CHAPTER 3

Decision Architecture Methodology: *Closing the Gap*

> One approach that gets inconsistent results, for instance, is simple data mining. Corralling huge data sets allows companies to run dozens of statistical tests to identify submerged patterns, but that provides little benefit if managers can't effectively use the correlations to enhance business performance. A pure data-mining approach often leads to an endless search for what the data really say.

This quote from the *Harvard Business Review* article, "Making Advanced Analytics Work for You," by Dominic Barton and David Court, sums up one of the biggest challenges that exist in analytics today: organizations are throwing data at the problem hoping to find a solution versus understanding the business problem and aligning the right data and methods to it. The premise of this book addresses this shortcoming and we focus on the importance of connecting data to decisions in order to truly monetize the wealth of business data accessible.

The Decision Architecture methodology laid out in this chapter helps you make practical use of the waves of information flooding your desktop. The methodology provides a framework to translate the business problem into hypotheses, questions, decisions, action levers, metrics, and data needed to build an analytical solution tied to a monetization strategy. The monetization strategy is a major component to the overall methodology and has its own dedicated section.

The frameworks, techniques, and tools in the Decision Architecture methodology are similar to Lego™ pieces you can select to assemble the analytical solution appropriate to the problem or opportunity at hand. Putting the Lego pieces together is a complex task, not always occurring in a straight line; accordingly we have found that an iterative approach delivers the best solutions. As you build your analytical solution, you should expect to iterate through components of the methodology several times.

Your solution may vary in the level of automation, from an spreadsheet to a fully automated solution. The degree of automation that will work for your case depends on the desired repeatability and scale of deployment. As each of these steps in the methodology are repeated, templates and tools can be built, accelerating the process for subsequent projects.

In this chapter we describe how the Lego pieces fit together in the Decision Architecture methodology. This book pivots around three core concepts—Decision Analysis, Agile Analytics, and Monetization Strategy; accordingly in this chapter we provide an overview of the Decision Architecture methodology that encompasses the three concepts.

Methodology Overview

The Analytical Cycle, from the previous chapter, guides us in the problem-solving process (Figure 3.1). Cycling through the Inform,

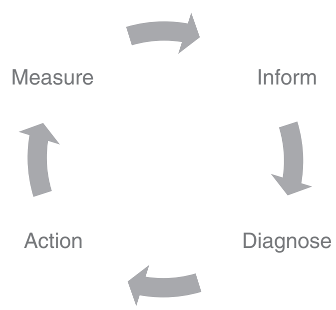

Figure 3.1 The Analytical Cycle

Diagnose, Action, and Measure steps, supported by quality data at each step, empowers managers and analysts to make better-quality decisions.

To build solutions that empower the analytical cycle, we developed the Decision Architecture methodology. The five phases include: Discovery, Decision Analysis, Monetization Strategy, Agile Analytics, and Enablement. Since the majority of the phases are iterative in nature, you may find yourself cycling through them several times during the life of the project. Additionally, you will notice in the Decision Analysis phase we spend significant energy capturing requirements centered on each step in the Analytical Cycle (see Figure 3.2).

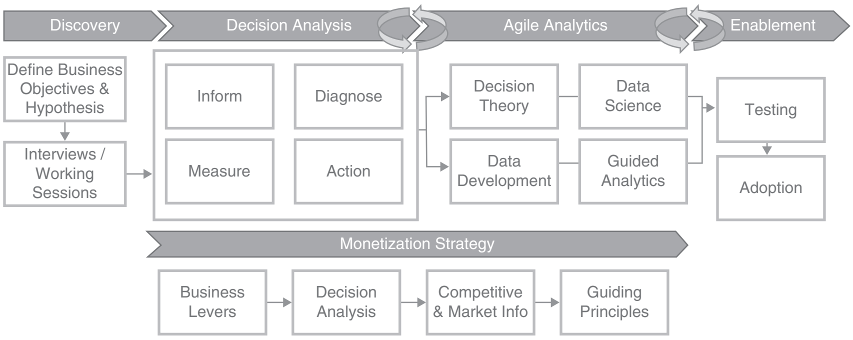

Figure 3.2 High-Level Decision Architecture Methodology

Our approach is novel because we integrate several traditionally siloed disciplines into a continuous process comprising Decision Theory, Decision Analysis, Data Science, Data Development, Monetization Strategy, Dashboard Development, and UI and UX Development. We have found integrating these disciplines into a common methodology delivers superior results when building analytical solutions that monetize data.

