INFLUENCE DIAGRAMS FOR COMPLEX LITIGATION

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ABSTRACT: Effective advocacy depends critically on the ability of attorneys to formulate, analyze, and compare rival courses of action. Whereas attorneys have been doing these things for centuries using little more than their gut instincts and experiences, sophisticated decision aids are now available that can improve the way attorneys assess the value of their cases and the strategic decisions that they make. These aids are proving valuable in medicine and business, but they have not impacted legal practice. This Article seeks to correct this oversight by showing how easy-to-use graphical models provide guidance for strategic legal decisions. Beginning with a paradigmatic example of a plaintiff who must choose between proceeding to trial or settling out of court, the Article shows how decision aids handle the uncertainties and interdependencies that arise when real-world considerations are introduced. In particular, the Article makes the case that influence diagrams, a relative newcomer in the field of decision analysis, should be the decision aid of choice in complex litigation matters.

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In the late 1990s, Billy Beane, the general manager of the Oakland Athletics baseball team, did something that no other professional sports team manager had been willing to do: he made decisions about player value based on empirically derived probabilities and statistics (so-called "sabermetrics"). Before this time, such decisions were largely based on the unaided experience-based gut-feel evaluative judgments of baseball scouts and others in a team's organization. By strictly relying on the numbers, Beane gained an edge over other baseball teams despite having a relatively small payroll. Beane's phenomenal success with this strategy is detailed in the 2003 best-selling book *Moneyball*[1] and in the 2011 movie of the same name starring actor Brad Pitt.[2]

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1. MICHAEL LEWIS, MONEYBALL: THE ART OF WINNING AN UNFAIR GAME (2003).
2. MONEYBALL (Columbia Pictures 2011).

In hindsight, Beane's sabermetric successes are not surprising. Decades earlier, quantitative psychologists essentially proved that decisions based on empirically derived probabilities and statistics are superior to those made by unaided expert decision-makers.[3] Indeed, the question that remained was not so much whether reliance on statistics and probabilities could help decision-makers, but whether there were *any* situations in which unaided expert decision-makers could so much as *match* the performance of the mathematical models. Best of all, the mathematical models were uncomplicated. In most cases, they were simple linear aggregations of a few agreed-upon input variables. Regarding these models, the authors of one paper concluded, "the whole trick is to know what variables to look at and then know how to add."[4]

This isn't to say that people can or should be discarded from the decision-making process and replaced with mathematical formulae. People with domain-specific knowledge are needed to identify critical inputs,[5] assess the likelihood that different events and scenarios will occur, and—in some cases—attach values to various possible outcomes. Indeed, people are actually very good at identifying relevant input variables and coding them in ways that make sense for the decision task at hand.[6] But people, including experts, are not so good at combining multiple inputs from different sources, particularly in cases that involve multiple contingencies.[7]

Recognizing that mathematical algorithms can improve decision quality in many areas, the statistical approach that Billy Beane took to field his baseball team is being emulated in other domains.[8] However, until now, mathematical models have infrequently played a key role at trial. Perhaps courts are reluctant to offer jurors quantitative tools that might appear to invade the jury's decision-making function. However, attorneys should not take their cues from the courts. Instead, they should welcome the strategic assistance that decision aids can provide.

Consider, for example, that most civil cases include settlement negotiations and most criminal cases include plea discussions.[9] Settlements, plea deals, and other legal compromises do not occur for altruistic reasons. Presumably, legal

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3. Robyn M. Dawes et al., *Clinical Versus Actuarial Judgment*, 243 SCIENCE 1668, 1668–69 (1989) (reviewing studies that compared unaided expert clinical judgments to actuarial (i.e., statistical) models and finding "[i]n virtually every one of these studies, the actuarial method has equaled or surpassed the clinical method, sometimes slightly and sometimes substantially").

4. Robyn M. Dawes & Bernard Corrigan, *Linear Models in Decision Making*, 81 *PSYCH. BULL.* 95, 105 (1974).

5. Robyn M. Dawes, *The Robust Beauty of Improper Linear Models in Decision Making*, 34 AM. PSYCH. 571, 573 (1979).

6. *Id.* at 574.

7. As one decision researcher concludes: "[H]uman expertise should be used to identify important variables and . . . the task of summarizing or aggregating information should be left to computers." ROBIN M. HOGARTH, EDUCATING INTUITION 150 (2001).

8. *See* Thomas H. Davenport, *What Businesses Can Learn from Sports Analytics*, 55 MIT SLOAN MGMT. REV. 10, 13 (2014); HARRY GLORIKIAN & MALORYE ALLISON BRANCA, MONEYBALL MEDICINE, at xix (2018).

9. MARK MOTIVANS, U.S. DEP'T OF JUSTICE, FEDERAL JUSTICE STATISTICS, 2016—STATISTICAL TABLES 21 tbl.4.2 (2020) (98% of federal convictions disposed of via guilty plea).

compromises occur because the parties engage in an intuitive calculus that balances trial outcomes and various personal considerations. In most cases, it is impossible to know what outcome would have occurred had a compromise not been reached. Research shows that the intuitive strategies people employ in negotiations and a variety of other decision contexts are subject to a variety of psychological influences. Many of these demonstrated influences or "cognitive biases" are undesirable and normatively indefensible.[10] Even in situations where systematic cognitive biases pose less risk, random "noise" will often reduce the accuracy and quality of the judgments that people make.[11]

Economists, psychologists, decision theorists, logicians, legal scholars, and others have developed an extensive set of tools and strategies to reduce the impact of many of the undesirable influences on decision behavior.[12] Some decision-making tools provide decision-makers with a framework for making choices that offer the best prospect of receiving outcomes consistent with their aspirations. They typically do so by making use of available empirical data and by relying on mathematical principles for aggregating those data to produce probabilistic recommendations. These tools have proven valuable in contexts that include databases where the sample spaces are clear and individual cases are easily classified according to agreed-upon rules.

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10. The list of cognitive biases that can cause people to make judgments and decisions that are not in their best interest is extensive and growing. It includes loss aversion (Amos Tversky & Daniel Kahneman, *Loss Aversion in Riskless Choice: A Reference-Dependent Model*, *in* CHOICES, VALUES AND FRAMES 143, 150 (Daniel Kahneman & Amos Tversky eds., 2000)); the status quo bias (William Samuelson & Richard Zeckhauser, *Status Quo Bias in Decision Making*, 1 J. RISK & UNCERTAINTY 7, 8 (1988)); the endowment effect (Daniel Kahneman et al., *Experimental Tests of the Endowment Effect and the Coase Theorem*, 98 J. POL. ECON. 1325, 1326 (1990)); sunk costs (Hal R. Arkes & Catherine Blumer, *The Psychology of Sunk Cost*, 35 ORG. BEHAV. & HUM. DECISION PROCESSES 124, 124–25 (1985)); the availability bias (Amos Tversky & Daniel Kahneman, *Availability: A Heuristic for Judgment Frequency and Probability*, 5 COGNITIVE PSYCH. 207, 207–08 (1973)); framing effects (Amos Tversky & Daniel Kahneman, *The Framing of Decisions and the Psychology of Choice*, 211 SCIENCE 453, 453 (1981)); omission bias (Jonathan Baron & Ilana Ritov, *Omission Bias, Individual Differences, and Normality*, 94 ORG. BEHAV. & HUM. DECISION PROCESSES 74, 74–75 (2004)); betrayal aversion (Jonathan J. Koehler & Andrew D. Gershoff, *When Agents of Protection Become Agents of Harm*, 90 ORG. BEHAV. & HUM. DECISION PROCESSES 244, 244–45 (2003)); normality bias (Robert A. Prentice & Jonathan J. Koehler, *A Normality Bias in Legal Decision Making*, 88 CORNELL L. REV. 583, 585–87 (2003)); regret (Chris Guthrie, *Better Settle than Sorry: The Regret Aversion Theory of Litigation Behavior*, U. ILL. L. REV 43, 45–46 (1999)); hindsight bias (Jeffrey J. Rachlinski, *A Positive Psychological Theory of Judging in Hindsight*, 65 U. CHI. L. REV. 571, 571 (1998)); confirmation bias (Raymond S. Nickerson, *Confirmation Bias: A Ubiquitous Phenomenon in Many Guises*, 2 REV. GEN. PSYCH. 175, 175–76 (1998)); and optimism bias (Neil D. Weinstein, *Unrealistic Optimism About Future Life Events*, 39 J. PERS. & SOC. PSYCH. 806, 806 (1980)). For a discussion of many of these biases in a legal context, see EYAL ZAMIR & DORON TEICHMAN, BEHAVIORAL LAW AND ECONOMICS (2018).

11. DANIEL KAHNEMAN ET AL., NOISE: A FLAW IN HUMAN JUDGMENT 6, 7 (2021) ("To improve the quality of our judgments, we need to overcome noise as well as bias.").

12. Christine Jolls & Cass R. Sunstein, *Debiasing Through Law*, 35 J. LEGAL STUD. 199, 234 (2006); Richard P. Larrick, *Debiasing, in* BLACKWELL HANDBOOK OF JUDGMENT AND DECISION MAKING 316, 317–18 (Derek J. Koehler & Nigel Harvey eds., 2004); Lawrence J. Sanna & Norbert Schwarz, *Debiasing the Hindsight Bias: The Role of Accessibility Experiences and (Mis)Attributions*, 39 J. EXPERIMENTAL SOC. PSYCH. 287, 293 (2003).

Attorneys who must assess the relative merit of settlement and plea options have fewer databases and predictive metrics at their disposal. Even in cases where relevant databases exist, past legal cases are often difficult to classify, and present cases often have so many unique features that comparisons to other cases may seem misguided. Even still, decision aids can be quite useful, particularly when they include attorneys' subjective assessments of the chance that various outcomes will occur in various circumstances. Indeed, decision tools built on well-reflected subjective judgments have the potential to outperform the unaided intuitive approaches that attorneys typically use. The tool that we consider to be more important than any other—a tool that has not yet taken hold in the legal world—is the *influence diagram*.

Influence diagrams are intuitively appealing visual displays of well-structured decision problems. These diagrams enable decision-makers to define and represent the key elements of even the most complex decision problems and the logical relationships between those elements. They do so by breaking problems into their constituent parts, thereby treating large, complex problems as a series of smaller ones that are evaluated independently. This approach is consistent with the "decision hygiene" recommendations offered by the Nobel Laureate Daniel Kahneman for reducing the deleterious effects of random noise on human judgment.[13]

Influence diagrams are also valuable because they allow users to examine how changes in the assumptions, scenarios, and probabilities in their cases are likely to affect decision points. Although some decision aids might become unwieldy following such scenario building, the underlying mathematics behind influence diagrams stays "under the hood" where they belong. Influence diagrams have the potential to enlighten current approaches for identifying litigation strategy well beyond what can be achieved with more traditional decision aids, such as decision trees. In particular, influence diagrams can help attorneys focus on the parts of their cases where attorney expertise and input is needed, while simultaneously reducing the risk that the attorneys or other members of their team will fall prey to any number of tempting, well-documented reasoning fallacies.[14] Simply put, influence diagrams can help attorneys think through plausible versions of how alternative decision paths may unfold, and be ready to respond to each path in ways that are probabilistically superior to the types of responses that even experienced decision-makers would offer.

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13. KAHNEMAN ET AL., *supra* note 11, at 9, 372.

14. These fallacies include the prosecutor's fallacy (*see* William C. Thompson & Edward L. Schumann, *Interpretation of Statistical Evidence in Criminal Trials: The Prosecutors' Fallacy and the Defense Attorney's Fallacy*, 11 LAW & HUM. BEHAV. 167, 170 (1987) (confusing the chance of a coincidental forensic match with the probability that a defendant is not guilty)), the conjunction fallacy (*see* Amos Tversky & Daniel Kahneman, *Extensional Versus Intuitive Reasoning: The Conjunction Fallacy in Probability Judgment*, *in* HEURISTICS AND BIASES: THE PSYCHOLOGY OF INTUITIVE JUDGMENT 19, 20–21 (Thomas Gilovich et al. eds., 2002) (occurs when people judge that the chance that both of two events will occur is higher than the chance that one of the individual events will occur)), and the base rate fallacy (Jonathan J. Koehler*, The Base Rate Fallacy Reconsidered: Descriptive, Normative, and Methodological Challenges*, 19 BEHAV. & BRAIN SCI. 1, 2 (1996) (the tendency to ignore background (i.e., base rate) information when estimating the chance that an event will occur)).

The remainder of this Article is structured as follows. Part I provides an overview of the earliest efforts to structure decision problems and to identify an important normative decision rule (expected value). This Part also illustrates the application of this basic form of decision analysis to litigation using hypothetical examples in which attorneys must decide whether to accept a settlement (civil case) or a plea offer (criminal case). Part II introduces advanced decision-analytic concepts that are more personal and helpful for determining the best legal strategies for particular clients. These concepts include utility functions, risk attitudes, and probability-equivalents. Part III shows how to construct decision trees and influence diagrams for legal problems. Part IV extends the basic principles to more complex litigation examples in which we show how attorneys can conduct sensitivity analyses to test variations in assumptions and scenarios. Although these analyses may be conducted by a decision analyst, they require little more than proficiency in the software programs that most attorneys already use in the workplace. Part V identifies several obstacles to the use of decision aids. The Article ends with a brief conclusion.

I. EARLY NORMATIVE DECISION RULE: EXPECTED VALUE

The standard theory of litigation is rooted in an economic perspective.[15] According to this theory, litigation proceeds in several distinct stages. Initially, a party that has suffered a loss or damage must decide whether to bring suit or do nothing (i.e., accept the loss). Civil actions of this sort involve costs and the plaintiff typically bears those costs. Following a choice to bring suit, the plaintiff must decide whether to settle (on terms agreed to by the opposing party) or proceed to trial. Deciding to settle, and thus to drop suit, has a rather foreseeable consequence in monetary terms: the plaintiff can expect to receive the settlement amount. The situation is different for the decision to proceed to trial because the costs and outcomes of trial are less foreseeable. This Article focuses on the decision to settle versus proceed to trial. We analyze this decision using elements of normative decision theory. That is, we focus on models that describe how a rational decision-maker should make judgments and choices. In this context, the words "rational" and "should" are best understood in relation to some stated criterion, usually a mathematical model.

Normative decision theory has its roots in the so-called *expected value* model. This model was formalized in an exchange of letters between the French mathematician Blaise Pascal and the French mathematician and attorney Pierre de Fermat in 1654.[16] Pascal and Fermat were interested in identifying optimal gambling strategies. Focusing on quantifying uncertainty in dice games, the work of Pascal and Fermat led to the creation of modern probability theory. Around the same time, the book *La logique ou l'art de penser*, known com-

15. *E.g.*, STEVEN SHAVELL, FOUNDATIONS OF ECONOMIC ANALYSIS OF LAW 387–463 (2004).

