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# Attribute-based differentiation of alternatives

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# Attribute-based differentiation of strategic alternatives

***Abstract**: An intermediate step is introduced to the decision dialogue process for decision analysis. Alternatives are refined after they have been generated within a strategy table but before they are subject to more detailed evaluation. Two or more judges create a subjective mapping from alternatives to attributes that will later be mapped to criteria. In strategy tables, each of the alternative strategies consists of a coherent set of choices made across several decisions that are to be coordinated. These strategic alternatives are modified so as to increase their differentiation in the attribute space, rather than in the decision space alone. When criteria weights are unknown, the best alternative from the modified set may be superior to the best alternative from the original set. Furthermore, analysis of the resulting alternatives may yield a better mapping of the value response surface for the action space, in the sense that this mapping leads to eventual construction of a higher value alternative. Results are reported for a consulting engagement incorporating the proposed step.*

***Keywords**: Alternative generation, creativity, multi-criteria decision analysis, decision-making, strategy.*

## 1. Introduction

A quality decision process requires the generation of a set of creative and doable alternatives (Howard, 1988), and these alternatives should be significantly different from one another (Matheson and Matheson, 1998). Typically, alternatives are understood to be significantly different when they differ across many sub-decisions. If relatively few alternatives can be investigated in detail, there are few degrees of freedom with which to generate such differences and it is important that the differences between alternatives be important ones. But how can we tell until we've analyzed them?

If the reason for seeking such differentiation is to ensure that all promising possibilities are examined, it may be more useful to strive for alternatives that are differentiated in the attribute space rather than in the control space. This MCDA-inspired idea was translated into a specific modification to the Decision Dialogue Process (DDP), developed by Howard, Matheson and others at Strategic Decisions Group and its clients (e.g., Barabba, 1995). This modification was applied in a pharmaceutical product decision analysis, with promising results. Specifically, after alternatives were generated using a strategy table, a set of attributes was identified. Alternatives were qualitatively scored against these attributes, and then were modified in order to increase their differentiation with respect to the attributes. At the time it occurred, this application was not intended as a scholarly study, but its archival information was sufficient to construct an illustrative case.

Section 2 gives background on approaches to alternative generation in decision analysis, along with an interpretation that motivates modifying the DDP. Section 3 describes the proposed new step in detail, including its practical application. Section 4 presents the case study. Results include the quantitative output obtained during the new step, specifically, its measures of differentiation as well as levels of agreement about the scores of alternatives. These outputs were used to materially improve the set of alternatives. Section 5 discusses lessons learned from the engagement and potential future research.

## 2. Background

Decision analytic practice includes numerous techniques for alternative generation. These techniques can be viewed as variations on a more or less common process, each variation having its specific purpose. The approach described here, attribute-based differentiation of strategic alternatives, will combine elements of several of these techniques. The literature on decision analytic processes does not offer much explanation for why differentiation of alternatives is desirable – although no one argues that it isn't. We should first articulate the rationale. There seem to be two main reasons for differentiation: ensuring that potentially strong alternatives are not missed, and exploring more broadly what drives value.

If alternatives are not significantly different, it is likely that other alternatives that are significantly different have been overlooked – and one of them might be better. If there are to be meaningful alternatives, there must be tradeoffs. If the value associated with the attributes that must be traded off and the exact magnitude of those tradeoffs cannot be known in advance, then it is imprudent to rule out certain tradeoffs. For example, a consumer intending to purchase a used car is looking for a "bargain" in the sense that the attributes on which the car performs well are of high value to that consumer but are attainable because the market does not value them so highly, while the attributes that the market values highly are not of much importance the consumer. If the consumer never considers cars with, say, low acceleration, a car that is otherwise especially attractive, might be overlooked. Such a neglected option could be more attractive than other choices, depending on the precise weights the consumer eventually assigns to various attributes.

Especially when the exact mapping from alternatives to criteria is not known at the time alternatives are generated, the best alternative from a well-differentiated set of alternatives is likely to have higher value than the best alternative from a narrow set where no intentional pre-processing of alternatives has occurred. The reasoning here is that when the value of alternatives to be examined is uncertain, and when the best alternative from the set will eventually be chosen, the option value inherent in the alternative set is maximized by maximizing variance in the value of possible outcomes. Harrison and March (1984) argued on similar lines that expected value increases in the number of alternatives generated, and in the heterogeneity of those alternatives.

In practice, there is additional value to considering even alternatives that are not selected. If we only consider a narrow range of alternatives, then we will only learn about what drives value to the decision maker over a narrow range. By considering a wider range of alternatives, the natural outcome of the decision analytic process will be a richer understanding of what makes alternatives attractive. This, in turn, can lead to more efficient development of high-value alternatives. Variations on these two reasons help motivate the treatment of alternatives in most of the processes addressed here.

