13 From Findings to Knowledge

Although the overall analytical proficiency is probably the strongest predictor of the quality of data-analysis-derived decision-guiding insights, it is the ability of the organization to "absorb" the so-created knowledge that determines the value of analytics to an organization. The most ingenious analysis, best-fitting models or most eye-opening findings will have little business value, unless they are put to a productive use. The attainment and preservation of *informational advantage*, discussed in the opening chapter, is contingent on two, equally important factors: 1. the ability to create competitively advantageous and decision-aiding knowledge, and 2. the consumption of that knowledge. The previous chapters were all focused on the former—in this chapter, we turn our attention to the latter.

The ensuing discussion addresses some of the more commonly encountered impediments to taking the full advantage of analytic findings. It is important to note that those "barriers to usage" combine obstacles that need to be overcome by the prospective users of analytic insights, such as brand managers, as well as some interpretational "hang-ups" of marketing analysts.

Knowledge Implementation

The point made repeatedly throughout this book is that database analytics is about the creation of unique, competitively advantageous knowledge. In a business sense, it means transforming raw, generic data into unique insights capable of shedding explanatory light on past outcomes and directing future courses of action. As a result, the bulk of the ideas outlined in earlier chapters was directed toward the "how-to" of effective analytics, which, as discussed in Chapter 2, makes up the lion's share of the knowledge creation process discussed in this book. However, from the business standpoint, putting the resultant knowledge to work is just as important. After all, knowing without doing is of little business value, since it is unlikely to lead to any tangible benefits.

Although not as self-evident, making use of analyses-generated insights is also quite important from the standpoint of statistical analyses, for two, distinct reasons. First and foremost, it makes possible the in-market validation of analyses-derived recommendations. For instance, the efficacy of predictive models can be calibrated by contrasting the expected outcomes (i.e., model-predicted) to actual outcomes, such as purchase rates. The second statistical-analyses-related results implementation benefit is a bit more abstract: Result implementation lays the foundation for *successively approximating* expansion of the knowledge base.

In-Market Validation

The crafting of business recommendations stemming from the analysis of data is an inferential process built on the notion of probability. Originally defined by a French mathematician, Pierre Simon Laplace, "*The probability of an event is the ratio of the number of cases favorable to it, to the number of all cases possible when nothing leads us to expect that any one of these cases should occur more than any other, which renders them, for us, equally possible.*" In that sense, data-based recommendations represent the "best guess" at the appropriate, or in the case of the knowledge creation process, the most competitively advantageous course of action.

The in-market validation combines the elements of the (previously discussed—see Chapter 11) action-attributable incrementality quantification and the deployment of knowledge, which amounts to the "translating" of the often abstract relationships and coefficients into well-defined courses of action. The upcoming section offers an in-depth treatment of this topic.

Expansion of the Knowledge Base

Consider Figure 13.1, showing an outline of the now-familiar database analytical process. As depicted by the process flow, the initial roll-out of the database analytical insights-driven business actions represents a culmination of a single cycle of the knowledge creation process, which in turn kicks off the follow-up stage. In that sense, the implementation of the results of database analytics, such as the fielding of carefully constructed marketing promotions aimed at increasing the value or the productivity of the customer base, should ultimately lead to a "re-thinking" of the original analytical plan, with a resultant carry-over into data requirements setting, follow-up analyses and database re-scoring. In principle, the business knowledge creation process continues in perpetuum, to the degree to which the requisite data remains available.

In a conceptual sense, the best way of thinking about the *ongoing learning loop* characteristic of the database analytical process is in the context of the notion of *successive approximations*. The basic idea conveyed in this frequently used notion (in fields as diverse as behavioral psychology and electrical engineering) is that empirical data analyses do not instantaneously yield the best insights, but rather deliver progressively more accurate estimates, with each subsequent estimate representing an improvement over the previous one. The growing body of empirically derived and in-market-tested insights (shown as the "feedback loop" in Figure 13.1) will lead to progressively more accuracy and depth in the generated knowledge, which will ultimately evidence itself in superior decision making; i.e., sustainable competitive advantage.