16. KEITH DEVLIN, THE UNFINISHED GAME: PASCAL, FERMAT, AND THE SEVENTEENTH-CENTURY LETTER THAT MADE THE WORLD MODERN 14, n.* (2008).

monly as the *Port-Royal Logic*[17] was published. (Pascal is believed to be a contributor.[18]) This book contained the first statement of the principle of maximizing expected value.[19] Specifically, this book advised decision-makers to evaluate decision consequences based on two features of those consequences: their "goodness" (or, value) and their probability of occurring.[20] Thus, what underlies the notion of expected value is the "weighing" of the goodness (or badness) of a set of potential consequences by the probability that those consequences will occur.

To illustrate the basic normative approach, consider a hypothetical civil case[21] in which the parties must decide whether to accept a proposed deal or proceed to trial. Plaintiff Paula sues Defendant Daniel for \$1,000,000 claiming that Daniel misused money that Daniel was supposed to keep in a trust for Paula until Paula turned eighteen years old. Plaintiff Paula says that there is presently \$500,000 in the trust, but the trust, appropriately invested, should now be worth \$1,500,000. Defendant Daniel says that he did not misuse the trust funds and that he owes Paula nothing more. However, Daniel offers Paula \$300,000 to settle the case. Paula knows that it may be difficult to prove her case. She assesses her chance of winning at 50% and thinks that if she does win, she has an 80% chance to be awarded \$1,000,000, a 10% chance to be awarded \$500,000, and a 10% chance to be awarded some amount less than \$500,000 (e.g., \$250,000). Should Paula accept Daniel's settlement offer?

This case contains all of the information needed for an expected value analysis. For example, Paula's option to accept Daniel's settlement offer is characterized by the monetary value of \$300,000. Note that this is a sure value—meaning, there is no uncertainty involved—hence terming it *expected* value may seem unnecessary. The notion of expected value is better illustrated with the option to go to trial, as it involves the following combination of probabilities and monetary values:[22]

$$0.5\times[0.8\times\$1{,}000{,}000+0.1\times\$500{,}000+0.1\times\$250{,}000]+0.5\times\$0=\$437{,}500.$$

17. Jill Buroker, *Introduction* to ANTOINE ARNAUD & PIERRE NICOLE, LOGIC OR THE ART OF THINKING ix (trans. & ed. Jill Vance Buroker, 5th ed. 1996) (1662); ARNAUD & NICOLE, *supra*, at 273–74. For a concise overview of the history of decision theory, see also MARTIN PETERSON, AN INTRODUCTION TO DECISION THEORY 10–14 (2d ed. 2017).

18. PETERSON, *supra* note 17, at 12.

19. *Id.*

20. ARNAUD & NICOLE, *supra* note 17.

21. The normative idea could also be illustrated using a criminal case hypothetical. For example: Jack is accused of criminal copyright infringement for having recorded several advance screenings of movies using a pocket camera and sharing these recordings on several platforms on the internet. The prosecutor must prove that Jack acted willfully, and she assesses her chance to win at trial at 80%. But Jack has filed a motion to dismiss and the prosecutor believes that this motion has about an even chance to succeed. What sort of deal, if any, should the prosecutor put on the table for Jack to avoid the costs and risks of moving ahead in court to fight Jack's motion to dismiss? What sort of deal, if any, should Jack accept?

22. For simplicity, we leave out of our equations the baseline value of \$500,000 which currently remains in the trust, irrespective of whether suit will be brought. We also leave aside factors such as litigation costs for now, but do address such considerations in later parts of this Article.

Here, in square brackets, is the expected value of winning at trial, which is given by the sum of each possible court allocated award times the probability of obtaining the respective award. The resulting value is multiplied by 0.5 because the chance of winning at trial is considered to be 50%. In addition, there is a 50% chance of losing at trial and ending up with nothing, accounted for by the product to the immediate left of the equal sign. The result, \$437,500, is the expected value of going to trial.

When using the expected value as the criterion for rating and comparing rival options, our template decision rule indicates that going to trial is the "better" decision because the expected value of trial (\$437,000) is larger than the settlement value (\$300,000). The normative status of the expected value rule is most easily justified through reference to outcomes over repeated play situations. For example, if the case involving Paula and Daniel were to play out in the courts many times, our best estimate is that over the long run, Paula's take at trial would average \$437,000, whereas her take in a settlement would, of course, average \$300,000. Accordingly, it would seem that the "rational" thing for Paula to do would be to take her chances at trial.

However, many rational people in Paula's position would *not* choose to go to trial under these circumstances. The expected monetary value (EMV) associated with different options may not be the only relevant consideration. Perhaps Paula, or someone in Paula's position, is averse to risk or is risk-sensitive. For example, if Paula could not afford to end up with nothing, she may wish to avoid the inherent risk in going to trial, even knowing that the EMV associated with trial is higher than the settlement amount. Moreover, this case, like most cases, is not a repeated-play situation. This is a one-shot situation, and therefore it is not clear how much Paula should care about how much she would earn in a hypothetical repeated-play situation. Paula might also feel, quite reasonably, that a settlement of \$300,000 is an excellent outcome and that going to trial may be draining, time-consuming, and risky. So why not settle?

The paragraph above shows that identifying a normative strategy for strategic legal decisions may be more complicated than identifying a normative strategy for monetary gambling games of the sort studied by Fermat and Pascal. The different ways people think about risk, and the different subjective values that people derive from particular monetary outcomes, mean that normative decision theory may need to be individualized to some extent in contexts of the sort illustrated by Paula and Daniel's case. The following section describes the notions of utility and risk attitude that add a personal element to decisions of the sort that Paula and other legal actors face.

II. UTILITY AND RISK ATTITUDE

There are several good reasons for using money as the primary way to compare decision options in civil cases. Money is a familiar measure of value. It is physically transferable and substitutable across most conceivable uses.[23] Money is also the primary way in which the law makes plaintiffs "whole." But as suggested by the civil case of Paula and Daniel above, when the potential monetary costs and awards get large (particularly relative to the wealth of the parties involved), EMVs over a hypothetical long-run set of repeated events may not be an appropriate guide for one-shot decisions.

Consider, for example, an offer to play one of the two following games a single time:

- Game 1: Win \$3,000 with probability 0.5
  Lose \$2,000 with probability 0.5
- Game 2: Win \$50 with probability 0.5
  Lose \$2 with probability 0.5

The EMV of Game 1 is \$500, which is more than 20 times greater than the EMV of Game 2, which is \$24. Game 1 is clearly the superior choice in a repeated play situation. Those who play Game 1 about 100 times can expect to earn approximately \$50,000 in total, and have more than a 90% chance to earn at least \$5,000. In contrast, those who play Game 2 about 100 times can expect to earn approximately \$2,400 in total and have essentially zero chance to earn at least \$5,000. However, many people will prefer to play Game 2 in a one-shot situation because it appears to be less "risky." Specifically, the 50% chance of losing \$2,000 in a single play of Game 1 is a risk that, for many people, dominates any type of long-run analysis. Even if the games were played more than once, many people will worry about the large potential loss associated with Game 1. Whereas the worst outcome across 10 plays of Game 2 is a loss of \$20, the worst outcome across 10 plays of Game 1 is a much larger loss of \$20,000.

A decision-maker who chooses an option that is suboptimal in terms of EMV is called *risk-averse*. Applied to our civil case example, a risk-averse plaintiff chooses to settle for a "sure value" (the settlement amount) that is *lower* than the EMV of going to trial. A common way to capture and explain the notion of risk aversion is to think about the subjective value that different dollar amounts have to different decision-makers.

Consider, for example, awards of \$1,000 and \$2,000. How much is \$1,000 worth to a decision-maker relative to no award at all? How much more is \$2,000 worth? Although one may think that \$1,000 is worth a lot to any decision-maker, it may not be worth much to one who has great wealth. Therefore, the difference in value between no award and \$1,000 will be highly person-specific. Now consider the difference between a \$1,000 award and a \$2,000 award for a given individual. Although one might at first presume that the larger award will be

23. Ward Edwards, *Unfinished Tasks: A Research Agenda for Behavioral Decision Theory*, *in* INSIGHTS IN DECISION MAKING: A TRIBUTE TO HILLEL J. EINHORN 44, 59 (Robin M. Hogarth ed., 1990).

twice as valuable to that person as the smaller award, this is almost certainly not the case. A $2,000 award is worth more than a $1,000 award, but it is not twice as valuable. This phenomenon lies at the core of risk aversion and is commonly modeled with the aid of a *utility function*.

A utility function describes the subjective value that a person derives from a set of outcomes, including dollar outcomes. In the example above, a risk-averse plaintiff may derive an amount of utility X from an award of $1,000 and an amount of utility somewhat less than 2X from an award of $2,000. The graph of a decision-maker's utility function typically provides monetary values on the x-axis and "translates" them into utility values on the y axis as shown in Figure 1.

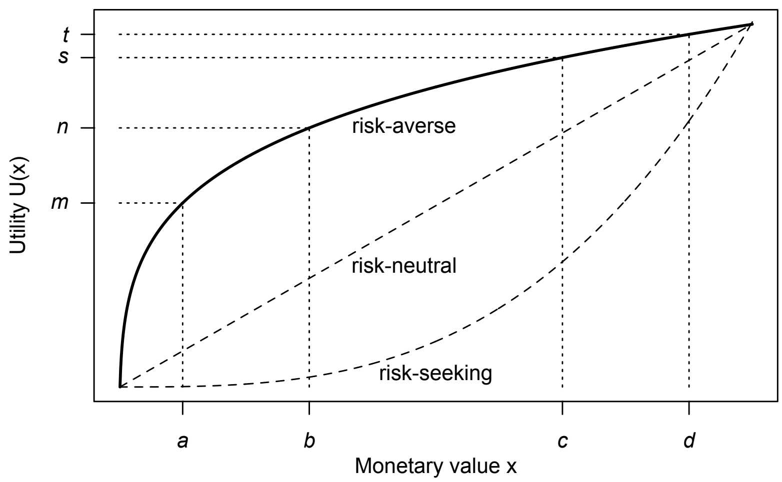

Figure 1. Graphical representation of utility functions that translate monetary values *x* into utility values U(*x*). The function highlighted with a bold concave curve reflects risk aversion, that is, the view that utility does not increase linearly with monetary value: increases in monetary values from *a* to *b* and from *c* to *d* are the same, but the increase in the corresponding utility is smaller in the latter case. The dashed straight line illustrates a risk-neutral attitude and the dashed convex (upward sloping) curve illustrates a risk-seeking attitude.

The concave shape of the curve depicted in Figure 1 is typical of utility curves for dollar gains and reflects risk aversion. Suppose the interval between *a* and *b* on the x-axis represents an increase in assets from, say, $1,000 to $3,000. This asset increase corresponds to an increase in utility from *m* to *n* on the y-axis. However, note that a further increase of $2,000—for example, from $7,000 to $9,000 (points *c* and *d*)—is associated with a *smaller* increase of utility: the distance between *s* and *t* is smaller than the distance between *m* and *n*. The overall concavity of the function depicted in Figure 1 reflects the view that the higher one's initial asset position, the smaller the increase will be in utility gained from a fixed asset increase such as $2,000. The function is bounded, meaning that there comes a point in terms of one's wealth level when increases in assets are no longer associated with perceptible increases in utility.

Of course, different people will have different risk attitudes, and therefore the utility function may take on different shapes. Whereas *risk aversion* is indicated by a downward sloping concave curve, *risk seeking* is indicated by an upward sloping convex curve (see Figure 1). *Risk-neutrality*—in which a linear relationship exists between assets and utilities—is indicated by the approximately 45-degree dashed line.

The introduction of utility curves raises the question of how we might identify such curves for a given decision-maker. Various techniques may be used to accomplish this. Here, we provide a brief illustration of the *probability-equivalent* (PE) assessment technique. It works as follows.

Imagine a situation in which the consequences of the decision you face are uncertain. In the best case, you gain \$1,000 and in the worst case, you gain nothing. Various possible decisions exist, each leading to a different payoff between \$0 and \$1,000. Your task is to specify a utility U(x), for each possible monetary outcome x. The PE technique starts by setting the endpoints of the utility scale. A simple way to do this is to assign the value 0 to the worst consequence and a value 1 to the best consequence. Thus, U(\$0)=0 and U(\$1,000)=1. Next, suppose you wish to elicit your utility for the outcome \$500, that is, U(\$500). This value will lie somewhere between the previously identified utility endpoints 0 and 1. The PE assessment technique requires you to consider the following pair of options:[24]

A. Win \$1,000 with probability p, or else win nothing with probability (1–p)
B. Win \$500 with probability 1.0

For most people, if p in option A is very high (e.g., 0.99), then option A will be preferred to option B. Likewise, if p is low (e.g., 0.10), then option B will be preferred. If this is the case, then, presumably, some value of p exists that lies between 0.10 and 0.99 for which a given decision-maker will be *indifferent* between the so-called *reference gamble* in option A and the fixed amount in option B.[25] This is known as *the equivalence rule* and can formally be stated as follows:

$$\$500 \sim \begin{array}{l} \$1{,}000 \text{ with probability } p \\ \$0 \text{ with probability } (1-p) \end{array}$$

Here, "~" denotes equivalence, \$500 is called the *certainty equivalent*, and p is your *preference probability*. The beauty of the PE procedure is that once you have identified p, you have simultaneously identified your utility for the value (\$500) identified in option B. For example, suppose that you are indiffer-

24. Readers who find the device of a gamble or lottery unsuitable may consider thinking in terms of an investment that leads to a particular gain or loss with probabilities p and (1–p), respectively.

25. Note that one could represent this comparison as a decision tree where one decision branch has \$500 as an endpoint, and another branch leads to a chance node with two branches, one leading to \$1000 with probability p and another to \$0 with probability (1–p). Decision trees are discussed *infra* in Section III.A.

ent between (A) a 70% chance to win \$1,000 (and a 30% chance to win nothing), and (B) a 100% chance to win \$500. Here, p=.70, and your utility for \$500—U(\$500)—is 0.70. More formally, the PE elicitation procedure invokes the known utilities U(\$1,000)=1 and U(\$0)=0, and relates them to the "unknown" U(\$500) as follows:

$$\begin{aligned} U(\$500) &= p \cdot U(\$1{,}000) + (1-p) \cdot U(\$0) \\ &= p \cdot (1) + (1-p) \cdot (0) \\ &= p = 0.7 \end{aligned}$$

Using the same procedure, one can assign utilities for all intermediate outcomes between \$0 and \$1,000.