**MCDA processes:** Henig and Buchanan (1996) provide a useful framework for discussing alternative generation techniques. They divide decision models into two parts: an (ideally) objective mapping from alternatives to attributes, and a subjective mapping from attributes to criteria, i.e., what Keeney (1992) calls fundamental objectives. An analytical decision process must include what they call component identification (of the alternatives and criteria themselves), identification of attributes (which they include as part of the mapping step), and, as part of an overall iterative process, understanding the decision maker's preferences and expanding the set of alternatives.

In such a process, several characteristics would be desirable in an alternative set. Specifically, there should be a few well-differentiated alternatives. These alternatives should present high potential value, and they should be realistic. These desiderata for an alternative set are intuitively appealing for the reasons described above.

**Attribute-based methods:** These methods are practical when there are relatively few alternatives, as they keep the number of assessments and computations reasonable. Keller and Ho (1988) describe and recommend attribute-based methods of alternative generation, where a set of alternatives is narrowed down by screening against attributes, i.e., by using "feed-forward". This minimizes time spent analyzing less-promising alternatives. Value focused thinking (Keeney, 1992) extends this idea and identifies key objectives as a precursor to alternative generation, so that all alternatives generated are likely to have high value; more complete models are then constructed to evaluate and refine alternatives. Outranking techniques (Jaskiewicz and Slowinski, 1997) implement in multi-criteria programming environments something resembling Keller and Ho's idea. Outranking is applicable when the range of alternatives can be expressed as a region in nspace and where there is partial information about the relationships between attributes and criteria. In this approach, after attributes and the directions in which change is desirable are identified, the set of non-dominated corner solutions is enumerated and is fairly small. For these solutions, further development of local preference models ensues.

**Early ranking:** A technique often used by Stewart (e.g., Stewart and Scott, 1995) is to add an intermediate step of ranking, holistically, each alternative against each attribute on a 0-100 scale. At this point, formal measures are not yet developed and attributes have not yet been mapped to criteria. Stewart proposes using this “quick and dirty” method to refine the set of alternatives in order to find ones that perform well against the attributes. No explicit weighting scheme is used, but at the very least, this approach identifies dominated alternatives. If all attributes are treated equally at this point, Stewart’s method can be thought of as a heuristic that will tend to pick higher performing alternatives. Research on SMART techniques (e.g., Edwards and Barron, 1994) suggests that this could work well. While Stewart’s approach is typically used to reduce the set of alternatives based on preliminary information, its successful application suggests that there is potential value to performing more general manipulations of the set of alternatives based on preliminary information.

**DDP and Strategy Tables:** According to Howard’s decision quality framework, alternatives must be creative and well differentiated. Within Howard’s Stanford school of decision analysis, commonly identified with the DDP, strategy tables are used to generate strategic alternatives (also called strategies), i.e., alternatives composed of coordinated choices over a set of decisions. A strategy table contains a column for each decision dimension (not necessarily quantitative), and for each decision dimension, the choice set is laid out with one possible selection in each row. Strategy tables are especially well suited to situations where there are more than a few simple alternatives, and where different dimensions of the action space are not easily quantified (unlike linear programming).

A rich description of the practical use of strategy tables is given in Matheson and Matheson (1998, p. 185), who define a strategy table as “a matrix that casts alternative strategies against the decisions that would logically flow from them.” They describe the process of constructing a strategy table as follows (ibid, p. 187):

> “In the remaining columns of the table [the project team] listed the major decision areas the company would need to address to flesh out these strategies. The heading of each column describes the decision area and the entries under it represent strategic options in that area. A complete strategic alternative (or strategy) was specified by selecting one option from each column and connecting them to make a path from the theme through their choices in each column. … Over the course of several weeks, the team came up with new strategy themes, defined them carefully by making the appropriate choices in each column, adding columns for new decision areas or new options within decision areas, compared them, and then boiled them down to a small set. The final set of strategic alternatives was selected to define several significantly different strategic visions of how to manage the overall business. After approval of the entire set by the decision team, each strategy was slated for evaluation in the next phase of the DDP.”

In business settings, the DDP typically (and intentionally) focuses on a single criterion, maximization of expected net present value. Alternative generation is only one phase. In the complete DDP process, differentiated alternatives are constructed as diverse paths through the strategy table, where each path represents a logically consistent theme. After the set of alternatives is generated, influence diagrams are used to model the relationship between decisions and value. A deterministic model is created, and after preliminary assessments, “tornado diagrams” are constructed using sensitivity analysis. These in turn are used to select variables to incorporate in a full probabilistic analysis and, after value of information calculations are performed, a final decision is made. Each stage of the process is marked by a meeting in which a conversation is facilitated between a senior “decision board” and a “decision team consisting of decision analysts and staff from the client. The meeting ends with agreement about which parts of the model are complete, and which assumptions are accepted, along with commitments on further action and directions for analysis.