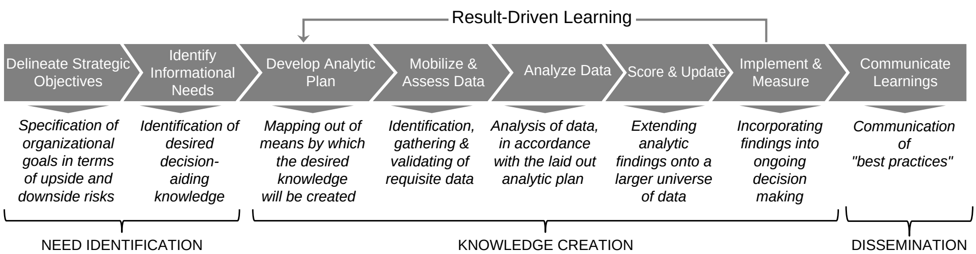

Figure 13.1 The Database Analytical Process

The cumulative learning is possible because the individual components of the broadly defined database analytical process, such as *informational needs identification*, *analytic planning* and *data mobilization* are all highly interdependent, with decisions made in antecedent stages shaping each of the successive stages. An obvious, near-term informational benefit of this "analytic coordination" is the creation of competitively advantageous data insights, rather the proliferation of generic, low-impact informational tidbits. A somewhat less obvious longer-term benefit of the analytic coordination is a gradual buildup of the organization's knowledge base, ultimately contributing to not only the sustaining but also the strengthening of the firm's competitive advantage.

No Pain—No Gain

Change is never easy. In an organizational sense, learning to "trust the numbers" represents one of the most challenging aspects of the database analytical process, largely because it requires a considerable departure from intuitive decision making, which for many business managers is the only decision mode they ever knew. The required transition can be likened to learning to fly a plane by relying on instruments, rather than visual or physiological (e.g., a feeling of descending or turning) clues and references. Because all of us grow so reliant on our own senses, we generally find it quite difficult to trust mechanical gadgets when they contradict what our own "instruments" tell us. Yet, doing just that is a critical component of safely piloting a plane. Similarly, learning to trust empirically generated insights requires a concerted effort on the part of the decision makers, but the rewards can be considerable—just ask Walmart, Capital One, Marriott, Harrah's Entertainment or any other of the analytically excellent organizations mentioned in the opening chapter.

Deployment

Putting results of empirical database analyses into action can take many different forms, ranging from product redesign to promotional mix changes and could even include expansion or divestiture decisions. In many instances, as the knowledge accumulates, the resultant decisions may take on an increasingly broad scope.

Regardless of the scope, however, results of empirical analyses usually need to be "translated" business terms and/or processes. What is important here is not just the conversion of *numerical effect estimates* into *applicable business terms*, but also the proper framing of these results in terms of (any) applicability limits. In general, no empirical results are universally and indefinitely true and applicable, which means that the deployment of these learnings needs to encompass explicit usability limits. It might sound somewhat counterintuitive, but excessive reliance on rigid, standard measures assessing the decision making worthiness of analytically derived insights should be approached carefully. In particular, the use of statistical significance tests as the basis of differentiating between important and trivial insights needs to be approached especially cautiously. Some of the reasons behind that recommendation were outlined in Chapter 8—a more explicit treatment of this topic, as it relates to the implementation of analytically generated insights is presented below.

Also important is a proper framing of numerical coefficients. Recall the two examples discussed in Chapter 11. Example 1 illustrates the often-seen tendency to report as valid statistically computed sales lift that lacks (statistical) significance. Example 2 brings to light the even more commonly observed tendency of ascribing statistical significance levels to exact (point estimates, in statistical jargon) values. Both can have a profound impact on the validity and the reliability of the resultant knowledge and both are highly dependent on the application of statistical significance tests.

Effect Quantification vs. Significance Tests' Applicability Limits

Although the proliferation of their usage might suggest a universal acceptance of statistical significance testing (SST) as an effect validation standard, that is not at all the case. In fact, it is hard to think of another statistical concept that continues to generate as much controversy among methodologists. Although widely used on the one hand, these tests' validity and credibility as an impact confirmation tool continue to be assaulted, particularly in the academic/scientific literature. Some of the most pungent points of view relating to that debate are outlined below.