With these ideas in mind, let us briefly review the civil case example presented in Section II. Recall that Plaintiff Paula's view is that, if she wins at trial, she has an 80% chance to be awarded \$1,000,000, a 10% chance to be awarded \$500,000, and a 10% chance to be awarded some amount less than \$500,000, such as \$250,000. Defendant Daniel's settlement offer was \$300,000. Recall also that the EMV for going to trial was \$437,500. Because the EMV value for going to trial is larger than the settlement offer, we provisionally concluded that going to trial is the better decision.

But now consider an analysis that focuses on the *utilities* of the potential dollar values rather than on the dollar values themselves. We begin by assigning a utility of 0 to the worst-case outcome (\$0) and a utility of 1 to the best-case outcome (\$1,000,000). Suppose that the client uses the PE assessment technique to elicit the following utilities: U(\$250,000)=0.5 and U(\$500,000)=0.8. Note that such a utility function roughly corresponds to the type of risk-averse curve shown in Figure 1. We can now compute the *expected utility (EU)* associated with the decision to go to trial as follows:

$$\begin{aligned} &EU\ (trial)=0.5\times[0.8\times1+0.1\times0.8+0.1\times0.5]+0.5\times0 \\ &=0.465. \end{aligned}$$

Because we assigned U(\$250,000)=0.5, the utility of the settlement amount \$300,000 must be greater than 0.5. Thus,

$$EU(settle)>0.5.$$

As we can see, now EU(settle)>EU(trial). Therefore, using an analysis that relies on the utilities of a risk-averse plaintiff rather than the raw dollar values themselves, settling is the better decision.

This example illustrates that an expected *value* analysis of decision options may not always yield the same recommendation as an expected *utility* analysis of those same options. Whereas *expected value* analyses are simpler to conduct and yield the same recommendations for all decision-makers who rely on the same probabilities, *expected utility* analyses provide a more individualized approach.

Earlier, we noted some of the shortcomings associated with using EMV as a normative choice rule in single-shot legal cases. Likewise, EU has its own shortcomings. First, a decision-maker's utilities may change over time. Second, even if they do not change, it may not be a simple matter for decision-makers to identify those utilities by identifying indifference points among options. Third, academics have identified several paradoxes associated with EU[26] even though its normative status has largely remained intact.[27] A further complication is that empirical studies indicate that people commonly make choices that neither maximize EMV nor EU.[28] As noted previously, research indicates that the way people make decisions leaves them vulnerable to various undesirable psychological and emotional influences.[29]

Having noted that (a) our normative models are descriptively inadequate, (b) people may value identical dollar amounts differently, (c) legal cases are single-shot events that have unique features, and (d) people are influenced by a variety of factors that are difficult to model or that harm good decision-making, it is tempting to conclude that little can be done at a formal level to improve litigation decision-making. We reject this conclusion. Instead, while fully accepting the uniqueness and complexity of litigation decision-making, we suggest that decision-makers will generally be better off in terms of achieving their own goals by considering the recommendations provided by a structured and logical analysis of the primary monetary elements. Note that such analyses, properly conducted, will include—not replace—the thoughts and insights of legal counsel.

For reasons of simplicity, the examples of decision aids that we offer henceforth use monetary values rather than utilities. Of course, litigants can, in a subsequent step, convert those monetary values to utilities. Doing so may provide a more personalized and context-specific recommendation from the decision aid of interest. But for our purposes here—and to avoid repeated reminders about the role that personal risk attitudes and utilities may play—our discussion of decision aids assumes a risk-neutral approach based on maximizing EMV. The focus in the remainder of this Article will be on how legal decision-makers can employ modern, computer-based methods to produce decision aids that can inform—though not necessarily dictate—litigation strategy.

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26. The Allais paradox, the Ellsberg paradox, and the St. Petersburg paradox are well known. *See generally* EXPECTED UTILITY HYPOTHESIS AND THE ALLAIS PARADOX (Maurice Allais & Ole Hagen eds., 1979); Daniel Ellsberg, *Risk, Ambiguity and the Savage Axioms*, 75 Q. J. ECON. 643 (1961); Christian Seidl, *The St. Petersburg Paradox at 300*, 46 J. RISK & UNCERTAINTY 247 (2013).

27. DENNIS V. LINDLEY, MAKING DECISIONS 11 (2d ed. 1985) ("[D]ecisions should be made by maximizing expected utility."); *id.* at 60 ("[E]xpected utility . . . stands up to all the counter-attacks . . . .").

28. Substantial evidence indicates that people systematically violate expected utility when making decisions. *See, e.g.*, Daniel Kahneman & Amos Tversky, *Prospect Theory: An Analysis of Decision Under Risk*, 47 ECONOMETRICA 263 (1979). This descriptive observation means that there is room for improvement in our decision-making.

29. *See supra* note 14.

III. DECISION AIDS: DECISION TREES AND INFLUENCE DIAGRAMS

Following the development of normative strategies for decision-making, twentieth-century scientists began to focus on developing decision-support tools that help decision-makers structure their problems, provide visual representations of the issues, and handle complexity when choosing among various available options. Two important tools are decision trees[30] and more recently influence diagrams.[31] Both tools are based on the idea that decision-making requires identifying states of nature or events of interest (e.g., the outcome of a trial), a measure of the uncertainty of those states of nature (generally, in terms of probabilities), and a measure for the relative desirability of the associated outcomes (e.g., monetary value or utilities). According to this "decision theory" framework,[32] these three components should be combined and used to compare rival decision options. Our discussion of decision aids begins with decision trees.

A. Constructing Decision Trees

Decision trees[33] were developed by statisticians[34] and now are routinely used in the world of business decision-making.[35] Their easy-to-follow pictorial nature goes a long way toward communicating the inherent risks, costs, and benefits associated with important decisions. Business students are routinely taught to use decision trees, and this aid has proven useful in negotiations.[36] Law students are less likely to encounter decision trees or other statistical or graphical support tools.[37] Nevertheless, decision trees have been used to analyze stra-

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30. *See* HOWARD RAIFFA, DECISION ANALYSIS, INTRODUCTORY LECTURES ON CHOICES UNDER UNCERTAINTY 10 (1968).

31. *See* Ronald A. Howard & James E. Matheson, *Influence Diagrams*, *in* 2 READINGS ON THE PRINCIPLES AND APPLICATIONS OF DECISION ANALYSIS 719 (Ronald A Howard & James E. Matheson eds., 1984).

32. Professor John Kaplan is generally credited with providing the first formal decision-theoretic account of legal proof. John Kaplan, *Decision Theory and the Factfinding Process*, 20 STAN. L. REV. 1065, 1065–66 (1968).

33. RAIFFA, *supra* note 30.

34. *See, e.g.*, HOWARD RAIFFA & ROBERT SCHLAIFER, APPLIED STATISTICAL DECISION THEORY (1961); DENNIS V. LINDLEY, MAKING DECISIONS (1971); Stephen E. Fienberg, *The Early Statistical Years: 1947–1967, A Conversation with Howard Raiffa*, 23 STAT. SCI. 136 (2008).

35. *See, e.g.*, C. JACKSON GRAYSON, DECISIONS UNDER UNCERTAINTY: DRILLING DECISIONS BY OIL AND GAS OPERATORS 323–336 (1960) (using the expression "Information Flow Diagram"); THOMAS HOWARD, DECISION THEORY AND THE MANAGER (1972); RONALD A. HOWARD & ALI E. ABBAS, FOUNDATIONS OF DECISION ANALYSIS (2016).

36. *See, e.g.*, ROBERT T. CLEMEN & TERENCE REILLY, MAKING HARD DECISIONS WITH DECISION TOOLS (3d ed. 2014).

37. Carole Silver & Louis Rocconi, *Learning from and About the Numbers*, 4 J. LEGAL METRICS 53, 80 (2015) (reporting the results of a survey from more than 8,000 law students enrolled in 34 U.S. law schools: "Overall, students do not report learning to use NGS [numerical, graphical or statistical] information in law school"); HOWELL E. JACKSON ET AL., ANALYTICAL METHODS FOR LAWYERS, at v–vi (2011). For an exception and early description in the legal literature of a graphical method for evidential reasoning, see Richard D. Friedman, *A Close Look at Probative Value*, 66 B.U. L. REV. 771 (1986) and Richard D. Friedman, *A Diagrammatic Approach to*

tegic litigation matters,[38] forensic science evidence,[39] and decisions regarding the ultimate issues at trial.[40]

1. *Example 1: A Generic Case of Trial Versus Settlement*

Consider the construction of a decision tree for litigants who must choose between proceeding to trial or settling out of court. The starting point for a decision tree is a *squared decision node*, usually drawn on the left, from which branches—representing available actions—emanate toward the right. See Figure 2. At the *circled nodes*, representing uncertain events, branches divide with each new branch representing a state of nature (i.e., a way in which the world may turn out). Alongside nodes and arcs, decision trees depict key items of information such as probabilities (for states of nature), value assessments for decision consequences (e.g., the settlement amount), costs, and expected (monetary) values.

Suppose a plaintiff and defendant in a contract dispute engage in pre-trial settlement negotiations. The plaintiff believes that the probability of winning the case at trial is about 80% and the amount to be awarded is $8,000. If the case proceeds to trial, each party expects to incur $2,000 in litigation costs.[41] Suppose further that a contract provision calls for the losing party to pay all litigation fees.[42]

Evidence, 66 B.U. L. REV. 571 (1986) (offering a modification of probability trees called "Route diagram").

38. Marjorie Corman Aaron & Wayne Brazil, *Shaking Decision Trees for Risks and Rewards*, DISP. RESOL. MAG., Fall 2015, at 12; PAUL BREST & LINDA HAMILTON KRIEGER, PROBLEM SOLVING, DECISION MAKING, AND PROFESSIONAL JUDGMENT, A GUIDE FOR LAWYERS AND POLICYMAKERS 461–83 (2010); JOHN CIRACE, LAW, ECONOMICS AND GAME THEORY 355–61 (2018); Craig B. Glidden et al., *Evaluating Legal Risks and Costs with Decision Tree Analysis*, *in* SUCCESSFUL PARTNERING BETWEEN INSIDE AND OUTSIDE COUNSEL § 12-2 (Robert L. Haig ed., 2000); David P. Hoffer, *Decision Analysis as a Mediator's Tool*, 1 HARV. NEGOT. L. REV. 113, 120–29 (1996); JACKSON ET AL., *supra* note 37, at 3; Donald R. Philbin Jr., *The One Minute Manager Prepares for Mediation: A Multidisciplinary Approach to Negotiation Preparation*, 13 HARV. NEGOT. L. REV. 249, 257–76 (2008); Jeffrey M. Senger, *Decision Analysis in Negotiation*, 87 MARQ. L. REV. 723, 724–27 (2004); Steven Shavell, *Suit, Settlement, and Trial: A Theoretical Analysis Under Alternative Methods for the Allocation of Legal Costs*, 11 J. LEGAL STUD. 55 (1982); Marc B. Victor, *The Proper Use of Decision Analysis to Assist Litigation Strategy*, 40 BUS. LAW. 617 (1985).

39. Alex Biedermann & Joëlle Vuille, *Understanding the Logic of Forensic Identification Decisions (Without Numbers)*, 83 SUI-GENERIS S. 397, at S. 401–02 (2018), https://sui-generis.ch/article/view/sg.83/985 [https://perma.cc/6H4V-JALG]; Simon A. Cole & Alex Biedermann, *How Can a Forensic Result Be a "Decision"? A Critical Analysis of Ongoing Reforms of Forensic Reporting Formats for Federal Examiners*, 57 HOUS. L. REV. 551, 571 fig. 1 (2020).

40. Alex Biedermann et al., *Decision Theory, Relative Plausibility and the Criminal Standard of Proof*, 15 CRIM. L. & PHIL. 131, 150 (2021); REID HASTIE & ROBYN M. DAWES, RATIONAL CHOICE IN AN UNCERTAIN WORLD (2001); Larry Laudan & Harry D. Saunders, *Re-Thinking the Criminal Standard of Proof: Seeking Consensus about the Utilities of Trial Outcomes*, 7 INT'L COMMENT. ON EVIDENCE 1, 2–8 (2009).

41. For simplicity, the currency sign $ will be omitted in the remainder of this Article.

42. *See also* SHAVELL, *supra* note 15, at 428ff., for further discussion of the American rule in which each party generally bears its own fees, as compared to the so-called English rule under which fees are paid by the losing party at trial. The decision analysis tools we recommend here can handle

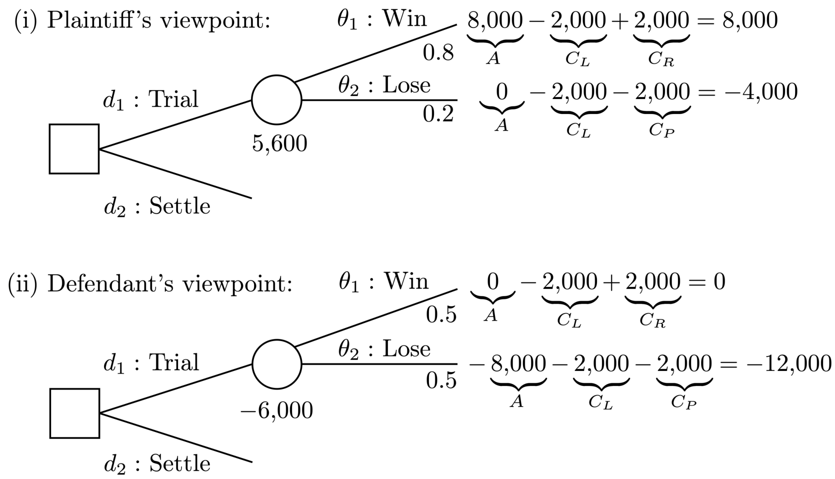

Figure 2. Partial decision trees for the EMVs of going to trial from the plaintiff's (top) and the defendant's (bottom) points of view. Notation definitions are as follows: A ("award") is the amount awarded to the prevailing party at trial, paid for by the losing party. C_L are litigation costs. C_R are litigation costs recouped by the winning party, paid for by the losing party. C_R needs to be paid by the losing party and is denoted as C_P. The variable θ denotes the possible trial outcomes (i.e., uncertain states of nature): winning (θ_1) and losing (θ_2). Probabilities for these possible outcomes are denoted below each chance branch. The value below the circled chance nodes represents the EMV of the decision d_1 of going to trial.

