

DECISION
MANAGEMENT
SOLUTIONS

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Analytics Capability Landscape

Identifying the right analytic capabilities for success

Organizations need to ask themselves:

- ▶ What situations need which capabilities?
- ▶ Who is the target user for these capabilities?
- ▶ How can this portfolio of capabilities be managed most effectively in an era of Big Data?

Organizations today are turning to analytic capabilities to drive decision-making. But with the different types of decisions that need to be made, multiplied by the different types of analytic capabilities available, it can be difficult for organizations to choose the right capabilities for the situations at hand. Some decisions require simpler capabilities, while others require complex capabilities that need the support of a talented IT team.

Additionally, organizations also need to consider the user of the analytic capabilities. While some users have the experience and skills to leverage tools that require programming and heavy analysis, others may benefit more from a simpler drag-and-drop graphical user interface. Choosing a tool that the intended user is unable to get the most from – no matter how great the tool itself is – means that the tool will go unused, affecting decisions across the organization.

With the tools comes the ability to handle Big Data as well. No longer a buzzword, the era of Big Data means that analytic capabilities must extend to both structured and unstructured data, parsing the information to assist organizations with informed decision-making.

Ultimately, any analytic capabilities used by the organization must align with business needs, be geared toward the intended user, and support decision-makers, both human and automated.



ACTUATE



Executive Summary

This research was conducted by Decision Management Solutions and sponsored by Actuate and FICO to examine the different types of analytic capabilities available to organizations and the business situations for which they are most appropriate.

The research draws attention to the different types of analytic capabilities, the different roles in an organization that use analytics to drive decisions, and most importantly, the different categories of decisions that must be made within an organization. This report covers the business needs that motivate an organization to turn to analytics, including:

- ▶ Reporting
- ▶ Monitoring
- ▶ Decision-making

Along with the business needs that are driving analytic adoption, this report also discusses how to choose analytic capabilities with a decision-led, role-centric, and style-based approach. The research found that roles across the organization are using analytic capabilities, and different departments need different approaches. This report offers practical applications for analytic capabilities, illustrating examples of analytics in action. In addition to covering analytic styles and roles-based applications, the report discusses the importance of scaling analytics using either do-it-yourself (DIY) or factory-made applications.

The report also details the different type of analytic capabilities available to organizations:

- ▶ Descriptive analytic capabilities
- ▶ Diagnostic analytic capabilities
- ▶ Predictive analytic capabilities

Other analytic adoption considerations are considered, including:

- ▶ Execution Approach
- ▶ Data Types
- ▶ Data Storage Location
- ▶ UI Style

The research also found that the Decision Model and Notation (DMN) can also assist with analytic capabilities, particularly when mapping processes that require analytics.

Business Needs for Analytics

Overview

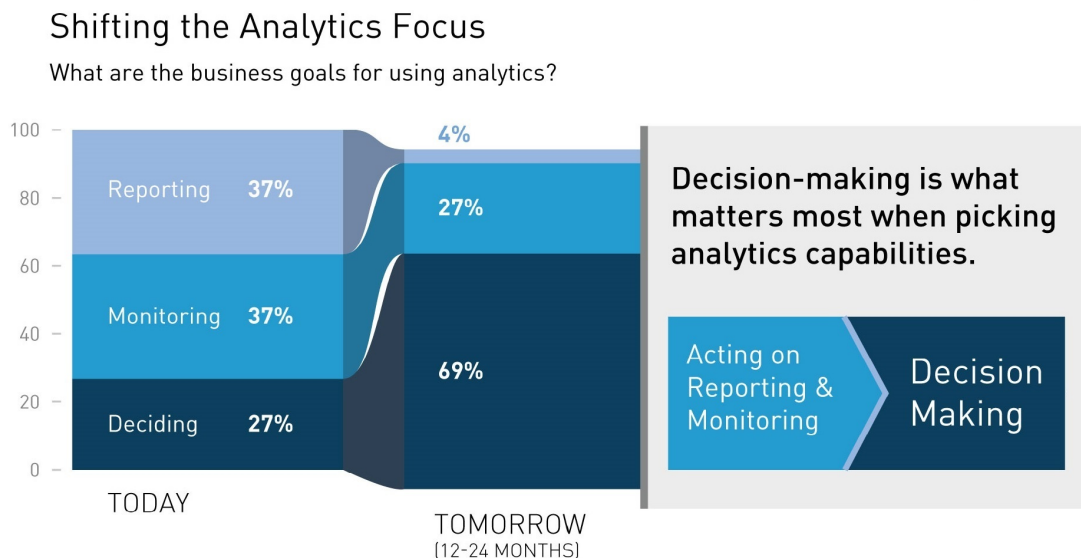
While there seem to be as many reasons for adopting analytic capabilities as there are organizations adopting analytics, the reality is that three key business needs are driving analytic adoption:

- ▶ A need to report on some aspect of the organization
- ▶ A need to monitor the organization's behavior or performance
- ▶ A need for the organization to make data-driven decisions

Historically, the focus for most organizations has been reporting. Recently, this has shifted to a balance of reporting and monitoring. With the growth of Big Data Analytics as a focus for companies and companies' desire to become data-driven, the next 12-24 months is likely to see a shift toward decision-making as a focus.

For instance, a recent live poll (results summarized in Figure 1) showed that three quarters of respondents were focused on reporting or monitoring today and were evenly split between the two. But fast-forward 12-24 months, and almost eighty percent of respondents are focusing on decision-making instead.

Figure 1: Shifting the Analytics Focus



A Decision-centric approach is becoming the central analytics focus for most businesses.

Source: Analytics Capabilities Landscape Infographic

Reporting

All organizations need reporting. Ever since organizations started to collect data, someone has wanted to see it. To meet a reporting need, an organization must present some or all of the data it has gathered in a report to some internal or external body. For instance, the Dodd-Frank act requires that all financial trades meeting certain criteria are reported to the federal government, and most organizations with hourly workers need to provide employee hours to HR.

These reports are generated for compliance or policy reasons to someone who generally is authorized to request data at a specific level of detail or timeliness. The organization that produces the report is only required to provide that data in report form.

Typically, these reports rely on simpler analytic capabilities like tabular or document layout. In theory, a report could use any analytical technique, but in practice it will focus on those with a textual or visual output. Reports are often constrained by circumstances and delivery style. Analytic software adds value by making it faster and more cost-effective to produce a report containing the right data in the right format.

Two final observations: Reporting is not the only use case for reports, as a report may be used to monitor performance and as the basis for decision-making. Acting on a report is a decision-making scenario, not a reporting one.

Monitoring

An increasing number of organizations are using analytic technology to monitor their performance. Generally, an organization identifies metrics that are important enough to monitor, based on departmental or organizational needs. Each department receives the tools necessary to monitor the requested metrics. For instance, an organization might have a group of managers and executives that track total sales, customer retention rates, and average customer profitability.

Monitoring can rely on reports issued over time, but it generally uses graphical or visual dashboards that clearly illustrate how the metrics change from baseline values over time. Monitoring environments increasingly use more sophisticated analytics like forecasting and predictions *in-situ*. This allows those doing the monitoring to view trend projections and likely seasonal impacts as well as historical data.

As in the reporting scenario, taking action on the basis of what is seen (or projected) is a decision-making scenario, not a monitoring one. Similarly, a dashboard might be used to both monitor something and to decide what to do about it.