**Iteration:** Several approaches exist along these lines. Requisite decision modeling (Phillips, 1984) makes explicit the idea that any part of the decision model may be refined if, based on the assessment at that time, it seems refinement would significantly improve the decision.

The Unifying Vision Process or UVP described by Kusnic and Owen (1992), has become an important variation of the DDP. With the UVP, there is a plan to design a new “hybrid” alternative based on sensitivity analysis-type insights from the models that are developed to evaluate an initial set of alternatives. In concept, the UVP starts with a set of feasible alternatives from which the analyst iterates, stitching together pieces of each alternative into combinations that approach a more optimal solution. (In contrast, Keeney’s value focused thinking approach may involve iteration in which a set of creative alternatives, each of which is intended to perform well on some subset of the key objectives, is stitched together by first taking the union of many of these actions and then easing back the plan until it is feasible.) Similarly, Corner et al (2001) suggest an approach that switches between alternative generation and refinement of the value function. A more formal approach that explicitly seeks to map out the value corresponding to various alternative inputs is Bauer et al's (1999) response surface mapping (RSM). In this approach, numerous points in the attribute space are selected for detailed evaluation. These assessments are then used to form a response surface map that interpolates between the assessed points. Detailed evaluation of points is costly, so RSM incorporates principles of experimental design to construct as robust a map as possible.

In both of these iterative processes, new alternatives are defined after a model is built to evaluate other specific alternatives. Here, the set of alternatives that are first used for the model should be constructed so as to facilitate learning that will lead to eventual discovery of high value alternatives. It seems that differentiation would be even more important with such an iterative process than with a sequential process.

## 3. Synthesis

The ideal situation with which we are concerned has the following characteristics: we may want to use iteration and may want to create a RSM, but not with so formal a mapping process. We also want to map high value regions. We are willing to refine the set of alternatives. Several challenging factors may be present: feasibility is not easily achieved, so we want to start with feasibility and work up toward optimality; the mapping from attributes to criteria is complex and not easily identified; and tradeoffs will likely be necessary. These characteristics are common in many, if not most, decision contexts, particularly the difficult task of defining the means-ends relationships between attributes and criteria. Using elements of the various approaches, we can propose using the process sketched below:

(1) Define a set of alternatives, using strategy tables in the usual DDP.

(2) Construct (quickly and at low cost) a coarse model relating alternatives to attributes, scoring it using Stewart's method, and identify the directional relationship between attributes and criteria.

(3) Then, in the spirit of Keller and Ho and other attribute-based approaches, use this assessment to refine the alternatives.

(4) In the spirit of RSM, take measures of the spread of alternatives across attributes and then refine alternatives (as does Philips) to get a set of points to evaluate that better spans the attribute space (rather than the input space).

(5) Use this as the input to the rest of the process (developing complete mapping from alternatives to criteria) and then

(6) Either select the best alternative (with possible refinements) or use insights from this mapping to generate a new better alternative (as in the UVP).

To enable the creation of high-impact alternatives, the columns of a strategy table should contain not only those quantities over which decision makers have the most control, but also those that are most easily controlled in general, and those whose effects are most important. By merging MCDA with strategy tables, we can identify value drivers and create alternatives to affect them, even before their precise nature is known.

If there is a high level of control over quantities that are not especially valuable, we should ask whether there is a cost to having the control and, if so, whether it should be abandoned, or whether there is some other possible route to deriving value from that control. An effective strategy table would have a high correlation between controllable variables, attributes that can be influenced, and important criteria, i.e., it would explore the action space in the right dimensions. We are not at this stage aiming to create all high-value alternatives. It is challenging enough to pursue the more modest goal of developing well-differentiated alternatives.

The mathematical justification for this type of differntiation is easily seen in a linear programming setting. Other things being equal, the more alternatives differ in terms of resource allocations, the more we expect the alternatives to diverge in terms of value. However, even in the simple case where the value of an alternative is the product of an input vector, an input-output matrix and a price vector, the Cartesian distance between two input vectors alone does not reliably predict their difference in value.

For instance, consider the following situation in which we wish to compare alternative inputs. The input-output matrix is 2 x 2, each entry in it is 1, and outputs are transformed to a single value by the price vector: (1, 1). If we have as alternatives the two input vectors X1: (1, -1) and X2: (–1, 1), resulting in an output vector of (0, 0) in each case, the Cartesian distance between the alternatives is $2\sqrt{2}$ in the input space, while the distance between them in the attribute space (as well as in value) is 0. The input vectors X1: (1, -1) and X2’: (1.5, -0.5) are separated by a Cartesian distance between them of $1/\sqrt{2}$, i.e., they are closer together than X1 and X2. But their outputs (0, 0) and (1, 1) have a Cartesian distance of $\sqrt{2}$ in the attribute (output) space and their resulting values differ by 2.0. With rough information about the price vector, one could correctly predict that the second pair of alternatives has greater difference in value based on the distance between the output vectors, in spite of the fact that this pair has smaller distance between the input vectors.