The partial decision trees in Figure 2 show the financial perspectives of the plaintiff and defendant. These decision trees are partial because only the branches for option d_1 (going to trial)[43] are developed. If the plaintiff wins (event θ_1), the plaintiff will receive the litigated amount of A = 8,000 as well as the compensation C_R = 2,000 equal to costs C_L = 2,000 incurred for legal representation. The monetary value (MV) of the decision consequence (d_1,θ_1), short for deciding d_1 when θ_1 (plaintiff wins) proves to be the case, thus is MV(d_1,θ_1) = 8,000. The top branch in Figure 2(i) shows how to compute this value. In case the plaintiff loses (event θ_2), the plaintiff will incur costs for legal representation C_L = 2,000 and be required to pay the same amount to their opponent, denoted C_P = 2,000. The monetary value of the decision consequence (d_1,θ_2), that is, deciding d_1 when θ_2 (plaintiff loses) proves to be the case, thus is MV(d_1,θ_2) = −4,000. We are now ready to compute the EMV of going to trial from the plaintiff's viewpoint:[44]

either approach, as well as more complex variations. Most of our examples adopt the loser-pays rule to show how easily this additional source of uncertainty can be incorporated into the decision aids.

43. We use the terms *option* and *decision* interchangeably throughout, acknowledging that a decision amounts to a choice made by the decision-maker among the available options.

44. The sign Σ denotes the sum over the terms on the right, that is, the monetary value of each decision outcome multiplied by the probability of obtaining the respective outcome. Here, we are

$$\begin{aligned}\mathrm{EMV}(d_1) &= \sum_j \mathrm{MV}(d_1,\theta_j)\cdot \Pr(\theta_j)\\ &= 8{,}000\cdot 0.8+(-4{,}000)\cdot 0.2=5{,}600.\end{aligned}$$

The defendant's viewpoint is different. If the defendant prevails, the litigated amount *A* does not need to be paid, hence $A = 0$. The defendant will incur costs for legal representation, $C_L = 2{,}000$, but will receive compensation from the plaintiff in the same amount, that is, $C_R = 2{,}000$. Therefore, the monetary value for the decision consequence (d_1,θ_1) is $\mathrm{MV}(d_1,\theta_1) = 0$. If the defendant loses, the defendant will need to pay the amount $A = 8{,}000$ to the plaintiff, as well as the plaintiff's legal fees $C_P = 2{,}000$. The defendant will also incur his or her own costs for legal representation, that is, $C_L = 2{,}000$. Thus, the monetary value of the consequence (d_1,θ_2) is $\mathrm{MV}(d_1,\theta_1) = -12{,}000$. The defendant thinks that the plaintiff has a 0.5 probability of winning at trial, hence the EMV of forgoing a settlement offer and going to trial, is

$$\mathrm{EMV}(d_1)=0\cdot 0.5+(-12{,}000)\cdot 0.5=-6{,}000.$$

So far, the analysis shows that, for the defendant, the expected monetary *cost* of going to trial is 6,000. This is larger than the EMV of going to trial from the plaintiff's perspective, that is, 5,600. Hence, there should be room for an out-of-court settlement. Stated otherwise, any settlement amount between 5,600 and 6,000 should be acceptable to *both* parties because such a settlement will cost a defendant less than 6,000 (i.e., the defendant's $\mathrm{EMV}(d_1)$ value) and benefit a plaintiff more than 5,600 (i.e., the plaintiff's $\mathrm{EMV}(d_1)$ value).

2. *Example 2: Accounting for Additional Fees*

Consider now the situation in which the prevailing party not only receives the compensation C_R in the amount equal to the fees for their legal representation C_L[45] but also payment of legal fees incurred *prior* to trial (e.g., costs for a mediator). We denote these costs *F*. Suppose *F* is 1,500 and will be paid (received) by the party losing (winning) at trial. The partial decision trees presented in Figure 3 show how *F* impacts the EMV of going to trial from the plaintiff's and the defendant's points of view. Now the EMV of going to trial for the plaintiff has increased to 6,500 which is larger than the EMV of trial as assessed by the defendant (6,000). This implies less incentive to settle exists. That is, this analysis indicates that the defendant should not offer more than 6,000 to settle, but the plaintiff should not settle for anything less than 6,500.

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concerned with the decision outcomes following a decision to go to trial, which may result in either a win (θ_1) or a loss (θ_2).

45. These legal fees may include court costs, attorney costs, transcript fees, etc.

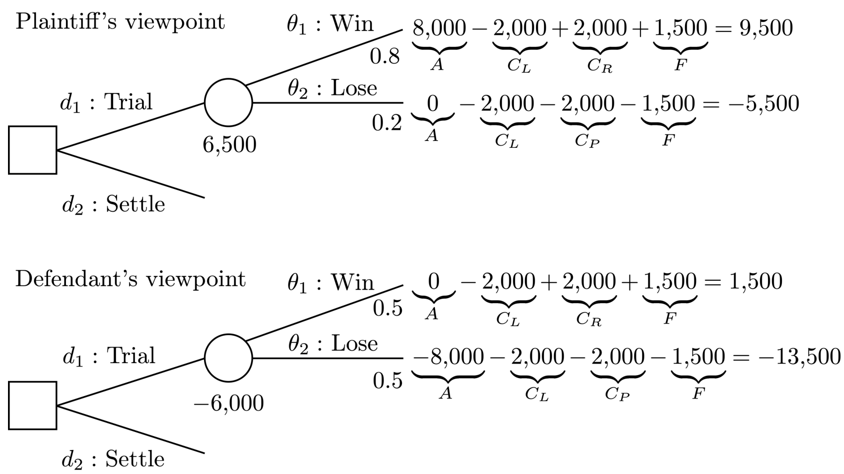

Figure 3. Partial decision trees for the EMVs of going to trial seen from the plaintiff's and defendant's points of view, including the additional variable *F* (pre-trial costs).

This example shows that the addition of a single procedural aspect—compensation for pretrial costs (to be paid by the losing party)—may change the recommendation provided by the decision aid. Without the benefit of a decision tree analysis, it may be difficult for a litigant to have a rational basis for determining and combining the available information to identify the best litigation decision.

B. Constructing Influence Diagrams

1. *Preliminary Comments*

Influence diagrams are graphical models that provide a detailed and compact representation of the full range of uncertainties and values in a decision problem.[46] Influence diagrams emerged from intelligence research conducted in the 1970s to support decision analysis applied to political conflicts.[47] Following technical developments in the 1980s,[48] influence diagrams became influential in business decision-making,[49] artificial intelligence,[50] statistics,[51] medical deci-

46. Howard & Matheson, *supra* note 31, at 721–22, 728–32.

47. Ronald A. Howard et al., *Comment on Influence Diagram Retrospective*, 3 DECISION ANALYSIS 117, 117–18 (2006).

48. *See, e.g.*, Howard & Matheson, *supra* note 31; INFLUENCE DIAGRAMS, BELIEF NETS AND DECISION ANALYSIS (Robert M. Oliver & James Q. Smith eds., 1990); Ross D. Shachter, *Evaluating Influence Diagrams*, 34 OPERATIONS RSCH. 871 (1986).

49. *See, e.g.*, CLEMEN & REILLY, *supra* note 36.

50. Eric J. Horvitz et al., *Decision Theory in Expert Systems and Artificial Intelligence*, 2 INT'L J. APPROXIMATE REASONING 247 (1988); KEVIN B. KORB & ANN E. NICHOLSON, BAYESIAN ARTIFICIAL INTELLIGENCE (2004); STUART RUSSELL & PETER NORVIG, ARTIFICIAL INTELLIGENCE: A MODERN APPROACH 610 (3d ed. 2014).

51. KEVIN P. MURPHY, MACHINE LEARNING: A PROBABILISTIC PERSPECTIVE 328–35 (2012).

sion-making[52] and, to some extent, forensic science.[53] But, as noted earlier, influence diagrams have not established a presence in the law in general or in the world of litigation strategy in particular.[54] This is a regrettable oversight because the party that can quickly and critically deploy "what-if analyses" to review their strategies may obtain a sizable advantage.

Influence diagrams include three types of nodes: *chance nodes* (circles), *decision nodes* (rectangles), and *utility*[55] *nodes* (diamonds). Chance nodes capture the probabilities of various propositions and events. Decision nodes capture the available options at given decision points. Utility nodes capture the values associated with decision consequences.

Influence diagrams are related to Bayesian networks, which are graphical probabilistic models that contain only probabilistic nodes.[56] Bayesian networks have been discussed in many disciplines—including, on occasion, the law[57]—as a framework for reasoning under uncertainty. In such models, "reasoning" means using the rules of probability to address questions of the following kind: "Given knowledge of the occurrence of event *A*, what is the probability of event *B* occurring (or having occurred)?" For example, a medical professional may wish to assess the probability that a patient has a particular disease given the results of the patient's blood test and other relevant background information (e.g., whether the patient is a smoker or has recently traveled to countries where particular diseases are prevalent). Bayesian networks can handle complex situations involving many variables and complicated relationships among those variables, representing so-called *inference networks*.

But, in our view, influence diagrams are even more useful than Bayesian networks in the world of litigation because they do more than represent uncertainty and facilitate probabilistic reasoning. By including nodes for decisions and utilities, influence diagrams extend complex inference networks to *a framework for reasoning about decision-making in dynamic environments*. In the medical example above, an influence diagram may contain a node to represent the decision to conduct (or not conduct) a particular blood test, or to apply various treatments once the test has been performed. In a legal context, a plaintiff

52. Robert F. Nease Jr. & Douglas K. Owens, *Use of Influence Diagrams to Structure Medical Decisions*, 17 MED. DECISION MAKING 263 (1997).

53. FRANCO TARONI ET AL., BAYESIAN NETWORKS FOR PROBABILISTIC INFERENCE AND DECISION ANALYSIS IN FORENSIC SCIENCE 58–60 (2d ed. 2014).

54. Alex Biedermann et al., *Computational Normative Decision Support Structures of Forensic Interpretation in the Legal Process*, 17 SCRIPTED 83, 86–87 (2020).

55. Note that the term *utility* is understood here as a generic expression, including the use of monetary values (rather than utilities as defined in Part II) for characterizing the value or merit of decision consequences.

56. *E.g.*, UFFE B. KJÆRULFF & ANDERS L. MADSEN, BAYESIAN NETWORKS AND INFLUENCE DIAGRAMS: A GUIDE TO CONSTRUCTION AND ANALYSIS 8 (Michael Jordan et al. eds., 2008); FINN V. JENSEN & THOMAS D. NIELSEN, BAYESIAN NETWORKS AND DECISION GRAPHS 302 (Michael Jordan et al. eds., 2d ed. 2007).

57. *E.g.*, Ward Edwards, *Influence Diagrams, Bayesian Imperialism, and the* Collins *Case: An Appeal to Reason*, 13 CARDOZO L. REV. 1025, 1025 (1991); JOSEPH B. KADANE & DAVID A. SCHUM, A PROBABILISTIC ANALYSIS OF THE SACCO AND VANZETTI EVIDENCE (1996); Bernard Robertson & G.A. Vignaux, *Taking Fact Analysis Seriously*, 91 MICH. L. REV. 1442, 1454 (1993).

may need to decide whether to search for more evidence prior to trial or to reassess the decision to go to trial once a search has been conducted.

Simply put, graphical probabilistic models help people deal with questions of *what to think* (or believe) in an uncertain environment. Influence diagrams go a step further by helping people decide *what to do*, given what they think is true or will happen. Both questions are relevant to litigation: litigants need to assess the strength and value of their case and they must also reflect on what actions to undertake *given* those case assessments. Sound legal decision-making requires more than the application of basic logic. It also requires a decision-maker to consider potential decision consequences and to make value judgments regarding the desirability (or undesirability) of those potential consequences. Influence diagrams are better suited for this type of complete analysis than Bayesian networks.[58]

Our claim that influence diagrams are superior to most other decision analytic techniques for structuring questions of legal strategy rests on the assumption that legal decisions commonly involve many interrelated variables. For complicated problems, legal decision-makers will likely find influence diagrams to be more versatile and friendlier than other decision aids. For example, when working with decision trees, uncertainty about a given target event (state of nature) is modelled with a single chance node. This is fine for simple problems but may not suffice when the probability assessment for a target event depends on a host of other contingencies. However, when working with an influence diagram, a chance node can be linked to an entire inference network, specifically designed to deal with uncertainty assessment for the target event at the desired level of granularity.

The compact nature of influence diagrams also works to their advantage as problems become more complex. For example, imagine a case in which a party needs to decide between accepting a settlement offer of 10,000 and going to trial, where the plausible trial outcomes range from 0 to 50,000. In a decision tree, each possible outcome needs to be drawn as a distinct branch, as illustrated in Figure 4(i). Contrast this diagram in 4(i) with the compact influence diagram in Figure 4(ii). Here, the various ways a trial may turn out (e.g., win "big," "intermediate," "small") are modelled as distinct states within the circled chance node "Trial outcome." The probabilities with which these outcomes are thought to occur are organized in a probability table, not shown in Figure 4(ii), associated with the node "Trial outcome." In turn, the values associated with all decision consequences, including the settlement amount, are modelled by the internals of the diamond-shaped utility node.

58. For the same reason, influence diagrams are also a common tool in the world of business analytics. They are routinely used by decision analysts to assist with such business decisions as where to drill for oil, whether to expand a product line, and the like. *See, e.g.*, CLEMEN & REILLY, *supra* note 36.

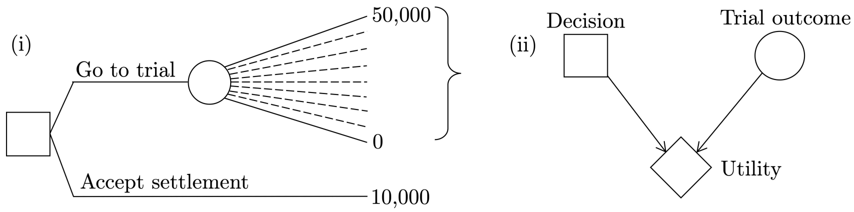

Figure 4. Example of a generic decision problem of trial versus settlement, represented in terms of (i) a decision tree, and (ii) an influence diagram. The dashed branches in tree (i) represent a range of plausible trial outcomes.

Influence diagrams also provide more compact representations of the available decision options. In the decision tree shown in Figure 4(i), the decision options "Go to trial" and "Accept settlement" are represented as distinct branches. In an influence diagram, these two options are modelled in terms of distinct states of the decision node. As this example shows, whereas decision trees can become quite "bushy" for complex problems, influence diagrams maintain a more compact representation for equally complex problems.

Figure 4 also illustrates that decision trees and influence diagrams provide different levels of representation. A decision tree provides an exhaustive representation of all the possible ways that decisions may unfold. Influence diagrams focus on the main ingredients of a decision problem, that is, variables for decisions, outcomes and values for outcomes (e.g., utilities), and the logical relationships among these ingredients. Thus, rather than mapping decision paths in a temporal outline as decision trees do, influence diagrams focus on relationships between the basic elements of decision problems. Influence diagrams leave the combinatorial complexity resulting from decisions and states of nature "under the hood."

