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ESG Market Summary Report: Decision Analytics: Building the Foundation for Predictive Intelligence and Beyond

ESG Market Summary Report

Decision analytics may appear to some as the light at the end of the tunnel, but most will experience it as the oncoming train that is hard to dodge. Decision analytics is the process of rendering decisions supported by analytic capabilities that improve the decision-making process and reduce decision time, complexity, and uncertainty. Decision analytics will have a transformative impact on the IT market. This union of decisioning tools and advanced analytics enables enterprises to become more precise and confident in making complex forward-looking decisions. To date, IT and BI have been all about understanding the past and present. A comprehensive understanding of the past and present is invaluable and is a critical prerequisite for making forward-looking decisions. However, in order to effectively make informed forward-looking decisions that will have lasting utility, reliance on predictive analytic techniques is paramount.

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Executive Summary

Decision analytics may appear to some as the light at the end of the tunnel, but most will experience it as the oncoming train that is hard to dodge. Decision analytics is the process of rendering decisions supported by analytic capabilities that improve the decision-making process and reduce decision time, complexity, and uncertainty. Decision analytics will have a transformative impact on the IT market. This union of decisioning tools and advanced analytics enables enterprises to become more precise and confident in making complex forward-looking decisions. To date, IT and BI have been all about understanding the past and present. A comprehensive understanding of the past and present is invaluable and is a critical prerequisite for making forward-looking decisions. However, in order to effectively make informed forward-looking decisions that will have lasting utility, reliance on predictive analytic techniques is paramount. Enterprises should understand the potential value that can be delivered through predictive intelligence and carefully consider creating a decision analytics programs office led by a chief data officer.

The remainder of this document focuses on the architectural model needed to support decision analytics, the categories of analytics that are leveraged in decision analytics, the subset of decision analytics that supports predictive intelligence, and some of the more common use cases for decision analytics.

The decision analytics journey will be challenging, but can be greatly simplified based on:

- The commitment of the enterprise to utilize decision analytics.
- The identification of decision analytics objectives.
- Astute choices made regarding a decision analytics architecture.
- The careful selection of your decision analytics product and service technology partners.

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Introduction

Decision making and analytics have coexisted since before the advent of IT. IT simply made it easier to leverage analytics and apply it to decision making.

Advances in modern decision analytics are highly correlated with the evolution of IT. The advent of the mainframe (the first platform) enabled access to decision support system (DSS) tools during the 1970s and 1980s. The introduction of the PC (the second platform), client/server computing, and cheaper storage gave rise to data warehousing and business intelligence (BI) in the 1990s and 2000s. The evolution of smartphones (the third platform) coincided with cloud, social, and mobile computing and today's emphasis on big data and decision analytics in the 2010s, and will extend into the 2020s.

The big change that is coming in analytics is the transition from looking backward to looking forward. Descriptive analytics give managers a historical view of how the business is performing. Business intelligence and data warehousing are prime examples of how descriptive analytics have been put to use. Although the term historical means past, it can also mean recent past, meaning up to the current point in time. The utility in looking backward is that data is no longer a moving target for analysis. This removes ambiguity from the analysis and enables a factual point of view to be established and captured in a system of record. Looking backward is a core competency that all organizations should exercise and is a prerequisite for looking forward.

Looking forward is where new opportunities exist in decision analytics. Predictive analytics includes a wide variety of analytic techniques that leverage historical data and relationships to help us identify and evaluate the opportunities and risks that will shape the future. Once these opportunities and risks have been identified and evaluated, this knowledge can be leveraged to make informed decisions. While enterprises may struggle to get their heads around some of the concepts associated with predictive analytics, there are obvious entry points, such as the use of "scoring models," that have broad familiarity. Vendors that have a long tenure in decision analytics, including FICO, IBI, IBM, Oracle, Pegasystems, SAP, SAS, and TIBCO, are actively pursuing ways to make decision analytics easier to understand, adopt, and implement.

Decision Analytics Defined

Decision analytics is the process of rendering decisions supported by analytic capabilities that improve the decision making process and reduce decision time, complexity, and uncertainty. Decision analytics therefore includes an analytic component that performs analysis and a decisioning component that uses the outcome of the analysis to either make or refine a decision. Automation is an important goal of decision analytics—but not all decision analytics activities, especially strategic ones, lend themselves to automation.