Your final solutions may have varying degrees of automation. On one end of the spectrum, your solution may be a spreadsheet with a well-formed decision matrix and monetization strategies that produce clear decisions for a manager or analyst. The other end of the spectrum might include a fully automated application with embedded analytics driving automated actions. A few suggestions for you to consider when you think about the appropriate degree of automation to implement for your organization:

- **Quick Wins—**We are a big fan of getting something in people's hands sooner rather than later. Small, quick wins are far better than a big-bang approach. Iterate your way through the solution and get tons of feedback as you go.
- **Results—**As you are developing your solution, get early reads on whether the results align back to the original hypothesis and are impactful enough to continue. If the end result delivers only a meager improvement in performance, it may not be worth the cost and organizational energy to move forward.
- **Repeatability—**Is this a one-off exercise or is it something that can be repeated many times by various groups and users? In order to automate, your solution should have a high degree of repeatability.
- **Scalability—**The solution needs to be scalable to many users. Does the solution focus on two or three individuals or 20–30 or 200–300? You will generally want a larger base of potential users for the automation to be worth the costs. However, if the solution is impactful enough to the organization in driving revenue, it may make sense to automate even for only two or three people.
- **Technology Footprint—**Depending on the technology footprint of your organization, there can be many paths to automation, such as through an enterprise business reporting platform, an embedded analytical solution in your Enterprise Resource Planning (ERP) system, or a highly flexible data visualization tool like Tableau.
- **Data Plumbing—**If you have to patch the data together with duct tape and bubble gum, it might not be a candidate for a high degree of automation. If the data sources are delivered through repeatable or automated processes and the quality of the data is high, then it may be a good candidate.

We also want to emphasize the iterative nature of the analytical exercise. You will find yourself going back and forth between the phases as you iterate through development of your analytical solution. We often find ourselves starting with a metric that drives a decision in the Decision Analysis phase and by the time we get to the Agile Analytics phase we may determine that some of the data does not exist or the quality of the data is so poor we cannot use it. At this point, we will iterate through Decision Analysis again to find relevant information that is actionable and supported by quality data. There are several disciplines in play and the dance between them causes rework as each discipline continues to refine their part of the solution.

A high-level overview of each of the phases may be in order before we go too deep into the specific areas. Let's begin with the Discovery phase. The Discovery phase starts with aligning your project goals to organizational objectives to ensure alignment. Next we identify the business priority, which may be a problem or opportunity. From our business priority we develop one or more hypotheses we believe articulate the priority in an actionable manner. Once we know what we are looking to address, we conduct interviews and working sessions to ramp up on the subject matter, understand existing systems, and fine tune the hypothesis and scope.

Decision Analysis, the next phase, is designed to capture questions, key decisions, action levers, metrics, data needs, and a category tree. We leverage specific facilitation techniques in working sessions designed around topics and compile this information into the various Decision Analysis components. This information drives the building of *category trees, key decisions, action levers,* and *success metrics,* providing requirements for the Agile Analytics and Monetization Strategy phases.

During the Decision Analysis and Agile Analytics phases, you build and refine your monetization strategy. In this phase you develop specific strategies, identify business levers, and assign actions from the earlier phases to deploy to drive revenue or reduce costs.

The Agile Analytics phase encompasses building a solution from the requirements gathered in the Decision Analysis and Monetization Strategy phases. This phase is composed of several process steps: Data Development, Analytical Structure, Decision Theory, Data Science, and Guided Analytics. These components may vary in size and length depending on the level of automation and technology.

Finally, in the Enablement phase, once a solution has been developed, it is rolled out to the user base. Adoption, a key theme in this phase, only occurs if adequate testing and training have been successfully conducted.