To start, acknowledging the ongoing methodological debate still in need of a resolution, a sweeping review of SST applications by one researcher concludes that "*. . .researchers have inappropriately utilized statistical significance as a means for illustrating the importance of their findings and have attributed to statistical significance testing qualities it does not possess*" (Daniel, 1998, p. 23),[1] echoing an earlier conclusion that "*. . .it is more difficult to find specific arguments for significance testing than to find arguments decrying their use*" (Henkel, 1976, p. 87).[2] Alarming conclusions like these prompted the establishment of the Task Force on Statistical Inference to study the issue and make usage recommendations. The group's initial conclusion was to recommend that significance testing be abandoned as a hypothesis testing tool, which stance was later softened to instead urge caution in the tests' application and interpretation. Interestingly, even proponents of SST are careful to qualify its applicability by declaring on one hand that "there is nothing wrong with statistical tests themselves," while qualifying the tests' applicability by continuing to say that significance tests are valid "*. . . when used as guides and indicators, as opposed to a means of arriving at definitive answers*" (Huberty, 1987, p. 7).[3] Unfortunately, as detailed earlier, that somewhat fine line rarely gets clearly noticed in practical (i.e., business analyses) SST applications.

To a large degree this is due to the fact that in purely scientific research, not arriving at definite answers is a reasonable constraint, but it is not so in the context of practical business applications, such as marketing program impact measurement. The usually significant level of capital expenditures associated with large-scale promotional programs translates into heightened expectation of definite program performance answers. The inability of significance tests to support such informational needs is among the key indications of the lack of *program measurement objectives–SST applicability* fit discussed earlier in this text.

This is not to say that statistical significance testing should never be used as a business analysis tool, as there are situations where SST can deliver robust and reliable insights. I *am* suggesting, however, that it is irresponsible to "default" to it as the measurement norm without explicitly considering its merit in the context of specific business objectives, data and generalizability constraints. This can be accomplished by assessing the goodness-of-fit between measurement objectives and SST applicability limits using the evaluative dimensions listed and discussed below.

1. Sample size dependence.
2. Replicability fallacy.

3. Exact quantity fallacy.
4. Representativeness fallacy.
5. Impact fallacy.

Why these specific criteria and why are they important? The short answer is that they represent potentially the most influential misapplications of the statistical significance testing to the creation of robust and competitively advantageous business insights. Their "fallacy" stems from the degree to which each of those specific factors tends to represent a practical business analysis misapplication of a distinct theoretical notion—in other words, some of the commonly accepted practical applications are in fact in direct violation of the individual concepts' theoretical rationale. Both the validity and the reliability of the data-derived insights can be severely impacted by any of these fallacies.

The ensuing discussion is built around questions highlighting the potential pitfalls, followed by clarifying discussions and corrective recommendations. Although not always explicitly stated, individual recommendations combine the academically rooted methodological considerations with practically acquired cumulative empirical experience.

Sample Size Dependence

Question:

What will be the impact of SST sample size dependence on the validity of the findings?

Discussion:

It is apparent from SST formulations that the likelihood of detecting statistically significant differences increases as a direct function of sample size, so much so that the initially statistically insignificant *treated–control* differences can gain statistical significance with relatively modest sample-size increases. In general, keeping everything else the same and doubling the sample size will lead to more-or-less doubling of the probability of finding statistically significant results; tripling the sample size will lead to approximately tripling the probability of finding statistically significant results, etc.[4] In many instances, a sample size of several hundred records will lead to inordinately trivial differences becoming statistically significant.[5]

Promotional programs generally involve large sample sizes, as their business viability depends on scale. Not surprisingly, in the context of many typical programs even the most trivial cross-group differences will attain statistical significance casting doubt on SST's ability to differentiate between spurious and persistent effects. To counter that, it is often argued that a clear distinction be drawn between "statistical" and "practical" significance, which is almost always a highly subjective undertaking. As argued in Chapter 8, the "statistical" vs. "practical" significance split is an artifact of SST misapplication in the first place, in addition to which, the necessity of drawing such an arbitrary line of demarcation leaves one pondering the very value of significance testing as an objective benchmark.

Recommendation:

Make sure group-level sample sizes are in the range of 150–500 usable records; if any of the group-level sample sizes are in excess of 500 records, select a smaller subset of 500 or fewer records using a random, stratified or other appropriate sampling technique.