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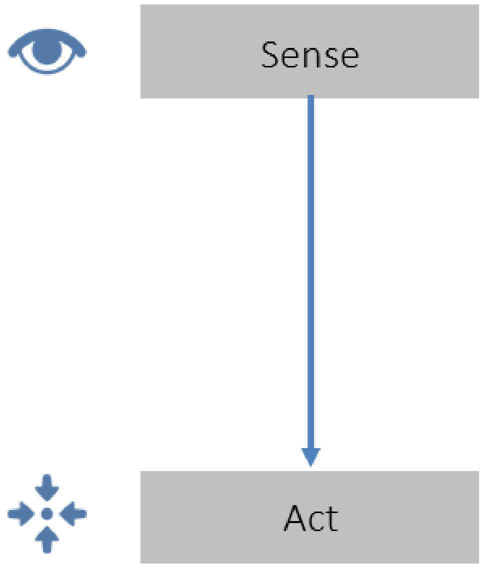
The Decision Analytics Reference Model

Most of us are comfortable with making decisions. This is good because each of us makes an incalculable number of decisions every day. The most interesting and complex decisions that we make are voluntary decisions where we are able to apply discretion in why, how, and what decisions are made. However, it would be a mistake to ignore the fact that we also make an immense number of involuntary decisions every day. These range from decisions largely beyond our control like the electrical signals that are evaluated by our CNS and cause our heart to beat to reflexive behavior (remove your hand from a hot stove) and ultimately learned behavior (don't touch a hot stove). The common pattern that unites all of these behaviors is stimulus-response (S-R) theory. Figure 1 shows a schematic of the S-R model. In this S-R model, the *sense* activity recognizes a change in the environment. This change is a trigger, event, or simple change of state. The *act* activity is an action taken in response to a particular sensation.

Figure 1. Stimulus-response Model



Source: Enterprise Strategy Group, 2014.

While S-R theory is conceptually simple, it does raise a question about what happens when a choice can be made regarding what action to take. Early thinking on the topic of event-driven architecture mimicked S-R processing by having events directly associated with actions. While this approach is extremely efficient, it is also brittle, which limits its utility in today's IT environment where applications must be engineered for change and therefore loosely coupled. Without the ability to support a level of indirection between *sense* and *act*, there is no way to easily accommodate change. By introducing a decision node between sensing and acting, we now have clear separation

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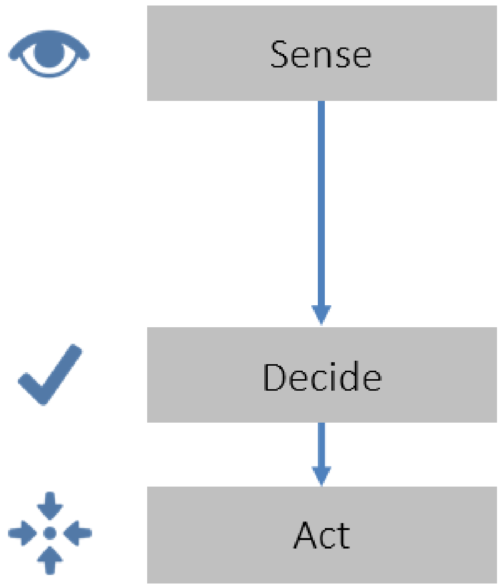
of concerns and the flexibility to link any sensory event with any action, as shown in Figure 2. This enables us to refer to this modified S-R model as a decision model.

Figure 2. Decision Model



Source: Enterprise Strategy Group, 2014.

By introducing a decision node, we allow for different types of decisions. This more robust model can also emulate an S-R model simply by either always choosing the same action or defaulting the decision (such as the "else" clause in an "if-then-else" expression). However, the value of this decision model is that it recognizes that:

- There is a decoupling between sensing and acting, and actions are governed by decisions.
- The existence of competing alternative actions to a particular set of stimuli mean that a decision process is needed.
- A decision process must take into account that available stimuli may not be sufficient or specific enough to clarify what action to take.
- Decision outcomes, actions, and impact may be useful in influencing future decisions.
- The ability to align specific stimuli with a particular action through a decision provides flexibility and consistency.
- The act of decisioning is complex and many techniques can assist in the decision making process.

Despite the importance of decisions, we live in an action- and process-centric world. Decisions determine the potential utility to be gained, but actions are what drive kinetic utility or recognized utility. Actions (or behavior) are what define and differentiate an enterprise. Because actions can be directly tied to utility, it is easy to dismiss the importance of the decisioning. However, no action should ever be taken unless preceded by a decision. Decisioning is where context, alternatives, potential utility, objectives, constraints, and trade-offs are evaluated and a next-based action is determined. Therefore, support for comprehensive decisioning is critical because the

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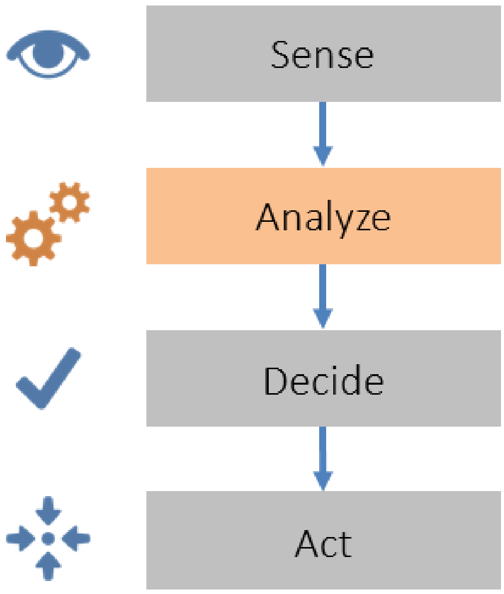
decision is where the choice is made between competing actions. This choice can have lasting impact especially if it is strategic and this also means that decisions can have significant consequences, both positive and negative. Consequently, organizations will want to always make the best possible decisions that they can in order to maximize benefit and minimize risk over some time horizon.

