CHAPTER 4

Developing a Predictive Business Analytics Function

Think of analytics as a toolbox. One screwdriver of a particular size and style isn't going to build you a chest of drawers—much less so in the hands of an inexperienced carpenter.

—John Lucker, "Business Analytics: Fad or Fundamental?," Deloitte Development LLC, 2012

> Although some amount of predictive modeling can be done by means of pre-formed queries, pivot tables, summarized reports, and so on—that's just rudimentary. The ultimate value of all that data will only become evident if the people who know how to think about the data can access it easily, explore different views, test various hypotheses, and share their findings effectively.[1]

Many organizations have often introduced or at least recognize the need for an analytical capability to better understand how past events might influence future plans, shape decisions, and impact expected operating results. These organizations may develop specific applications or practices such as forecasting, scenario modeling, and contingent planning, to name a few, to address these analytical needs. While these tools and techniques address specific requirements, they can vary in terms of usefulness, relevance, and responsiveness.

In essence, what organizations are seeking is to make informed decisions based on the most current, relevant information available at the time. What distinguishes predictive business analytics (PBA) is that the decision-making process is rooted in a structured, continuous, and data-driven process that enables an organization to select actions with a fair degree of understanding of how these decisions and actions were determined and to have a reasonable level of confidence regarding outcomes and impacts.

An effective way to determine the need and potential benefits for developing a PBA capability is to assess the need according to your organization's level of maturity and capabilities. A simple but illustrative chart, Exhibit 4.1, allows you to gauge your organization's level of maturity and capabilities as a starting point to determining how to best structure a PBA function that is sustainable and will be viewed as a value contributor to your company's success.

Once you have gauged your organization's level of maturity and current capabilities, the next step is to set a direction. Our experience tells us that to best achieve success it is advisable to follow two concurrent paths to getting started. First, adopt a change management process, and second, envision a desired target state.

GETTING STARTED

> People change what they do less because they are given analysis that shifts their thinking than because they are shown a truth that influences their feelings.[2]

In John Kotter's landmark book on organizational change, *Leading Change*,[3] he described a process for effecting change in an organization. The art of starting a PBA process can leverage from his Eight-Stage Process of Creating Major Change (see Exhibit 4.2). This initial set of steps is particularly critical to achieving a solid start.

Exhibit 4.1 Predictive Business Analytics Maturity Capability Map

Stage	I	II	III	IV
Characteristics	**Traditional Analytics**	**Specific Events**	**Functional Silos**	**Integrated**
Process	■ Reacts to ad hoc inquiries ■ Reviews and decision making follow routine practices ■ Gut feel	■ One-off analysis of a specific event or transaction ■ Team formed for purpose and disbands after completing analysis	■ Established function but is limited to designated area of focus ■ Informal interactions and sharing of results and data	■ Well-developed process with established rules of governance and communications ■ Track record of success
Data	■ Historic and available ■ Little validation of cause and effect ■ Primarily internal and single data type	■ Collecting available data on an ad hoc basis ■ Purchased database or benchmark	■ Fragmented and stored within functional area ■ Limited awareness across organization ■ Data-driven decisions	■ Routinely captured and stored ■ Tested for relevance and integrity ■ Data-driven decisions
Tools	■ Nonspecialized (e.g., MS Excel)	■ Some level of analytical data mining software ■ Some level of statistical modeling	■ Some level of analytical data mining software ■ Some level of statistical modeling	■ Use of recognized tools for analytical purposes ■ Adaptive to prior uses and future needs
Skills	■ Nonspecialized generalist ■ Subject matter expert as requested	■ Skill contributed by team members and possible use of outside consultants/SMEs	■ Skill contributed by team members and possible use of outside consultants	■ Skill contributed by team members and possible use of outside consultants ■ Supplemented easily from other functions within the company
Organization	■ Functional group (e.g., Finance)	■ Sponsor is focus on specific project ■ Sponsorship varies from project to project	■ Supervision is within functional area ■ Culture is accepting but with need for tight control and validation	■ Supervision is within functional area ■ Culture is accepting but lesser need for tight control and validation
Management Process	■ One-off reviews and decision making	■ One-off reviews and decision making	■ Decisions and actions are often focused on functional area ■ Lack of system integration of decisions and actions	■ Decisions and actions are focused on cross-functional impacts ■ Highly developed sense of system integration of decisions and actions