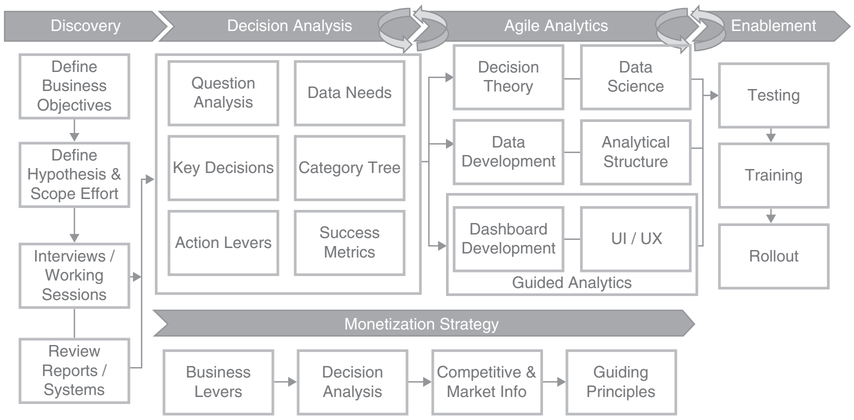

Figure 3.3 Decision Architecture Methodology

Figure 3.3 lays out the complete methodology. We describe each of the process steps in detail in the following sections and chapters but first let's go through a high-level overview of the primary phases.

Discovery

The Discovery phase starts with defining business objectives and aligning these to corporate goals. For example, the objective may be to "Grow Revenue by 10% through marketing activities focused on the Millennial generation." If the end analytical solution does not align to the company's objectives and goals, you may want to question whether the project is worth doing.

Once you know your business objective, it is time to define the hypothesis and scope the overall effort, a necessity in any analytics project. Your goal is to confirm or reshape the hypothesis from your learnings as you progress through the project. An example hypothesis is that by combining social media data with our existing customer data, we can drive more relevant and targeted marketing activities, achieving an 10 percent lift in our Millennial Segment credit card campaigns.

In order to develop a monetization strategy, anticipating the business levers that will drive your strategy is important. It will impact the development of your hypothesis and the levers that should align to your actions. Our chapter on Monetization Strategy (Chapter 5) introduces the *business lever* concept and provides more information on the topic.

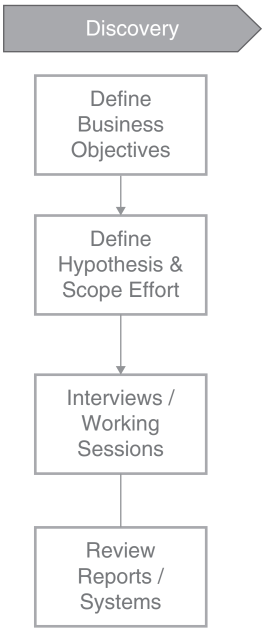

Figure 3.4 Discovery Phase

Figure 3.4 is a visual of the steps within the Discovery phase.

Along with developing a hypothesis, we need to scope the effort. In the Scoping process step we develop our project plan, project charter, and scoping document. The project plan should include scope, schedule, budget, and project team. The schedule provides an overall timeline for completing various phases in the project. While the process is agile in nature, some stakes should be driven into the ground to help with prioritization and to push the team toward a completion date knowing that they will learn and adjust along the way.

The next process step is the Interviews and Working Sessions step. To complete our discovery of the possible solutions paths, we conduct interviews and working sessions to get an understanding of the current state. What are the existing processes, business practices, and business rules? Do they leverage data science and in what capacity? What data do they normally use? The answers to these questions help us narrow our scope and get the team up to speed on the particular subject matter.

The final process step in the Discovery phase is to Review Reports and Systems. In this step we review each of the existing reports and the various information systems to gain an understanding of the current state of the analytics in use. This step helps us understand what data is currently available and the capabilities that currently exist.

Each of the components in the Discovery Phase feeds our Decision Analysis phase, which is where we explore and document the details of the decision process.

Decision Analysis

We cover the Decision Analysis phase in depth in the Decision Analysis chapter (Chapter 4), but present here a high-level review of the information so you can see how everything fits together. This phase maps to our Analytical Cycle: Inform, Diagnose, Action, and Measure. In this phase there are six process steps: Data Needs, Category Tree, Question Analysis, Key Decisions, Action Levers, and Success Metrics. Figure 3.5 is a visual of how the four stages in the Analytical Cycle map to the six process steps in Decision Analysis.

