as introduced by Herbert Simon and what he calls effective "ecological rationality" (i.e. heuristic decision making) do not contradict each other and in fact often co-exist together closely (Gigerenzer and Goldstein [1], Gigerenzer [20]). The original thinking behind this idea is that heuristic decision making, i.e. decision-making that is not based on an exact number or their calculations, is more efficient than decision making based on classic utility maximization. In other words, heuristics are particularly efficient in situations with limited information and time for decision making were mathematical optimization is impossible, which is regularly the case for decisions in managerial or political (and also personal) decisions. Heuristics, nevertheless, need to constantly be adapted to fit the contexts in which they are applied in as no heuristic is effective or useful in all decision situations.

In the following, we present examples for heuristics, namely the *representativeness heuristic*, the *availability heuristic* and the *affective heuristic*.

The *representativeness heuristics* refers to judgments of probabilities of a future event or the representativeness of a sample. In other words, it describes individuals' subjective assessment of probabilities based on the comparison of previous experiences with events or individuals that represent a current event or sample. Particularly important is the subjectively perceived similarity, which can lead to misjudgments because the more individuals perceive events to be similar the more they are likely to ignore important information and previous probabilities about a current situation or sample.

Another important heuristic is the *availability heuristic*, which refers to the evaluation of the probability of events based on one's own previous experiences and memories, which can be easily recalled. The more easily they are recalled, the higher individuals evaluate the likelihood of similar current events (Kahneman and Tversky [22]).

A number of recent approaches focus on the role of *affect in risk perception* (Loewenstein et al. [4]). The "risk-as-feeling" hypothesis (Slovic et al. [40], Slovic and Peters [39]) implies that affects are important determinants for risk perception and evaluation. Loewenstein et al. [4] argue that individuals perceive risk depending on their emotions. Researchers have repeatedly shown that emotions have the potential to influence human decisions through human information processing of the perceived risk. For example, Finucane et al. [15] and colleagues showed that people use affective cues in decision situations under risk. A potential implication of the risk-as-feeling hypothesis would be that positive affect could lead to a biased estimation of risk perception and evaluation.

4 Discussion

All models are wrong, but some are useful.[5]

This chapter has outlined a number of different decision theories, all of which have their merits and their limitations. The choice of the theoretical approach must thus be problem dependent, as emphasized throughout the text. Table 3 summarizes the three main decision theories presented in this chapter.

The classical decision theory is relatively far refined and current research in this area focuses mostly on computational aspects of the optimization problem in various fields of application. There are, however, some alternative novel developments, which address the difficulty in realistically assessing probabilities in real decision situations. One example is the info-gap theory, which is developed to provide robust decisions on a non-probabilistic basis (Ben-Haim [9]). The descriptive and the heuristic theories, due to their empirical nature and shorter history, seem wide open for development and adaptation. In addition, there is ample potential for research on the application of both lines of decision theory to practical problems involving risk. Real decisions (be it in business, technology, politics or other fields) are seldom based on rigorous applications of decision theory, be it normative, descriptive or heuristic. One reason for this lack is the gap between researchers living in an "idealized world" and the practitioners dealing with the "dirty reality".

Concerning the different lines of decision theory, researchers should aim to link the formalism of classical utility analysis with the empirical appropriateness of descriptive and behavioral models. In order to understand and improve decision making on systemic and complex risks, an integrative perspective of normative, descriptive and heuristic decision making may offer many benefits. Another promising area for future research would be to study the normative and behavioral perspectives looking at group decisions as opposed to individual decisions. Furthermore, scholars may want to examine which institutions (rules, regulations, etc.) can be successfully implemented in order to enhance the effectiveness and efficiency of individual and group decisions (e.g. debiasing strategies).

[5] Quoted from the statisticians Box and Draper [12].

Table 3 Overview on the three decision theories presented in this chapter

Decision-theory	Approach	Decision criterion	Suitable for/applicable to	Tools
Classical (normative) decision theory, expected utility theory	Normative (how decisions should be made), mathematical, axiomatic theory	Expected utility (reflecting attributes such as money, safety, happiness); objective/observer-independent; consistent rules; sometimes reduced to cost-benefit analysis	Optimizing decision-making when problems are well-defined, i.e. when probability and consequences can be reasonably quantified. Sufficient time for calculations is available. Important to reduce risks related to technological and environmental hazards	Expected utility maximization. Decision trees and influence diagram, Mathematical optimization, Advanced probabilistic models
Descriptive (descriptive, behavioral) approaches of human decision making	Descriptive (how decisions are made) Empirical, i.e. fitted to observed human behavior (behavioral economics, e.g. prospect theory)	The aim of descriptive decision theory is to describe what people will actually do, not necessarily what they should do. According to prospect theory, individuals compare decision criteria (objective and subjective) against a reference point	Describing (and predicting) actual human behavior Understanding how people actually make decisions (important to reduce risks associated with human and organizational behavior)	Empirical analyses (e.g. experiments or questionnaire studies) to describe actual decision behavior
Heuristic decision making	Descriptive (how decisions are made) Empirical Normative elements (decision heuristics in certain situations) Assumption: Decision makers have intuition on the problem	Subjective/observer-dependent cost-benefit analysis Utility (money, safety happiness)	Optimizing decision making under certain conditions (little time and limited information) and within complex systems	Use of decision heuristics (e.g. representative-ness heuristic; cause and result; availability heuristic; heuristic)

5 Food for Thought

- What is the value of economics and classical utility theory given that they make a number of often unrealistic assumptions? Where can they and where can they not create value added by applying them?

- It has been said, that all models are wrong to some degree—is there a point however, where a model becomes "too wrong" or "right enough"—if so, how would one know?
- How can economic theory account for the role of subjective perception of "objective" values and probabilities in human decision making?
- What is the value of information and how can it be assessed?
- How does one (theoretically) construct a utility function for a decision maker, following the classical utility theory?
- From two engineering designs for a tunnel construction, which only differ in safety and cost, one is selected. How can the implicit trade-off between safety and risk be deduced from this solution?
- It has been argued that by not following the expected utility principle when making decisions involving life safety, "we are in effect killing people". Discuss this statement.
- A popular "economics joke": what do economists mean when they write in the conclusion of their paper: "The evidence for our hypotheses is mixed?" It means that economic theory supports the hypotheses but the empirical data does not. Discuss.

6 Summary

Classical normative decision analysis, which is based on the expected utility theory developed by mathematicians, provides an axiomatic framework for optimizing decisions under uncertainties. It is well suited for identifying optimal decisions when copying with risks if probabilities and consequences of adverse events can be reasonably well quantified. Descriptive decision analysis is a generalization of the expected utility theory, accounting for the influence of psychological factors on the decisions made. It is better suited than the classical theory to describe the behavior of humans under uncertainty and risk. Finally, the chapter outlines newer attempts to formalize heuristic decision making, which is based on relatively simple rules, and which assume that these heuristics have developed in an evolutionary process. These theories are particularly well suited to describe (and sometimes optimize) decision making under uncertainty and limited time and information.

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