Exhibit 4.2 Eight-Stage Process of Creating Major Change

Step	Action	New Behavior
1	Increase urgency	People start telling each other, "Let's go—we need to change things!"
2	Build the guiding team	A group powerful enough to guide a big change is formed and they start to work together well.
3	Get the vision right	The guiding team develops the right vision and strategy for the change effort.
4	Communicate for buy-in	People begin to buy into the change, and this shows in their behavior.
5	Empower action	Most people feel able to act, and do act, on the vision.
6	Create short-term wins	Momentum builds as people try to fulfill the vision, while fewer and fewer resist change.
7	Don't let up	People make wave after wave of changes until the vision is fulfilled.
8	Make change stick	New and winning behavior continues despite the pull of tradition, turnover of change leaders, and so forth.

Source: John P. Kotter and D. S. Cohen, The Heart of Change *(Boston: Harvard Business School Press, 2002).*

SELECTING A DESIRED TARGET STATE

Once the change management process is recognized and being applied, the guiding coalition team should size up an area to examine where improvement opportunities exist for predictive business analytics. Though major wins and successes are showcases, the path of concept proving will likely be a more desirable approach. Proof of concepts should be short term and have easily definable expected outcomes; require a reasonable level of resources, both people and tools; and strive for short-term wins that are tangible, impactful, and readily implementable.

The team needs to evaluate target-state alternatives, with each alternative evaluated based on decision criteria that achieve a best fit for launching the process. A tool used by many companies to review best-fit options is the quality functional deployment (QFD) approach. The value of QFD is that:

- The customer's wants and needs are inputs to this process.
- A matrix format is used to record vital information.

- Customer needs are translated into requirements.
- An analysis of requirements is facilitated and priorities are determined.
- The output is key to actions and issues for improving customer satisfaction based on customer inputs.

The QFD work involves a series of interrelated steps, as follows:

Step 1: Identify the customer wants and needs, often called the "whats."

Step 2: Customer ranking or weighting of customer needs:

- How important are the "whats" to the customer?
- Usually ranked on a 1 to 5 scale.

Step 3: How will we satisfy the customer needs ("whats")? What are the actionable items (process steps, inputs, etc.) to meet needs ("hows")?

Step 4: Understand the influence of each "how" on the "whats"—to what extent does each action correlate to the customer needs? Usually, a weighting is associated with each "what." For example, we could use a weighting scale of Strong = 9, Medium = 5 or 3, and Low = 1. These are wide enough to provide distinction in assigning weights. A caution: Often groups will try to put too fine a point on these weights and offer 8.5 instead of 9. This will make the evaluation process more difficult without adding much value.

Step 5: Identify the critical few "hows," multiply the "whats" weightings times the "how" relationship scores, and add together to obtain the total for the column.

A simple example (Exhibit 4.3) can best illustrate how QFD might be applied to delivering pizza. We have identified the "whats" and "hows" and assigned to each "what" an importance ranking. We then assign a rating to the "how" for each "what" and multiply the importance ranking times the requirements rating. For example, "Take order" is rated a 9 for "Ingredients are correct," and since this "what" has a ranking of 4 assigned to it, the total value of this "what" is 36 (i.e., 9×4). The next "what," "Pizza tastes good," is ranked a 5 in importance, but for taking the order it is only a 1 (least important) to satisfying this "what" or need. The total score is 41 (i.e., 36 + 5). By

Quality Function Deployment Matrix		Requirements (Hows)				
Customer Needs (Whats)	**Importance Ranking**	Take order	Transfer order to kitchen	Prepare pizza	Bake pizza	Deliver
Pizza is hot	5				9	9
Ingredients are correct	4	9	3	9		
Pizza tastes good	5	1		9	3	1
Low cost	2			3	1	3
Timely arrival	3		9	3	1	9
Relative importance		41	39	96	65	83

Exhibit 4.3 Importance Ranking

processing each of the cells, we can deduce that the best fit to satisfying the customer needs is finding a restaurant that prepares the best-tasting pizza with the correct ingredients and can deliver it hot.