2. *Influence Diagram Basics*

How does one set up an influence diagram? We provide some instruction and an example below. But we also recommend that attorneys avail themselves of some of the excellent software programs and written materials that guide users through the process.[59] Those who would rather not become intimately acquainted with the nuts and bolts of influence diagrams may prefer to pass on these resources (and, perhaps, this Section of the present Article) and simply hire an expert decision analyst to direct the process.

Returning to the running litigation decision problem (settle vs. go to trial) from the perspective of the plaintiff, consider a situation in which there is a

59. Examples of influence diagram software are Hugin (www.hugin.com), Netica (www.norsys.com) and GeNIe/SMILE (www.bayesfusion.com). These programs come with online tutorials, introductory examples, and case studies (e.g., www.hugin.com/index.php/resources/, www.norsys.com/netlibrary/, support.bayesfusion.com/docs/GeNIe/id_tutorial.html). For an accessible textbook with a focus on business as well as some legal examples, see CLEMEN & REILLY, *supra* note 36.

10,000 settlement offer on the table and two possible trial outcomes: lose (0 award) and win (50,000 award).

Figure 5(i) shows an influence diagram for this decision problem. The general structure is the same as the diagram shown in Figure 5(ii), but further details are given here on the "internals" of each node in the form of tables displayed next to each node. The rectangular decision node has two states (decision options): "Go to trial" and "Accept settlement." The circled chance node represents the two possible outcomes of trial. In a fully quantified version of this influence diagram, a probability would be assigned to each of these two states, representing the decision-maker's uncertainty about the outcome of trial. The diamond-shaped utility node specifies the monetary values associated with each decision outcome. Figure 5(i) shows that if a plaintiff goes to trial and wins, the award will be 50,000. If the plaintiff loses, the award will be 0. If the plaintiff accepts the settlement offer, the award will be 10,000, and potential trial outcomes become irrelevant.[60]

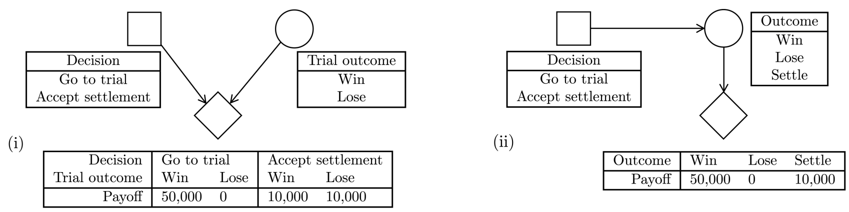

Figure 5. Two possible influence diagram structures for a basic decision problem of trial versus settlement.

The setup in Figure 5(i) may seem somewhat awkward, because the utility node is conditioned on winning and losing the trial if the plaintiff accepts the settlement (i.e., if there is no trial at all). To avoid this feature, Figure 5(ii) includes a chance node that is more generically identified as "Outcome." This node aggregates the three states "Win," "Lose" and "Settle." Consequently, the utility node in Figure 5(ii) contains only three values: the settlement amount and the amounts associated with winning and losing at trial.

Note that the number of utility node entries depends on the number of entering arrows (i.e., arrows pointing to the utility node) and the number of states of the parent node(s). In the language of graphical models, a *parent node* (or predecessor) is a node that has an arrow (or arc) pointing to another node (called a *child node* or descendant). A node can have multiple in- and out-going arrows. In Figure 5(i), the utility node has two entering arrows: one from the decision node, and one from the chance node. The decision node and the chance node each have two possible states, creating a total of four possible combinations. For each of these combinations, the utility node specifies a monetary value. Compare this with Figure 5(ii) where the utility node has only one entering arc from

60. Similarly, in a case where one must decide whether to keep money in savings versus invest money in a business, the return from savings is not affected by the success of the business.

the chance node "Outcome." Here the chance node has three possible states ("Win," "Lose" and "Settle"), hence the utility node specifies only three values (one for each state of the chance node).

In these examples, the arcs specify relationships (or influences) between nodes. For example, in Figure 5(i), arcs are pointing from the decision node and the chance node to the utility node. This indicates the natural understanding that the monetary consequence depends on both the decision regarding trial versus settlement and, eventually, the outcome of trial.

Another type of arc, not used in our simple example, is the *precedence* or *sequence arc*. It is used in situations where, at the time a decision needs to be made, particular information is known to the decision-maker or a particular decision has already been made. In such cases, precedence arcs may be drawn from the anterior chance node or decision nodes to the decision node at hand. Such arrows indicate that the actual state of the predecessor nodes is known when the decision is made.

3. *Examples 1 and 2 Revisited*

At this point, readers may wonder whether influence diagrams provide enough benefit beyond that provided by decision trees to justify the additional effort needed to master them. Our answer is that decision trees are a fine choice for decision-makers who are looking for a detailed "map" of specific decision paths, particularly when there are a limited number of paths to consider. If one needs to convey a concise presentation of a large and complex decision problem, an influence diagram is the better choice. However, both models are valuable and they complement each other well. We suggest that lawyers who master both frameworks will be in the best possible position to adapt and respond to the specific and shifting needs in a case.

Recall the examples 1 and 2 introduced in Section III.A. In these examples, different assumptions regarding the fee structure were made and represented in the decision trees shown in Figures 2 and 3. But now suppose that a decision-maker wished to incorporate these assumptions about fee structure into a single model. An influence diagram can handle this. These features are illustrated below by revisiting examples 1 and 2 and providing a detailed description of the resultant influence diagram.

Suppose a plaintiff and a defendant are engaged in pretrial settlement negotiations. Assume that the parties are only concerned about the expected (monetary) value of their potential gains and losses. The plaintiff believes that if she proceeds to trial (i.e., no settlement), the probability of winning the case is about 80% and the amount awarded will be 8,000. If the case proceeds to trial, each party will incur 2,000 in litigation costs, all of which must be paid by the losing party. For now, assume there are no other fees to consider.

Our analysis will focus on the computation of EMVs to compare the perspectives of the plaintiff and defendant. Two situations will be considered. In situation 1, there are no fees associated with the pretrial settlement procedure. In situation 2, the losing party must pay 1,500 for legal fees incurred prior to trial (e.g., costs for a mediator); this amount will be received by the party that wins at trial.

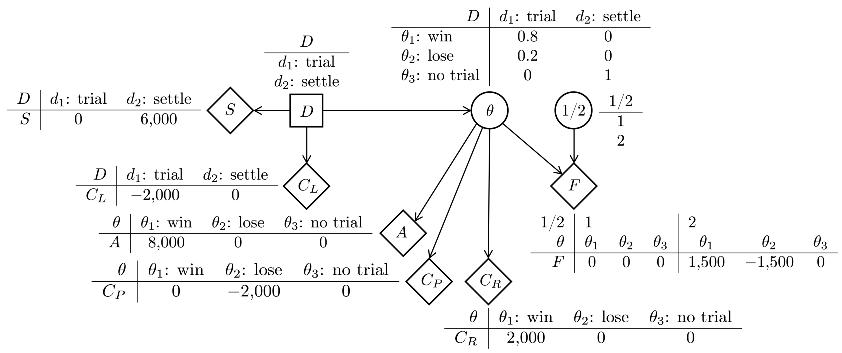

Figure 6. Influence diagram, including node tables, for the decision about whether to settle or proceed to trial. Node definitions are given in Table 1. The logic of filling the tables associated with each node is explained in note 62.

Figure 6 represents a possible influence diagram structure for situations 1 and 2, including the internal details (i.e., tables) associated with each node. This model is inspired by the template structure introduced in Figure 5(ii). Table 1 summarizes the definitions of the nodes. Note that most nodes have a table that specifies various numerical values[61] (i.e., probabilities or monetary values), all of which relate to specific properties of the decision problem under consideration. Figure 6 represents these tables in full detail, displayed next to each node.[62]

61. The decision node *D* is an exception to this general claim. There are no numerical values assigned to this node. *See also infra* note 62.

62. More technical details of the model structure shown in Figure 6 are as follows:

Node *D*: This is a decision node. It has two states: d_1 (trial) and d_2 (settle). As a root node, it does not have entering arcs.

Node θ: This is a chance node. It represents three possible states of nature: θ_1 (Win trial), θ_2 (Lose trial), and θ_3 (No trial). It is conditioned on node *D*. The associated node probability table contains the following entries: if going to trial (d_1), the probability of winning the trial, losing the trial, and having no trial (θ_i) are $\Pr(\theta_i|d_1) = \{0.8, 0.2, 0\}$ for $i = 1,2,3$. The probabilities 0.8 and 0.2 represent the plaintiff's probabilities of winning and losing at trial, respectively, as discussed in Section III.A. If the plaintiff decides to settle (d_2), the probability node contains the values $\Pr(\theta_i|d_2) = \{0, 0, 1\}$ for $i = 1,2,3$. The state 'no trial' ($i = 3$) is assigned a probability of 1. This means that 'no trial' is a logical consequence of settling, an event that occurs with probability 1 under this circumstance.

Node 1/2: This is a chance node with two states 1 and 2. As discussed in Section III.A.2, the party prevailing at trial in state 1 is not reimbursed for expenses it paid as part of the settlement procedure. In state 2, the prevailing party is reimbursed by the losing party for expenses the prevailing party paid as part of the settlement procedure. The amount of this compensation is modelled by the utility node *F*.

Node *S*: The table associated with this node contains the settlement amount. Suppose a settlement amount of $\mathrm{MV}_S(d_2) = 6{,}000$. If the plaintiff decides to go to trial, d_1, there is no settlement amount, and $\mathrm{MV}_S(d_1) = 0$. More generally, note that in the notation adopted here, $\mathrm{MV}(d_i)$ designates the monetary implication of deciding d_i.

Node	Definition
D	This is a decision node with two states "trial" (d_1) and "settle" (d_2).
θ	This is a discrete chance node that models the possible states of nature: 'win' (θ_1), 'lose' (θ_2), and 'no trial' (θ_3).
1/2	This node defines the type of case as one in which (1) the parties share settlement costs equally, or (2) the losing party incurs all costs for the settlement procedure.
S	This is a utility node that models the settlement amount.
A	This is a utility node that models the litigated amount (in favor of the plaintiff in the case of winning at trial).
C_L	This utility node models the costs for legal representation at trial.
C_P, C_R	These utility nodes model the compensation for fees for legal representation: node C_P models the fees that the losing party needs to pay to the prevailing party; C_R models the amount received by the prevailing party.
F	This utility node models the compensation for legal costs incurred prior to trial (i.e., during the settlement procedure) in cases of type 2, to be paid (received) by the losing (prevailing) party.

Table 1. Node definitions for the influence diagrams shown in Figures 6 and 7.

Figure 7 presents an alternative influence diagram for the settle vs. go-to-trial problem. A key difference between this diagram and the one shown in Figure 6 is that the node θ does not depend on the decision node D. In Figure 7, the node θ is a root node that has only two states: win (θ_1) and lose (θ_2), for which probabilities $\Pr(\theta_1) = 0.8$ and $\Pr(\theta_2) = 0.2$ are specified. The significance of *not* conditioning node θ on node D is to convey the understanding that a trial occurs *only if* the parties do not settle. Moreover, the litigant's probability for the win and lose outcomes at node θ are not "determined" by the decision to proceed to

Node A: This node models the amount the plaintiff receives from a favorable judgment at trial (θ_1). Let $\mathrm{MV}_A(\theta_1) = 8{,}000$. In case of losing at trial (θ_2) and no trial (θ_3), the table associated with the node A contains the value 0, hence $\mathrm{MV}_A(\theta_i) = 0$ for $i = 2{,}3$.

Node C_L: This node models the costs for legal representation at trial and contains the following values: if going to trial, d_1, the expenses are $\mathrm{MV}C_L(d_1) = 2{,}000$. Note that in the table of the influence diagram, this amount is specified as $-2{,}000$ because it is a *cost* that the party incurs. If the plaintiff settles, d_2, then no expenses are incurred for legal representation at trial, that is, $\mathrm{MV}C_L(d_2) = 0$.

Nodes C_P and C_R: These nodes model additional costs. The node C_P models the amount the plaintiff needs to pay to the defendant for legal expenses if the plaintiff loses at trial (θ_2). Let $\mathrm{MV}C_P(\theta_2) = -2{,}000$ and $\mathrm{MV}C_P(d_i) = 0$, for $i = 1{,}3$, that is, the plaintiff pays nothing to the defendant if the plaintiff wins (θ_1) and when there is no trial (θ_3). Similarly, the node C_R represents the amount the plaintiff receives from the defendant for legal expenses if the plaintiff wins at trial (θ_1). Thus, for node C_R, let $\mathrm{MV}C_R(\theta_1) = 2{,}000$ and $\mathrm{MV}C_R(d_i) = 0$, for $i = 2{,}3$, that is, the plaintiff receives no compensation for legal expenses if the plaintiff loses the case (θ_2) and if there is no trial (θ_3).

Node F: This node models the amount the party losing at trial must pay for expenses incurred during the settlement procedure, that is, in cases of type 2 (*see* Section III.A.2). Thus, in case of winning at trial (θ_1), $\mathrm{MV}_F(\theta_1, 1) = 1{,}500$; in case of losing at trial (θ_2), $\mathrm{MV}_F(\theta_2, 2) = -1{,}500$. If there is no trial ($\theta_3$), the table of the node MV_F contains the value 0, irrespective of the type of case. More generally, for the conditioning on 1, $\mathrm{MV}_F(\theta_i, 1) = 0$, for $i = 1{,}2{,}3$, because in cases of type 1 there is no compensation F (a reimbursement) paid for the settlement procedure.

trial, but are a function of the overall strength of the case as perceived by the litigant. This structure replicates the logic depicted in Figure 5(i), whereas the model in Figure 6 replicates the template shown in Figure 5(ii). Note also that the utility nodes A, C_R, C_P, and F in Figure 7 have an additional entering arc from the node D. The monetary values specified in these nodes are as explained above, though with the constraint that they apply *only* if decision d_1 (going to trial) is made. The utility nodes contain the value 0 under the state d_2 (settle) of node D. This makes the model structure denser and is why we have not used it here as our main model for discussion.

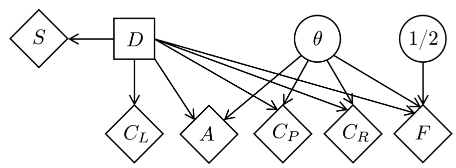

Figure 7. An alternative influence diagram structure for the model shown in Figure 6, representing the same problem of deciding whether to settle or proceed to trial. Node definitions are given in Table 1. The model here implements the template structure shown in Figure 5(i), emphasizing the view that the actual probability of winning and losing at trial, at the node θ, is an assessment made in the light of the overall strength of the case as perceived by the litigant. These probabilities are not directly depending on any other variable in the model.

