Adding Value in the Process of Selecting a Testifying Expert

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This discussion considers the selection of a testifying expert in valuation and/or economic damages controversies in connection with a business, security interest, or intangible asset (and intellectual property). The process of identifying, interviewing, and ultimately selecting a testifying expert requires a multidimensional approach on the part of the litigation team. This discussion recommends a decision framework to litigation counsel for purposes of selecting the "right" testifying expert from a "top shelf" slate of candidate experts.

Introduction

Financial consulting experts and testifying witnesses play a wide variety of roles in different controversy matters involving valuation or economic damages analyses in business disputes. As one would expect, determining when a forensic analyst consulting or testifying expert is needed, and then selecting from the candidate experts, is amongst the more difficult tasks that counsel and their clients will address.

There is a significant amount of published literature regarding the role of the forensic analyst expert in the dispute resolution process. Generally, forensic analysts are needed when the facts and circumstances of a case require the trier of fact to reach an opinion that is not easily attainable without the judge being well versed in the relevant domain knowledge.

Moreover, there is a significant amount of literature published about the behavioral aspects of expert testimony—such as being persuasive, competent, knowledgeable, likeable, and confident without arrogance.[1]

The federal standards for expert witness testimony were first crafted through the seminal trilogy of Supreme Court decisions in *Daubert*,[2] *General Electric*,[3] and *Kumho Tire*.[4] The federal expert witness standards are now codified in Federal Rule of Evidence ("FRE") 702.

With increasing state court adoption of the FRE 702 principles, albeit with much more unsettled governing standards and uniformity, there is no shortage of points of view addressed in the public domain.

Moreover, there are empirical studies on the perceived value—or the differential value—of forensic analyst experts. These empirical studies specify considerations and outcomes without statistical or causative significance.

In fact, one recently published study goes so far as to posit conclusions, perhaps unknowingly, requiring 144 predictor variables based on a survey of 12 licensed attorneys and accounting academics.[5] Suffice it to say that any statistical regression involving just 20 predictor variables would require a sample size of between 80 and 500 participants to be statistically significant.[6]

Finally, a plethora of sources and tools for locating and selecting potential financial experts are available, including several articles that provide general and intuitive guidance.[7]

However, the selection of the forensic analyst expert in valuation or economic damages analyses (involving business enterprises, security interests, or intellectual property) requires a multidimensional approach to identify a "top shelf" slate of candidate experts. However, little has been written suggesting a methodology or "assessment process" to meet this overall objective.

> **"[P]eople tend to seek information to confirm their judgment, rather than to look for possible disconfirming evidence."**

The objective of this discussion is to demonstrate, by way of example, a robust, reproducible, scalable, and flexible decision-making framework (the "Proposed Model"). The Proposed Model is based on using unstructured data that embody preferences and uncertainties, with a process conducive to negotiation and small group decision-making, to select the "right" expert testifying from a pool of candidates.

The Proposed Model can—but does not require—incorporating such typical considerations as finance or economics expertise, industry domain knowledge, and "on-point" experience with any specific adverse party matter.

Backdrop

According to behavioral scientists, people are generally unaware of *how* they make decisions and sometimes *why* they make certain decisions. Moreover, research suggests that people are minimally concerned about the quality of their decisions, but show great concern about the quality of decisions made by *others*.[8]

There are two different types of decisions requiring consideration in an implementation of the Proposed Model, specifically:

1. evaluations or preferences and
2. predictions or beliefs.[9]

Generally, subjective decisions involve intuitive choices and judgment. However, intuitive processes are not adequate for discriminating between testifying expert candidates.

The Proposed Model provides legal counsel, or other professionals involved in the identification of a candidate pool of experts, the ability to manipulate their specialist knowledge using a codified process leading to better decisions in selecting the most compelling forensic analyst expert.