Replicability Fallacy

Question:

Should statistical significance be used to project the current program's results onto future replications of the current program?

Discussion:

In spite of misperceptions to the contrary, statistical significance testing does not support longitudinal generalizations, or result replicability. If a particular program generated statistically significant sales incrementality, it is not correct to ascribe any confidence (in a statistical sense) to the expectation of that program generating similar results when replicated in the future. SST is limited to generalizing sample-based results to the population from which the sample was drawn at a given point in time—and that's all.

For example, if we started out with a population of 2 million first-time buyers from which we selected a random sample of 200,000 to be targeted with a particular offer, we could expect to generalize any statistically significant results onto the original 2 million starting universe. We could not, however, draw any conclusions regarding future replicability of the results, which is a considerable limitation from the marketing point of view. The reason future-pointing generalizations are not plausible is due to the test statistics' cross-sectional rather than longitudinal emphasis. In other words, the t-test, χ^2 or the F-test (used to detect persistent vs. spurious differences between/among group means or proportions) utilize cross-individual and a single point-in-time information—not cross-individual and cross-time patterns. Consequently, significance testing supports sample-to-universe, but not today-to-future generalizations. This is an example of SST application and interpretation limits running counter to business users' (e.g., promotional program managers') informational needs and it is one of several reasons for why significance testing is not a universally applicable tool.

Recommendation:

Do not use statistical significance testing as the basis for making result replicability claims; use it only to generalize sample-based findings onto a larger population (from which the sample came) but without any future-pointing implications. You might have reasons to believe that similar-to-current results can be expected in the future, but SST should not be used to substantiate those claims.

Exact Quantity Fallacy

Question:

Should the results of a statistical significance test be applied to an exact quantification of the program impact (e.g., a buy rate of x%)?

Discussion:

This topic has already been covered in a sufficient level of detail earlier in this book, thus the current remarks are a summary of the previously made observations (see *Example 2: Ascribing Statistical Significance to Exact Values*, discussed in Chapter 11). As discussed there, it is common to interpret statistical significance in the context of what is technically referred to as a "point estimate," which is statistical jargon for describing an exact quantity such as an incremental buy rate of 15%. In spite of it being a relatively common practice, statistical significance cannot be ascribed to an exact value—it can only be associated with a range of values known as a *confidence interval*. This means that it is incorrect to associate confidence levels (e.g., 90%, 95% or 99%) with a specific numerical quantity, such as a sales lift of 15%, as doing so will likely produce misleading or outright inaccurate results.

Recommendation:

Do not apply statistical significance to exact impact quantifications, such as a response rate of x%; limit its application to range-based estimates.

Representativeness Fallacy

Question:

Should statistical significance be used to verify the representativeness of the program targeted sample (i.e., to attest to the degree to which the sample looks like the population from which it came)?

Discussion:

Again, despite common misperceptions to the contrary, statistical significance testing does not measure the degree to which a sample represents the population (from which it was drawn). The only way to make that determination is to develop a carefully constructed sampling plan on the front end and take appropriate sample-to-population cross-validation steps on the back end. All too often, however, there is a tendency to use the results of significance testing to validate the sample representativeness, which is erroneous. As a matter of fact, the frequently seen and somewhat counterintuitive "negative incrementality" results are indicative of some level sample-to-population incomparability, more so than they are manifestations of a promotional program depressing sales (which, frankly is hard to accept on its face value).

Recommendation:

Do not use SST as a basis for verification of the program sample's representativeness; develop a robust sampling plan as a basis for selecting program targets and follow up with a sample-to-population cross-validation.

Impact Fallacy

Question:

Should statistical significance be used as a proxy for business importance of results in question?

Discussion:

Frequently, the term "statistical" is dropped and the results are described as being "significant," rather than merely "statistically significant." Particularly in the business context, the former might be taken to mean "being of practical relevance and/or importance," which is a considerably stronger characterization than might be warranted, especially when put in the context of the previously discussed SST's sample-size dependence. Imagine the following scenario: A large-scale (read: large sample size) marketing initiative testing an unorthodox offer generates statistically significant results, which are then presented as being "significant" with the statistical descriptor dropped to enhance user-friendliness of the results intended for a non-technical audience. The unorthodox offer is then heralded as the approach to replace current practices. . .