Whether a litigant prefers to structure the influence diagram as described in Figure 6 or 7 is largely a matter of taste. It might make sense for one litigant to use Figure 6 for its simplicity: it has fewer edges and, therefore, the node tables contain fewer entries. These features make this model relatively easy to maintain and adjust. On the other hand, a litigant who prefers more detailed modelling of the event of winning and losing at trial (node θ) might prefer to use the model shown in Figure 7 and add additional variables that may have a bearing on the trial outcomes (node θ). For example, the probability of winning and losing at trial might depend on case features such as the type or level of court and legal precedents in comparable cases. For the remainder of this Article, we use the influence diagram depicted in Figure 6 because it contains a less dense structure and because the chance node θ, which models *all* possible states of the world (including settlement),[63] is specified naturally as depending on what the plaintiff decides to do (i.e., decision node D).

IV. INFLUENCE DIAGRAMS FOR COMPLEX LITIGATION

We have already acknowledged that influence diagrams are relatively user friendly; however, some attorneys may prefer leaving the technicalities associated with building these models to expert decision analysts because sophisticated computer software is used. But even lawyers who have little or no experience using decision aids should be able to acquire a basic understanding

63. Note that in Figure 7, the chance node θ does *not* cover settlement.

of what the software programs are doing, what the resultant models look like, how they work, what the output means, and how this output should be interpreted in the light of the circumstances of the instant case. In this Part, we show how influence diagrams come alive using standard computer software (Section IV.A). Next, we show how to assess the extent to which changes in the various assumptions and inputs affect the practical messages conveyed by the influence diagram (Section IV.B). Finally, we show how uncertainty about litigation outcomes (e.g., size of damage awards) and costs can be incorporated into an influence diagram (Section IV.C).

A. Computational Implementation

Figure 8 depicts the details of the influence diagram shown in Figure 6, using a commercially available graphical modelling software program called Hugin® Researcher 9.0. The nodes D, θ, and 1/2 are shown in expanded form, that is, with so-called monitor windows that display node states and additional information. Figure 8(i) shows an application for a case of type 1, that is, when the parties share settlement costs equally. This case feature is communicated to the model by setting the state of the node 1/2 to 1.[64] The expanded node θ shows the three outcome states—win, lose, and no trial—and the monetary values associated with each state.

To understand these numbers, it is useful to recall that if the plaintiff wins, the plaintiff receives the litigated amount (A = 8,000) and the plaintiff's 2,000 legal fee is paid by the defendant. Recall also that the net value, 8,000, corresponds to the top branch of the decision tree shown in Figure 2(i). In the influence diagram shown in Figure 8(i), the 8,000 value is attached to the win state on the node θ. Similarly, the lose state in Figure 8(i) shows the value −4,000 which corresponds to the second uppermost branch in Figure 2(i). This value reflects the sum of the plaintiff's legal fees (C_L = 2,000) and those of the defendant (C_P = 2,000), both of which the plaintiff must pay. If the parties settle (i.e., no trial), the settlement amount (6,000) applies as indicated in the no trial state on node θ in Figure 8(i).

Because trial outcomes are uncertain, a decision-maker may wish to take account of the expected values for the various options as discussed in Part I. This is accomplished by weighing the monetary consequences of each possible outcome by the probability of its occurrence. In Figure 8(i), this is shown in the monitor window attached to the node D. It shows that the value 5,600 is attached to option d_1 (trial). This value corresponds to the EMV of going to trial rather than settling.[65]

With a few clicks of a mouse, it is easy to compute the EMV of going to trial for type 2 cases in which the losing party pays all settlement fees. Note that

64. More generally, setting a node to a particular state is also called *instantiating* a node. Instantiating a node to a particular state means assuming that the respective state of nature holds.

65. The value 5,600 is obtained by computing the product of the damages award and its probability and adding it to the product of the potential loss and its probability. *See supra* Section III.A. This computation yields (8,000*0.8) + (-4,000*0.2) = 5,600. Note that this result corresponds to the value obtained by the decision tree analysis that appears in Figure 2(i).

this allows us to illustrate a key advantage of influence diagrams over decision trees. Rather than recreating the influence diagram (as in Figure 3, which recreates a decision tree to reflect the addition of a legal cost variable), we can rely on the same influence diagram but simply make a different assumption at the node 1/2, which controls the case type (in which the parties pay settlement fees equally under case type 1, or the loser pays all settlement fees under case type 2). When the 1/2 node is changed from state 1 to state 2, the influence diagram directly updates the EMV for option d_1 (trial) on the node D to 6,500,[66] and the monetary values attached to the states θ_1 (win) and θ_2 (lose) on the node θ become, respectively, 9,500 and −5,500. These values correspond to those in the decision tree shown in Figure 3, representing the plaintiff's point of view. Here, in Figure 8(ii), this value is attached to the trial state on node D. Thus, with suitable computer software, we can easily switch among different case types and associated assumptions and identify the impact on output in real time.

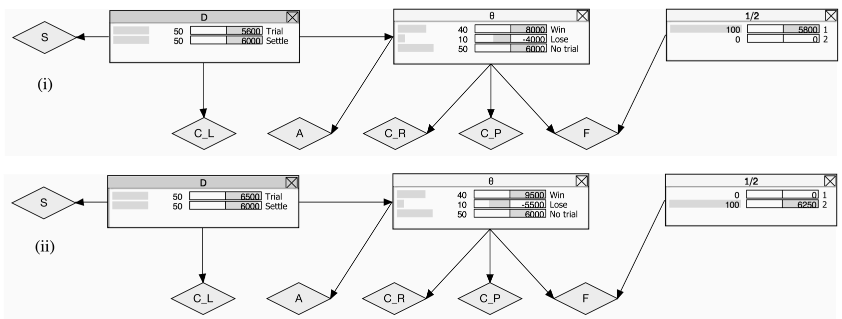

Figure 8. Influence diagram with the structure shown in Figure 6, implemented in Hugin® Researcher 9.0. The numerical specification of the model is explained in Section III.B.3 In Figure (i), the node 1/2 is set to 1 to represent a case where parties share settlement costs. In Figure (ii), the node 1/2 is set to 2 to represent a case in which the losing party reimburses the prevailing party for the portion of the settlement fee it paid (1500).

Although the example is a relatively simple one, Figure 8 shows how a single model, created using an operationally implemented influence diagram, can be used to create a real-time analysis of different case types. This feature opens the door to exploring "what-if" scenarios that go well beyond changes in case type. The scenarios that we have in mind here are *sensitivity analyses*. Sensitivity analyses examine the impact of changes in node table assignments (utilities or probabilities) on target output (e.g., the EMV of decisions of interest). It is important to be able to perform such analyses because it is often difficult to pin down particular values for these node table entries. Is the probability that a judge orders an admissibility hearing on an item of proffered evidence 20% or 30%? Is the value of a particular concession by the opposing party worth twice as

66. The expected value of the decision to go to trial is: $9{,}500 \cdot 0.8 + (-5{,}500) \cdot 0.2 = 6{,}500$.

much as another concession or three times as much? Similarly, there may be uncertainty about legal fees. Instead of assuming a fixed value here, several different possibilities may be considered, each with a distinct probability of occurrence. Such extensions can be built into an existing model seamlessly by adding graphical elements (i.e., nodes and arcs) in a modular way. That is, one can "piece together" graphical models through a visual interface while leaving computational aspects of the various extensions to the computer program. The following section details how sensitivity analyses may be conducted within the structure of influence diagrams.

B. Sensitivity Analyses

As previously noted, many aspects of legal decision-making problems will be uncertain. What is the probability that a particular outcome will occur? How large will expenses be? Different people will assign different probabilities and values, and it may even be the case that a particular person's assessments vary over time. Consequently, a decision model will need to be flexible enough to deal with various "what-if" questions and modifications. Sensitivity analysis deals with such questions, and influence diagrams provide a powerful environment in which to implement them.[67]

1. *Sensitivity Analyses for Value Measures*

The influence diagrams shown in Figure 8 provide a snapshot in the sense that they are based on a set of fixed values that express the beliefs and value judgments of a particular decision-maker at a particular time. Varying the quantitative assignments may change the model's rankings of the various decision options. One-way and two-way sensitivity analyses can be used to address this concern. In a one-way sensitivity analysis, the assignment for one component of the model (i.e., a node table assignment) is varied over a certain range and changes in a target output variable are observed. In a two-way sensitivity analysis, two model components are varied simultaneously and the impact on a target output variable is monitored. We start by examining the impact of changes in the value of the litigated amount (node *A*, Table 1) on the expected values of the options "go to trial" and "settle."[68]

Figure 9 shows an example of a one-way sensitivity analysis applied to the example described in Section IV.B. This is a type 1 case that has a litigated amount of 8,000 specified in the node *A*. Recall that, in the default analysis, the EMV of going to trial is less than the settlement amount, hence d_2 (settle) was the better option. Suppose now that the trial award is 10,000. The lower part of Figure 9 shows how to rerun the computation of the expected value of option d_1 (trial) in node *D*. The box named "Parameter: A" displays the table underlying the utility node *A*. The values in the events of 'Lose' and 'No trial' are un-

67. KJÆRULFF & MADSEN, *supra* note 56, at 273–90.

68. Technically, this is called a *utility sensitivity analysis*, with utility being used as a generic term to designate the value of a decision consequence. As noted in Part II, monetary values can be converted to personal utilities if desired.

changed at 0. If the plaintiff wins the case, there is now a positive value of 10,000. The box to the left in the Utility Sensitivity Analysis displays the updated expected values for options d_1 (trial) and d_2 (settle). The 6,000 settlement amount remains unchanged, but the EMV of option d_1 (trial) has increased from 5,600 to 7,200.[69] The optimal decision d_{opt} now is d_1 (trial) because EMV(d_1) > EMV(d_2).

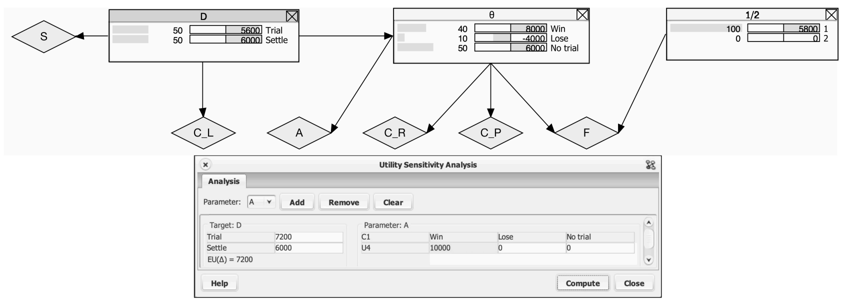

Figure 9. Influence diagram shown in Figure 8(i). The lower part of the figure shows a sensitivity wizard window that includes the result of a computation using an alternative value for the litigated amount *A* (called "Parameter: A") and its impact on the EMV of the decision to go to trial (referred to as "Target: D").

One may also consider the impact of a range of plausible values for the litigated amount *A* and plot the corresponding expected values for option d_1 (trial). This graph is shown in Figure 10. The dotted lines indicate the EMV for decision d_1 given the litigated amounts 8,000 and 10,000. The horizontal line at EMV = 6,000 indicates the assumed settlement amount, that is, EMV(d_2). The bold line shows the optimal decision d_{opt} as a function of the litigated amount. Note that EMV(d_1) = EMV(d_2) when the litigated amount is 8,500 (dashed vertical line). Thus, for litigated amounts less than 8,500, decision d_2 (settle) is optimal, and for amounts greater than 8,500, decision d_1 (trial) is optimal.

69. $EMV(d_1)=10{,}000 \cdot 0.8+(-4{,}000) \cdot 0.2=7{,}200$.

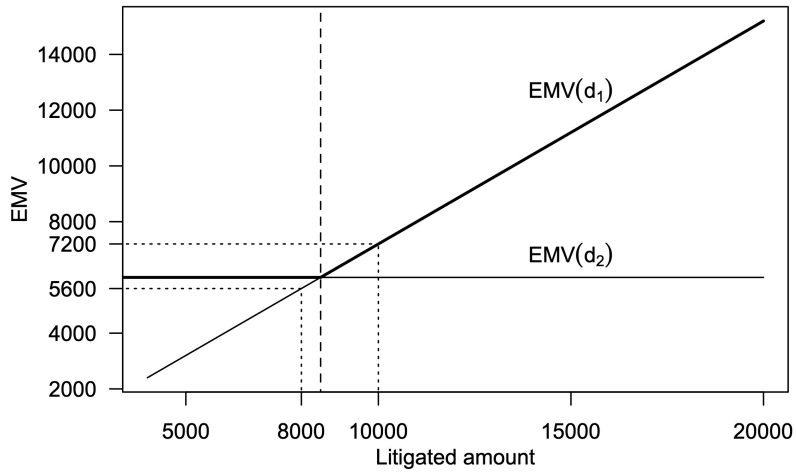

Figure 10. Plot of the EMV of going to trial (decision d_1) as a function of the amount obtained upon prevailing at trial (x-axis). The dotted lines indicate the EMV for the litigation amounts 8,000 and 10,000 as discussed in the text. The horizontal line at EMV = 6,000 indicates the assumed settlement amount, that is, EMV(d_2). The bold line shows the optimal decision d_{opt} as a function of the litigated amount. Note that when the litigated amount is 8,500 (as indicated by the dashed vertical line) then EMV(d_1) = EMV(d_2). Thus, for litigated amounts smaller than 8,500, decision d_2 (settle) is optimal. For values greater than 8,500, decision d_1 (trial) is optimal.

2. *Sensitivity Analyses for Probabilities*

Sensitivity analyses can be performed for value nodes (as illustrated above) or chance nodes. This section provides an example of a sensitivity analysis for a chance node. This analysis is accomplished by varying the entries of a node probability table. In our example, there is one chance node (θ), and it models the states win, lose, and no trial.[70]

Suppose again a case of type 1 as described in Section III.A. and a fixed litigated amount of 8,000 specified in the utility node *A*. Recall that, in this case, the EMV for electing to go to trial rather than settling is 5,600. This computation is based on an assumed probability of winning at trial of 0.8 used throughout all examples discussed so far. But what if the probability of winning is 0.7, 0.9, or some other value? When will changes in the resultant EMV be such that a party should prefer to proceed to trial rather than settle?