Once priorities and capabilities are recognized, your organization needs to adopt a desired target state that is built on a solid analytical foundation. A suggested PBA continuous framework is discussed next and is depicted in Exhibit 4.4.

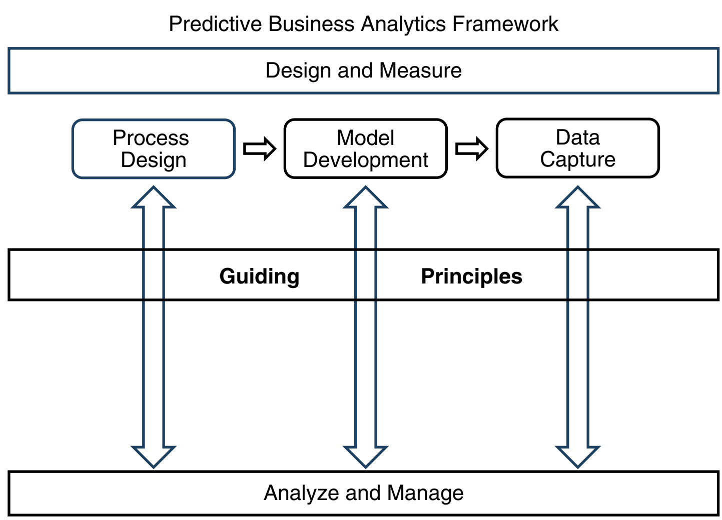

Exhibit 4.4 Predictive Business Analytics Framework

ADOPTING A PBA FRAMEWORK

As the opportunities for PBA become more important to the company based on early wins and success stories, it is now positioned to design and develop a process framework. An effective approach to developing and sustaining an integrated and continuous PBA process is best accomplished by deploying a framework that is continual (i.e., ongoing), coherent, and collaborative throughout the organization.

Exhibit 4.4 illustrates a framework that has been demonstrated to work effectively in numerous organizations. Although adaptations are always necessary, this framework can serve as a navigation or starting point to enable and encourage an organization to begin to build its capabilities and competences. It is important to recognize in setting up the analytical process that it should be organized to manage the whole value stream (i.e., all processes required to create value for the customer), rather than manage and optimize each process step in isolation.

DEVELOPING THE FRAMEWORK

For PBA to be effectively deployed by an organization, a continuous framework is essential to an effective understanding of the events, their relevant drivers, and their impact on decision making. The framework has two major components: (1) a structural element that focuses on design and measurement and (2) a managerial element that focuses on analysis and management.

In this chapter, we address the structural element, which is developed in three key steps:

Step 1: Process design.

Step 2: Model development.

Step 3: Data capture.

In Chapter 5, we address deploying the PBA function, which involves analyzing and reporting on the data and managing the process to take actions and make decisions.

Step 1: Process Design

The objective is to develop a process that enables the organization to predict a future outcome based on expected cause-and-effect relationships. The ability to leverage and/or refine historical relationships based on changes in current business conditions, competitive landscape, economic trends, and so forth is an inherent aspect of the process. But there needs to be caution about fundamental changes regarding the future that are not currently apparent. In essence, the ability to distinguish an anomaly from a fundamental change in cause-and-effect relationship is critical to implementing an effective process. It is important during process design to keep the guiding principles discussed in Chapter 3 continually in mind, and to test whether the new process highlights (1) a cause-and-effect relationship; (2) a balance of financial and nonfinancial, internal and external measures; (3) relevance, reliability, and timeliness; (4) integrity; (5) accessibility; and (6) the potential to drive desired behaviors.

The process design can be accomplished using a range of techniques, from highly quantitative mathematical models often used by investment banking organizations to drive their trading operations and trading decisions, to anecdotal approaches sometimes referred to as trial and error or experiential models (see discussion of Delphi method in the next subsection). Many organizations adopt a hybrid approach, and use regression analysis to form the baseline model. They then refine outcomes based on experience of senior managers and employees, who provide subject matter expertise due to their broad and deep experiences in the subject area. Although regression is more definable, is less subjective, and encourages collaborative involvement, managerial experience can help to foster ownership of the process among users within the organization.