Some decisions are simple and some are complex. Complex strategic decisions are often wide in scope, high in risk, few in number, and difficult to automate, and leverage inputs from many sources. Simple tactical decisions are typically the opposite; limited in scope, require few inputs, are low in risk, are large in number, and easy to automate. As decisions increase in complexity, so too does the need for analytics to support the decision making process. The point is that the decision model can be extended to include an analysis activity where the heavy lifting of evaluating alternatives is performed prior to decisioning. Figure 3 presents this as a decision analytics model.

Figure 3. Decision Analytics Model



Source: Enterprise Strategy Group, 2014.

Separating *analyze* from *decide* has distinct advantages. The primary advantage is a separation of concerns. The *analyze* activity is focused on understanding, quantifying, and normalizing alternatives so that a rational and informed decision can be made. It should be noted that this decision analytics model does not state any requirements regarding latency. While S-R models typically have a distinct real-time orientation, this is not the case for all decision and decision analytics models. Not all decisions that require analysis can or need to be pursued in real time. There is, however, a growing emphasis on and trend toward real-time decision analytics, so adoption of application architectures that support real-time decision analytics is appropriate although not all decisions will need to be made in real time.

When we evaluate the decision analytics model in Figure 3, it is apparent that we can improve on this model in several ways. The *sense* activity can be improved if we explicitly specify that a discovery activity's whole role is to

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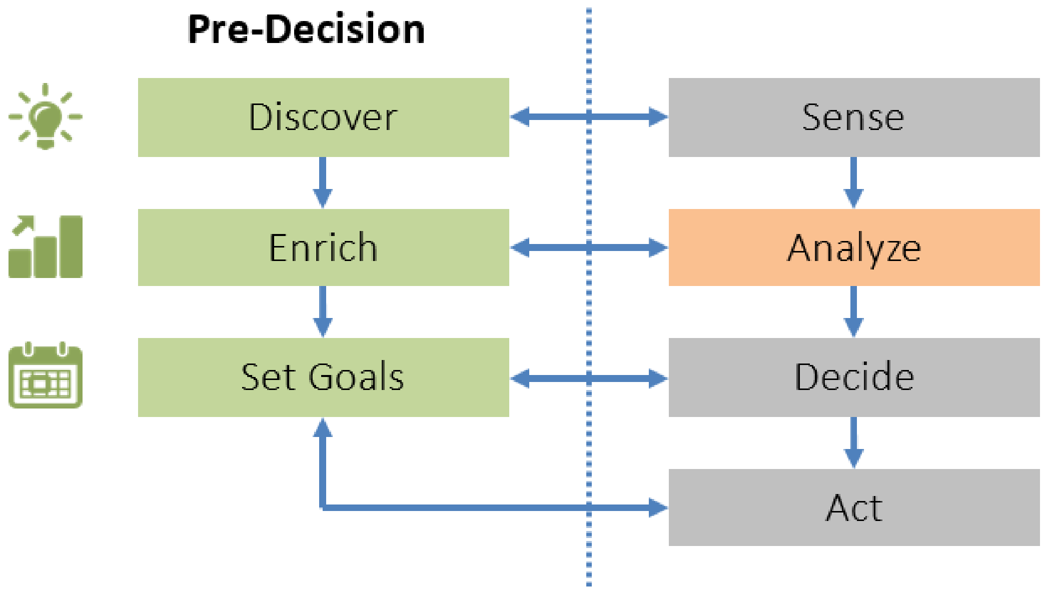
consider the relevance of new and different types of events and triggers that will have an impact on decisioning. The *analyze* activity also benefits from an enrichment activity that improves the understanding of context, alternatives, and additional information related to decisioning. The *decide* activity also benefits from an understanding of policy expressed by objectives and constraints that govern decisioning. Figure 4 improves upon the decision analytics model by adding *discover*, *enrich*, and *set goals* activities, which move the model toward a true reference model for decision analytics.

Figure 4. Toward a Decision Analytics Reference Model



Source: Enterprise Strategy Group, 2014.