In the Discovery phase we uncover a rich background of information that enables us to execute focused interviews and working

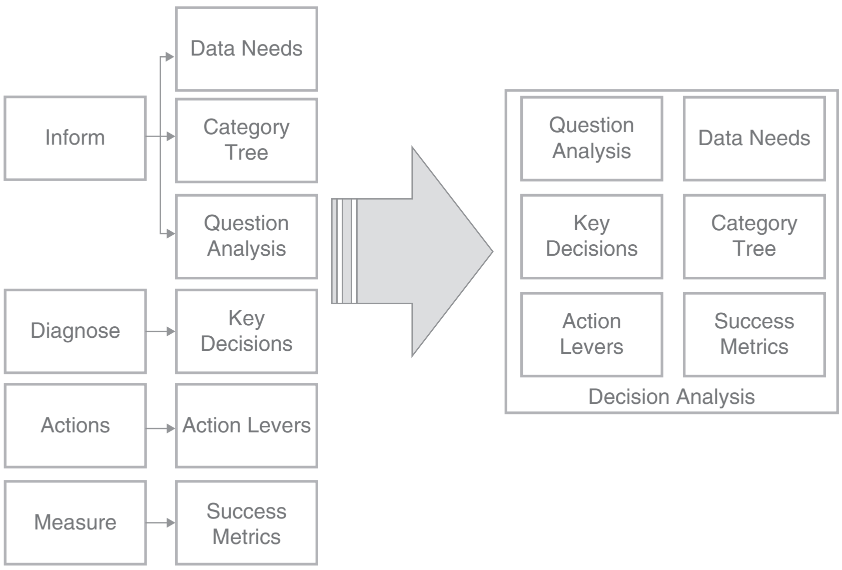

Figure 3.5 Decision Analysis Phase

sessions in the Decision Analysis phase. The Inform process step determines the questions that the manager asks when considering a problem. The output of this step, the Question Analysis, points us to the data and data sources needed to support the analytic effort. In addition, in this process step we produce the Category Tree, a diagram outlining the various information and diagnostic categories. We view the nodes in the Category Tree as groupings of like information such as sales performance or a particular diagnostic like call center performance.

If we go back to our doctor's example from the prior chapter, also repeated later, the Inform section covers the questions that help us get to the root cause of the issue. Once we get to a narrow enough understanding of the issue, the questions then turn to more of a Diagnostic exercise. We can see that the initial questions in the Inform section help us narrow down what is wrong with the patient so we get to a final diagnosis and treatment plan (Figure 3.6).

The Diagnose stage in the Analytical Cycle focuses on questions associated with the root-cause issue and determines the final diagnosis that enables a quality decision. The decisions that someone takes during this process step are important to uncover and