Let's now take a look at what information might have been skipped over: Although the response rate to the above "unorthodox" promotional initiative was low it was higher that its control group, by a small amount, but because of the larger sample size the trivial size lift was statistically significant (see *Sample Size Dependence* discussion above). In addition, there might have been profiling differences between treated and control groups, introducing another and confounding source of cross-sample variability, which is another way of saying that the observed treated vs. control difference might be, at least in part, due to the inherent differences between the two groups. Moreover, once the confidence level around the lift was calculated as required (see the *Exact Quantity Fallacy*), what appeared as a small but positive lift as a point estimate all but disappeared once expressed as a range. That coupled with the inability to make future replicability generalizations (see the *Replicability Fallacy*) showed the "unorthodox" treatment as a risky venture with still unproven promise.

Recommendation:

Do not use statistical significance as a proxy for business impact; consider an alternative approach discussed later in this chapter.

Framing of Coefficients

As mentioned earlier, there is a tendency to report as "real," sales lifts lacking statistical significance, and to ascribe statistical significance levels to exact, rather than ranges of values. Keeping in mind the potential misuses of the broadly defined statistical significance testing discussed above, even when a particular quantification (e.g., a relationship between two measures expressed as a correlation, an impact quantification expressed as dependence) lends itself to statistical significance "validation," the resultant interpretation of numerical coefficients calls for close scrutiny.

Rule #1

Numeric coefficients lacking statistical significance (i.e., those falling short of a stated threshold, such as $\alpha = 0.05$) are spurious and should not be interpreted as anything other than random noise.

Rule #2

Exact quantities (such as sales lift or bivariate correlation) should not be ascribed a level of significance. Confidence intervals (see Chapters 8 and 10 for details) should be computed for each quantity, and statistical effects should be expressed as ranges of values.

The above rationale is straightforward: In situations where statistical significance testing can be used within its applicability limits and its use is deemed beneficial, the notion needs to be interpreted correctly to ascertain valid practical interpretation of findings.

Updating

As illustrated in this book, in order to deliver the most value to an organization, database analytics should be viewed as a process, rather than a singular event. Consequently, the results it generates should be additive as singular contributions and also lead to a progressively more robust organizational knowledge base. In other words, the individual analysis-generated business insights ought to make incremental contributions to the overall organizational informational reservoir. In a more abstract sense, they could be thought of as representing successive approximations to the optimally effective business decision making model.

In contrast to most of the procedures and approaches described in the previous chapters, the task of updating the firm's knowledge base with results of successive database analytical "cycles" is somewhat softer in a procedural sense, while at the same time it is highly dependent on the type of analysis driving a particular update cycle. Overall, the importance of cycle-specific updating is a function of the expected stability of findings, with the need to update being inversely related to said stability—i.e., the more stable the results, the lower the update need.

There are four broad types of analysis (detailed in Chapters 8 through 11) that could be employed as a part of the database analytical process described in this book: Exploratory Analyses, Segmentation, Behavioral Predictions and Incrementality Measurement (see Figure 13.2.). It seems intuitively obvious that Exploratory Analyses, as described in Chapter 8, will yield the most stable results, while Incrementality Measurement, as described in Chapter 11, will be the most update-intensive, because of its "action–result" capture orientation. In general, Segmentation results will usually be updated with a relatively low frequency as well, but for a different reason. Most firms use the results of segmentation analysis as basis for crafting a part of its customer/ competitive strategy, which makes frequent segmentation updates relatively undesirable as it would translate into corresponding changes to the strategy as well as its execution, which under most circumstance would be cost-prohibitive. Thus in a practical sense, it is appropriate to conduct segmentation updates on less frequent basis.