The *discover, enrich, and set goal*s activities are classified in Figure 4 as "pre-decision" activities. Pre-decision activities improve the *sense* and *analyze* activities by enabling a more comprehensive analysis of events, information, and factors that will influence the decision. These pre-decision activities also improve the *decide* activity by defining policy-oriented objectives and constraints apriori. Objectives are goals intended to shape decisions so that an organization has targets that it aspires to achieve. Constraints are goals intended to shape decisions so that an organization operates within limits that will minimize its risk exposure legally, financially, or ethically.

These pre-decision activities are a first step in bringing a lifecycle to decision analytics. Pre-decision activities have strong bi-directional relationships with analytic decisioning because of their focus on decision improvement and the support they can provide prior to decisioning. Also, consequently, a separate set of post-decision activities complete the feedback loop. Figure 5 introduces these post-decision activities.

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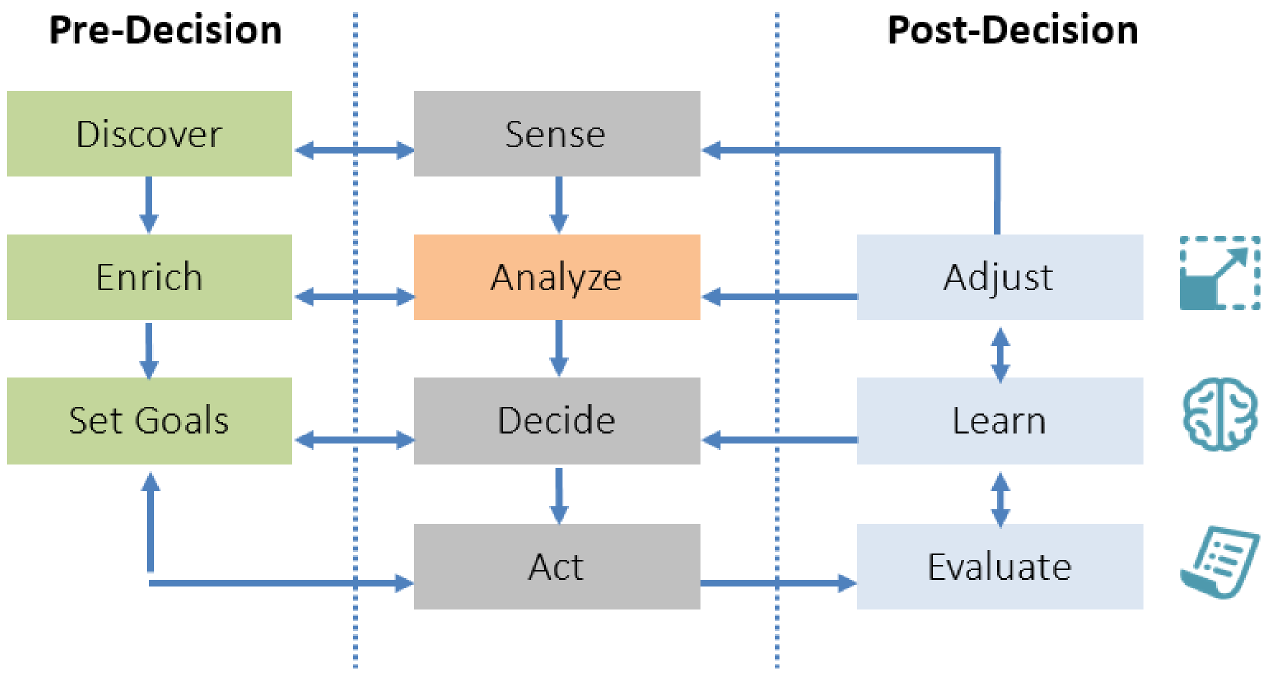
Figure 5. Decision Analytics Reference Model



Source: Enterprise Strategy Group, 2014.

The post-decision activities in Figure 5 consist of *evaluate*, *learn*, and *adjust* activities. The intent of the *evaluate* activity is to assess the utility generated by an *act* activity and compare it with the desired utility as defined by the *set goals* activity. The *learn* activity is the capability to remember the output of the evaluate activity. The *evaluate* activity also factors what has been learned into its assessments so that the utility of the current action can also be compared with past actions. The role of the *adjust* activity is to consider the goals, decisions, actions, and what has been learned to improve performance by changing the triggers, events, analysis, and decisions. The *adjust* activity is where the loop is closed as in a closed loop system. The *adjust* activity is also one of the most complex activities that exists in this system. This is because changing policy and decisions changes actions, which will have a different impact than that to which the organization is accustomed. Changes to policy that correct errors are expected to increase utility. However, changes to policy in search of added revenue are more challenging and must be evaluated more carefully to ensure that the return outweighs the risk. Economic models are very effective at evaluating risk and return and can be incorporated in either the *adjust* or *analyze* activities. A summary of pre- and post-decision activities is as follows:

- **Discovery** is the identification of events, objects, situations, and relationships that will have a bearing on decisioning.
- **Enriching** is the process of incorporating content surfaced in the discovery process into the decision making process.
- **Setting goals** is the specification of objectives to guide the decision making process.
- **Evaluation** is the process of assessing the impact of the action taken.