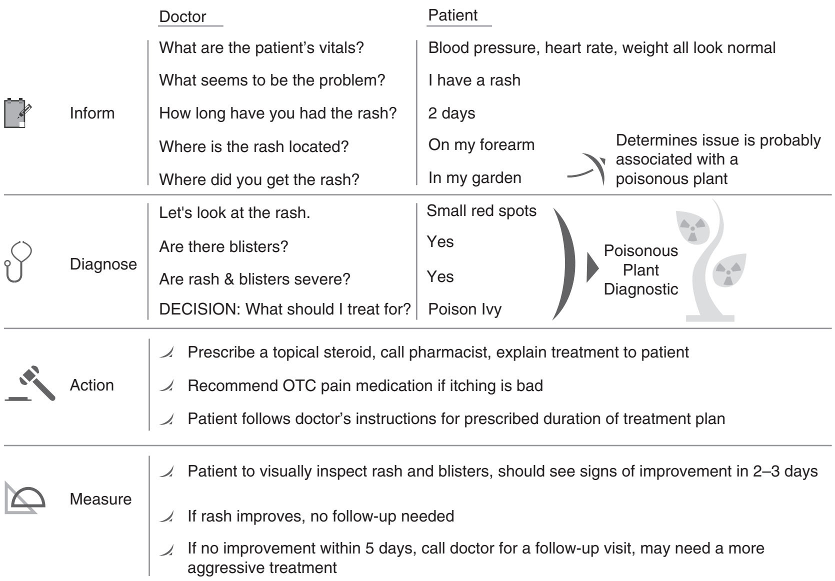

Figure 3.6 The Analytical Cycle in Action

are captured through Key Decisions. For example, once the doctor determines that the rash has something to do with a poisonous plant, she then goes into a diagnostic about poisonous plants to determine severity and treatment plan. Once the doctor narrows down the probable cause of the rash to poison ivy and the severity of the rash, she knows what decision to make.

The Action stage in the analytical cycle takes the Key Decisions and maps Action Levers to each of them. These Action Levers are specific initiatives that you can take to capture an opportunity or resolve an issue. This step also ensures that our Success Metrics are actionable. In the doctor example, we see the action is to prescribe medication and explain the treatment plan to the patient. It is important in this step for the patient to agree with the diagnosis and fully understand the treatment plan. By taking this final step, we can have a higher confidence that the plan will be acted on.

Lastly, the Measure stage of the analytical cycle captures the success metrics that help drive our decisions and measures our outcomes. From our example, the Measure stage determines if the treatment plan is effective. If it is effective, there is nothing more to do. If the treatment is not effective, the patient will need to go back to the doctor to get a more aggressive treatment.

Monetization Strategy

The Monetization Strategy phase runs concurrent with Decision Analysis and Agile Analytics phases and employs data science and decision theory to structure the actions that guide you to the best decision. We utilize the requirements from our Decision Analysis to formulate our strategy. This phase has four process steps: Business Levers, Decision Analysis, Competitive and Market Information, and Guiding Principles (see Figure 3.7). It is important to apply an economic benefit to an action which enables someone to make a more informed decision. We devote an entire section to this topic

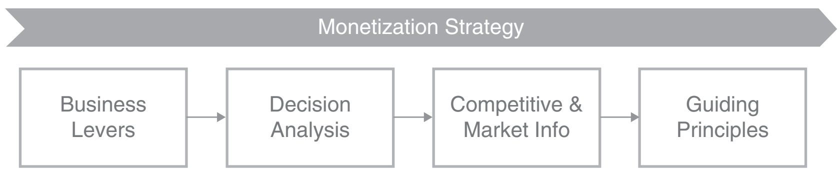

Figure 3.7 Monetization Strategy Phase

later in the book and provide a framework and case study to help you adopt these concepts.

Agile Analytics

The Agile Analytics phase has five components: Data Development, Analytical Structure, Decision Theory, Data Science, and Guided Analytics (see Figure 3.8). Each of these components interlink with each other during the development phase. For example, as data is sourced and integrated, it is provided to the Data Science team to analyze and discover correlations and thresholds. After reviewing the data, the data scientist may need additional data, which in turn involves Data Development work. This interplay between the process steps occurs often through the life of the project.

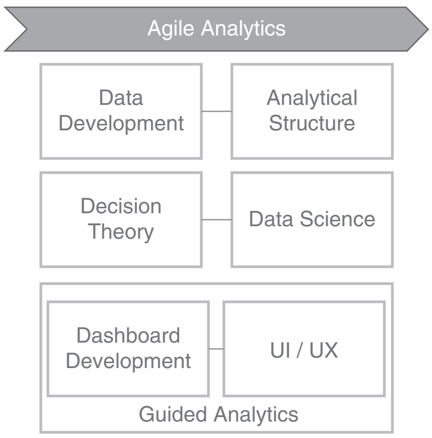

Figure 3.8 Agile Analytics Phase

Let's review the components of the Agile Analytics phase:

Data Development/Analytical Structures

The Data Development and Analytical Structures process steps involve the preparation of a dataset that can be used for analytics. The data process step starts with the data sources identified in the Inform and Diagnose process steps along with the metrics, business rules, transformations, and calculations. At this point, your job becomes sourcing and transforming quality data to answer the questions and decisions you have identified. Some of this data may come from within the walls of the company; other data you may need to purchase to round out the picture.