Decision-making

Improved decision-making is the critical business need driving the adoption of analytics. This need can be explicit, identified at the very beginning as the rationale for an analytic capability. It can also be implicit, as organizations that think they need reporting or monitoring realize that it is acting on the reports and monitoring dashboards that is critical to success. While reporting and monitoring are important in their own right, the breadth and depth of analytic capability required comes from decision-making. Monitoring is generally straightforward unless the person doing the monitoring needs to make a decision based on what they see. At that point, the complexity comes from the decision(s) they have to make, rather than the monitoring itself. Similarly, reporting is well-defined and largely straightforward until there is a need to make decisions based on the content being displayed. In both cases, the complexity comes from the decisions being made.

The many decisions made by organizations vary widely, and it is useful to categorize them for discussion purposes. It's generally useful to divide them up into strategic, tactical, and operational decisions, as shown in Figure 2.

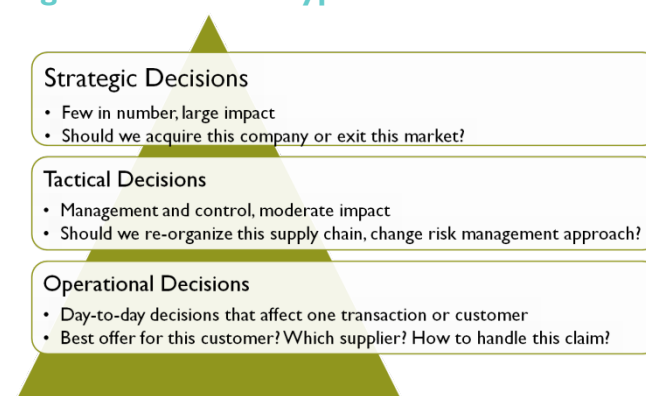
Organizations make infrequent but large-impact strategic decisions. These one-off decisions typically involve a lot of people and significant time and capital investments. Much analysis is done before the decision is made, and the implications for a business can be dramatic.

Regular tactical decisions involving management and control are also made. These have less impact on the business, and there is generally still time and energy for significant analysis. However, there can still be time limitations, as well as a need for consistency and to learn what works.

Finally, every organization makes large numbers of operational decisions surrounding individual transactions or customers. Time constraints often are extreme, and these decisions must generally be embedded into operational systems and processes.

Analytic capabilities play a role in all these decision types.

Figure 2: Different types of decisions



Decision-Making Scenarios

Analytic capabilities play a role in a wide range of decision-making scenarios. In previous research (Raden & Taylor, 2008) a variety of decision-making scenarios were identified. A comprehensive analytic capability should allow an organization to

apply analytics to all of its decisions. To select appropriate analytic capabilities, an organization needs visibility into the decisions it makes and into the classification of those decisions.

“Understanding what kinds of decisions there are, how they differ, who makes them, and how to make them better presents a substantial opportunity to improve the performance of an organization.”

Neil Raden and James Taylor

Strategic Decisions

Strategic decisions are the ones executives and their staff are paid to make. These complex decisions are generally made for a one-time, specific purpose. They require a lot of analysis, hypothesis testing, and exploration and are generally collaborative. Even if one person is going to be the final decision-maker, it is unlikely that no one else will be involved.

It is often not clear what leads to success, and the outcomes of the decisions made are not known for an extended time period. Although a lot of data is available for the decision-makers, it is unlikely that they will be provided with much history about similar decisions, which limits their ability to derive trends or predictions. There is a lot of uncertainty in these decisions, and the scope of data to be considered and the range of measures are typically both broad.

Tactical

Tactical decisions are those that determine how the organization operates and is managed day to day. These decisions can be complex but must nevertheless be made repeatedly. Each time they are made, the circumstances, constraints, and participants may vary, but the core decision remains consistent over time—what budget should be assigned to this team, what kind of quality problems are being seen at the moment, will a new product have the desired outcome, or should the risk management policy be changed.

▶ **Planning Decisions**

Planning decisions are those made as part of a regular planning cycle. This might be an annual planning cycle, a quarterly update to such a plan, or even, in the most dynamic companies, a continuous planning exercise.

▶ **Knowledge Worker Decisions**

Knowledge worker decisions are relatively complex decisions made by a single person – a knowledge worker or manager to deal with a repeating but highly variable circumstance.

▶ **Research Decisions**

Research is, by its nature, unstructured and uncertain, as decision makers constantly are searching for new insights. It is typically some time before the

success or failure of a research decision can be judged, and a wide gap often exists between a successful and an unsuccessful research decision. There is usually some indirect link to a business need, but the decisions being made are unplanned.

► **Policy Decisions**

Many operational decisions (see below) are driven by policies that are periodically reviewed and updated. The decision as to whether such a policy—a credit risk policy, life underwriting policy, or marketing strategy—needs to be updated is a tactical decision.

Operational Decisions

Operational decisions are the highest volume, most transactional decisions that an organization makes. Many operational decisions are formulaic, following a very fixed approach with little room for maneuver. Formulaic decisions are generally heavily regulated or very constrained by company policy and include examples such as eligibility, approval, validation, and calculation decisions.

► **Eligibility or Approval**—Is this customer/prospect/citizen eligible for this product/service?

These are made repeatedly and should be made consistently every time. The use of a business rules-based system to determine eligibility or to ensure that a transaction is being handled in compliance with applicable policies and regulations is increasingly common. These decisions are policy and regulation-heavy, making the use of a Business Rules Management System very effective. While eligibility and compliance decisions can seem fairly static, changes that must occur are often handed down outside the organization and can be imposed at short notice.

► **Validation**—Is this claim or invoice valid for processing?

Validation decisions are overwhelmingly rules-based, and the rules are generally fixed and repeatable. Validation is often associated with forms, and online versions of these forms are of little use without validation. The move to mobile apps makes validation even more important.

► **Calculation**—What is the correct price/rate for this product/service?

Calculations are also overwhelmingly rules-based. The rules are generally fixed and repeatable, but making them visible and manageable using business rules pays off when changes are required or when explanations must be given. Sadly, calculations are often embedded in code.

Others are focused on risk assessment because there is a significantly greater risk if the decision is made poorly. Examples include credit or delivery risk, as well as fraud detection and prevention.

► **Risk**—How risky is this supplier's promised delivery date, and what discount should we insist on?

Making a decision that involves a risk assessment, whether delivery risk or credit

risk, requires balancing policies, regulations, and some formal risk analysis. The use of business analytics to make risk assessments has largely replaced “gut checks,” and predictive analytic models allow such risk assessments to be embedded in systems.

- ▶ **Fraud**—How likely is this claim to be fraudulent, and how should we process it? Fraud detection generally involves a running battle with fraudsters, putting a premium on rapid response and an ability to keep up with new kinds of fraud. Managing the expertise and best practices required to detect fraud using business rules gives this agility, while predictive analytics assists with outlier detection and pattern matching to increase the effectiveness of these systems.

Operational decisions can also be focused on adding value. Decisions like cross-selling or retention typically have little or no downside risk, and the focus is on creating opportunity and maximizing the value of assets.

- ▶ **Opportunity**—What represents the best opportunity to generate revenue? Especially when dealing with customers, organizations want to make sure they are making the most of every interaction. To do so, they must make a whole series of opportunity decisions, such as what to cross-sell or when to upsell. These decisions involve identifying the opportunity with the greatest propensity to be accepted, as well as when and where to promote the opportunity. A combination of expertise, best practices, and propensity analysis is required.
- ▶ **Maximizing**—How can these resources be used for maximum impact? Many business decisions are made to maximize the value of constrained resources. Whether it is deciding how best to allocate credit to a card portfolio or how best to use a set of machines in a production line, deciding how to maximize the value of resources involves constraints, rules, and optimization.

Finally, operational decisions can be about focusing content or activities on specific transactions or customer contexts, such as dynamically assigning transactions or targeting customers with specific content.