In addition to determining the appropriate techniques, other factors that influence the process design are the resource requirements and organizational context. Resource considerations typically include defining the requisite analytical skills, functional knowledge and capabilities, and scope of decision authorities that need to operate to sustain the PBA approach. In terms of organizational context, the culture and the roles and responsibilities play a critical part in determining how best to deploy the process, and set the necessary boundaries around analysis and decision making. Understanding the cultural boundaries is critical to ensure that the PBA process assists in driving the right cultural incentives.

For example, a new product launch requires close coordination among several organizational functions, including marketing, sales, distribution, and manufacturing. The PBA process must (1) integrate the key drivers for each function, (2) reliably link cause and effect across the process, and (3) display alternatives for several key decisions and actions associated with the new product launch. Any one flaw in this chain of events could undermine the overall success of the product launch. In addition, the PBA process must demonstrate balance between internal (e.g., new product cycle time) and external (e.g., first-year sales) measures. Small to midsize organizations have an inherent advantage in that their size can facilitate more direct communications and interactions and better promote coordination of decisions and actions than is easily achieved in a large organization, where there can be a wide scope of responsibilities for decision making.

The decision as to which process design is better may be determined by a variety of considerations, including:

- **Industry dynamics** may affect an organization's business model and cycle (e.g., long cycle versus short cycle), competitive position, and regulatory and environmental boundaries.
- **Degree of impact** is another factor that influences the process design in terms of response time, cost impacts, order cycle, inventory levels, staffing levels, and capital investment.
- **Materiality and volatility** can also be key factors to consider in designing a workable process, especially by viewing the balance between these two factors. Exhibit 4.5 illustrates a set of managerial actions based on these factors, and appropriate actions arising from balancing these relationships in a way that would support the selected process design.

Step 2: Model Development

The initial step in model development is to determine the relevant relationship(s) between an input and its outcome. Inputs can be discrete events (e.g., change in London Interbank Offered Rate (LIBOR), new product launch); aggregated events (e.g., unemployment rates, consumer delinquencies); or structural events (e.g., new plant,

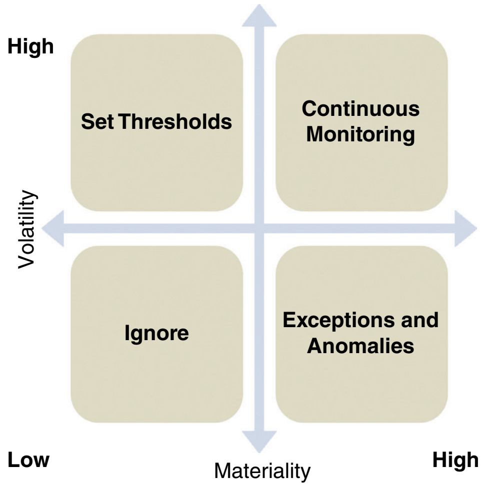

Exhibit 4.5 Suggested Actions in Relation to Materiality and Volatility of Data

regulatory approval). Often these inputs are referred to as "drivers," and can be viewed as leading indicators of future outcomes. Outcomes are the results of events, can be measured over a period of time, and can be viewed as lagging indicators. This is the basis of the "strong cause-and-effect" principle discuss in Chapter 3. For example, an airline makes reservations for a scheduled flight (input/aggregated event) and immediately can measure its change in passenger revenue (output/result). What is essential is to determine the likelihood that this relationship between events and outcomes has been consistent over time and that there is a reasonable expectation that these relationships will continue into future periods. There are numerous refinements to the airline example, such as pricing of reservations, cancellation policies, and historical trends (do airlines ever overbook?). After an organization understands and determines its drivers and results relationships, it can begin to develop, refine, and apply these relationships to its PBA process. A critical few driver relationships can account for a significant portion of the predictive results.