The Nature of Human Judgment

Research indicates that during a 30-minute hiring interview, the interviewer forms a judgment about a candidate early on, and then spends the greater balance of the discussion seeking confirmation. Empirical observations suggest that people learn primarily based on what they observe. And, people tend to seek information to confirm their judgment, rather than to look for possible disconfirming evidence.[10]

When interviewing either valuation or economic damages experts, much of the information is redundant—much is also consistent—however, consistency of information without independence adds little to no predictive ability.

Consider a hypothetical example, whereby a search of public record cases shows that a candidate expert testified on behalf of plaintiffs 50 percent of the time for 80 identified cases in the public record. However, the trial team is unaware that 20 percent of all the candidate's expert cases are not accessible from all records.

The litigation team observes from the cases that the candidate expert's opinions are objective and independent. This fact does not give rise to caution in hiring this forensic analysis expert. However, each of the cases examined is not by default independent from all cases where that expert has testified.

In statistical terms, the probability that the expert is "plaintiff-neutral" is not 50 percent. Rather, that probability is only 50 percent if that expert testified similarly with a 50/50 objective point of view in the 20 unknown cases.

A litigation team can take two actions to enable better future choices:

1. Bolster memory by benchmarking both past predictions and their basis; this leads to heightened self-awareness of one's judgment
2. Accept the fact that one does not necessarily learn from experience, and often cannot

Moreover, an effective decision support framework should incorporate the evaluation of alternative preferences. That is, the *evaluative* dimension of what is at stake, and the uncertainties relevant to the decision, that is, the *predictive* dimension.[11]

Figure 1 presents a taxonomy and framework for implementing the Proposed Model.

Structuring the Decision-Making Framework

Conventional wisdom and typical practice encourages an unidimensional or linear scale in which to measure or differentiate choice. For example, in conflict resolution matters, two parties often see the best solution as a compromise when there may be better solutions requiring creative thinking.

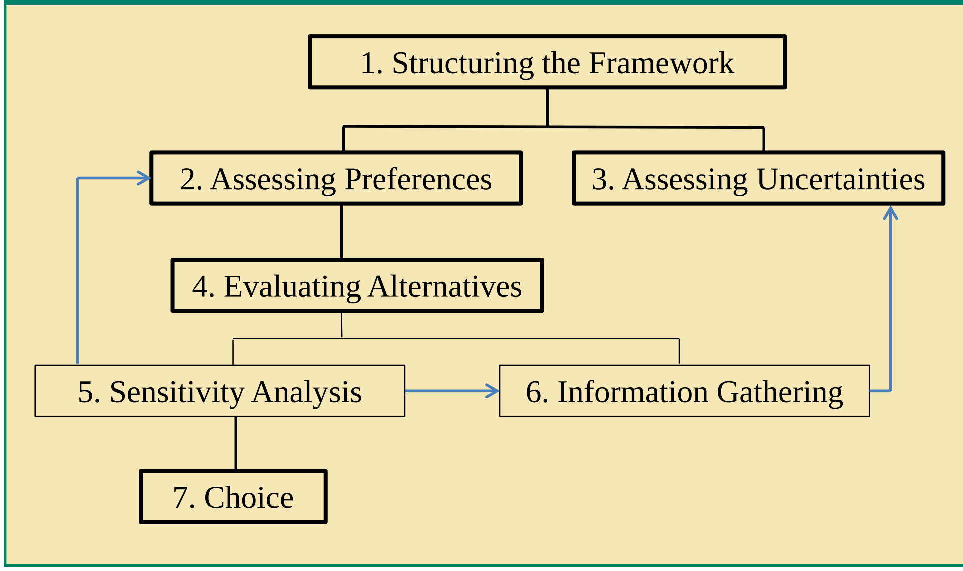
As a result, both parties have the same "question" requiring the same "answer." Therefore, questions and answers presuppose each other.

A multidimensional scale to measure candidate experts puts emphasis on identifying the right variables, or questions to consider. This is the hard part in a decision-making process. The answers are the easy part, as they are a function of the questions that are considered.