In contrast to segmentation, behavioral predictions are more tactical in nature, which makes more frequent updates both more practically feasible and desirable. A typical application of a behavioral prediction is a customer type-based treatment differentiation. Here, a typical update is represented by a re-calibration of a predictive model (see

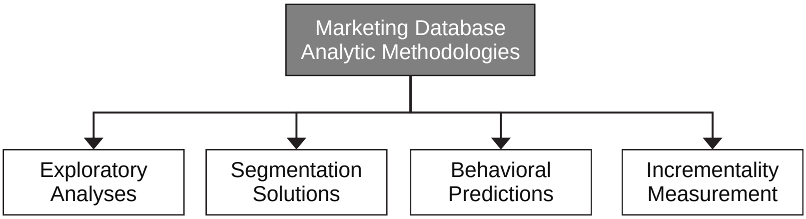

Figure 13.2 Types of Updatable Analyses

Chapter 8) used to estimate record-level response propensities. An update, again under most circumstances, would translate into some amount of re-shuffling of the customer base and a resultant re-designation of high- vs. low-value customers. In practice, the same strategy and offers could be used, but would be targeted at a different group of customers.

The last of the four general types of analyses, Incrementality Measurement, calls for the highest update frequency. In fact, each set of results should be added to the previous. However, in contrast to segmentation or behavioral predictions updates (where the focus is on refresh and replacement of old values by new ones), successive incrementality estimates are additive in nature and knowledge insights are generated from the accumulated total, rather than the most recent results.

Hence it follows that update considerations should take place in the context of the type of analyses, the type of update action required (i.e., accumulation vs. replacement) and lastly, update frequency, as summarized in Table 13.1.

Table 13.1 Update Decision Criteria

Type of Analyses	*Update Action*	*Update Frequency*
Exploratory Analyses	Adding to the “catalogue” of observed patterns and relationships. *Action: Accumulation.*	Lowest
Segmentation	Re-definition of segments and/or refresh of segment profiles. *Action: Replacement.*	Low
Behavioral Predictions	Adding new and/or refresh of existing record-level propensities. *Action: Accumulation or replacement.*	Medium
Incrementality Measurement	Adding new “action–response” results to the existing catalogue. *Action: Accumulation.*	Highest

Mini-Case 13.1: Deploying Database Marketing as a New Customer Acquisition Tool

Database marketing is a relatively recent promotional tactic leveraging stored current customer and prospect information as the basis for designing targeted, direct-to-consumer purchase-inducing programs. It is one of the most efficient and effective methods of systematically growing brand sales, as it supports result-based pairing of consumers and promotional investment. In other words, the higher expected future-value targets, representing either the current customers or prospects are allocated a larger share of the promotional investment than their lower-value counterparts, which is the essence of *look-alike* targeting (which is a tactical application of the earlier discussed look-alike modeling). Using that approach, the initial analysis of the current buyer base gives rise to the identification of high- and low-value customer segments, which in turn supports profile-based similarity matching, where consumers (i.e., potential buyers) who most closely resemble the high-value customers (i.e., current buyers) are identified and set apart from the rest.

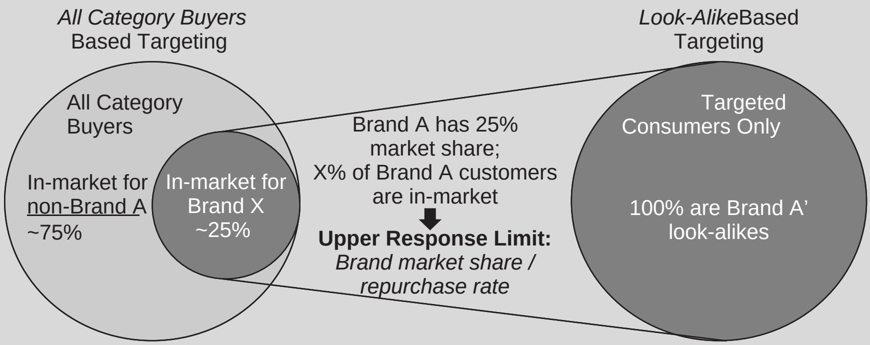

Figure 13.3 Look-Alike Targeting

Finally, the resultant promotional efforts are directed toward those high-value customer look-alikes, as illustrated in Figure 13.3.