Extracting data may involve various source systems, internally and externally, and is often one of the most complicated steps. Once you have extracted the necessary data, you need to stitch it together into an Analytical Structure via some type of key value relationship between the datasets regardless of whether the data is structured or unstructured.

Ensuring the data correctly represents the subject of analysis is critical; as the saying goes, "Garbage in, garbage out." You will be hard pressed to derive any meaningful analytics from a poor-quality dataset.

Finally, an analytical structure needs to be developed that encompasses the values, transformations, and aggregations to answer the various questions and decisions. For example, if the doctor wants to build a report to understand the most effective treatment options based on the historical performance of various medications for the treatment of poison ivy, she may have to combine several datasets. First she looks at patient records and then combines them with efficacy data for each of the medications. The ability to combine both datasets, the quality of the data, and the structuring of the data for analysis is the focus for this process step.

The Data Development process step drives the Data Science and Guided Analytics process steps. Without a solid dataset to analyze, you cannot perform the Data Science process step. Likewise, without the right analytical structure, dashboard development is not possible.

We will go into depth on this process in the Data Development chapter.

Data Science/Decision Theory

The Data Science and Decision Theory process steps help you find insights and then structure the insights into a decision process to drive the best actions for the company.

The Data Science process step comprises descriptive and predictive analytics techniques. The inputs into this process step are the Data Development process step and requirements from the Decision Analysis phase, which include the Question Analysis, Key

Decisions, Action Levers, and Success Metrics process steps. With further analysis of our metrics, informed by our Question Analysis, we can specify particular Data Science studies we want to perform to further develop the solution.

For example, having identified a particular metric that drives a decision, we will want to establish thresholding for the metric to determine when it has hit a boundary. This boundary serves as a signal that there may be an opportunity or issue. To continue with our poison ivy example, our doctor wants to know the threshold for blister sizes and treatment options. When the blisters reach over a certain threshold, she knows a more aggressive treatment is needed. If the blisters are within range or below, it might warrant a less aggressive treatment. This is a perfect exercise for a data scientist and we cover this in greater detail in the Data Science chapter (Chapter 9).

Whereas data science helps you turn information into insights that are actionable, we need tools that help us structure the decision process to guide a person to the correct decision. Decision Theory, along with Behavioral Economics, focuses on understanding the components of the decision process to explain why we make the choices we do. It also provides a systematic way to consider tradeoffs among attributes that helps us make a better decision. There are several tools and techniques in the Decision Theory chapter (Chapter 8) that help you structure your analytical solution.

Guided Analytics

Guided Analytics is the process you use to take your users through the analytical journey to make effective decisions. Guided Analytics depends on a solid foundation of User Interface (UI)/User Experience (UX) and Dashboard Development. We discuss these concepts in depth in the Agile Analytics section.

For now, let's give an overview of some of the key concepts as well as describe two experiences, one unguided and one guided.

Unguided—This is the state most analytical solutions are in today. For now, let's assume that we have a report that has been developed that has Sales by Region, Sales by Product, and Sales by Channel. There are pie charts that break out each of these dimensions to let us know our sales mix. After we view the information, we begin to wonder, How does this information compare with last month? Are we trending up or down? Do we have any opportunities or issues that we need to be aware of? What decisions are we supposed to make from this report? The issue we run into with unguided solutions is that the data on the report is simply informative and does not guide us to an opportunity or issue.

Guided—You log onto your dashboard to see how the organization is performing today and over the past year. Your eyes are drawn to the Northeast region as a threshold has been triggered on the metric associated with your Electric Car division sales volume. You click on the metric and are taken to another dashboard to view the metric over a period of time to see if the spike in sales is a onetime occurrence or a trend. You notice that it seems to be a short-term trend that has been in place for the last several months. You also notice that sales have increased to the point where you are having out-of-stock issues, so you then drill down to the sales volume diagnostic. In the diagnostic you are presented several metrics and a decision matrix that has been formulated into a monetization strategy. In the decision matrix you have five decisions presented to you of various opportunities to help close the shortage gap. Each decision has a monetary value and probability score associated with it so you can determine which decision has the highest chance for success to return the largest amount of revenue to the company.