Example questions requiring consideration include the following:

1. Who is (are) the decision maker(s)?
2. What sourcing methods exist?
3. What dimensions should candidate experts be evaluated on?
4. What are the key uncertainties?
5. To what level of detail does the decision need to be structured, what level of detail can it be structured, and on what measurement basis?

Figure 1
Taxonomy and Framework Implementation



Decision Makers

Determining the identity of the decision maker(s) is a necessary, but not always evident, step. Lack of clarity can lead to disagreements, and difficulties can arise in the selection process, particularly when multiple parties are involved. What is optimal for one party may not be for another. Differences in opinion will likely have to be reconciled.

When selecting a testifying expert, litigation teams should consider such questions as the following:

1. What departments should be involved in identifying candidate experts, such as subject matter practices (e.g., tax or intellectual property), a specialty commercial litigation practice, or both?
2. Who will "first-chair" any given litigation matter and what witness personalities are seemingly preferred?
3. What client-side participation will be involved, such as inside counsel, the C-suite, board of directors, and to what extent, if any?

Sourcing Candidate Experts

Common sources that litigation teams rely upon in sourcing experts include past precedent, an internal firm database, or external insight with perhaps the most fundamental example being "word of mouth." However, alternative sourcing practices are not necessarily a given, but should be sought or created.

Imagination in the creation of alternatives greatly increases the scope for choice. For example, imagination might include invoking an "executive search-type" process for greater breadth and depth in outreach.

Candidate Expert Preferences

Alternative dimensions for assessing preferences should be specified a priori, as opposed to in real time, and align with the overall objective in selecting a testifying expert, such as the following:

1. Testimony experience
2. Academics
3. Certifications
4. Professional associations
5. Past testimony
   a. Venues
   b. Subject matter
   c. Party alignment (i.e., defendant versus plaintiff; court or jurisdiction, etc.)
6. Relevant publications or presentations
7. Past industry functional or line management expertise

Identifying Important Uncertainties

While assessing uncertainties is a separate step in the decision-making process, it is important at the outset to establish what the uncertainties are. For example, consider the following:

- Geographic restrictions for sourcing candidate experts
- Client fee barriers
- Expert conflict checks
- Personality clashes
- Accessibility
- "Bench strength"

Measurement of Dimensions

Perhaps of most importance is defining the measurement basis for "scoring" evaluative and predictive dimensions within a pool of candidate experts.

Nominal data are items differentiated by a simple naming system. A nominal scale simply establishes that items have something in common, even if not described. Nominal items may have numbers assigned to them, but they are only used to simplify capture and referencing (e.g., the number pinned on an athlete or a set of countries).

Nominal items are usually categorical, in that they belong to a definable category, such as "accountants," "economists," "financial experts," "professors," "title in organization" (partner versus director), and so forth. Nominal data do not comport to a measurement scale.

Items on an ordinal scale are set into order by their position on a scale. This may indicate temporal position, such as deciles, quartiles, or rank, and so forth. The order of items defined is often by assigning numbers to them to show their relative position. Letters or other sequential symbols are also assignable, if appropriate.

Ordinal items are usually categorical, in that they belong to a definable category, such as the number of years of experience, number of jury versus bench trials, number of plaintiff versus defendant representations, and so forth. Moreover, ordinal numbers cannot be manipulated through arithmetic, they show sequence only.

Interval measurements are along a scale in which each position is equidistant from one another. This allows for the distance between two pairs to be equivalent in some way. This is often used to measure attributes along an arbitrary scale between two extremes (e.g., rating a potential expert between 1 and 10 along a dimension, etc.). Like ordinal data, interval data are not multipliable or dividable.

In a ratio scale, numbers compare multiples of one another. Important also, the number zero has meaning. Thus, the difference between a person of 35 and a person 38 is the same as the difference between people who are 12 and 15. A person can also have an age of zero.

Ratio data can be multiplied and divided. This is because not only is the difference between one and two the same as between 3 and 4, but also that 4 is twice as much as 2 (e.g., number of books or articles written, number of times quoted, percentage of cases deemed successful, etc.).