The rationale of look-alike-based prospect selection is compelling, especially when compared to an undifferentiated approach (selecting prospects at random), which tends to be highly ineffective, especially when looked at through the prism of the cost per acquired buyer metric. The *efficacy differential* separating these two new customer acquisition approaches is well-illustrated by an automobile repurchase example, in which case, most of the "in-market" (a probabilistic estimate based on time since the last purchase, which is knowable because vehicle registration data is commercially accessible) prospective buyers are not likely to be interested in Brand X. Targeting the entire in-market universe of prospective buyers, i.e., all category prospects, would lead to a considerable dilution of promotional resources, as the more-or-less fixed amount of resources would have to be divided across a very large base. That means that the same amount of resources would be allocated to all prospects, regardless of how likely or unlikely they might be to be interested in Brand X. To make things even worse, the anticipated response rate to just about any promotional offer will also be diluted, as illustrated in Figure 13.3, as 75% of all of those who are in the market for a new car are not likely to be interested in Brand X.

Given these and other disadvantages of an undifferentiated acquisition strategy where all category buyers (e.g., all current auto owners who are deemed to be in-market) are effectively presumed to be equally good prospects, Brand X elected to make use of the look-alike-based campaign logic (graphically shown in Figure 13.4) by limiting its promotional efforts to only the "pre-qualified" prospective buyer segment, which is comprised of that subset of the total best resembling its current owners. Operationally, the said resemblance was estimated based on a comprehensive, multivariate profiling composite, which made use of all available and applicable metrics and allowed all prospects to be rank-ordered based on their individual score of *current brand buyer resemblance*, as illustrated here. The advantage of the look-alike targeting approach was twofold: First, it led to a greater concentration of promotion-based persuasion on the highest brand purchase propensity