In real situations, of course, there is a nearly infinite range of possible relationships between actions and value, but the same thinking ought to apply. If we want the alternative generation phase to produce a set of well-differentiated alternatives, then even rough estimates of how alternatives perform against different attributes should help.

In the case study that follows, this concept was implemented at the end of the alternative-generation phase in the DDP, but prior to the detailed evaluation of the different alternatives. The plan was for a process where, after the initial strategy table and a first set of alternatives has been developed, the decision team does the following:

1) Identifies a list of attributes anticipated to be significant value drivers.
2) Holistically rates each alternative as being in the $1^{st}$, $2^{nd}$, $3^{rd}$ or $4^{th}$ quartiles of what could be expected for each attribute, where the $1^{st}$ quartile is most desirable (Stewart's 0-100 scales might be too fine for this purpose). This wording is similar in spirit to commonly used qualitative scales where 1 = Excellent, 2 = Good, 3 = Fair, and 4 = Poor. Although summary statistics from such scales must be taken with a grain of salt, survey results[1] of this nature are commonly used.
3) Computes (easily found) descriptive statistics for each of the following:

    Inter-judge agreement on scores for alternatives

    Inter-judge agreement on scores for each attribute

    Spread of scores among alternatives (over all attributes)

    Spread of scores across each attribute

[1] We would ideally use ratings from multiple judges to help ensure reliability, given the preliminary nature of the attributes used here. Although in the case study the judges were the decision analysts, actual decision makers could certainly serve as judges in addition to or instead of the analysts.

4) Uses results from (3) for guidance about where to refine definitions, utilizing comparisons of scores from different judges in a manner reminiscent of Delphi techniques, (Sackman, 1975), and

**5)** Refines the original strategy table and alternative set in order to increase the differentiation of alternatives with respect to attributes. The abstract guidance from (4) can be applied by inquiring about specific ways in which, by modifying an alternative in a manner that decreases performance on one attribute, it would be possible to increase performance on another attribute. We might expect these prompts to suffice because they are similar to techniques that Keeney (1992) uses successfully, i.e., by asking decision makers to develop alternatives that maximize a single attribute score.

## 4. Application

### 4.1 Case study

The proposed approach was used in a decision analysis consulting engagement at a Fortune 500 pharmaceutical company. Consistent with the hurdles to doing research as a practitioner, as described by Platts (1996), this application was intended primarily to be of benefit to the client, and not to be a controlled experiment in which a pre-determined method would be compared against a control situation. Nonetheless, it was a conscious attempt at innovation and good records were kept. The process followed the proposed plan for the most part, differing in minor details where necessary for the flow of the engagement.

For this discussion, it is necessary to use several technical terms commonly heard in the pharmaceutical industry: A c*ompound* is a specific chemical formulation used as a medicine. A *trial* is (in the U.S.) a U.S. Food & Drug Administration (FDA) approved scientific test of a compound used in a specified way on a selected set of subjects. An *endpoint* is a target quantity that is to be measured by a trial, e.g., 50% rate of absorption of a fixed dose of medicine achieved by 90% of subjects within 40 minutes. An *indication* is a medical use approved by the FDA based on the results of trials for a compound.

The new step was introduced a few days after it was informally proposed (thanks to a cooperative project manager and client). The business problem was that a pharmaceutical product that had been generating in the hundreds of millions in annual revenue was past the end of its patent life. For reasons relating to the difficulty of obtaining regulatory approval and of manufacturing, and the medical complexity of using this product, the company was still enjoying strong profitability from it. However, in several of the medical indications, there were potential regulatory concerns on the horizon, as well as potential competition.[2]

The company had engaged decision analysis consultants to develop a plan of action for the product area, with the primary objective being to maximize net present value. We had anticipated that during the alternative generation phase of this project, a key challenge would be creating sufficiently well differentiated alternatives (because of our own difficulty in imagining them), and this fact motivated use of the approach

[2] Company and product details are disguised. This example bears a similarity to one given by Philips' in his comments on Henig & Buchanan (1996), but the similarity is entirely coincidental.

described here. Materials were prepared to run this as an exercise with the client team. In the actual case we explained the exercise to the client team, but ran out of meeting time after the client team generated a strategy table.

The most easily identified decisions involved whether to run each of many possible trials for each of the three possible compounds. We determined that, although specifying these trials would be an essential piece of implementation, it would not suffice to merely construct and compare lists of possible trials. Alternatives defined in this way would be hard to interpret other than literally – and therefore hard to connect to a theme and thus to other necessary business decisions. We quickly gravitated toward a more business-oriented strategy table.