Interval and ratio data measure quantities and hence are quantitative, and are often referred to as "scale data" because they measure items on a relative or differential basis.

Moreover, interval and ratio data are parametric, and measured with tools such as distributions that are predictable, and often normal. Nominal and ordinal data are nonparametric, do not assume any distribution, and can only be measured with tools such as a histogram.

Data measured on a continuous scale are dividable into fractions, such as temperature. Continuous variables allow for infinitely fine subdivision, which means if you can measure data sufficiently and accurately, you can compare two items and determine the difference.

Discrete items or variables measure fixed values, such as age in years, and often on arbitrary scales, such as scoring your level of happiness, although such scales can also be continuous.

The following illustrative implementation of the Proposed Model relies on the use of ratio metric scale data, which allows for both evaluative and predictive measurement being considered.

Assessing Preferences

The dimensions of choice reflect evaluative judgment or preferences. There are two major issues at this stage, namely, dimensional adequacy and combinatorial power.

First, how adequate are the measures of the dimensions for comparing alternatives? How well does the selection criteria cover all relevant domains? Has an important dimension, for example, "character," been omitted? Where and how are the measures of the dimensions obtained? How do you judge a person's motivation or intelligence? Will you need outside assistance—from who?

Second, what scheme will best combine or weight differing dimensions taken individually and in whole?

By way of example, Figure 2 illustrates an example construction of preferences. The preferences are considered on a relative basis to each other, and define a single weighted average metric for vetting the evaluative dimension of candidate experts.

Assessing Uncertainties

The uncertainties of choice reflect predictive judgments or beliefs. There are two major issues at this stage as well.

First, what information is relevant to the uncertainties? Second, what people or resources can provide information, to make the necessary probabilistic judgments?

A single overall metric to discriminate candidate experts may reflect the weighted average consideration of such uncertainties as cost or fee barriers, accessibility, and potential business conflicts of interest, among others.

Typically, uncertainties are quantifiable in terms of probabilities. For example, what is the chance that expert services from the "Big-4" will cost, on a weighted average team basis, greater than $400 per hour? What is the chance that a certain professor in academia will not be readily available? How much risk is the firm willing to assume, if any, that a business conflict could be perceived, in hiring a candidate expert?

Evaluating Alternatives

At this stage, combining the criteria and constructing a decision rule is required, such as weighting the assessed dimensions with the assessed uncertainties. This method of evaluating alternatives emphasizes the importance of separating evaluative or preference dimensions from predictive or uncertainty dimensions.

Although the relative values of alternative experts combine preferences and uncertainties, the assessment of preferences is independent from the assessment of uncertainties, to avoid the pitfalls of "wishful thinking" (or "persecution mania").[12]

Figure 3 continues with the example assessment combining independent evaluative dimensions of preferences above, with independent predictive dimensions of uncertainties below, for vetting candidate experts.

Sensitivity Analysis

The objective of sensitivity analysis is to estimate to what degree are evaluated preferences and predicted uncertainties incorrect. In other words, what degree of variation in the inputs of assessed preferences and uncertainties would change the decision indicated when evaluating alternative candidate experts?