- ▶ **Assignment**—Who should see this transaction next? Many business processes involve routing or assignment. Additionally, when a complex decision is automated, it is common for some portion to be left for manual review or audit. The rules that determine who best to route these transactions and how to handle problems can be numerous and complex.
- ▶ **Targeting**—What exactly should we say to this person? In many situations, there is an opportunity to personalize or target someone very specifically. Combining everything known about someone with analytics predicting likely trends in their behavior and best practices, and constraining this to be in compliance with privacy and other regulations, individuals can feel like the system is interacting only with them.

Navigating the Analytic Landscape

Given the wide range of analytic capabilities available, the various roles that can be involved in using these capabilities, and the range of analytic styles available, navigating the analytic landscape requires a new approach. This approach is decision-led, role-centric, and style-based. It allows an organization to navigate the analytic landscape, selecting appropriate analytic capabilities for each decision-making problem based not on the kind of analytic capability but on its fit for the intended purpose. By focusing on the kind of decision-making problem and on the role(s) involved in solving the problem, organizations can identify a suitable style of analytic capability - descriptive, diagnostic, or predictive - to ensure the chosen capability will be used effectively.

Decision-Led

As organizations shift from a focus on reporting and monitoring to one focused on decision-making, the most important thing to know about each project is which decision(s) are being targeted for improvement. Only a clear view of the decisions will allow selection of appropriate analytic capability.

“What the world ideally needs is a clear taxonomy of decision types and the technologies that support each one. Short of that, a simple inventory of decisions that an organization needs to make, and some of the attributes of each decision, would be very helpful.”

Tom Davenport, Professor Babson College

The characteristics of the decision to be improved are at the heart of selecting an appropriate analytic capability. The four characteristics that matter most in describing a decision at this stage are:

- ▶ Volume, or how often a decision is made
- ▶ Repeatability, or how similar each decision is
- ▶ Latency, or how long the organization has to make the decision
- ▶ Complexity, or how difficult the decision is

Many organizations are finding that being more specific about how they make a particular decision is also important. Modeling how the decision will or should be made clarifies the role of analytics in the decision. This makes it more likely that an effective analytic will be developed and that the analytic(s) developed will be used. An emerging standard for modeling decisions is the Decision Model and Notation standard, described below.

Figure 3: A New Approach

A New Approach: The Analytics Capabilities Landscape

What are the business goals for using analytics?

DECISION-LED
Begin with the decision.



ROLE-CENTRIC
Identify the roles involved.

Know the decision you are trying to improve and characterize using four critical characteristics:

Volume

How often must we make this decision?

ONCE ALL THE TIME

Repeatability

How different is making the decision each time?

UNIQUE CONSISTENT

Latency

How long do we have to make a decision?

IMMEDIATE DELAYED

Complexity

How many factors must be considered in the decision?

SIMPLE COMPLEX

Once you know the decision, determine who's on point to improve it.



Business Decision-Maker

EXECUTIVES, KNOWLEDGE WORKERS, LINE OF BUSINESS, FRONT-LINE WORKERS



Business Analyst

BUSINESS ANALYSTS, DATA ANALYSTS, BI ANALYSTS



IT Data Professional



Analytic Professional

DATA SCIENTISTS, FORECASTERS, DATA MINERS, PLANNERS

STYLE-BASED

Identify the right style of analytics.

Decision characteristics and roles intersect to determine what **style** of analytic capability you need.



Explorer

INTERACTIVE
DRILL DOWN, NAVIGATE
CHANGE PERSPECTIVE
CHANGE PRESENTATION



or Settler?

MORE STATIC
APPLY INSIGHT TO NEW DATA
RAPIDLY CONSUME



Visual

HUMAN USER FOCUS
VISUAL PRESENTATION
PATTERN RECOGNITION



or Numeric?

MACHINE FOCUS
MATHEMATICAL PRECISION
EXECUTABLE



DIY

ONE PERSON BUILDS & USES
CODELESS DEVELOPMENT
LESS TECHNICAL
HUMAN DECISIONS



or Factory-Made?

SEPARATE BUILDER AND USER
SKILLED BUILDER - LESS SKILLED USER
CAN BE MORE TECHNICAL
REPEATABLE & AUTOMATED DECISIONS

Source: Analytics Capabilities Landscape Infographic

Role-Centric

Decision-making problems can be solved in a variety of ways. The people who will be involved and their roles that will play a part in improving the decision will further constrain and direct the type of analytic capability to be used. While many roles exist in organizations, they can generally be classified as one of four types:

- ▶ Business decision-makers
- ▶ Business analysts
- ▶ IT data professionals
- ▶ Analytic professionals

A clear understanding of who is going to be involved in solving a decision-making problem is the next step.

Style-Based

With a clear understanding of the decision that is to be improved and the role(s) that will be involved, it is possible to identify the right type of analytic capability that is required. Three elements define analytic style:

- ▶ Interactivity: Is the capability designed for explorers or settlers?
- ▶ Presentation: Does the capability deliver a visual result or a numeric one?
- ▶ Scaling approach: Is the capability a DIY one or a factory-made one?

This analytic style will determine if the roles involved can use the capability to solve the decision-making problem at hand far more effectively than the capability's position on an arbitrary maturity curve.

Becoming an analytic organization is going to require a broad portfolio of analytic capabilities. These capabilities will need to include descriptive, diagnostic, and predictive analytic capabilities. Different capabilities do not replace each other so much as complement each other. Different problems will require different capabilities, depending on the decisions being improved and the roles involved. Making sure that capabilities can be selected from a broad portfolio will be important for long-term success.

Decision-Led

When starting a new analytic project, the first step is to identify the decision(s) being improved and the KPIs or metrics that will show that the decision has, in fact, been improved. To select appropriate analytic capabilities, the basic characteristics of the decision need to be understood.

Volume

One of the first things an organization must know about a decision is how often the decision will be made. The volume of a decision can vary between one-off, unique decisions that are made only once to high volume decisions about customers that might run into tens of millions of decisions a month, to decisions about transactions that might reach millions per day.

The way analytics will be developed and deployed to improve a decision will vary widely based on the volume of the decision. In particular, the style of analytic that is suitable will vary based on the volume. For instance, a decision that is only going to be made a few times is unlikely to require an investment in a factory-made analytic because there simply won't be enough opportunities for users to take advantage of the pre-made analytic. Instead, something more DIY-oriented is likely to be useful. Similarly, a very high-volume decision being made millions of times a month may be automated and require a more numeric output.

Repeatability

Any decision made more than once can be assessed for repeatability. Repeatability measures how similar the decisions are within a category. Generally, lower volume decisions tend to be less repeatable, while most high-volume decisions are very repeatable. However, this is not always the case, as some low-volume decisions are highly repeatable, and some reasonably high-volume decisions are not. For instance, a weekly decision about staffing a call center might be highly repeatable, with the same inputs and calculations being done each week. In contrast, a decision as to the most appropriate investment suggestion for a high net worth individual might be made by each sales person multiple times a day but be made very differently each time.

Low repeatability in a decision tends to put more value on exploratory tools, while high repeatability may favor tools geared at more settled analytics. When decisions are both highly repeatable and high volume, automation becomes very realistic, and a numeric output may be particularly valuable thanks to its easy consumption by programs and business rules.

Latency

The third property of a decision that matters is that of latency—how long does the organization have to make the decision. This may be determined either by some absolute limit or by a more general “decay.” Some decisions must be made with a particular latency, such as decisions about a trade that must be made in a specific time window as the trade flows to an exchange or the routing of a call in a contact center, which must be made fast enough to meet a defined service level.