The actual strategies varied across the following resource dimensions:

- investment in trials for uses that are already common in practice although not explicitly approved by the FDA, with specific endpoints that could improve the product's credibility with physicians (possible combinations of trials),
- investment in capacity (possible different levels for different products),
- investment in new indications (different indications for different products)
- investment in sales and marketing,
- speed of the various tests (compressing tests in time and performing multiple simultaneous tests could increase costs.)

The team was familiar with the financial commitments each of these types of investments would require, but the dollar amounts were not explicitly estimated. Using this strategy table, the client's core decision team (with consultants facilitating) generated a set of alternative strategies. They started with themes and then constructed paths through the strategy table consistent with those themes. As alternative strategies were defined, they were tweaked to ensure that they did not have much overlap, and for each column most of the alternatives implied different choices. In the stylized version of our strategy table shown in Table 1, the alternatives appear to be well differentiated. The five strategies were:

- "Minimum Investment" (I): Keep the current product's market share as long as possible without significant new investment in drug trials, production capacity or new medical indications.
- "Grow" market (G): Attempt to expand the market for the product with current and closely related medical indications.
- "Switch" product (S): Attempt to maintain the core market by switching it to a new and improved chemical formulation of the product (one with similar effects, but better).
- "Leverage" product (L): Attempt to expand the market for the product by getting new indications and selling additional products related to current medical indications.
- "Multi-use" products (U): Maintain a family of related formulations, marketing different formulations for different market segments and indications.

Each strategy is thus a path through the table defined in terms of the choices indicated by its code for each of the decisions that must be coordinated. For example, the "Grow" strategy (G) would allocate a high level of resources to capacity, medium resources to running trials for safety and efficacy, and low (but non-zero) resources to running other trials, developing indications, enhancing sales and marketing, and speeding up the product development cycle.

Following the meeting with the client team, the project manager and I (judges A and B) constructed a list of attribute dimensions that might be of interest to decision makers. Although we had enough experience to generate a nearly complete list based on analyses for similar decisions, it would be better, if practical, to involve the client team in this step. The attributes we identified along with their orientiations were as follows:

- Minimize marketing complexity (similar products could cause confusion)
- Minimize organizational complexity (involving multiple divisions)
- Minimize technical risk (efficacy and safety of different formulations are uncertain pending clinical trials at early and later phases)
- Minimize regulatory risk (regulators have concerns about certain formulations, production methods, and uses, and overcoming these would require greater lobbying effort and success)
- Minimize commercial downside risk (do not want to lose existing market share)
- Maximize commercial upside potential (want to penetrate new market segments)
- Minimize investment resources required
- Minimize time required to market

At this point, we did not expect to be able to quantify alternatives against these attributes and we did not intend to conclude the project with a multi-attribute utility analysis. Note, the term "attribute" as used here is close to what Keeney calls a "means objective."[3] As is typical for this type of engagement, it was already established that the primary "end" objective (criterion) would be to maximize expected net present value (ENPV) for the product family. We suspected that these attributes would all drive ENPV in an as yet to be defined way and hoped that by making them explicit early in the decision process, we would focus subsequent analysis. We fully anticipated that with more detailed analysis later on, a model that further clarified these attributes would be developed (in the form of a detailed financial model with intermediate variables resembling our attributes). In order to refine alternatives before entering the time-consuming modeling phase of the project, we chose to use this list as is.

After developing the list of attributes, we each scored each of the alternatives on a scale from 1 (best) to 4 (worst) for each attribute dimension (tables 2a and 2b). These were entered in a spreadsheet, and data in these and the other tables was presented to the client in the form of bar graphs. The spreadsheet calculated statistics such as standard deviation on each attribute measure across alternatives (table 3), as well as correlation between judges on attribute measures and by alternative. To calculate these measures required nothing more complex than application of standard spreadsheet functions, specifically: standard deviation, correlation, average, and basic arithmetic (sometimes with arrays).

Some of the statistics had obvious, if superficial, implications. A high correlation between judges' scores in a given dimension indicated sufficient clarity to use the findings about that dimension. One use of the correlation statistic was as a warning that

[3] If there was a richer set of final criteria, the same technique could be used, but the process of identifying and scoring preliminary criteria might merit more effort with correspondingly greater benefit. We could call this criteria-based-differentiation. It could also work to apply the technique twice, first to create a more differentiated set of feasible alternatives with respect to attributes and use this as a basis to generate a more differentiated set of alternatives with respect to criteria.

later models would need more detail to fully capture these considerations. Where the standard deviation statistic among attribute scores is high, it means the alternative set provides good coverage on an attribute dimension. Where there is high correlation between scores for a pair of alternatives, it means there is insufficient differentiation between them. If none of the correlations is high, this indicates significant differentiation.