Figure 2
Decision Tree for Vetting the Evaluative Dimension of Candidate Experts

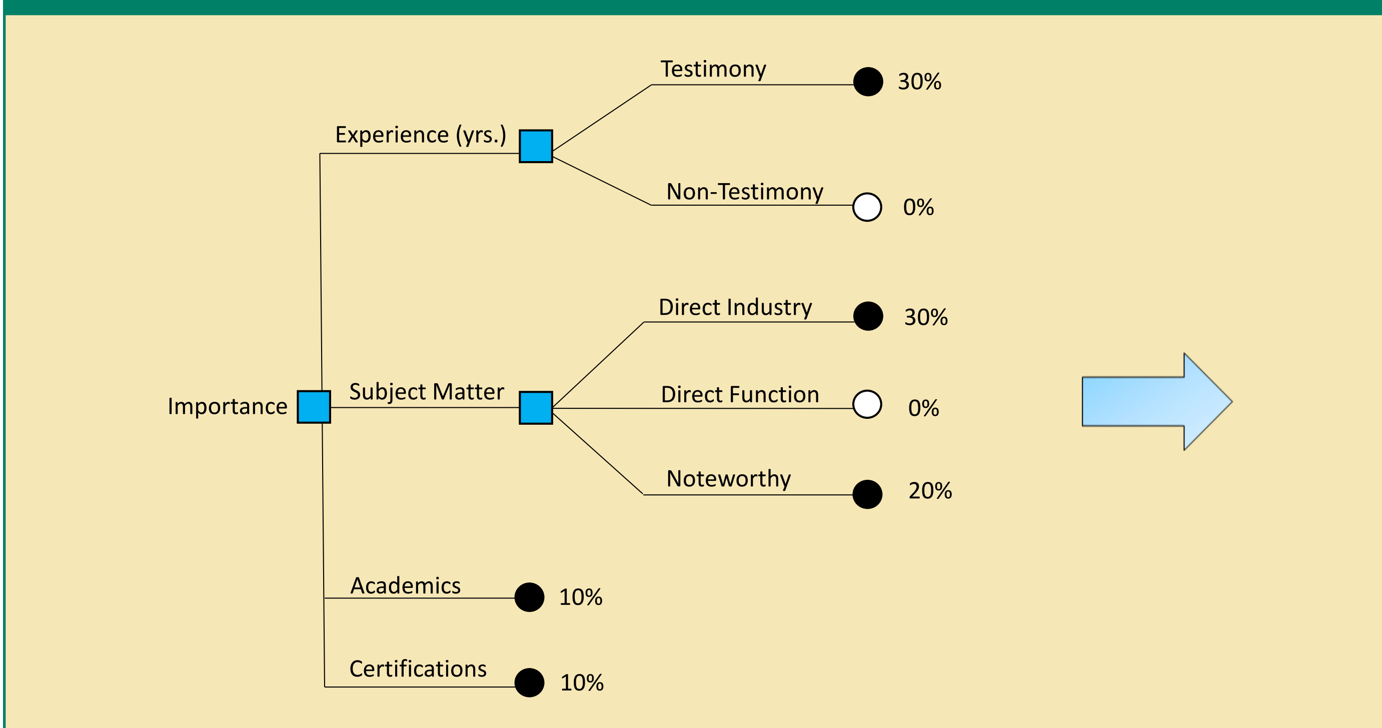
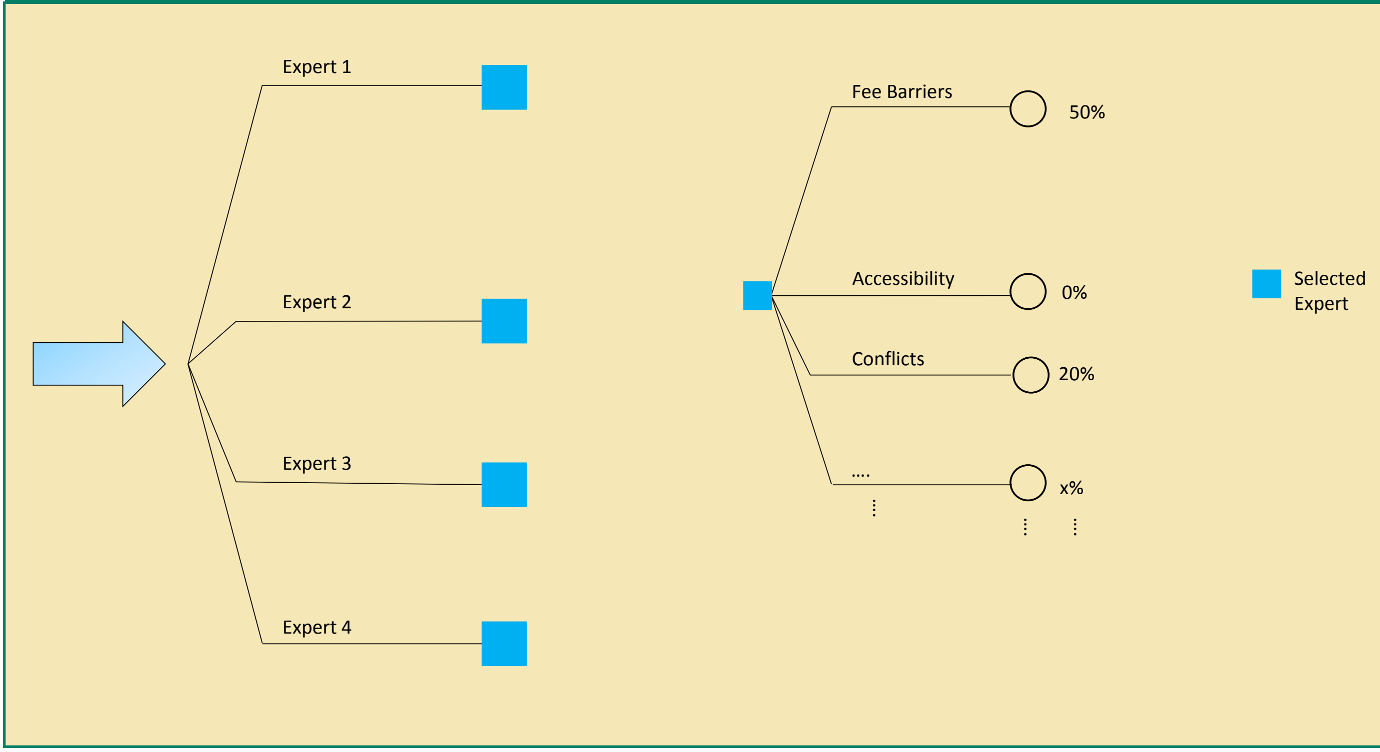