Other decisions do not have a “hard” value for required latency, but the latency still matters. Richard Hackathorn developed the concept of using a value-time curve for decisions where, the longer it takes to make a decision, the less value is derived from that decision, assuming a constant quality of decision. Different decisions have decay curves of different shapes—some decay quickly, some much more slowly—but the general decay in value as decision latency increases is widely consistent. One decision may therefore need to be low latency to capture the most value, while another can be high latency, as there is little or no advantage to a faster decision.

“As quicker actions are taken, we move up the value-time curve, increasing the value gained”

Richard Hackathorn, President of Bolder Technology, Inc.

A low latency decision is likely to result in the use of more settled analytics that can be consumed quickly, while higher latency decisions can allow for more interactive analytics, as the user has time to come up with the right answer.

Complexity

The final property of a decision that drives analytic capability selection is that of overall decision complexity. Several factors may make a decision more complex:

- ▶ The number of possible actions and outcomes that may be selected
- ▶ The breadth of the data that is available and relevant to the decision
- ▶ The degree of uncertainty regarding whether a decision is a good one or not
- ▶ The number and scope of policies or regulations that constrain the decision

Decisions where experience really matters or where there are large variations between outcomes across different decision-makers are often complex decisions.

Low complexity decisions may well allow for settled analytics and for DIY approaches, while high complexity decisions might require exploratory analytics or the use of a factory-made approach so that deep expertise can be applied cost-effectively.

Role-Centric

In analytics projects, understanding the role of the user accessing the analytic capabilities is every bit as important as identifying the decisions to be made. As the analytics market has matured, the capabilities available have evolved so that most capabilities are now available in forms that work for a variety of user types. The same technique may be available for a business user, a data scientist, an IT practitioner, or a data analyst. As a result, it is important to know who is going to be using an analytic capability before a suitable one can be selected.

While there are many different types of analytic users, they can be grouped into four readily understandable roles across the three areas typically involved in analytics: business, IT, and analytic users. Business users can be subdivided into two roles, that of decision-maker and analyst.

Business Decision-Maker

Business decision-makers are central to most of the decisions an organization makes. Whether these decisions are strategic, tactical, or operational, decisions generally involve someone on the business side of the organization acting as a decision-maker.

“Most discussions of decision-making assume that only senior executives make decisions or that only senior executives' decisions matter. This is a dangerous mistake.”

Peter Drucker

Business decision-makers range from the most senior executives that often make strategic decisions to managers making tactical decisions and front-line staff making operational decisions about a single customer or even a single transaction. Analytic capabilities increasingly are required to support all these decision-makers so that decisions are made based on the data available.

Business decision-makers at any level are focused on business outcomes. They are less interested in the analytic techniques involved, the data being analyzed, or the technology involved. They just want a positive business outcome for their part of the organization. With business decision-makers, no analytic or analysis skills can be assumed, no matter how senior the decision-maker involved.

Analyst

The second business role is that of analyst. Analysts may have many job titles:

- ▶ Business analyst
- ▶ Data analyst

- ▶ BI analyst
- ▶ BI expert
- ▶ Role-specific analyst such as a risk analyst or marketing analyst

While these analysts are generally familiar with technology, they are typically not “coders” or developers. Similarly, while they may have good analysis skills, this does not mean they necessarily have good analytic skills. As a result, they may be better at consuming the results of analytic capabilities than they are at using them.

Analytic Professional

Many organizations are investing in hiring analytic professionals as they try to move to a more data-driven organization and become what Tom Davenport, author of *Competing on Analytics*, calls an “analytic competitor.” These analytic professionals have many different names also:

- ▶ Data scientist
- ▶ Forecaster
- ▶ Econometrician
- ▶ Statistician
- ▶ OR analyst
- ▶ Data miner

These professionals generally have deep skills in and understanding of a subset of analytic capabilities. They may be steeped in knowledge about how forecasting or optimization technology works or how to use data mining techniques to find insight. Many have a broad portfolio of analytic skills, while others are incredibly well-versed in a specific area. Most will be willing and able to code and “tinker” in their chosen domain.

No matter what they are called or what skills they have, it can be assumed that they are a very constrained resource in almost every organization.

IT Data Professional

Finally, there is the role IT plays in analytic capabilities. Many analytic capabilities are initially configured, deployed, and managed by the IT department in an organization. These organizations focus on scalability, performance, and delivering a broad horizontal capability that can be widely used by many departments and roles in the organization.

Most IT organizations have skilled coders and professionals who understand the technical details of the data sources. However, they may not know the business side well enough to see the decisions that must be made or the analytic skills to develop the insight required to make them.

Analytic Style-Based

Organizations need a broad range of analytic capabilities—descriptive, diagnostic, and predictive, as discussed in the Appendix: Analytic Capabilities. While different analytic capabilities have differing value for various decision-making scenarios, this is not an effective way to differentiate between products or vendors. The reality is that most vendors offer a wide range of analytic capabilities, and a given capability varies in how it works and can be used. To select analytic capabilities, it is more important to consider the **style** of an analytic capability.

Three elements of analytic style matter particularly when selecting an analytic capability:

- ▶ How interactive is the capability?
- ▶ How visual is the output of the capability?
- ▶ How does the capability scale?

These elements of analytic style determine which roles can use the capability effectively and what problem can be solved with it.

Interactivity: Explorer or Settler?

The first element of analytic style that should be considered is that of interactivity. Some analytic capabilities support a highly interactive, exploratory style of use, while others do not. These two approaches can be viewed as one designed for explorers and one designed for settlers.

- ▶ An analytic capability aimed at explorers will present its results such that the user can interact with them extensively, changing parameters or selecting subsets of data, drilling into a specific area, etc. This kind of capability is designed to help a user explore the data and to help them find new insights. What data or analysis might be useful may not be initially obvious, and the user is expected to be able to navigate and interact with the data effectively to find answers.
- ▶ Other analytic capabilities are more settled, designed to let the user view or "farm" a kind of insight that has been established as successful or useful. A settler-oriented capability applies known analyses to new data or to a particular slice of data relevant to the user in question.

Either type may be descriptive, diagnostic, or predictive, depending on the circumstances. What's critical here is the degree to which the way analytics should be used is understood in advance. Where the role of analytics is understood, a Settler capability will work well. Where it is not, a more interactive Explorer-oriented capability will be more useful.

Output: Visual or Numeric

The second element of analytic style is all about the presentation or output of the analysis.

- ▶ Some analytic capabilities are focused on delivering results primarily for a human user with visual representations of results. Regardless of how the analytic has been generated, the results are aimed at a human decision-maker. The use of color, font, layout, infographics, maps, and more all play a role in clarifying and explaining the analytic result. Visual representations lend themselves to make the gist of an analytic result clear, showing the overall pattern or trend.
- ▶ In contrast, other analytic capabilities present their results purely numerically. While numbers can, and often are, consumed by humans, they can also be consumed by a machine or program. Numeric representations lend themselves to precision but can result in the view of the forest being lost in the trees. They can also result in a spurious sense of precision, one not really supported by the accuracy of the analytic.

Many analytic capabilities across the descriptive–diagnostic–predictive landscape can present their results visually, and many can do so numerically. Many techniques can be used to produce either kind of presentation. However, the way a specific product or capability presents results is critical to how it can be used. Human users increasingly prefer and even insist on visual presentations of results, especially when they have any degrees of freedom in action. Computers and computer programs require numeric results. The degree to which a decision is automated or highly prescriptive therefore drives the degree to which visual or numeric presentation is to be preferred.

Scale: DIY or Factory-Made?

The final element of analytic style is focused on how users of the capability actually use it and how it can therefore scale across the enterprise. In particular, are there two different roles in the use of the analytic capability (a builder and a user) or just one?