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- **Learning** is the act of acquiring knowledge specific to decisions made and actions taken.
- **Adjusting** is the act of applying knowledge gained from the learning process to improve the decision process.

It is important to note that while we have identified pre-decision and post-decision activities, we have not made any claims regarding temporal requirements for decision analytics. We do, however, expect a wide variety of use cases depending upon the analytical techniques employed that range from offline to real-time decision analytics.

Figure 5 is labeled as the decision analytics reference model. The reason for this is that this model captures the key activities and relationships that should exist within any organization that intends to address analytic decisioning both comprehensively and effectively. This decision analytics reference model primarily focuses on decisioning and how leveraging analytics to do both support and improve decisioning. The decision analytics reference model also means that consideration has to be given to application architecture. If there is an assumption that some decision analytics activities must be supported in real time, then events, messaging, state, push, and mobility must be factored into system design.

Real-time Decisioning and the Internet of Things

Real-time decisioning is an important area of investment for many enterprises. Infrastructure is now being put in place to capture data streams in real time, analyze this data, and make decisions in real time. Examples of real-time systems are everywhere. Simple real-time systems are S-R systems such as a home alarm system. More sophisticated decision analytics systems are event-based and perform some analysis before making a decision as to what action to take. An example of this would be the grocery store checkout, which generates coupons based on your purchases and frequency of visits. Even more complex decision analytics systems use feedback to adjust actions in real time. An example of this would be an automotive accident avoidance system, which monitors your distance and closing speed to an object and then applies the brakes progressively to prevent an accident. All of these real-time examples involve a subset of capabilities resident in our decision analytics reference model.

The Internet of things (IoT) is going to be very effective at connecting people and "things," whereby a thing is an electro-mechanical device that could range from a simple sensor to an intelligent micro-processor enabled device. The utility of the IoT will be derived from its support for all person/system interactions patterns. The most interesting of these patterns will include *system to person* and *system to system*. The *system to person* interaction pattern will present a person with opportunities or concerns that warrant her attention. The *system to system* interaction pattern will need to unfold in an as-of-yet undefined way but will likely involve gateways for gathering and consolidating domain-specific information and new communication architectures, some of which will mimic high-level architecture (HLA) that was developed by the Department of Defense.

The decision analytics reference model is important because it not only identifies the significant role of analytics in decisioning, but also provides the necessary context for describing the decision analytics continuum.

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The Decision Analytics Continuum

The decision analytics continuum was born out of a need to help organizations understand the various analytic techniques that they can employ to support or improve decisioning. The principles of the decision analytics reference model are to provide a generalized decision making model that also emphasizes the importance of decision improvement. This ensures continued relevance of the decision model given a changing environment and creates opportunity for vendors that deliver these capabilities and enterprises that leverage these capabilities effectively. Opportunity in this context is defined as:

- Greater precision in responding to needs.
- Faster understanding of changing conditions, which encourages innovation.
- Improved operational efficiency due to more comprehensive understanding and rendering of organizational activities.
- Better decision making.
- Improved time to decision/action.

Now that we have established the importance of decisioning and the framework for decision improvement, we can explore differing analytic techniques to support decisioning. When we examine what analytic techniques support decisioning, it is useful to select criteria that will allow us to categorize these analytic capabilities. Four criteria have significant relevance in this task and include the following:

1. Decision Scope. Decision scope refers to how focused the decision is as measured by the cardinality of its alternatives or intended audience. Course-grained decisions are ones that have few choices and apply to only a few market segments (large groups). Fine-grained decisions can have many possible choices and apply to many market segments (such as markets of one).

2. Decision Execution. Decision execution refers to how much is known about the decision outcome. Deterministic decisions are ones where a particular set of stimuli always lead to the same decision. Non-deterministic decision outcomes vary based on accumulated knowledge at the time of the decision.

3. Decision Uncertainty. Uncertainty is a cornerstone of modern statistics. Analytical techniques enable us to evaluate past and present decisions as well as gain insight into how actions may influence future decisions. Since the future is not certain, understanding and quantifying the likelihood of a future event is useful to support future decision making. Collaborative decisioning, Bayesian statistics, and adaptive systems all should or do factor uncertainty into their decision making activities.

4. Decision Complexity. Decision complexity is driven by the number of factors that must be jointly considered when making a decision. The greater the number of factors (or variables) the more potential outcomes and the more complicated it is to make a decision.