Figure 3
Decision Tree for Vetting Candidate Experts



Sensitivity analysis is rooted in varying the estimated evaluated preferences, using different weighting schemes and the probability of events. In other words, what is the extent to which the decision is sensitive to such changes? Sensitivity analysis is important for two major reasons.

First, most inputs to the decision are subjective. If the choice between two candidate experts is relatively insensitive to ranges of inputs as opposed to point estimate values, this provides some answer to the question concerning how wrong evaluated preferences and predictive uncertainties can be, and yet not affect the decision process.

Second, when people disagree concerning subjective inputs to a decision, disagreement does not necessarily imply different actions. Through sensitivity analysis, one can test the extent to which actions—that is, hiring candidate expert "A"—are compatible with ranges of opinions and values (i.e., weights accorded to dimensions of preferences).

Information Gathering

An important outcome of sensitivity analysis can be the revelation that the decision is sensitive to lack of knowledge concerning certain dimensions—that is, there is a need for more information. At the same time, the analysis should also take into consideration the costs and benefits of securing additional information.

What are the costs and benefits of securing additional information? Such costs include "soft costs" such as the delay in deciding (i.e., the cost of deferral).

Perfect information suggests that decisions are always correct. Suppose that when testimony experience is highly weighted, a selected candidate always reflects the "right" testifying expert and never results in a compromised choice. In this case, the probability of placing great weight on testimony experience increases the chances of picking the right testifying expert.

The following notation can illustrate this dependency:

Π (great weight on testimony experience | always results in selecting the right testifying expert) = 1, where Π represents probability. However, because probabilities should add up to 1, we should also have the condition that Π (little weight on testimony experience | always results in selecting the right testifying expert) = 0.

Nevertheless, this is only half the story. Selecting the right expert should also never result by placing less weight on testimony experience. There should be no chance that placing higher weight on testimony experience results in not choosing the right expert, or, Π (great weight on testimony experience | always results in not selecting the right expert) = 0.

Notice the difference between this probability statement and the preceding probability statement. Both statements are "conditional probabilities," but the conditions are different.