- ▶ Some analytic capabilities are focused on a single builder/user. They are intended to be built and used by the same person. These kinds of capabilities rarely involve code, and often utilize a drag-and-drop, codeless development environment. The person doing the analysis and building the analytic is the person who must also make the decision. These capabilities can be considered DIY capabilities.
- ▶ Alternatively, an analytic capability might be designed for a builder and user separately. In this model, a builder will do some analytic work to derive the analytic result, and then a differently skilled user will consume the results to

make decisions. These capabilities are analogous to a factory model where many can consume something created for them elsewhere.

With a factory-made capability, there is often less need for a codeless or drag-and-drop environment. Because a smaller number of builders are required relative to the number of users, the builders can be more skilled with coding, and this enables them to take advantage of more complex analytic capabilities that are difficult to use or configure and too complex to put in a drag-and-drop environment. Increased compute power and a focus on usability means that most analytic capabilities are available in a DIY form, however. This style represents the two ways in which analytic capabilities can be made pervasive:

- ▶ DIY capabilities make analytics pervasive by making it easier for more people to do it themselves.
- ▶ Factory-made capabilities make analytics pervasive by allowing every decision to be based on analytics, even when the decision-maker is not building the analytic themselves.

Styles

These three analytic styles can be combined in eight ways. In practice, there is overlap between the styles, but these combinations are worth considering as examples of the kind of capabilities available.

Table 1: 8 style combinations

Interactivity	Output	Scale	Description
Explorer	Visual	DIY	Highly interactive and visually appealing tool that allows someone to develop their own understanding in a no-coding environment.
		Factory Made	Pre-packaged components that are highly visual and allow a user to interact and explore a set of data and analytics that were developed for them.
	Numeric	DIY	Highly interactive tools allowing a user to produce a numeric output, such as a forecast or prediction, for their own use. Simulation may be central to the interactivity offered.
		Factory Made	Interactive tools working within a predefined set of boundaries and parameters to allow exploration of a specific numeric output, such as a forecast.
Settler	Visual	DIY	Easy-to-assemble components that present standard data visually, e.g., a personal dashboard made from pre-built components.
		Factory Made	A set of visual representations that enable a user to make a decision based on pre-packaged analysis.
	Numeric	DIY	A set of standard formulae that can be assembled by a user as part of answering a question.
		Factory Made	A standard report, score, or forecast consumed as-is.

Example Decisions

To illustrate how this Decision-Led, Role-Centric, Analytic Style- approach works, this section includes a number of working examples.

Next Best Offer

Many organizations are trying to improve the cross-sell and upsell rates in their contact centers. To do this, they are offering their customers the next most attractive purchase for their situations, or the next best offer. For organizations of any size, these decisions are:

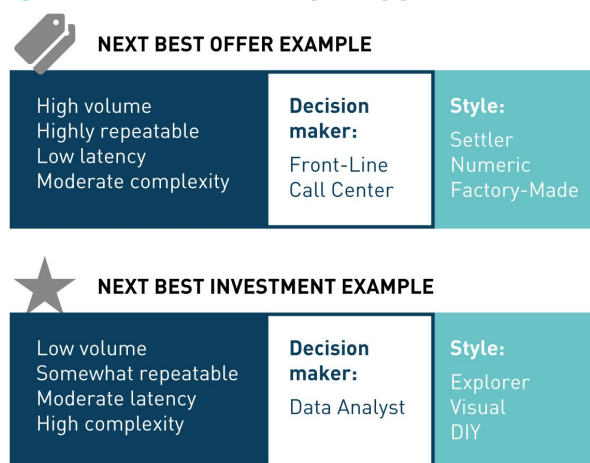
- ▶ **High volume** because the decision must be made for every customer interaction.
- ▶ **Highly repeatable**, as standard policies for eligibility must be applied and because most organizations do not want to treat their customers inconsistently.
- ▶ **Low latency** because the result of the decision must be available to the contact center representative at the end of a potentially short call.
- ▶ **Moderately complex**, as there may be many potential offers to select from.

In a typical contact center, the person making the decision is a front-line **business decision-maker**, though the reality is that this decision will be automated and provided through the contact center application much of the time.

Given these decision characteristics and the role involved, a suitable analytic capability is going to be:

- ▶ **Settler**—a highly repeatable decision being made by someone with little or no analytic or analysis skills is going to be best supported by a settled, repeatable analytic.
- ▶ **Numeric**—Given the low latency of the decision and its highly repeatable nature, an automated decision is likely, and automated decisioning systems are better able to consume numeric analytics.
- ▶ **Factory-made**—For a large group of lower-skilled users, a factory-made model would allow a small group of experts such as analytic professionals to create an analytic that can be readily consumed by a large group of users.

Figure 4: The Landscape Applied



Source: *Analytic Capabilities Landscape Infographic*

Next Best Investment

By way of contrast, consider a next best investment decision. This is also made customer-by-customer, but in this example, it would be for a small number of high net-worth individuals with complex investment portfolios. Determining what investment offer to make next is a quite different decision that is:

- ▶ **Low volume** because far fewer customers are in this category, and they call less often.
- ▶ **Somewhat repeatable** with higher variation in approach, given the greater divergence between investment portfolios when compared to typical variations in products purchased.
- ▶ **Moderate latency** because there is likely to be more preparation time for each such call, reducing the value of speed.
- ▶ **High complexity**, as the range of possible recommendations is very high while the environment is difficult to assess, given the existing investments could be very spread out among categories.

While many different roles might be involved in such a decision, for the purposes of this example we will assume that the organization has a team of **data analysts** who work on these decisions to support the client-facing team.

Given these characteristics and this role, a suitable analytic capability is going to be:

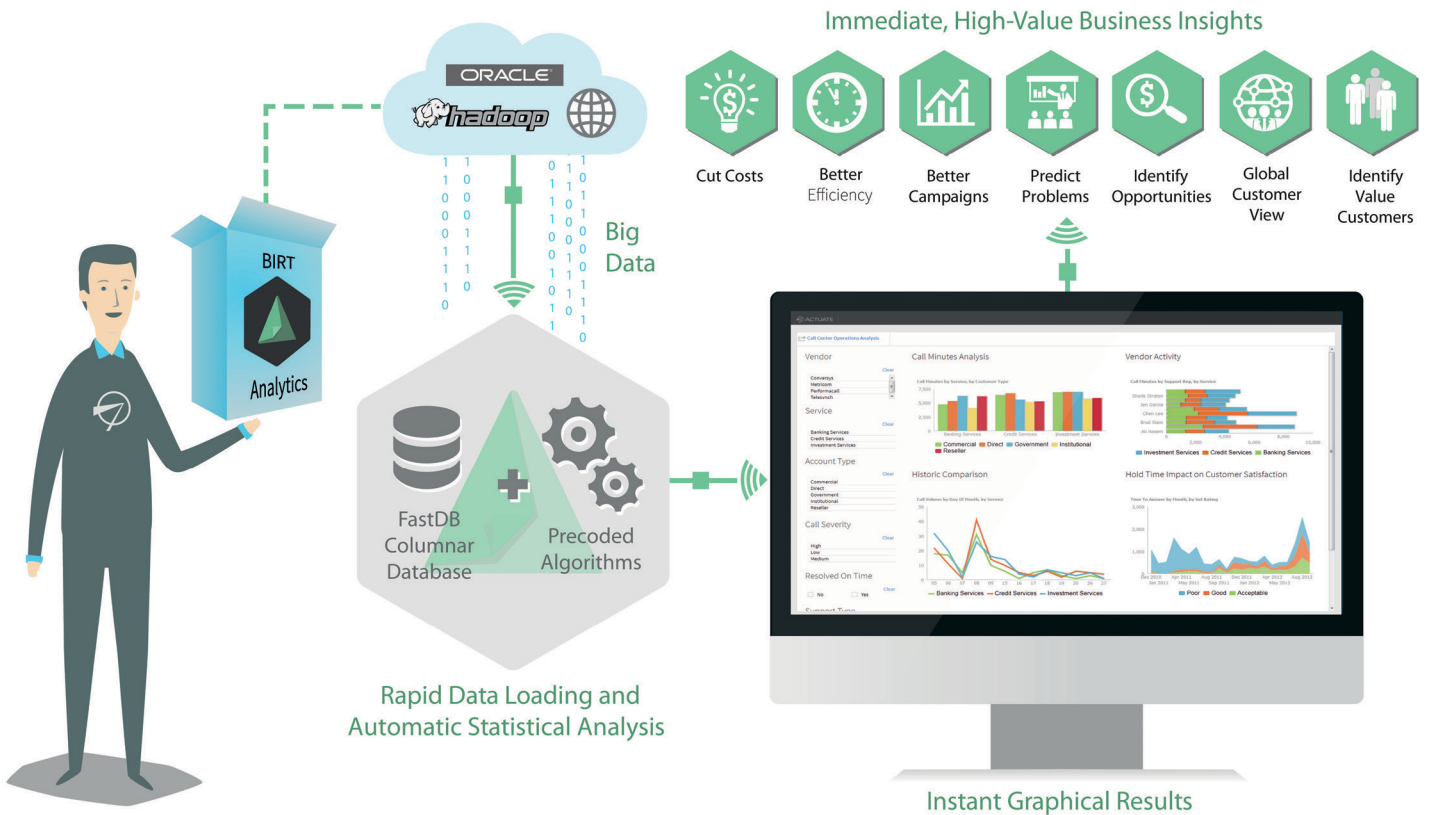
- ▶ **Exploratory**—A complex and only somewhat repeatable decision tends to be increase the value of exploratory capabilities. Multiple iterations, experiments, and approaches are likely to be tried with a mix of data, and this is exactly where most exploratory capabilities excel.
- ▶ **Visual**—Not only is the key decision-maker someone with analysis skills, there is also a clear need to explain the results to other human decision-makers. A highly visual capability is going to pay dividends here by presenting the analytic results to illustrate identified patterns.
- ▶ **DIY**—The users here have the kind of skills that lead to a DIY model, building and using the analytics they develop as part of developing an overall decision-making framework and a recommendation.

The following pages include information from the study's sponsors Actuate and FICO





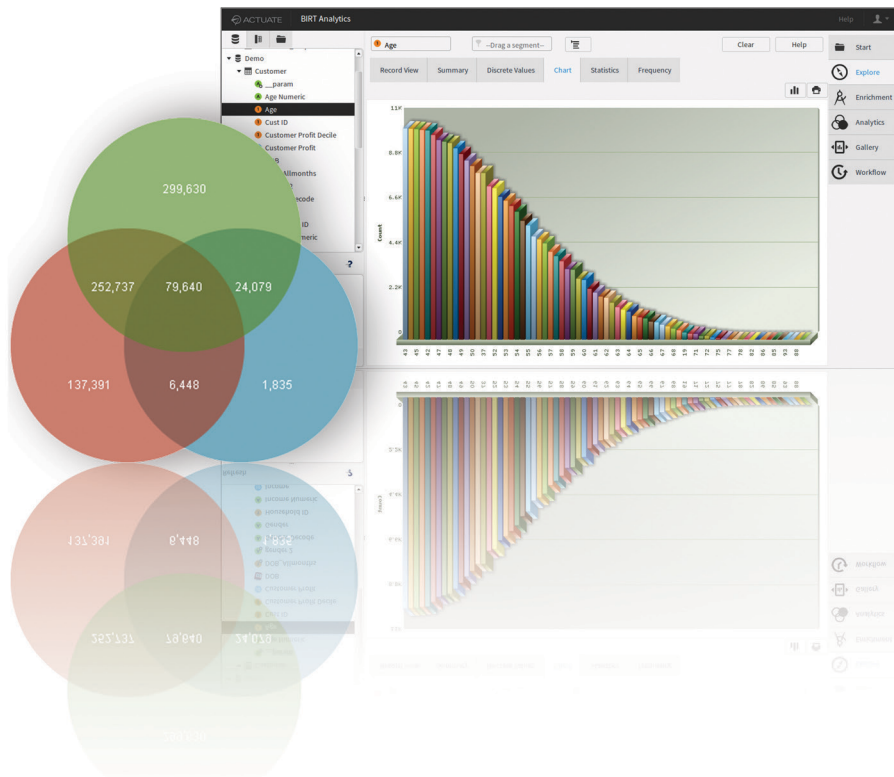
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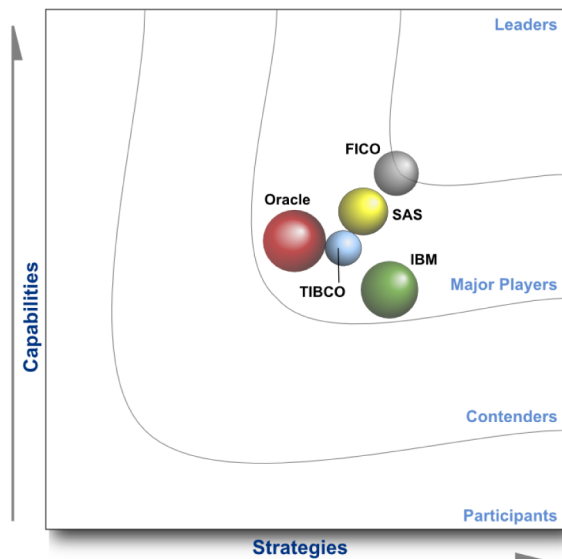
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Source: IDC 2014

SOURCE: IDC MarketScape Worldwide Decision Management Software Platform 2014 Vendor Assessment, by Brian McDonough, September 2014, IDC # 250351. Doc # 250351e_FICO.

IDC MarketScape vendor analysis model is designed to provide an overview of the competitive fitness of ICT suppliers in a given market. The research methodology utilizes a rigorous scoring methodology based on both qualitative and quantitative criteria that results in a single graphical illustration of each vendor's position within a given market. The Capabilities score measures vendor product, go-to-market and business execution in the short-term. The Strategy score measures alignment of vendor strategies with customer requirements in a 3-5-year timeframe. Vendor market share is represented by the size of the circles. Vendor year-over-year growth rate relative to the given market is indicated by a plus, neutral or minus next to the vendor name.

IDC just completed its first ever IDC MarketScape on Decision Management Software Platforms (doc #250351, September 2014).

In the MarketScape, IDC evaluated five decision management platforms in this study, defined as software offerings where a software vendor has pre-integrated components for advanced analytics, rules management, and model development and deploys them into a single decision management software platform.

In the evaluation, FICO was named a "major player." Besides being recognized for its strategy, the IDC MarketScape recognized FICO for the flexibility of its decision management tools and platform, and also praised FICO's sales and distribution strategy, specifically its community and partner network.

The evaluation validates FICO's fundamental belief in the power and value of decision management software to change the way business is conducted.



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Appendix: Analytic Capabilities

Although the analytic landscape is best navigating using a decision-led, role-centric, and style-based approach, organizations will still need to understand the basic capabilities. In this context, it can be useful to think of analytics as a process, one that reaches from data gathering to the development of insight, then to the deployment and sharing of this insight to improve decision-making.