Figure 11 illustrates the use of the sensitivity wizard in Hugin® Researcher 9.0. for alternative probabilities of prevailing at trial, Pr(θ_1). The alternative probabilities that we selected are 0.7, 0.85 and 0.95. The EMV of the decision to go to trial (d_1) corresponding to each of these probabilities is shown in the

70. Technically speaking, node 1/2 is also a chance node, though operationally it will be instantiated to either 1 or 2 because it is assumed to be known whether one is facing a case of type 1 or 2. Stated otherwise, there is no uncertainty regarding the type of case.

boxes labeled "Target: D" on the left-hand side of the interface window. This dashboard shows that decreasing the probability of winning from 0.8 to 0.7 decreases EMV(d_1) from 5,600 to 4,400, and this makes going to trial much less attractive than settling. Conversely, a slight increase of Pr(θ_1) from 0.8 to 0.85 increases EMV(d_1) to 6,200, which makes going to trial the preferred option. The difference in EMV for the two rival decisions further increases for higher values of Pr(θ_1), such as 0.95, which results in EMV(d_1) = 7,400 versus EMV(d_2) = 6,000.

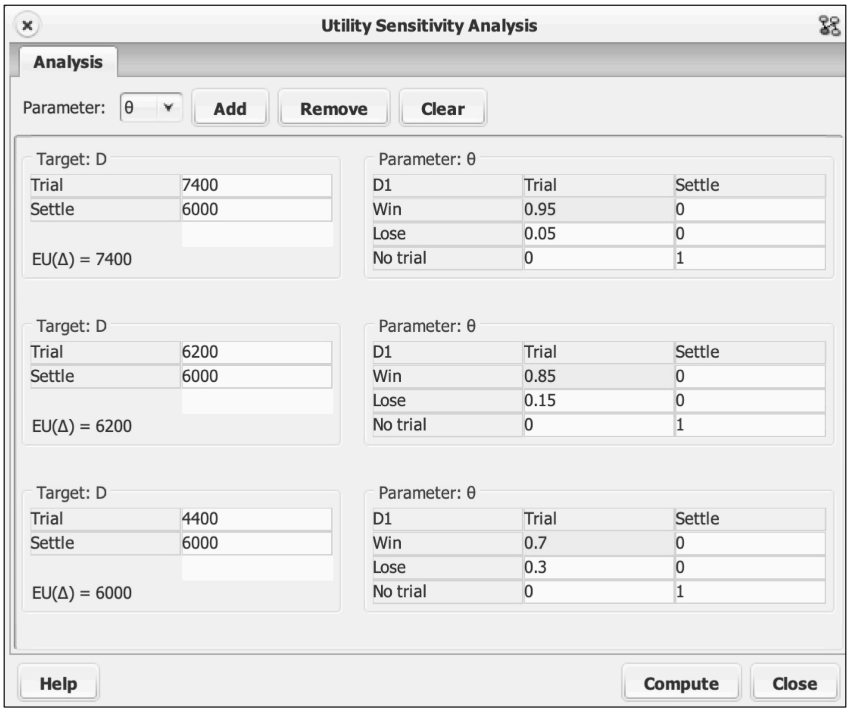

Figure 11. Illustration of the use of the sensitivity wizard in Hugin® Researcher 9.0 for a sensitivity analysis applied to the influence diagram shown in Figure 6. The numerical specification of the model is explained in Section III.B.3, and the node 1/2 is set to 1 (indicating a case where parties share costs for the settlement procedure). The sensitivity wizard window shows examples of probabilities for the event of prevailing at trial, that is, 0.7, 0.85, and 0.95, and the EMV for the decision to go to trial (shown in the boxes labeled "Target: D") corresponding to each of these probabilities.

Figure 12 presents a more detailed representation of the EMV as a function of the probability of prevailing at trial in the range between 0.5 and 1. The short-dotted lines highlight the specific results obtained above and represented in Figure 11. The dashed vertical at 0.833 on the x-axis indicates the probability for which the EMV for the option to go to trial (d_1) and to settle (d_2) is the same.

For a risk-neutral attorney or client, this 0.833 probability level identifies what is often referred to as an *indifference point*. That is, if the attorney, client, or other decision-makers believe that the probability of winning at trial is 0.833, they should be indifferent between settling this case or gambling on receiving a better outcome at trial. The bold horizontal line shows that for probabilities of winning smaller than 0.833, option d_2 (settle) is preferable (because it has the higher EMV); for values greater than 0.833, option d_1 (trial) is preferable.

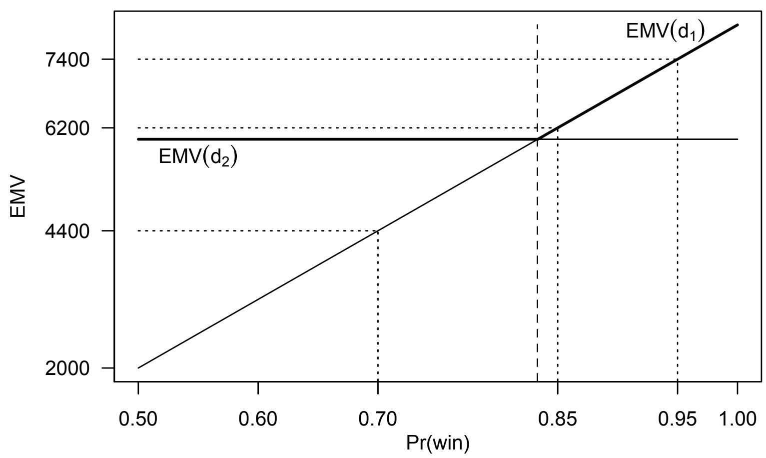

Figure 12. Plot of the EMV of going to trial (decision d_1) as a function of the probability of prevailing at trial (x-axis). The dotted lines indicate the EMV for selected probabilities of winning at trial. Note that the EMV corresponding to each of these probabilities is the same as the numerical results shown in Figure 11. The horizontal line at EMV = 6,000 indicates the assumed settlement amount, that is, EMV(d_2). The bold line shows the optimal decision d_{opt} as a function of the probability of winning. The dashed vertical line indicates the probability for which EMV(d_1) = EMV(d_2), that is, 0.833.

C. Uncertainty About Outcomes and Events

The sensitivity analyses presented in the previous section varied the outcome values and probabilities but they assumed a single target outcome (e.g., 8,000) for a trial award. When a winning litigant faces many possible outcomes, those outcomes may also be inserted into a sensitivity analysis. This situation for single and multiple sources of uncertainty is described below.

1. *Single Source of Uncertainty*

Consider again the one-way sensitivity analysis presented in Section IV.B.1. This analysis involved the repeated computation of the EMV for different values of a single litigated amount *A* (e.g., 8,000) for a plaintiff who prevails at trial. Now suppose that the plaintiff thinks that, if victorious at trial, the plaintiff may receive a low award (4,000), an intermediate award (8,000), or a high award (15,000). Suppose further that the plaintiff believes that the probabilities associated with each of these awards, conditioned on a victory at trial, are 0.25, 0.5, and 0.25, respectively. The EMV of the decision to go to trial (d_1) would now be calculated as follows:

$$\mathrm{EMV}(d_1) = \sum_i \mathrm{MV}(d_1, \theta_1, W_i) \cdot \Pr(W_i) \cdot \Pr(\theta_1) + \mathrm{MV}(d_1, \theta_2) \cdot \Pr(\theta_2),$$

where the terms $\Pr(W_i)$, for $i = \{1,2,3\}$, correspond to the probabilities of winning big (W_1), intermediate (W_2), and small (W_3), respectively. Note that here we work with the average payoff in the case of winning at trial, rather than with a single and fixed value. Specifically, the average gain for a winning plaintiff is computed by multiplying each possible outcome by its probability of occurrence, and summing these products: $15{,}000 \cdot 0.25 + 8{,}000 \cdot 0.5 + 4{,}000 \cdot 0.25 = 8{,}750$. The decision tree shown in Figure 13 updates the tree shown in Figure 2 by incorporating these computations.

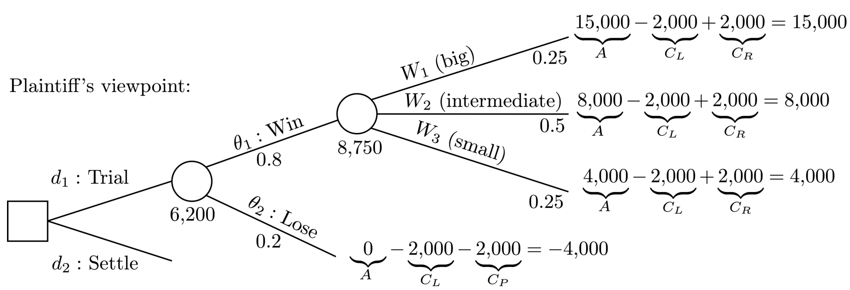

Figure 13. Partial decision tree for the EMV of the decision to go to trial (d_1) from the plaintiff's point of view. The litigated amount A (short for "award") takes on one of three values: 15,000, 8,000, and 4,000 referred to respectively as winning "big" (W_1), "intermediate" (W_2), and "small" (W_3). These three outcomes are assigned the probabilities 0.25, 0.5, and 0.25, respectively, and the probability of winning $\Pr(\theta_1)$ is assigned a probability of 0.8. EMVs are indicated below the circled chance nodes. Further variables and terms follow the definitions given in Table 1.

As noted previously, decision trees become increasingly complex, or "bushy" as the modelling of the underlying problem becomes more fine grained. Influence diagrams do not have this shortcoming because these complexities are mainly aggregated within nodes which allows the overall network structure to remain more constant. Thus, one can implement the extension of interest by adding a chance node W to Figure 6. The three states associated with this chance node are W_1, W_2, and W_3, representing the events of winning big, intermediate, and small, respectively. Node W is a parent node for the value node A. This extended model is shown in Figure 14. The probabilities assigned to the states W_1, W_2, and W_3 are $\{0.25, 0.5, 0.25\}$.

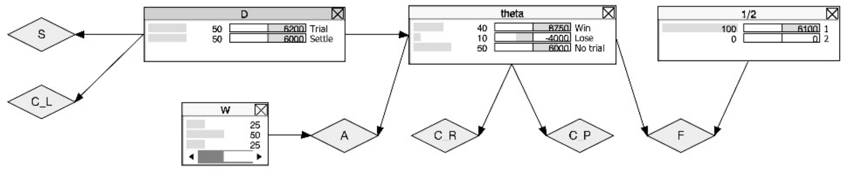

Figure 14. Influence diagram (implemented in Hugin® Researcher 9.0) based on the structure shown in Figure 6, with an added node *W*, specifying uncertainty about the amount awarded in case of winning at trial. The node 1/2 is set to 1 (indicating a case in which the parties share settlement procedure costs).

Figure 14 provides key information that can be read directly from the monitor windows attached to target nodes. For example, the monitor window for the node *W* graphically displays the assigned probabilities of winning big (W_1), intermediate (W_2), and small (W_3). In turn, the monitor window of the node θ displays the EMV associated with winning at trial: it displays the sum of the various court-ordered amounts weighted by their respective probability of occurrence. This value is 8,750. Recall that this value can also be found below the second chance node when moving from the left to the right in the upper branch of the decision tree shown in Figure 13. In case of a loss, the node θ has a monetary value of −4,000, which corresponds to the legal fees that the plaintiff would need to cover (2,000 for the plaintiff's own legal fees and 2,000 for the defendant's fees which the plaintiff must cover).

Finally, node *D* displays the EMV for the options to go to trial (d_1) and to settle (d_2), respectively. The optimal decision for the plaintiff is going to trial because EMV(d_1) = 6,200.[71] The EMV(d_1) = 6,200 can also be found below the first chance node when moving from left to right in the upper branch of the decision tree shown in Figure 13. The congruence between the influence diagram output and the decision tree results demonstrates that nothing is lost when the more visually appealing influence diagrams are used to model complex problems.

The example above shows how uncertainty about the size of a damage award can be incorporated into an influence diagram by adding a node (named here *W*). There was no need to update the formulae or modify other computations. But what if we wished to introduce yet another source of uncertainty into the diagram? For example, the cost of litigation (node C_L)—which to this point we have treated as a fixed value for cases that go to trial—is likely to vary as a function of time spent and case complexity. The introduction of such uncertainty would make it more difficult to compute the EMV of the decision to go to trial without an easy-to-use decision aid. The next section shows how to modify our influence diagram to incorporate this new consideration.

71. EMV(*d*1) is obtained by weighing the EMV associated with winning at trial by the probability of winning, and then subtracting the loss incurred by losing at trial weighted by the probability of losing at trial. Thus EMV(*d*1)=(8,750*0.8)—(4,000*0.2)=6,200.

2. *Multiple Sources of Uncertainty*

Suppose that in addition to uncertainty about the monetary award of winning at trial (node W), one wishes to account for uncertainty about litigation costs (node C_L). This aspect may be represented in terms of a chance node L, adopted as a parent node for the utility node C_L. Suppose further that the costs of litigation can be classified as low (1,000), intermediate (2,000), and high (4,000) with associated probabilities 0.1, 0.7, and 0.2. Table 2 specifies how these values are organized in the table associated with the node C_L.[72]

D	d_1 (go to trial)			d_2 (settle)		
L	L_1	L_2	L_3	L_1	L_2	L_3
C_L	–1,000	–2,000	–4,000	0	0	0

Table 2. Table associated with the node C_L, representing different amounts of legal costs when deciding to go to trial (d_1). These costs are identified as "small" (L_1), "intermediate" (L_2), and "big" (L_3).

The question now is how uncertainty about the cost of litigation affects the EMV of going to trial for the plaintiff. We have now reached the point of complexity in our sample problem where a decision tree representation would be difficult to read and interpret. In contrast, the corresponding influence diagram remains essentially the same as the diagram shown in Figure 14 except for the single added node L with an arc pointing to the node C_L (see Figure 15).

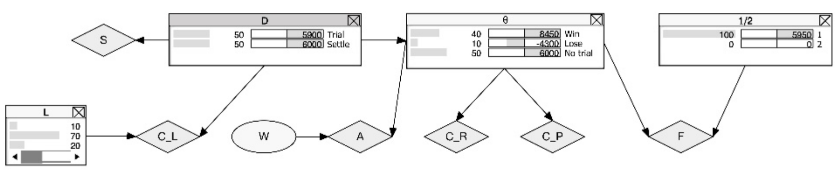

Figure 15. Influence diagram (implemented in Hugin® Researcher 9.0) based on the structure shown in Figure 6, with two additional nodes W and L. The node W specifies uncertainty about the amount awarded in case of winning at trial (Section IV.C.1). The node L models uncertainty about the cost of litigation. The node 1/2 is set to 1 (indicating a case in which the parties share settlement procedure costs).