According to David Brooks, "If you asked me to describe the rising philosophy of the day, I'd say it is data-ism. We now have the ability to gather huge amounts of data."[4] Some even term this *big data*. This raises the question: What situations do quantifiable measurements hold forth as a mechanism to predict the future, and in which situations should we rely on intuition or gut feel to anticipate future events and outcomes?

Anyone who has ever watched a sports competition is familiar with expressions like "on fire," "in the zone," "on a roll," and "momentum." But what do these expressions really mean? In 1985 when Thomas Gilovich, Robert Vallone, and Amos Tversky studied this phenomenon for the first time, they defined it as follows: ". . . these phrases express a belief that the performance of a player during a particular period is significantly better than expected on the basis of the player's overall record."[5] Their conclusion was that what people tend to perceive as a "hot hand" is essentially a cognitive illusion caused by a misperception of random sequences. Gilovich, Vallone, and Tversky argued that time series results from basketball are indistinguishable from repeated uneven coin tosses (the coin might have a probability of success that is different from 50 percent).

Despite being extremely influential in the scientific community, their conclusions were highly controversial, as the vast majority of sports fans remained confident that sometimes players are indeed "on fire." Could it be the case that fans were right after all? The answer is a little complicated and depends on the specific task, but data seems to suggest that a hot hand does exist after all.

When studying this phenomenon, one major complicating factor is the presence of an opponent. The success probability of the task is no longer only dependent on the skills of the player, but is also confounded by the performance and strategy of the opposing player(s). A player who gets "in the zone" is likely to change the defensive strategy of the opposing team, making it more difficult for him or her to perform. Moreover, different opponents have different skills, leading to tasks of varying degrees of difficulty. All these factors make testing the existence of a hot hand very difficult, and require more complex models. These confounding factors can be overcome by considering tasks with minimal external interferences.

So how can one distinguish between a pure random series (essentially repeated coin tosses) and something else? This is where statistics comes in handy. Without delving deeply into the technicalities of the different statistical tests, we would like to just make note of a crucial point: The fact that a statistical test does not detect a phenomenon does not mean that this phenomenon does not exist. Most statistical tests are meant to reject a null hypothesis, and the fact that it cannot be rejected does not mean that the null hypothesis is correct. It might be the case that the statistical test used is not sensitive enough for the type of data and phenomenon being tested. It can also be the case that data is insufficient to yield a definite answer.

Interestingly, another contradicting example was shown in basketball three-point attempts, where it was shown that data actually present an "anti-hot hand." But, as mentioned before, in this framework the defensive strategy is important and is likely to influence the performance of the player—a player who has a "hot hand" will attract more attention from the defense, which can directly influence the results of future trials.

These examples basically show correlation between current results and previous ones, so an athlete's performance is not just repeated coin tosses. Does this mean that "success breeds success" and "failure breeds failure," or is there something else at hand?

Correlation and causation are often mixed together. From a statistical point of view, this is a difficult question. Human minds are often after reasoning and tend to misinterpret correlation as causation. To prove that something is actually causing something else, one has to perform more detailed studies and not rely on statistical correlation only. Correlation is essential for causation but not sufficient.[6]

Several techniques can be used to define and refine an organization's approach to model development or, more specifically, to driver identification and its related results. These techniques vary from quantitative methods to empirical methods. Several recognized methods or techniques are discussed next.

Regression Analysis

Regression analysis includes any techniques for modeling and analyzing several variables, when the focus is on the relationship between a dependent variable (i.e., outcome or result) and one or more independent variables (i.e., drivers). More specifically, regression analysis helps to understand how the typical value of the dependent variable changes when any one of the independent variables is varied, while the other independent variables are held fixed. In all cases, the estimated value is a function of the independent variables, and the variation of the dependent variable can be described by a probability distribution. For example, in the banking industry, the mortgage interest income (dependent variable) can be estimated based on the change in several independent variables, such as interest rates and employment rates. Regression analysis is not useful in all situations. For example, many cause-and-effect relationships are nonlinear, having two, three, or more related effects that are not captured by the analysis.