Whole reports can be and are written on the technology for gathering, storing and managing data. Similarly, the deployment and sharing of analytic insight ranges from environments focused on decision support to those focused on Decision Management (Taylor, Decision Management Systems Platform Technologies Report, 2014).

This report focused on the analytic capabilities for developing insight. These capabilities are increasingly divided up into descriptive, diagnostic, and predictive capabilities, and this organization is used below.

- ▶ Descriptive analytic capabilities are focused on describing what was or is.
- ▶ Diagnostic analytic capabilities are focused on why something happened.
- ▶ Predictive analytic capabilities are focused on the future and what will happen.

Many authors add a fourth category to the descriptive, diagnostic, predictive trio—*prescriptive* analytics. This category is not used here because the analytic capabilities are not different for prescriptive. Prescriptive analytics is about applying other decision-making technologies and approaches, such as business rules, to analytic insight so as to make decisions. As such, it is not a class of analytic capability so much as a way to use analytic capabilities.

Descriptive Analytic Capabilities

Descriptive analytic capabilities describe what was—what happened. When used in a more real-time, monitoring scenario, these capabilities can also show what **is**—what’s happening right now. Descriptive capabilities are generally static or, if they are more dynamic, present the same data in different ways. Descriptive analytics can be thought of as “obvious,” providing little insight into the data beyond making it consumable—though this is non-trivial as the amount of data gets very large.

Capabilities in this category include:

- ▶ Report-based presentation and summary of data.
- ▶ Graphical presentation of data and visualization.
- ▶ Simple statistical analysis.
- ▶ Dimensional presentation of data.

For sales data, examples might include a report of sales by product line, a visual presentation of sales volume by region, analysis of sales data to show daily averages and distribution, and the analysis of sales data by sales person, team, and time in role.

Report-based presentation and summary of data

Report-based presentations involve the aggregation of data into a tabular or document layout with summarization, ordering, grouping, and structure. These reports can be fixed and generated on a regular schedule, or they can be more ad-hoc and developed as needed. Regardless, there is little or no analysis of the data inherent in the report.

Graphical presentation of data and visualization

As data volumes grow larger, it becomes increasingly difficult to get an overall perspective on the message in the data. Summarizing data in graphical format such as pie charts, bar graphs, or dials can make it much easier to understand what has happened. When these presentations are kept up-to-date, they can also show what is happening. Some graphical presentations layer the data being analyzed onto some other framework to visualize the data's distribution - for instance, showing how data varies by geography.

Time-based monitoring is a function of using these analytic capabilities and showing variation on a time dimension. The variation might be against a baseline, a target, or both. More sophisticated time series analysis is part of diagnostic and predictive capabilities.

Simple statistical analysis

Data can also be analyzed to show basic statistics such as distributions, minimum/maximum, rolling averages, etc. These analyses are often combined with tabular data and visualizations to eliminate the need for the user to do these calculations attempt to use visual clues.

Dimensional presentation of data

There are a variety of approaches for comparing data across multiple dimensions, such as OLAP. These techniques are often used to consolidate and summarize data in more complex ways so that it can be better understood. More interactive dimensional tools are often used in diagnostic analytics.

Diagnostic Analytic Capabilities

Diagnostic analytic capabilities tend to blur into the descriptive category, and some argue that this is a distinction without a difference—that capabilities that show what happened can be used to see why it happened also. In practice, however, there is enough of a difference to call this set of capabilities out separately.

Diagnostic analytic capabilities are all about understanding—why are we seeing what we are seeing? The techniques allow for in-depth analysis and profiling of data, include data mining and segmentation, and rely on increasingly mathematical techniques to reveal hidden relationships and meaning. If descriptive analytics are focused on what is “obvious,” then diagnostic analytics are focused on what is **hidden**.

- ▶ Dimensional comparison of data
- ▶ Mathematically-based visualization
- ▶ Data mining
- ▶ Optimization

Continuing with the sales data example, analyses might include comparing sales data against different organizational dimensions to see how last year’s organization compares to this year’s, a chord diagram of sales by product line by region, the identification of the characteristics of the organization’s most effective salespeople, or the optimal assignment of territories to sales people.

Dimensional comparison of data

Dimensional presentation of data is generally considered descriptive even when drill-down and “slice and dice” capabilities are provided. Because dimensional capabilities allow increasingly sophisticated comparisons of data across different dimensional models, users can compare data when displayed using different hierarchies for diagnostic analysis.

Mathematically-based visualization

While simply visualizations are descriptive, an increasingly wide array of diagnostic visualizations is available. These visualizations are driven by a mathematical function rather than simple aggregation, counts, or classifications.

For example, this could be a chord diagram showing relationships between groups of entities or a flow or path analysis visualization such as a Sankey diagram. The generation of these visualizations involves applying mathematical analysis to the data to support the visualization. This category of analytic capability overlaps with data mining, as many data mining techniques can produce graphical outputs.

Data mining

Data mining involves the application of advanced mathematical techniques for identifying and formalizing patterns or relationships in historical data. Data mining can be supervised or unsupervised, which means that techniques can be directed to find a specific pattern such as what kinds of customers are most profitable or used to find clusters that are alike without any specific objective. A wide variety of data mining techniques exist, including decision trees, classification, clustering, association, and affinity detection.

Data mining techniques are often used as part of developing predictive analytics but can also result in insight that can be directly applied to decision-making, such as identifying segments of customers who could be treated differently.

Predictive Analytic Capabilities

The final category of analytic capabilities is that of predictive analytics. These analytic capabilities are all about what is likely to happen next—what is the probability of something happening and the likely size of something. While definitive predictions remain the realm of science fiction, predictive analytics allow for the creation of probabilities or likelihoods in place of uncertainty.

- ▶ Forecast
- ▶ Predictive analytic model
- ▶ Adaptive or learning analytic model
- ▶ Simulation

For the sales data example, analyses might include sales forecasts for the coming year, predictions that specific deals will close or be profitable, a learning algorithm for making cross-sell offers to customers, or a simulation of the impact of a new pricing model.

Many assessments of analytic capabilities call out text analytics as a separate category, typically near the "top" of the analytic maturity curve. Many analytic techniques are used only against structured text and others only against unstructured text. In the approach being described, however, the ability to access different kinds of data is considered a prerequisite rather than a driver for selection. See the Appendix: Other Adoption Considerations for more details.

Forecast

A forecast is an aggregate estimate of demand or other value for each of a number of future periods based on direct, seasonal, or other comparison to historical data. In some ways, forecasts are a subset of predictive models that don't seek to explain

the data so much as model the natural shape of the data. Time series and seasonality analysis are the classic approaches.

Predictive analytic model

A predictive analytic model is built at a point in time from a data set of historical data to predict a value or score based on new data. The model relies on calculated characteristics that can be derived from this data, as well as the data itself, and applies a function to create a score or other result. The function at the heart of the model is derived by analyzing historical data using a variety of mathematical techniques such as linear and logistic regression, neural networks, outlier detection, and support vector machines. Each predictive analytic model predicts something specific, and these predictions are represented as a number in a defined range.

Adaptive or learning analytic model

A variant on a predictive analytic model, an adaptive or learning analytical model learns and adapts the function used to score new transactions while in use. This generally involves automatically experimenting with different approaches or variations and using a tight feedback loop to automatically update the model parameters to reflect what seems to be working for a particular segment, at a particular time, or both.

Any predictive analytic modeling exercise should involve experimentation and ongoing learning. New approaches to the model should be developed, back-tested, and then deployed as an experiment if they seem promising. When experiments succeed, they can be more broadly deployed or integrated into the overall model. What's different in adaptive analytic models is the automation of this experimentation, not the experimentation itself.