In the rightmost column of table 3, the alternatives' average scores (simply assuming equally weighted attributes) lie within a narrow range. Inspection of the table confirms that no one alternative is dominated on all dimensions by any other, so we did not immediately eliminate any of them. The average scores across alternatives (for both judges) for the attributes all lie between 2.1 and 2.7, again suggesting that attributes have not been treated as constraints in creating the alternatives, i.e., there is no attribute where all the alternatives were defined so as to maximize that attribute.

At this point, it is interesting to compare the set of alternatives presented in an attribute-based strategy table (table 4), with the alternative-based strategy table (table 1). The level of differentiation appears lower when alternative strategies are viewed in terms of attributes rather than decision dimensions. Specifically, we observe in table 4 several dimensions in which two or more alternatives perform at the same level while there are other performance levels that are not achieved by any of the alternatives. Any interpretation of the patterns here is, of course, dependent on the judges' estimates being reliable. With the small number of judges, gaps in table 4 might appear by chance if judgments were noisy. This concern is somewhat alleviated by the fact that judgments were informally reviewed when presented to members of the client team.

--- INSERT TABLE 4 ABOUT HERE ---

The difference in attribute scores across alternatives was substantial. The standard deviation of scores across alternatives (in the bottom row of table 3) is near 1.0 for most of the attributes, but is somewhat lower (0.74) for regulatory risk and much lower (0.45) for commercial risk. This suggests that the alternatives may reflect less inclination on the part of the client team to trade off performance on these two attributes for performance on other attributes.

Although the main reason for collecting the data was to evaluate alternatives, we can deduce from the same data something about how well defined our attributes are in relation to the alternatives by looking at the inter-judge consistency. This would be a more valid measure with more judges (and with judges from the client organization). Even with two judges, however, the results provided a rough indication of where further work on definition was needed. If several judges from the client had participated, the same type of results would be obtained but they could be used with more confidence. The spreadsheet calculated both the simple Cartesian distance between the two sets of assessments and the correlation between them, as shown in table 5.

--- INSERT TABLE 5 ABOUT HERE ---

There was generally high correlation in the judges' assessments of the different alternatives on each attribute. The exceptions were a low correlation (0.48) on regulatory risk, and zero correlation on judgments of commercial downside risk; we discussed this lack of agreement but concluded that it was not caused by a poorly defined attribute, but rather because the alternatives simply did not show much variation here.

Comparing each judge's scores one alternative at a time, we found that there was low agreement (0.51) on the attributes of the "Grow" strategy. Judges A and B had very different views of the relative attributes of "Grow" and "Leverage" (they were negatively correlated for judge B, and positively correlated for judge A, and essentially uncorrelated in our average scorings), even though we agreed on the resource allocations for them. We felt that what happened was that the "themes" that go with these strategic alternatives were unclear; when that happens there are more gaps (unarticulated or assumed decisions) that judges must fill and these judgments may differ. In particular, the "Grow" strategy may not be so well defined as the "Switch" and "Minimum Investment" strategies. This was noted as a point to revisit at the next decision team meeting.

The similarity of individual alternatives is estimated in table 6. Here, the correlations between ratings for each pair of alternatives are calculated with a simple spreadsheet formula copied to cells in a table. The "Minimum Investment" strategy is weakly correlated with "Grow" and has a strong negative correlation with the other alternatives. The "Grow" strategy is negatively correlated with the other alternatives (most strongly with switch). The "Switch" and "Leverage" strategies are weakly correlated, as are the "Leverage" and "Multi-use" strategies. The "Switch" and "Multi-use" strategies stand out as strongly and positively correlated.

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### 4.2 Case recommendations

This analysis led to incremental insights about our set of alternatives, without fundamentally shaking our confidence in them. The findings were used to identify directions for improvement of the alternative set, which were translated into changes in definitions of specific alternatives. The general recommendations were to:

1) Refine understanding of commercial and regulatory risk;

2) Make the "Multi-use” and “Switch” strategies more divergent (assuming that the results do not change after the the previous step); and

3) Increase the spread among alternatives with regard to commercial and regulatory risk.

Recommendation (3) could be enacted by modifying alternatives to increase their variation, or by adding new alternatives. We concluded that an ideal alternative set would combine recommendations (2) and (3), and make the “Multi-use” and “Switch” strategies more divergent on commercial and regulatory risk. For example, “Switch” could be made more commercially risky but less risky in terms of regulation, while making “Multi-use” could take on more regulatory risk.

The specific suggested directions for improvement of the alternative set were developed in an informal way based on the statistics described. It is worth mentioning that this approach could be formalized to varying degrees. Of course, spreadsheets could automatically calculate results of any contemplated change in strategies on the statistics calculated here – spread on scores for each attribute, variation on scores within an alternative, cartesian distance between alternatives, spread on average scores of each alternative, etc. Extending this idea would be a one-way sensitivity analysis on these statistics with respect to incremental changes in each alternative. Results could be used to generate a list of suggested one-way (or, with automation, more complex) changes that are effective enough to pass a screen, e.g., increasing average differentiation over all attributes by at least 0.2 and increasing the average difference in alternatives' average scores by at least 0.1 with a degradation in average score of less than 0.1. The question of whether the suggested changes translate to practical actions should probably to be left to human experts.