Nonlinear Systems

Nonlinear systems cannot be modeled as one-to-one, proportional relationships the way linear systems can. Rather, more complicated mathematical formulas that account for a greater number of variables are required to model nonlinear systems. As an example, if a company's sales perfectly predicted the price of that company's stock, the relationship would be linear. However, if the stock price is also influenced by market saturation, a decrease in available raw materials, and the introduction of new technologies by competing companies (e.g., commodity firms), the sales numbers alone may be insufficient to determine the value of the stock. Thus, sales figures alone cannot be used to linearly predict future stock price. Nonlinear systems use multiple variables to fit the data and do not fit the data with a straight line. The data may also be fitted through a series of successively better approximations as the equations used to describe the data are tweaked to better explain the overall pattern of that data. Nonlinear modeling is more complicated than simple linear or correlational modeling, and the skills needed to perform such modeling would be gained only with the required experience and expertise.

Monte Carlo Simulation

Monte Carlo simulation can help interpret the results of regression analysis. It is based on artificially re-creating a chance process over many occasions and observing the results.

Additionally, the impact of each independent variable can be measured and based on levels of confidence in the data. A series of scenarios can be developed and, based on managerial judgment and the data itself, used to effect operating decisions. For example, a consumer finance organization might seek to predict mortgage application fees and interest income, and establish a historical and statistically valid relationship with changes in interest rates, employment rates, and growth in national gross domestic product—that is, that the results were driven by these changes. Thus, when interest rates are lowered, employment rates increase, and there is growth in gross domestic product, it is then reasonable to expect increases in mortgage fee income and interest income over time.

Resource Capacity and Activity-Based Analysis

Resource capacity and activity-based analysis allows an organization to model how varying levels of resources (staff, working capital, and capacity) are being consumed through business processes to create end objectives such as a product or service. An organization needs to measure the effect its resource capacity and processes have on each other and how they contribute to overall profitability or service effectiveness. For example, a food distribution organization might consider an expansion of its business with a well-known food restaurant chain; this expansion of business would represent a significant increase in business volume of about 20 percent. The organization needs to understand the incremental impact the increased volume would have on the capacity of delivery, packaging, picking, and other warehousing resources and the expenses associated with the new business. They can determine the investments and operational changes necessary to meet the new level of demand. By analyzing the predictive nature of these process and activity relationships and their impact on consumed resources, the organization can negotiate higher prices and achieve higher margins that contribute to an over 20 percent improvement in profitability.

Delphi Method

The Delphi method is a systematic, interactive, nonquantitative technique for forecasting that relies on a panel of experts. The experts answer questionnaires in two or more rounds. After each round, a facilitator provides an anonymous summary of the experts' forecasts from the previous round, as well as the reasons provided for their judgments. Thus, experts are encouraged to revise their earlier answers in light of the replies of other members of their panel. It is believed that during this process the range of the answers will decrease and that the group will converge toward the "correct" answer. Finally, the process is stopped after a predefined stop criterion (e.g., number of rounds, achievement of consensus, or stability of results), and the mean or median scores of the final rounds determine the results. Digital communication has greatly facilitated the procedure.

One of the most important factors in Delphi forecasting is the selection of experts. The persons invited to participate must be knowledgeable about the issue and represent a variety of backgrounds. The number must not be too small to make the assessment too narrowly based, nor too large to be difficult to coordinate.

Experiential Insight

Experiential insight is a less structured form of the Delphi method. As a quick way to begin, operating managers often can select drivers based on operating experiences—but these need to be reliably correlated with results. Consequently, results should be tested against multiple variables using regression or statistical analysis. It is common to back-test these relationships, especially where these methods are based on experience and intuition. This is accomplished by applying actual historical data to these relationships, then measuring whether the cause-and-effect basis is within an acceptable margin of error given these known outcomes. After review, it is appropriate to adjust on an ongoing basis by looking for new drivers and/or by adjusting the weighting associated with each driver.