Optimization

Optimization is not always included in lists of analytic capabilities, and debate exists around whether to consider it predictive. In practice, however, it is useful to include it in this category as it involves the identification of a viable or optimal solution to a problem that has not yet been solved. Optimization involves the use of set of tools to formulate a problem as a mathematical function and the use of solvers based on linear programming, mixed integer programming, quadratic programming, or nonlinear approaches. The solvers maximize or minimize the result of the function or find a viable solution for the problem the function defines. Optimization results in a set of recommended actions designed to produce the best possible (or a viable) outcome.

Appendix: Other Adoption Considerations

The use of analytic styles to find analytic capabilities that will help specific roles solve specific decision problems enables an organization to pick from a broad landscape of analytic capabilities. Many vendors deliver a wide range of analytic capabilities and support. The style of these capabilities is central to selecting the right capability.

Analytic capabilities have other characteristics that are not considered as part of this style-based assessment. These characteristics may matter to a particular project or organization because of specific business or technical circumstances.

Organizations should regard these not as selection tools but as a way to identify which capabilities are candidates and which capabilities will form the landscape for an organization or project that can be navigated using the approach defined in Navigating the Analytic Landscape above.

Execution Approach

Analytic capabilities often require a significant amount of computing power. Additionally, many analytic capabilities must process a great deal of data which must be stored somewhere. Where an analytic capability executes and whether this requires moving the data to the execution location does affect the performance of the analytic capability. Possible execution approaches include:

- ▶ **In-database**
The analytic capability executes in the database management system or data warehouse system that stores the data it needs. This allows the analytic capability to be available to any system or user that can access the database and avoids moving the data to the analytic capability, a significant potential time savings.
- ▶ **In-Hadoop**
Similarly, an analytic capability may execute in the Hadoop stack. Especially as a singular focus on MapReduce is replaced with a broader approach to execution using Storm, the ability to store data in Hadoop and then execute analytics on the same commodity hardware offers both performance and cost improvements.
- ▶ **In-memory**
One of the challenges in analytics is that many capabilities require all the data involved to be processed as part of an analytic “run.” As memory has become cheaper and easier to access, an increasing array of analytic capabilities can run in-memory. This maximizes performance, though it may not be practical for the largest data sets and does require data to be moved into the memory space for processing.
- ▶ **Distributed/Grid-based**
Many analytic capabilities can take advantage of a distributed or grid-based

approach. This allows even very large datasets to be processed through complex analytic techniques.

- ▶ **Workstation-based**
Some analytic capabilities are fundamentally limited to a single workstation. Although workstations are increasingly powerful, this will generally limit the size of data that can be realistically processed.
- ▶ **Cloud – private, public, hybrid, managed**
The use of cloud resources to process data analytically supports the widely varying needs for computing power in a typical analytic process. By accessing more or less resources as required, a cloud-based approach can allow for cost-effective analytics scaling with a cost trade-off of moving data to the cloud if it is not already there.

The particular decisions being considered, especially their volume, latency, and complexity, will drive the need for execution performance.

Data Types

Different analytic techniques can be applied to different kinds of data. For a given decision-making problem, it may be critical that a particular capability can be applied to a particular data set. Such a need may make a product's support for a particular kind of data important for a specific project, but over time organizations will need a set of capabilities that allow them to process all these types of data in support of analytic decision-making:

- ▶ Structured data such as customer data in a relational database or data warehouse.
- ▶ Text or unstructured data such as call or collections notes in a CRM system.
- ▶ Semi-structured data such as logs from a web server stored on Hadoop.
- ▶ Audio data such as recordings of calls or interviews stored as files.
- ▶ Visual data such as pictures of damage to a car sent by email.
- ▶ Video such as security footage streamed to disk.

The specific decision being improved will drive the data that is available, its format, and the value of including specific data types in the analysis.

Data Storage Location

Where data is stored and whether an analytic capability can access it definitely matters regarding the effectiveness of a given capability in a given situation. However, most vendors now support a wide range of storage across on-premise and cloud storage formats as well as allow access to cloud APIs. As a result, this is unlikely to be a useful criteria for long-term capability determination. Again, the

decision being considered will drive the data involved and the immediate storage location for that data.

UI Style

Finally, the user interface (UI) style of an analytic capability can be considered. This might be based on:

- ▶ A mobile UI.
- ▶ A responsive UI designed for both PCs and mobile devices.
- ▶ Some other browser-based UI.
- ▶ A more traditional “heavyweight” client UI.

Almost all analytic capabilities are converging on a responsive, mobile-friendly, browser-based UI as a de facto standard. Instant access to analytic results on both standard and mobile devices is becoming the norm. As such, the current UI style of an analytic capability seems unlikely to be a determining factor.

As before, the decision being improved can provide critical guidance. If the decision is made by people when they are not in the office, then mobile support will be important. If a small number of builders are developing a factory-made numeric model, however, it may not matter that the current version only supports a heavyweight client UI.

Appendix: Decision Modeling

The key characteristics of decisions discussed above drive the selection of analytic capabilities. Before developing specific analytics, however, it is worth understanding the structure of these decisions. The most effective way to do this is to deconstruct decisions to show their requirements.

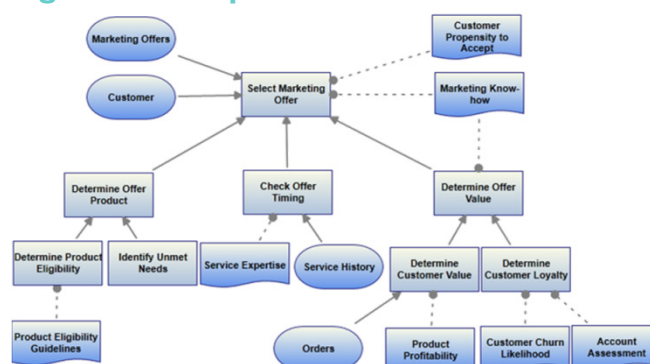
Decisions generally require information, know-how, or analytic insight, and other (typically more fine grained) decisions. Having identified the immediate requirements of a decision, any additional decisions identified can be evaluated to determine their requirements iteratively. The requirements model that results is a network, as decisions are reused when multiple decisions require a common sub-decision. This network reveals opportunity for reuse, shows what information is used where, and identifies all the potential sources of know-how for decision-making, whether they stem from regulations, policies, analytic insight, or best practices.

Building a decision requirements model using the new Decision Model and Notation (DMN) standard captures decision requirements and improves business analysis and the overall requirements gathering and validating process.

For a detailed discussion of decision modeling with the new Decision Model Notation (DMN) standard, download our white paper “[Decision Modeling with DMN.](#)”

For analytic projects, a clear understanding in terms of the decision-making to be improved by the analytic is essential for success. Organizations need to first define the decision-making required and only then focus on details like the specific analytic models involved. Specifying a decision model provides a repeatable, scalable approach to scoping and managing decision-making requirements.

Figure 5: Example Decision Model



For advanced analytics projects, established analytic approaches such as CRISP-DM stresses the importance of business understanding. A decision requirements model identifies and describes the decision for which analytics will be required. How the data requirements support these decisions and where these decisions fit is clarified, focusing the use of analytics more precisely.

About the Study

We would first like to acknowledge our research sponsors without whom this research would not have been possible—Actuate and FICO.



In addition to their sponsorship, both companies made experts available and provided valuable input and feedback on the research.

A number of other experts in the field of analytics also were interviewed to gather additional context and commentary about analytic capabilities and how organizations can adopt those capabilities effectively. Others provided their own research for us to consult. We would like particularly to acknowledge the assistance of Neil Raden, Donald Farmer, Tracy Altman, Dean Abbott, and Gagan Saxena.

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