Which of these experiences did you prefer? The first experience simply helps you "read the news." It tells you the current state of things but does not help you tease out any opportunities or issues. Nor does it provide a diagnostic experience to help you weigh alternative decisions based on monetization factors. In the guided experience, you are taken on a journey to uncover an opportunity and several decisions you can make to resolve it.

We hope you learn how to build these guided experiences, or stories, through the techniques in this book and that by doing so you empower your organization to be more competitive and drive revenue.

Storytelling is becoming a bigger movement in analytical circles. This is evidenced in Frank van den Driest, Stan Sthanunathan, and

Keith Weed's *Harvard Business Review* article, "Building an Insights Engine." Below is an excerpt from the article:

> The i2020 research imparts a final lesson about what makes for a strong insights engine: good storytelling. At overperforming firms, 61% of surveyed executives agreed that people in their insights functions were skilled at conveying their messages through engaging narratives; at underperforming firms, only 37% agreed.
>
> At Unilever, CMI has embraced storytelling. Traditionally its presentations were data-intensive, built on the assumption that a fact-filled talk would be more persuasive than a fact-based one with less data and more narrative. Although data has its place, CMI has moved away from charts and tables and toward provocative storytelling, embracing an ethos of "Show, don't tell."

These types of analytical stories are brought to life through UI/UX and analytics elements such as metrics, trends, patterns, diagrams, alerts, and decision matrixes. A big part of the story is how a user engages with the solution, which is done through thoughtful deployment of UI/UX standards. In Tom Davenport's article, "How P&G Presents Data to Decision-Makers," he argues that visual design commonality is more important than creativity. If you establish a common visual standard, it is easier for people to interpret the information. As a user navigates from dashboard to dashboard, they can spend their energy interpreting the data versus learning how to reinterpret the visual cues. These standards and guidelines help create consistent look and feel as well as better overall usability.

UI and UX development is part art and part science and iterative in nature. You will work with your users to see what is meaningful to them and how they interpret information. Next you create the visual elements that help the users answer questions and make decisions to drive actions. For example, what are the thresholds for a particular metric and what color should we choose to help draw the user's eye to an issue or opportunity? An easy-to-use interface that is intuitive and guides a user through the analytic story to a decision promotes usability and, therefore, adoption.

The Guided Analytics solution often deploys a dashboard tool, but not always. The inputs to the process step are the Decision Analysis, UI/UX Development, Data Development, Decision Theory, and Data Science. The Decision Analysis greatly influences the Dashboard Development process step. A major influence is the Category Tree, which maps out the thought process of how a user asks questions to diagnose an issue and then take action through an informed decision. This is your "story" that draws the user to engage with the solution. It is one of the most important components to get right.

Lastly, the Guided Analytics process step is one of the most user-engaged steps in the methodology. Working with the users to cycle through the various options in a dashboard tool and your Decision Analysis is time consuming, but a process that ensures you get it right. We recommend frequent checkpoints with the end user to review progress and adjust accordingly. This level of engagement results in an analytical tool guaranteed to meet user expectations as they have seen the end product evolve and are invested in its success.

Enablement

The Enablement phase is the last phase in the methodology and can vary in duration (Figure 3.9). It is also iterative in nature between earlier phases. For example, once you get to Testing, you may discover an issue that needs to be addressed in the Dashboard Development process step. You may find yourself repeating through these two steps until all the issues are resolved.

Continuous improvement, or the "good-enough" principle, is the recommended guidance during this stage. The solution will never be perfect but rather should be regarded as one that is constantly evolving on the path to perfection. At some point, the analytical solution is good enough to start providing value to the business and should be rolled out. Once rolled out, you can begin to develop the next wave of capabilities on your path to perfection.

Let's review each of the steps in the Enablement phase.

Testing involves each of the analysts/developers testing their components individually and as an integrated group. The testing process is focused on ensuring the functionality is correct, the data and calculations are accurate, and the solution responds as intended. It is the last step for the individual developers to make sure they get their piece of the solution correct before the users test the solution.