Once the changes in the case were suggested, it was relatively easy to identify a way to implement them. As noted, the original alternatives could have been stated literally in terms of which medical indications would go with which of three possible drug formulations. Specifically, there was a current formulation that was already in use, a new formulation similar to the current one but without one of its potential drawbacks, and an even newer formulation also without the main drawback of the current formulation with potentially greater or lesser benefits. In the "Multi-use" strategy, it was possible to re-assign the existing product formulation from innovative indications to a more basic application. At the same time, in the "Switch" strategy it was possible to assign the first new formulation to low-tech applications while reserving the newest formulation for new indications. This pair of changes led to precisely the desired change in differences between the two strategies and the corresponding desired differentiation in the set of alternatives as a whole. The product manager suggested a further improvement of assigning one other potential indication to the second formulation in the "Multi-use" strategy.

We did not consider certain other possible interpretations of the statistics, but these might merit exploration in future applications. For example, it is not clear that lack of divergence is always a shortcoming – perhaps the reason none of the alternatives had high commercial risk is that this is not really variable, or that it is easily optimized. Similarly, it is possible that alternatives achieve similar levels with respect to attributes, but achieve them through very different lower level tactics, i.e., their similar performance on attributes is mere coincidence. With more experience, it will become clear which questions of this type are important.

At the next team meeting, it was agreed that would be the basis for further modeling, assessment and analysis, all of which commenced soon after. Prior to the completion of the project, largely unanticipated outside events changed the business environment enough that the product was essentially abandoned (and therefore the "Minimum Investment" strategy became the obvious choice) and the decision analysis stopped, so there is no way to compare the ultimate incremental value of the new alternatives generated with this process.

Up to this point, the process innovation had tangible effects. The analysis led directly and quickly to insights about and improvements to the set of alternatives. The ratings were used to characterize the set of alternatives. The characterization was used to develop recommendations on how to improve the set as a whole, as well as specific ideas about where to change alternatives. These recommendations evoked specific suggestions for changes in the definitions of two of the alternatives.

## 5. Conclusion

A refinement was introduced to improve the alternative generation step of the DDP. This is a step that is often suspect, and the suggested change, though simple, has a theoretical basis that should increase differentiation of the alternatives that are defined. It should also make more defensible a consultant's assertion that this aspect of decision quality has been achieved.

As a process innovation, the case described was a success. The main question was whether the new step would provide any incremental benefit. The answer appears to be yes. As Clemen and Kwit (2001) have noted, it is very difficult to identify the actual value added, but we have available one piece of evidence of success. Specifically, the client could have asked us to retain our original set of alternatives but instead dictated that we work with the revised set of alternatives and then proceed with the rest of the standard DDP.

This revealed preference indicates that the set of alternatives was substantially improved by the guidance directly attributable to the new step. A secondary question was how much this added step would cost in terms of additional time, discomfort, etc. In fact, the additional analysis from this step required only a simple spreadsheet. The step was easily explained to client team members who were already familiar with decision analysis. It took less than one additional person day to conduct assessments, and a little more to analyze the data and develop recommendations. The client team found the discussion engaging. An incidental benefit of this discussion was helping people make the shift to thinking in terms of evaluation, which would be the next step of the DDP.

Although the case was an application of the DDP, the present ideas may be applicable in other incarnations of decision analysis. The integration of strategy tables with an MCDA modeling perspective seems promising. Decision analysts may improve alternative sets by considering, without too much effort, how alternatives differ in certain attribute dimensions and not just in terms of their inputs.

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**Table 1: Stylized version of strategy table developed with client team.**

| ***Strategic Dimension*** Resources allocated | ***Safety & Efficacy Trials*** | ***Capacity*** | ***New Indication Trials*** | ***Sales/ Mktg*** | ***Speed*** |
|---|---|---|---|---|---|
| None | I L | I | I | I | I |
| Low | G | S | G S | G | G L |
| Medium | S | L U | U | L S | U |
| High | U | G | L | U | S |

**Key:**

**I** = Minimum Investment strategy
**S** = Switch strategy
**L** = Leverage strategy
**G** = Grow strategy
**U** = Multi-Use Products strategy