If information is perfect, one will always select the right testifying expert. If prior testimony experience is highly important, then there is no doubt in selecting the right testifying expert. Having used conditional probabilities to model perfect information, we can use a statistical construct known as Bays' Theorem to "flip" the probabilities, and show that there is no uncertainty in placing great weight on testimony experience.

We want to know that Π (always choosing the right expert | always results from placing great weight on testimony experience) = 1.

Let us define the following variables:

A = Selecting the right testifying expert

B = Selecting the wrong testifying expert

C = Highly weighting testimony experience

D = Placing little weight on testimony experience

Now by applying Bay's Theorem,[13]

$$\Pi\,(A \mid C) = \frac{\Pi\,(C \mid A) \times \Pi\,(A)}{[\,\Pi\,(C \mid A) \times \Pi\,(A) + \Pi\,(C \mid B) \times \Pi\,(B)\,]} =$$

$$\frac{1 \times \Pi\,(A)}{1 \times \Pi\,(A) + 0 \times \Pi\,(B)} = 1$$

Note that the *posterior* probability, Π (A | C) = 1, regardless of the *prior* probability, Π (A). This is because of the conditional probabilities that are used to represent highly weighting expert testimony experience as the perfect choice. This is not typical in the real world.

In real choices, one rarely can eliminate uncertainty altogether. If highly weighting testimony experience sometimes results in choosing the wrong expert, these conditional probabilities would not be 1s and 0s, and the posterior probability would not be 1 or 0—there still would be some uncertainty about what would happen.

Information gathering follows sensitivity analysis, since it would be a waste to collect additional information on something that had little effect on the decision.

Choice

At this point, the litigation team should consider whether there has been sufficient analysis of the decision, relative to the costs, benefits, and constraints of the facts and circumstances. Which alternative candidates have the greatest chance of being the right testifying expert? In the final analysis, counsel should select the testifying expert with the greatest chance of being right.

Although the Proposed Model has been shown in a step-by-step process, in practice there is considerable recycling between steps. The process of analysis often indicates new alternative candidates, or dimensions of evaluation and prediction.

Moreover, while the aim of the Proposed Model is an explicit quantitative decision process, the use of sensitivity analysis enables one to see how quantitative the decision process needs to be. This is important because most of the dimensions are subjective.

If different members of the litigation team independently utilize the Proposed Model, selecting the right expert highlights the real extent of agreements and their relative importance.

By decomposing the selection process in this manner, it is possible to synthesize the opinions of different decision makers with different domain knowledge, to the extent their knowledge relates to different dimensions of choice.[14]

The Importance of Institutionalizing Forensic Analyst Expert Selection

The motivation for developing the Proposed Model is severalfold. Perhaps one significant example stems from empirical outcomes of recurring *Daubert* challenges.

According to one yearly study of *Daubert* trends and outcomes, 51 percent of financial expert testimony was excluded in 2016, the largest exclusion rate experienced between 2000 and 2016.[15] Both fully and partially excluded testimony comprise the overall exclusion rate. In fact, partial exclusion is a growing trend, as triers of fact want greater flexibility in admitting expert testimony over an all or nothing proposition.

It is probably no surprise that accountants, forensic analysts, and economists are the three most common types of financial expert witnesses, although actuaries, financial analysts, and academicians also comprise the mix.

However, it is interesting to see whether any type of financial experts experience higher exclusion rates. According to the study in 2016, economists had the highest number of *Daubert* challenges, and accountants had the highest exclusion rates of the three most common types of financial experts.

Between 2000 and 2016 in total, economists have been least frequently excluded, both accountants and analysts largely shared the same exclusion rates, and other financial expert types experienced the highest exclusion rates.[16]

While exclusion statistics of empirical expert challenges may or may not be surprising, past is not prologue. And, selecting the right forensic analyst expert is no easy matter. It is far better to systematize that choice, to the extent possible, to benchmark success in hiring the most likely qualified financial expert, in any given matter.

Notes:

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