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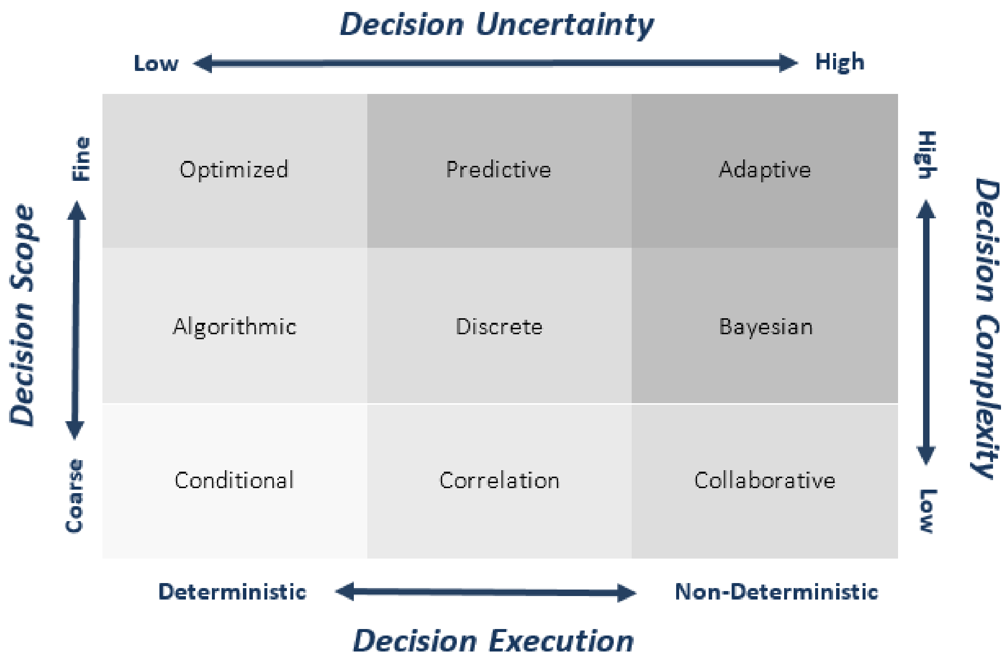
Decision scope and decision complexity are closely related. Course-grained decisions tend to have less complexity and fine-grained decisions tend to have much higher complexity. Decision execution and decision uncertainty also are closely related. Deterministic decisions operate with little or no uncertainty because they are well understood. Non-deterministic decisions, which are influenced by what information is known at the point of decision, tend to have far more uncertainty regarding the stability or consistency of their outcomes. Figure 6 segments the decision analytics capabilities into nine categories and positions them in a framework based on the four criteria.

Figure 6. The Decision Analytics Continuum



Source: Enterprise Strategy Group, 2014.

Figure 6 identifies nine analytic categories that support decision analytics. These categories are described as follows:

- **Conditional**. The conditional analytic category contains algebraic expressions combining Boolean operators that express decision rules that typically take the form of "*if x then y else z*" or "*when j then k else l.*" They are highly effective at describing and automating decision processes. Conditional logic forms the basis for business rule management systems (BRMS), which can render these relationships in multiple forms (decision rules, decision tables, and decision trees). Conditional logic that is event-based provides additional support for temporal constructs of the "*when j then k else l*" form. Conditional logic is often combined with other analytical techniques to quantify or refine a decision, providing powerful and flexible support for decisioning.

- **Algorithmic.** The conditional analytic category uses algebraic equations that leverage known variables and constants to create new variables. Algorithmic expressions are immensely powerful. Expressions can include transformations, reclassifications, aggregations, and functions.

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- **Correlative.** The conditional analytic category is a statistical technique that describes the strength of a relationship or dependency between variables. Simple forms of relationship analysis can include sentiment analysis or text analytics.
- **Optimized.** Optimization is typically the maximization or minimization of an objective function subject to goals and constraints. Optimization is important because it provides a method to achieve the best possible outcome given the resources currently available.
- **Discrete.** Discrete choice and conjoint analysis are survey-based research techniques that effectively reflect respondent preferences for a particular set of capabilities. Preferences are normalized and quantified, making them useful in understanding the relative strength of alternatives and the elasticity of demand. Survey execution also emulates the buying process, which improves data quality.
- **Collaborative.** Collaboration is generally a more qualitative approach to decisioning, which evaluates the contributions of various constituencies including: those people who are in your circle of trust, critics, friends, and everyone else. A wide number of collaborative techniques exists. Participant contributions can be weighted; decisions can be single pass, Delphi, or stepwise; decisions can be relative or absolute; and decisions can be made by consensus, majority, plurality, committee, or autocratically.
- **Predictive.** Predictive analytics leverages known data, relationships, and patterns to make predictions about future events. Results are sensitive to the quantity of known data and how this data is distributed.
- **Bayesian.** Bayesian analytics enable us to understand the impact that conditional probabilities have on an outcome. Bayesian inference embraces uncertainty and develops probabilities that provide an unbiased and rational way to quantify the likelihood of an outcome or series of outcomes.
- **Adaptive.** Adaptive systems (or complex adaptive systems) represent the frontier of decision analytics. Adaptive systems combine predictive, Bayesian analytics, economic models, and learning to govern and anticipate how to best respond to a changing environment. The challenging aspect of adaptive systems is finding new decision rules to improve operational outcomes in a changing environment while simultaneously minimizing risk.