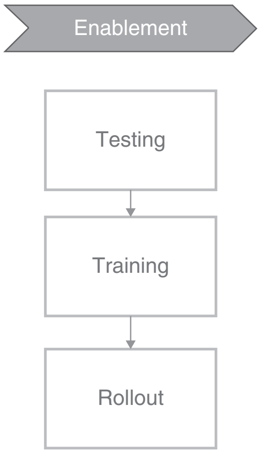

Figure 3.9 Enablement Phase

A component of testing is User Acceptance Testing (UAT). This component engages users of the solution to test it to make sure it meets the requirements laid out in Decision Analysis. During this phase the users of the solution are testing overall functionality, accuracy, and performance and finally accepting the solution before it goes live.

The Training process step involves a few activities geared toward helping users understand the solution and generate adoption. Training can involve the building of online, electronic, and paper training materials. These materials help walk a user through the functionality, usability, and often the decisions and actions that should be taken.

Executing on training can involve self-study, in-person, or online training classes. You need a plan with many options to help users absorb the material in a way that best suits them. Tailoring the type of material and delivery medium to the user base helps with the Rollout process step, adoption, and usage.

The Rollout process step is the deployment of the solution to the end users and is the last step in the methodology. After the user base is trained on the solution, you can flip the switch to have them begin using the analytical solution in a production environment. Adoption can often be a big issue and you will need to take special care to engage the user community early and often in the process. In their article, "Making Advanced Analytics Work for You," Dominic Barton and David Court talk about the importance of adoption of an analytical solution:

> Managers must come to view analytics as central to solving problems and identifying opportunities—to make it part of the fabric of daily operations. Efforts will vary depending on a company's goals and desired time line. Adult learners often benefit from a "field and forum" approach, whereby they participate in real-world, analytics-based workplace decisions that allow them to learn by doing.
>
> At one industrial services company, the mission was to get basic analytics tools into the hands of its roughly 200 sales managers. Training began with an in-field assignment to read a brief document and collect basic facts about the market. Next managers met in centralized, collaborative training sessions during which they figured out how to use the tools and market facts to improve sales performance. They then returned to the field to apply what they had learned and, several weeks later, reconvened to review progress, receive coaching, and learn about second-order analysis of their data. This process enabled a four-person team to eventually build capabilities across the entire sales management organization.

Let's review some techniques that can assist you in getting a high adoption level.

- **Coaches—**Typically, an analytical project can be complex; we recommend having coaches in the field to answer questions and ensure usage of the solution. Coaches can be peers or supervisors of the user of the solution. The frequency of coaching can be as often as daily and as far apart as monthly. We encourage a high frequency of touchpoints at the beginning of the rollout process.
- **Performance Management—**Another way to encourage adoption is performance management. If you can tie something in the employee's yearly goals to the solution, that encourages adoption. For example, if you have deployed an analytical solution that helps people solve for the best marketing campaign, you can layer into the person's yearly goals that they

have to find a certain amount of revenue-generating initiatives from the solution.

- **Embed the Process—**Embedding the analytical solution as a step in a broader process helps with adoption. If we know we need to use this tool before we are able to take the next step in the process, it is ingrained in how we work. Take care to ensure that the right handoffs are available in the solution to the next step in the broader process.
- **Create a Community—**Ongoing engagement and continuous improvement help build a user community that is engaged in the features and functionality for subsequent phases. Seek out feedback through newsletters, town halls, and ongoing meetings about the solution. During these meetings, encourage ideas around additional functionality that may be needed, maybe a new analytical function or new dataset that would support a new metric. These new features generate a backlog of work for the next phase and excitement about the expansion of the system.

Summary

We reviewed a lot of concepts in this chapter. You may have to refer to it often as you build out your solution. Do not feel obligated to use all of the methodology. If your situation does not require Data Science efforts, you can skip that process step. In addition, this is not intended to be a one-size-fits-all methodology and can be tailored to meet your specific needs. For example, you may need approval steps for funding in the Discovery phase or a data governance step for any new metrics created in the Data Development process step.

The book's website (www.monetizingyourdata.com) is a resource for you to review tools, templates, and research articles that might assist you if you are stuck in a given situation. Leverage this site as a community to post information to as well as seek out advice.