**Table 2a and 2b: Raw assessments and standard deviations (1 = best quartile, etc)**

| Judge A | Resources used | Timing | Org'l complexity | Market complexity | Tech risk | Reg risk | Commercial downside risk | Commercial upside potential |
|---|---|---|---|---|---|---|---|---|
| Min invest | 1 | 1 | 1 | 1 | 1 | 2 | 3 | 4 |
| Grow | 3 | 2 | 2 | 1 | 2 | 3 | 1 | 2 |
| Switch | 3 | 3 | 2 | 3 | 3 | 2 | 2 | 2 |
| Leverage | 4 | 4 | 3 | 2 | 3 | 3 | 2 | 1 |
| Multi-use | 3 | 3 | 2 | 4 | 3 | 2 | 2 | 2 |
| Std Dev | 1.10 | 1.14 | 0.71 | 1.30 | 0.89 | 0.55 | 0.71 | 1.10 |

| Judge B | Resources used | Timing | Org'l complexity | Market complexity | Tech risk | Reg risk | Commercial downside risk | Commercial upside potential |
|---|---|---|---|---|---|---|---|---|
| Min invest | 1 | 1 | 1 | 1 | 1 | 3 | 2 | 4 |
| Grow | 2 | 2 | 2 | 2 | 2 | 4 | 2 | 3 |
| Switch | 3 | 3 | 2 | 3 | 4 | 1 | 3 | 2 |
| Leverage | 4 | 4 | 4 | 3 | 3 | 2 | 3 | 1 |
| Multi-use | 3 | 3 | 2 | 3 | 3 | 2 | 3 | 1 |
| StdDev | 1.14 | 1.14 | 1.10 | 0.89 | 1.14 | 1.14 | 0.55 | 1.30 |

**Table 3: Average judge assessments**

| (A+B)/2 | Re-sources used | Timing | Org'l com-plexity | Market com-plexity | Tech risk | Reg risk | Comm. down-side | Comm. upside | Ave-rage |
|---|---|---|---|---|---|---|---|---|---|
| Min invest | 1 | 1 | 1 | 1 | 1 | 2.5 | 2.5 | 4 | 1.75 |
| Grow | 2.5 | 2 | 2 | 1.5 | 2 | 3.5 | 1.5 | 1.5 | 2.1875 |
| Switch | 3 | 3 | 2 | 3 | 3.5 | 1.5 | 2.5 | 2 | 2.5625 |
| Leverage | 4 | 4 | 3.5 | 2.5 | 3 | 2.5 | 2.5 | 1 | 2.875 |
| Multi-use | 3 | 3 | 2 | 3.5 | 3 | 2 | 2.5 | 1.5 | 2.5625 |
| Average | 2.7 | 2.6 | 2.1 | 2.3 | 2.5 | 2.4 | 2.3 | 2.2 | 2.3875 |
| Std Dev | 1.10 | 1.14 | 0.89 | 1.04 | 1.00 | 0.74 | 0.45 | 1.15 | 0.43 |

**Table 4: Attributes oriented strategy table.**

| Quartile | Resources used | Timing | Organiz-ational Complexity | Market Complexity | Technical risk | Regulatory risk | Com-mercial downside risk | Com-mercial upside potential |
|---|---|---|---|---|---|---|---|---|
| 1 | I | I | I | I<br>G | I | S | G | L<br>G U |
| 2 | G | G | G U S | L | G | U<br>L I | L I U S | S |
| 3 | U S | U S | L | U<br>S | U L<br>S | G | | |
| 4 | L | L | | | | | | I |

**Table 5: Differences between judges' assessments**

| Judge B score – Judge A score | Re-source use | Timing | Org'l com-plexity | Market com-plexity | Tech. risk | Reg. risk | Comm. down-side | Comm. upside | Distance | Correl A&B |
|---|---|---|---|---|---|---|---|---|---|---|
| Min invest | 0 | 0 | 0 | 0 | 0 | 1 | -1 | 0 | 1.41 | 0.89 |
| Grow | -1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 2.24 | 0.51 |
| Switch | 0 | 0 | 0 | 0 | 1 | -1 | 1 | 0 | 1.73 | 0.73 |
| Leverage | 0 | 0 | 1 | 1 | 0 | -1 | 1 | 0 | 2.00 | 0.77 |
| Multi-use | 0 | 0 | 0 | -1 | 0 | 0 | 1 | -1 | 1.73 | 0.64 |
| Distance | 1.00 | 0.00 | 1.00 | 1.73 | 1.00 | 2.00 | 2.24 | 1.41 | | |
| Correl A&B | 0.92 | 1.00 | 0.97 | 0.77 | 0.93 | 0.48 | 0.00 | 0.84 | | |

**Table 6: Similarity between alternatives: correlation of attribute scores, using average of both judges.**

| Correlation | Min invest | Grow | Switch | Leverage | Multi |
|---|---|---|---|---|---|
| Min invest | | | | | |
| Grow | 0.30 | | | | |
| Switch | -0.65 | -0.52 | | | |
| Leverage | -0.65 | 0.12 | 0.35 | | |
| Multi-use | -0.58 | -0.36 | 0.84 | 0.30 | |

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