Scenario Analysis and Planning Scenarios

Scenario analysis and planning scenarios are a powerful tool in the strategist's armory. Certified Management Accountants (CMA) Canada's 2020 Vision paper, "Forecasting the Future Role of the Management Accountant" (www.cma-canada.org), identifies scenario planning as the defining organizational capability and a primary management accountant skill for the coming decade. Scenarios are particularly useful in developing strategies to navigate the kinds of extreme events we have recently seen in the world economy. Scenarios enable the strategist to steer a course between the false certainty of a single forecast and the confused paralysis that often strikes in troubled times. Scenarios have various features that make them particularly powerful tools for understanding uncertainty and developing strategy accordingly, including (1) expanding your thinking, (2) uncovering inevitable or near-inevitable futures, (3) protecting against groupthink, and (4) allowing people to challenge conventional wisdom. Scenarios typically cover various future states, one of which can include challenging events and conditions for the organization.

Step 3: Data Capture

Data capture for PBA differs in many ways from financial accounting. In financial accounting, recorded financial information is based mainly on historical transactions and judgments, whereas in predictive business analytics, information is often a blend of historical as well as forward-looking financial and nonfinancial data. Consequently, organizations can develop a series of estimates for their drivers and compile a set of possible scenarios. These scenarios can be weighted as to their likelihood of outcome by applying regression analysis (see previous discussion) and assigning a probability to each of the possible outcomes or actions.

In determining the better option for data capture, it is important to consider the context and relevance of how the predictive business analytics will be used, and the impact of actions being considered by management. Exhibit 4.6, an example from Southwest Airlines, illustrates these considerations. Revenues have high economic relevance and high variability, and thus would be updated daily; the predictive time horizon might be monthly. However, fuel prices, which also have high economic relevance and high variability, would be updated weekly, and the predictive time horizon might be three months. These are in contrast to those categories that have medium to low economic relevance and variability, and thus would not need to be tracked or updated as frequently.

	Economic Relevance	Variability	Operating Plan Response Speed	Update Frequency	Forecast Horizon
Revenues	High	High	High	Daily	Month
Labor Costs	High	Low	Medium	Semimonthly	Six Months
Fuel Prices	High	High	Medium	Weekly	Quarter
Maintenance Spending	High	Medium	High	Semimonthly	Six Months
Advertising Spending	Medium	Medium	High	Monthly	Year
Aircraft Rental Prices	Medium	Low	Low	Quarterly	Year
Landing Fees	Low	Low	Low	Annually	Year
Agency Commissions	Low	Low	High	Semiannually	Year

Exhibit 4.6 Predictive Business Analytics: Summary Matrix
Source: Steve Morlidge and Steve Player, Future Ready: How to Master Business Forecasting *(Hoboken, NJ: John Wiley & Sons, 2010). Courtesy of Southwest Airlines. Used with permission.*

For many organizations, data capture is complex. Often, the requisite data for a defined driver may not be readily available or easily accessible. Organizations can discover that, in the early stages of implementing predictive business analytics, the delivery of information is inefficient, cumbersome, or costly to capture. Such problems are especially evident when (1) systems are highly fragmented, (2) data definitions are inconsistent, (3) data capture is redundant and manually intensive, and (4) access is limited. A workable alternative is to identify surrogate drivers. These are drivers that, as the name implies, are used as substitutes for the more preferred but less available drivers. An organization will often begin to collect the preferred driver data for future availability.

As organizations mature, they should use more automated technology tools, not only to capture data but also to store and access large volumes of financial, nonfinancial, and operational data that can be effectively integrated in performing data analysis.

SUMMARY

In this chapter, the key elements of change management and meaningful organizational design of the PBA function have been described. Each element builds on the other, a form of mutual interdependence. The chapter further emphasizes the importance to determine the organization's capability maturity. We have witnessed in numerous organizations that a slow but steady maturing approach usually results in a sustainable and successful function. Management is more receptive to throwing its support to this function as it demonstrates its value contributions and improvements in meaningful and impactful decision making. The selection of methodology is often less important than the effectiveness of its outcomes and results. An extremely complex process may be more accurate, but if it is not understood by managers who use it, then it will likely not be as successful as a simpler but well-understood function.

NOTES

1. EPM Channel, March 2013.
2. John P. Kotter and D. S. Cohen, *The Heart of Change* (Boston: Harvard Business School Press, 2002).
3. John P. Kotter, *Leading Change* (Boston: Harvard Business School Press, 1996).
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