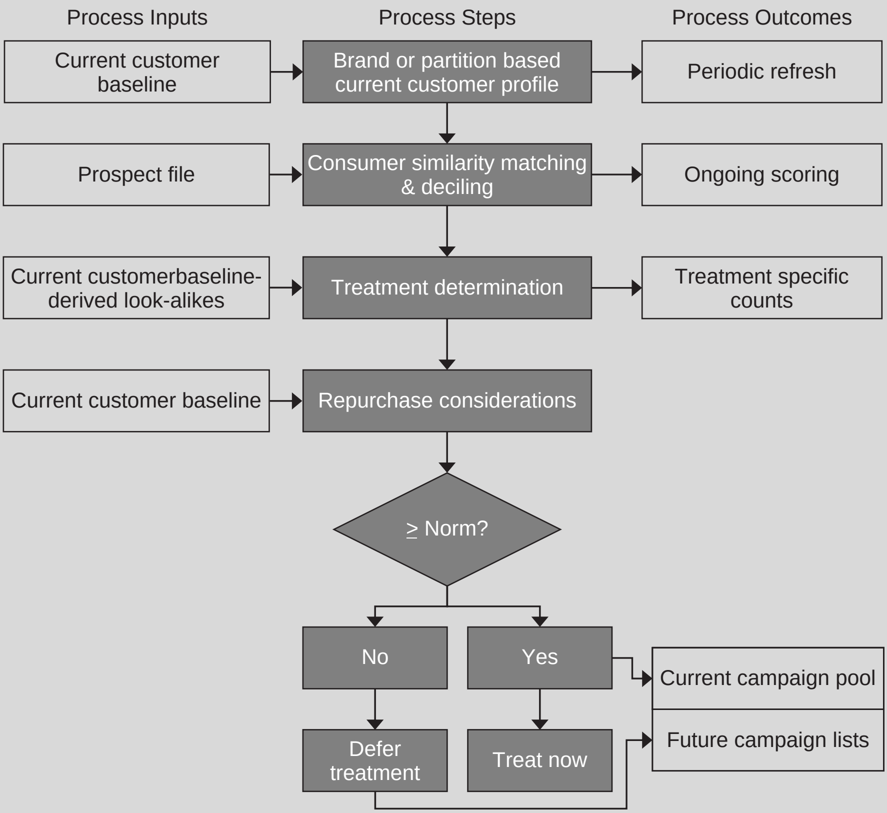

Figure 13.4 Differentiated Acquisition Logic: Getting Started

consumers, which in practice translated into more impactful (i.e., expensive) promotional materials. Second, it made possible further propensity-based treatment (i.e., offer type) and spending (i.e., offer value) differentiation. More specifically, the pre-qualified universe of prospective buyers meeting the minimum threshold of brand purchase propensity was further subdivided into high, medium and low opportunity groupings (highest, second highest and lowest, correspondingly, brand purchase propensity scores), which made possible even greater "fine-tuning" of the new customer acquisition strategy. The generalized flowchart shows the overall logic (Process Steps) as well as the requisite inputs (Process Inputs) and informational outcomes (Process Outcomes) of the overall process. It is important to note that the decision making steps depicted here describe only the "initial touch" considerations, which means the making of the initial promotional offer, based on the initially available data. Given the ongoing character of the database analytical process detailed in this book, the results of the "initial touch" shaped the design of the follow-up promotional steps. In an analytic sense, the initial look-alike-based selection strategy was extended longitudinally, which resulted in a repeatable, ongoing prospective buyer targeting process, graphically illustrated by the multi-step, extended diagram shown in Figure 13.5.

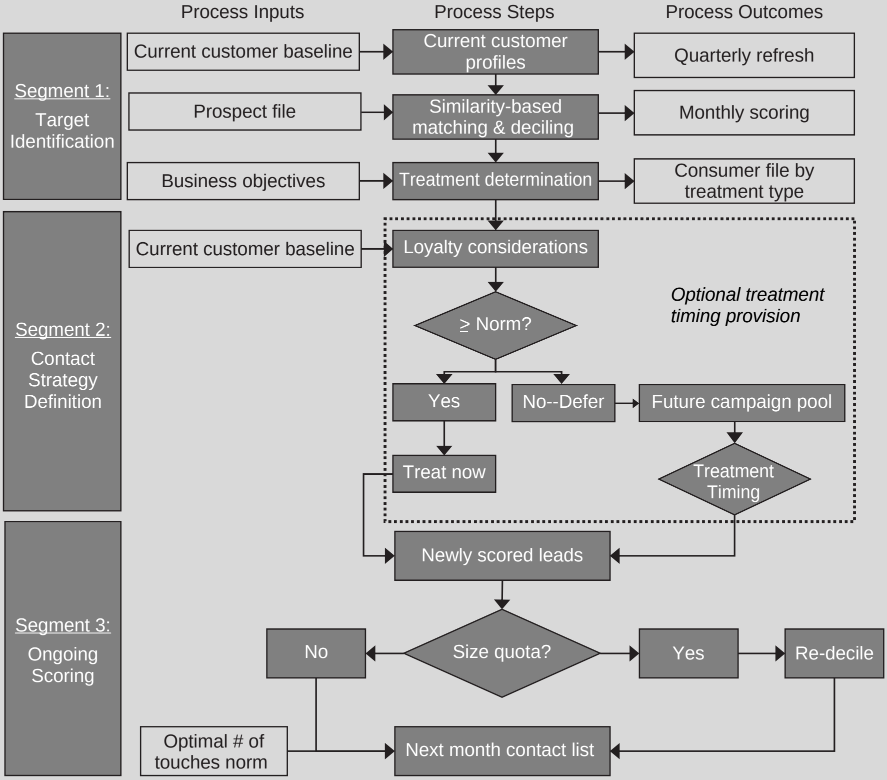

Figure 13.5 Differentiated Acquisition Logic: Ongoing

Although the logic illustrated by the extended diagram (see Figure 13.5) has the appearance of complexity, it is relatively intuitive and easy to implement. The process is comprised of three distinct segments: 1. *target identification*, built around look-alike modeling; 2. *contact strategy definition*, spelling out the specifics of the differentiated treatment investment allocation strategy; and 3. *ongoing scoring*, where the look-alike model-derived propensity scores are updated using recent behavioral patterns. Each of the segments is made up of multiple steps joined together by sequential logic; the entire process is a closed-loop system meant to repeat its steps until externally halted. The rationale embedded in this specific application (manufacturer-originated automotive marketing) can be easily generalized, which is to say it can be used to develop similar approaches in other product or service categories. The central notion of that rationale is an idea that customer retention as well as new customer acquisition efforts should be guided by the desire to align investment levels (i.e., per customer/prospect promotional spending) with anticipated benefits, which parallels the familiar return on investment considerations. In this sense, the knowledge derived from the database analytical processes described in this book can and should be used to provide empirical basis for making these decisions.