The categories presented in the decision analytics continuum are generally mutually exclusive but selectively employed together to address decisioning.

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Predictive Intelligence

Discrete choice analysis, predictive analytics, and Bayesian analytics all leverage observation to quantify relationships and serve as a foundation for predictive model development. The number of observations is critical to the reliability and utility of predictive models developed. Feedback confirming or weakening the strength of the predictive models is also key to keeping the model relevant. This is why much of the decision analytics reference model is focused on managing pre- and post-decision content. From the standpoint of feedback, decisions to accept an offer (positive reinforcement) are just as useful as decisions to decline or ignore (negative reinforcement) the offer.

Predictive intelligence allows IT-centric enterprises of all types (vendors, partners, and end-users) to more readily understand the competitive landscape that they are a part of and make better informed product, service, and strategy decisions that will improve their competitive position. We have been surprised to see the majority of enterprises that maintain they are market/data-driven or argue that innovation is core to their success are unable to point to any material decisioning based on predictive intelligence. This cobbler's children syndrome is largely driven by a combination of ignorance and neglect. Most enterprises simply aren't familiar enough with the benefit of decision analytics to know where to start. Those enterprises that do understand the potential of decision analytics may be stymied by the complexity of leveraging advanced analytics or finding a way to demystify the topic enough to gain the support of senior management.

For those enterprises willing to endure the adoption of predictive intelligence capabilities, the payoff can be transformative. Discrete choice modeling and conjoint analysis provide effective techniques to understand market dynamics and direction in a fully unbiased, normalized, and consistent way. This provides the perfect foundation to chart product roadmaps and identify the key messages by which to go to market. Predictive analytics enable an enterprise to compete more effectively and manage risk. A journey down the predictive analytics road can lead to many destinations. One way predictive analytics can be used is to scorecard customers and business partners. This will help an enterprise evaluate how to avoid risk and capitalize on opportunities. This enables the enterprise to reduce cost and increase revenue, which is the best approach to managing profitability. Bayesian analytics permits an enterprise to better assess the likelihood of events based on historical precedent and then monitor how the probability of occurrence changes as new evidence becomes available. Expressing outcomes in terms of probability is immensely useful because of the normalization that is inherent in how probability is expressed and the increased ability it provides to compare and contrast expected outcomes to enterprise governance, risk, and compliance standards.

There are a wide variety of use cases for decision analytics and predictive intelligence. These use cases can be broadly categorized into operational uses cases (internally focused) and go-to-market use cases (externally focused). These use cases can also be grouped either addressing existing capabilities (current needs) or new requirements (future needs). Figure 7 provides a list of selected predictive intelligence use cases.

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Figure 7. Selected Predictive Intelligence Use Cases

	Existing Capabilities	New Requirements
Go-To-Market	• Profit/revenue optimization • Risk minimization • Push marketing • Competitive positioning • Lead generation	• New product requirements • Build, buy, partner decisions • Competitive analysis • Precision marketing • Pricing
Operations	• Market identification • Market segmentation • Process automation • Process optimization	• New product development • Process improvement • Cost avoidance • Risk management

Source: Enterprise Strategy Group, 2014.

Decision analytics for existing capabilities that are operational frequently use correlation and algorithmic techniques to identify clusters that are very effective at identifying and segmenting/categorizing existing customers. Segmentation and categorization are critical prerequisites to facilitate decisioning through conditional logic. Process automation is the use of technology to automate manual activities or integrate process fragments and it primarily leverages conditional and algorithmic decisioning. Process optimization is just that: an optimization activity that enables the enterprise to make sure resources are used as efficiently as possible.

Decision analytics support for new requirements that are operational uses most of the capabilities in the decision analytics continuum. New product development often uses discrete choice analysis to prioritize development activities. Predictive analytics is used to evaluate customer worthiness which helps with cost avoidance, process improvement, and risk management.

Decision analytics for existing go-to-market activities can use discrete choice modeling to understand the elasticity of demand for your products and service and simulate how best to maximize revenue or profit and position against your competition. Bayesian inferencing is very effective at evaluating and helping minimize risk. Predictive analytics is well known for identifying how to better support your customers and prospects (lead generation) by recommending what promotions should be extended to which segments (push marketing).