Figure 15 shows that it is now the *expected* cost of litigation rather than a fixed cost that gets incorporated into the computation of the EMV in the decision to go to trial. The *expected* cost of litigation is obtained by multiplying the possible cost values by the probability of their occurrence, and then summing these products:

72. Recall that cost values in node tables of value nodes are specified as negative values. *See also supra* note 62.

$$0.1 \cdot 1{,}000+0.7 \cdot 2{,}000+0.2 \cdot 4{,}000=2{,}300.$$

Next, this 2,300 value is used for the variable C_L (instead of 2,000) in the decision tree shown in Figure 13. This leads to the following revised values for winning big, intermediate, and small, respectively: 14,700, 7,700, 3,700. As before, these outcomes are incurred with probabilities 0.25, 0.5, and 0.25, respectively, thus leading to

$$0.25 \cdot 14{,}700+0.5 \cdot 7{,}700+0.25 \cdot 3700=8{,}450,$$

as the EMV for a plaintiff who wins at trial.

The 2,300 expected cost of litigation also needs to be taken into consideration because the plaintiff may lose at trial. Replacing the fixed cost of litigation (2,000) with the *expected* cost of litigation (2,300) in the appropriate decision tree branch shown in Figure 13 implies a value of −4,300 for the event that the plaintiff loses at trial.

Combining the results of the above two steps, we can now obtain the EMV of going to trial:

$$\text{EMV}(d_1)=0.8 \cdot 8{,}450+0.2 \cdot (-4{,}300)=5{,}900,$$

where 0.8 and 0.2 are the probabilities of winning and losing at trial, respectively.

Of course, all of the algebraic computations shown here are performed automatically and instantaneously by the computer program. As Figure 15 illustrates, the decision node *D* shows the EMV for the option d_1 ("trial"), that is, 5,900. The influence diagram also shows the monetary values associated with winning and losing at trial (8,450 and −4,300 in node θ), the probabilities for winning big, intermediate, and small (0.25, 0.5, and 0.25 in node *W*) as well as the probabilities associated with different costs of litigation (0.1, 0.7, and 0.2 in node *L*).

If we also wish to account for the possibility that the *defendant's* legal expenses may vary, this consideration will yet again change the EMV of going to trial. For illustrative convenience, we will assume that the defendant's potential legal costs and the probabilities associated with each of those potential costs are identical to those of the plaintiff. Because the expected value of the defendant's cost (2,300)[73] is slightly higher under these assumptions than the fixed cost assumption that was assumed previously (2,000), and because the plaintiff would be responsible for paying those costs should the plaintiff lose at trial, the EMV of option d_1 ("trial") is slightly lower than the $\text{EMV}(d_1)$ of 5,900 computed above:

$$\text{EMV}(d_1)=0.8 \cdot 8{,}450+0.2 \cdot (-4{,}600)=5{,}840.$$

This computation of $\text{EMV}(d_1)$ for our modified problem is reflected in the influence diagram in Figure 16 below. Here we point out that the node C_P will now need a parent node that models uncertainty about the magnitude of the de-

73. The expected value of the defendant's legal cost is $0.1 \cdot 1{,}000 + 0.7 \cdot 2{,}000 + 0.2 \cdot 4{,}000 = 2{,}300$.

fendant's legal fees that the plaintiff needs to cover in case the plaintiff loses at trial. There are two ways in which such an extension may be achieved. The first way involves adding a new chance node to act as a parent node for the node C_P just as the node L was introduced as a parent for the node C_L.[74] Proceeding in this way would provide flexibility regarding the number of states for this node and the probabilities associated with these states. A second approach involves using the existing node L as a parent for the node C_P. This structure could be used when it is reasonable to assume that the legal fees for the plaintiff and defendant are similar and have similar probabilities of occurrence.[75] The influence diagram for our modified problem in Figure 16 adopts this second approach.

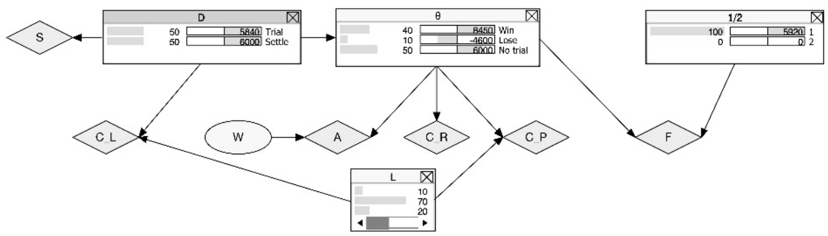

Figure 16. Influence diagram (implemented in Hugin® Researcher 9.0) based on the structure shown in Figure 6, with two additional nodes W and L. The node W specifies uncertainty about the amount awarded in case of winning at trial. The node L models uncertainty about the cost of litigation for the plaintiff (node C_L) as well the cost of legal fees for the defendant that the plaintiff needs to cover in case of losing at trial (node C_P). The node 1/2 is set to 1 (indicating a case in which the parties share settlement procedure costs).

The influence diagram in Figure 16 is similar to the one in Figure 15, but it now includes an additional arrow pointing from the node L towards the node C_P. Adding this arrow increases the number of entries of the table associated with the node C_P (see Table 3). Note that the value 5,840 in Figure 16, associated with the option d_1 ("trial") of node D, corresponds to the EMV of the option to go to trial. This value is identical to the one obtained using the computations informally outlined above.

74. Recall that the node L represents different orders of magnitude for the plaintiff's potential legal expenses and associated probabilities.

75. When this assumption is not reasonable, it may be preferable to model uncertainty about C_P using a distinct node.

θ	θ_1 (win)			θ_2 (lose)			θ_3 (no trial)		
L	L_1	L_2	L_3	L_1	L_2	L_3	L_1	L_2	L_3
C_P	0	0	0	–1,000	–2,000	–4,000	0	0	0

Table 3. Table associated with the node C_P, representing specific costs incurred in the event of losing at trial. The actual costs can take different orders of magnitude, represented by the conditioning variable L, broadly defined in terms of "small" (L_1) "intermediate" (L_2), and "big" (L_3).

To summarize, when considering a situation involving a single source of uncertainty (damage award amount), the result was EMV(d_1) = 6,200. This result suggested that a decision to go to trial would be preferable to a decision to settle (see Figure 14). But when we added a variable to the model that took account of legal cost uncertainty, EMV(d_1) became smaller and the model now indicated that it would be slightly better for the plaintiff to settle rather than go to trial (see Figure 15). Finally, in Figure 16, an analogous source of uncertainty was introduced for the cost variable C_P. This assumption further decreased the EMV of the option to go to trial, thereby strengthening the argument from Figure 15 that the plaintiff should settle. Regardless of which model is favored, sensitivity analyses should be conducted as described in Section IV.B.

The running example presented here highlights another, easily overlooked, advantage associated with decision analyses in general and influence diagrams in particular. Regardless of which model is regarded as most sensible, the analyses suggest that it is not obvious what the "right" decision is in this case. This case is a close call. Or at least it should be a close call for a decision-maker whose risk attitudes are relatively neutral. However, it is not clear whether intuitive decision-makers—that is, those who approach the problem without the benefit of a formal decision tool—will see it as such. Of course, in other situations, the opposite might be the case: the models may suggest that one litigation strategy is clearly superior to another possible strategy, but the intuitive decision-maker may see it as a close call. The danger in that situation is that the intuitive decision-maker may then choose a strategy based on a single consideration or two that breaks the deadlock, even when a more formal analysis might show that those considerations are—or should be—swamped by other features.

V. OBSTACLES TO ACCEPTANCE

Persuading attorneys that there is merit in creating probability-based decision trees and influence diagrams is one thing; persuading them to employ decision aids in their own cases to help identify strategic choices may be quite another. After all, most legal disputes do not have (or appear to have) an obvious underlying statistical structure that would seem to lend itself to probabilistic analyses.[76] Legal disputes typically have such unique circumstances and considerations that it may be hard to conceive of them as samples from a broader universe of common events. Consequently, it may seem fruitless to predict out-

76. Jonathan J. Koehler, *When Do Courts Think Base Rate Statistics Are Relevant?*, 42 JURIMETRICS J. 373, 386 (2002) ("[M]ost legal cases do not have a clear statistical structure").

come awards and assign probabilities through references to what happened in other cases.[77] Though common, this type of reasoning is a form of the base rate fallacy.[78] Outcome information gleaned from other cases generally *does* provide useful information about the probability of a favorable outcome in the target case.[79]

A second potential obstacle is that attorneys may be suspicious of statistical tools when developing legal strategies.[80] If attorneys do not understand how the probability models work, or what the underlying statistical assumptions are, they may dismiss the models at the outset. Strictly speaking, the modeling environment of influence diagrams is not about "statistics" in the frequentist sense of this term. The analyses really focus on the decision-maker's subjective views about the various potential risks, costs, and awards of the instant case. Because the responsibility for the assignment of these essential decision-analytic ingredients cannot be delegated, it is important to devise a strategy for handling these variables in a transparent and logically coherent way. Influence diagrams provide value that goes beyond unaided intuitive judgment because they (a) require decision-makers to be explicit about input values, (b) are less influenced by emotion or other factors that may distort judgment, and (c) combine information and compute critical output variables in ways that are logically consistent with the inputs provided. In the competitive and high-stakes world of litigation, attorneys should be motivated to provide their clients with the high-level analytical justifications that influence diagrams offer.

A third potential obstacle to acceptance is that attorneys may not think that they, or their clients, would benefit from decision aids. Studies show that professionals across a wide swath of fields have great confidence in their domain-specific knowledge and experience-based problem-solving abilities.[81] This confidence, which may spillover into overconfidence, may be most acute among

77. In some countries or jurisdictions, it may be possible to crawl through large databases to assess the probability of prevailing in different types of cases. However, some countries have barred the use of analytics for justice data. For example, France has barred the use and publication of behavioral data of judges. Loi 2019-222 du 23 mars 2019 de programmation 2018-2022 et de réforme pour la justice [Law 2019-222 of March 23, 2019 2018-2022 PROGRAMMING AND REFORM FOR JUSTICE], JOURNAL OFFICIEL DE LA RÉPUBLIQUE FRANCAISE [J.O.] [OFFICIAL GAZETTE OF FRANCE], Mar. 23, 2019.

78. *See generally* Daniel Kahneman & Amos Tversky, *On the Psychology of Prediction*, 80 PSYCH. REV. 237 (1973).

79. For a discussion of how and why background information in a reference class of cases informs probability assignments in a target case, see Jonathan J. Koehler, *The Normative Status of Base Rates at Trial*, *in* INDIVIDUAL AND GROUP DECISION MAKING: CURRENT ISSUES 137 (N. John Castellan, Jr. ed., 1993).

80. The aphorism "lies, damn lies, and statistics"—popularized by Mark Twain—is what comes to mind for many people who are suspicious of numerical arguments and claims. MARK TWAIN, CHAPTERS FROM MY AUTOBIOGRAPHY 471 (North American Review ed., 2006).

81. *See, e.g.*, J. Edward Russo & Paul J. H. Schoemaker, *Managing Overconfidence*, SLOAN MGMT. REV., Winter 1992, at 7, 9 (study showing that experts in advertising, data processing, money management, petroleum, and pharmaceuticals made accurate judgments about matters within their industry about 50% of the time when they estimated their chance of being correct at 90%).

those who have the most experience.[82] Those with the most experience may include law firm partners, lawmakers, and other influential legal decision-makers. Unfortunately, experience sometimes increases confidence without providing any corresponding benefits in knowledge, predictive accuracy, or judgmental competence.[83]

Finally, some attorneys may hesitate to use decision aids because they fear that such aids dehumanize the decision-making process or because they suspect that the aids are designed to replace them. These fears and suspicions should be challenged. The common sense, intelligence, training, knowledge, and experience that attorneys possess will always play crucial roles in the creation and interpretation of litigation decision aids. Indeed, without input from knowledgeable attorneys, decision aids would have little value. But once those inputs are identified and organized in a logical way, decision aids in general—and influence diagrams in particular—will often provide strategic insights that could not be reached by any other currently available means. And when the formal analyses that we recommend merely confirm the attorney's intuitions and initial plan, the attorney and client have good reason to feel more confident in their strategy going forward.

This Article argues that decision aids in general, and influence diagrams in particular, can improve legal decision-making. Similar to a wise human advisor, decision aids can benefit attorneys in various ways. By providing a structured approach to decision-making and taking advantage of normatively compelling rules for combining information and probabilities, these aids can help attorneys navigate the treacherous contours of uncertainty and conditional dependencies in complex legal disputes. Furthermore, the logic and visual appeal of influence diagrams can help attorneys communicate more effectively with their clients.

In short, we claim what decision analysts implicitly claim every time they provide a client with an analysis: *people who make important (legal) decisions with the aid of a detailed influence diagram can be more confident that they are making the best possible decision than those who rely on intuition and experience alone.* Now that attorneys have an easy-to-use decision tool at their disposal to assist with complex legal problems, it may only be a matter of time before the market for influence diagrams and decision analysts expands to accommodate repeat players in the legal community as well as newcomers who wish to remain competitive. Of course, this assumes that early adopters find influence diagrams helpful. We suspect that they will. As the late great decision

82. Hillel J. Einhorn & Robin M. Hogarth, *Confidence in Judgment: Persistence of the Illusion of Validity*, 85 PSYCH. REV. 395, 402 (1978) (offering a statistical model of confidence that speculates that "confidence in judgment is built up slowly with experience, rises rapidly with moderate amounts of experience, and then levels off (and reaches asymptote) with large amounts of experience").

83. Stuart Oskamp, *Overconfidence in Case-Study Judgments*, 29 J. CONSULTING PSYCH. 261, 261 (1965); Jane Goodman-Delahunty et al., *Insightful or Wishful: Lawyers' Ability to Predict Case Outcomes*, 16 PSYCH. PUB. POL'Y & L. 133, 133–34 (2010).

theorist Ward Edwards noted, "Customers [of decision analytic tools] keep coming back, so analysts must be doing something right."[84]

84. Edwards, *supra* note 23, at 50. Decision analyses are commonly conducted for important problems in medicine (Stephen G. Pauker & Jerome P. Kassirer, *Decision Analysis.* 21 N. ENG. J. MED. 250 (1987)), business (Thomas H. Davenport, *Make Better Decisions*, 87 HARV. BUS. REV. 117 (2009)), and public policy (Robin Gregory et al., *Acceptable Input: Using Decision Analysis to Guide Public Policy Deliberations* 2 DECISION ANALYSIS 4, 8 (2005) (discussing how a decision analysis applied to offshore oil and drilling policies "showed the need to expand an industry's initial problem representation," which, ultimately, brought stakeholders together to identify acceptable options)); *see also supra* note 58.