Decision analytics for new go-to-market activities leverages discrete choice modeling, conjoint analysis, and collaboration to understand new product requirements, pricing, and how effectively your products will compete against the competition. Predictive analytics and collaboration are very well suited to supporting build/buy/partner decisions and precision marketing.

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The Decision Analytics Challenge

Currently, one of the vexing issues in decision analytics is the integration of decisioning tools with analytic routines. The origin of this issue dates back many years. Decisioning tools were initially aligned with languages and environments that paired their capabilities with the application development domain. Analytic tools such as SPSS and SAS initially functioned as standalone tools. As these two domains have evolved, effort has been made to bring them closer together. Predictive Model Markup Language (PMML) was a good start and has a following of loyal users. PMML is XML-based and is Java-friendly. Python and R both have fairly comprehensive statistical capabilities, although no real intersection with decisioning tools. The near term solution to this issue is probably to address it through API services management. A rich set of public APIs for each tool and across tools will help significantly with interoperability issues—although true integration will probably come from within vendors that have both decisioning and analytics capabilities. The goal is being able to seamlessly traverse decisioning and analytic components in a stateful way so that context is preserved.

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The Bigger Truth

Decision analytics is a transformative technology.

End-users who do not yet have familiarity and IT experience with concepts like decision management, predictive analytics, and discrete choice analysis are advised to take aggressive steps to quickly move up the learning curve. While some areas of decision analytics such as Bayesian inferencing and adaptive systems do qualify as rocket science, many highly useful aspects of decision analytics are far more easily approachable. However, the scope of decision analytics is wide enough that it takes time and experimentation to fully appreciate how best to leverage these analytical techniques. Pursuing decision analytics is clearly a journey that will take time, investment, and experience. Having a Chief Data Officer (CDO) is a good start, and so is having a decision analytics programs office. Because of the time necessary to develop a decision analytics program with depth (which includes data and decision analytics that reflect policy and result in actions), it is important to start sooner than later. It's also better to force your competitors to come to terms with decision analytics rather than the unfortunate alternative.

There are vendors that have decisioning products such as business rule management systems. There are also vendors that provide advanced analytic products. However, there is only a rarified set of vendors that provide both decisioning and analytic products. Why is this important? Although most analytic models are developed offline, some of these models will need to be integrated with decisioning tools in order to address process automation and process improvement needs. To ease this integration process, you will want to look for vendors with explicit experience in both the decision and analytic dimensions of decision analytics to ensure the easiest and smoothest implementation of technology that some will find complex. Due to the large number of categories identified in the decision analytics continuum, enterprises should also look for a vendor that has deep product and service expertise across the decision analytics continuum. As we mentioned earlier, some of the leading vendors in the decision analytics domain include FICO, IBI, IBM, Oracle, Pegasystems, SAP, SAS, and TIBCO. Table 1 provides a list of these vendors and products that support decisioning and analytics.

Table 1. Leading Decision Analytics Vendors and Products

Vendor	Decisioning Products	Analytic Products
FICO	FICO Blaze Advisor, FICO Decision Management Platform	FICO Model Builder, FICO Xpress Optimization Suite, FICO Analytic Modeler, FICO Model Central, FICO Decision Optimizer
IBI	iWay Service Manager, iWay Event Manager	WebFOCUS Family of Products

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IBM	IBM Operational Decision Manager	IBM Analytics Decision Management, IBM SPSS Product Family, IBM Cognos Product Family, IBM Algorithmics Product Family, IBM InfoSphere Streams
Oracle	Oracle Business Rules, Oracle Real-Time Decisions	Oracle Business Intelligence, Oracle Endeca Information Discovery, Oracle Exalytics, Oracle Advanced Analytics
Pegasystems	Pega Decision Management, PegaRULES, Process Commander, Pega Visual Business Director	Pega Next Best Action Advisor, Pega Adaptive Decision Manager, Pega Predictive Analytics Director, Pega Firefly, Pega MeshLabs eZi product family
SAP	SAP Decision Service Management	SAP BusinessObjects Family, SAP Predictive Analysis, SAP Social Media Analysis
SAS	SAS Enterprise Decision Management	SAS Enterprise Miner, SAS Model Manager, SAS Visual Analytics, SAS Visual Statistics, SAS Forecast Server, SAS Contextual Analysis, SAS/OR, SAS In-Memory Statistics for Hadoop
TIBCO	TIBCO Business Events Decision Manager, TIBCO ActiveMatrix Decisions	TIBCO Spotfire

Source: Enterprise Strategy Group, 2014.

Vendors and end-users should both consider the implications of the decision analytics reference model. The application architecture necessary to deliver the decision analytics reference model involves a number of newer platform-based capabilities such as messaging, event servers, business rule management systems, business intelligence, advanced analytics, push technologies, and application management. Consequently, enterprises are advised to think strategically about their decision analytics needs and the technology stack necessary to deliver on these objectives even if the technology is to be phased in over time.

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