

Making Predictive Analytics Pervasive

Deployment Trends

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More organizations are recognizing very high or high value from their predictive analytics implementations.

Executive Summary

There is a lot of buzz around analytics in general and predictive analytics in particular. Despite the buzz, the market for predictive analytics hasn't changed much since 2006. Here are the key findings from our survey, which had more than 3,000 respondents, an unusually large response rate that is indicative of the increased interest in predictive analytics:

1. **Implementation status.** Despite the buzz, the percentage of organizations that have implemented predictive analytics has fallen slightly in the past eight years, from 21% to 18%.
2. **Value.** At the same time, slightly more organizations are recognizing very high or high value from their predictive analytics implementations, from 66% in 2006 to 74% today. Not surprisingly, almost three-quarters of respondents this year expect to increase their investments in predictive analytics in the coming years.
3. **Maturity.** Concurrently, more organizations have achieved an *Adult* state of maturity with predictive analytics, from 23% in 2006 to 32% today.
4. **Applications.** Budgeting/forecasting replaces cross-sell/upsell as the most predominant application of predictive analytics in 2014 compared to 2006.
5. **Users.** Managers are the predominant users of analytical output, followed by executives and business analysts, especially among organizations that have implemented predictive analytics (versus organizations planning to implement).
6. **Development.** Most analytical models (64%) are developed in house versus outsourced or purchased in packaged applications.
7. **Developers.** In the spirit of self-service analytics, the dominant group that develops or applies predictive analytics is business analysts (55%), followed by statisticians (44%) and data scientists (42%).
8. **Project Steps.** Companies are spending more time defining analytics projects (19% to 13%), managing completed models (13% to 9%) and exploring data (21% to 18%) compared to 2006 and slightly less time preparing data for modeling (23% to 25%). The amount of time spent modeling data has remained constant at 23%.
9. **Vendors.** SAS, Microsoft and the R open source project are the top three suppliers of analytical software. SAS dominates with large companies and Microsoft with medium- and small-sized companies.
10. **Features.** The most important features that customers seek today in analytical tools are: data visualization, integration with Excel and graphical development.

Statistics, with its ability to define the shape and nature of data, is the heart of predictive analytics.

Methodology

This report is based on primary research consisting of interviews with end users and briefings with vendors as well as secondary research consisting of articles, reports and websites that I've perused. However, the bulk of the report consists of a survey of 3,474 business and information technology (IT) professionals conducted in March and April, 2014. Not all respondents completed all questions, which is why the number of responses for some questions is lower than 3,474. The results in this report are based on 1,857 respondents who completed the entire survey and 1,617 who partially completed it.

Among the respondents, 61% are IT professionals and the remainder (39%) are business professionals. Almost one-third (28%) work in large companies with more than \$1B in revenue, while one-quarter (25%) work in medium-size companies with between \$100M and \$1B in revenues. The remainder, 47%, work in small companies with revenues under \$100M. Almost one-third (29%) of respondents are from the United States, followed by 22% from India, 13% from the United Kingdom, 7% from Australia and the rest from other countries.

Introduction

Definition

Eckerson Group defines **predictive analytics** as the use of statistical or machine-learning models to discover patterns and relationships in data that can help business people predict future behavior or activity. Also known as advanced analytics, data mining or knowledge discovery, predictive analytics involves:

1. Creating models using data that represents past business activity.
2. Applying these models to new business data to make predictions and create rules.
3. Embedding models into applications to optimize business processes, improve business decisions and automate responses.

Statistics, with its ability to define the shape and nature of data, is the heart of predictive analytics. But machine learning is now a coequal partner in creating predictive models. That's because machine learning leverages compute power to run complex algorithms against data that manual statistical techniques could never accomplish. Machine-learning models can build more accurate models against more data to help address a wider variety of applications.

To be honest, predictive analytics is a misnomer. Not all analytics defined above are predictive. Most of the time, the output of an analytical model is simply

Many BI professionals now see predictive analytics as the next wave of technology that can help their organizations leverage their investments in data.

descriptive: it describes a pattern or relationship that can help business people better understand what's happening and what to do about it. It's not until the model (or mathematical equation) is applied to new records through a process called scoring that a model becomes predictive. The scores, usually a decimal between 0 and 1, define the propensity of the record to exhibit a specific behavior.

For example, a model may score a customer's likelihood to respond to a particular marketing offer. A marketer might use that score to determine whether to send the customer a direct mail offer. Or a bank teller might use the score to determine whether to offer a premium rate for a certificate of deposit to a customer who just made a deposit. An e-commerce application might look up the score of a customer who just purchased a product, feed it into a dynamic rules engine and display a cross-sell offer to the customer in real time.

Looking Back and Ahead

In 2006, I wrote a report on predictive analytics for The Data Warehousing Institute (TDWI). That report, like this one, surveyed business intelligence (BI) professionals about their adoption of predictive analytics. During the intervening eight years, several things have changed in the market for predictive analytics.

Buzz. First, there is a lot more awareness about predictive analytics now than in 2006. This interest has been stoked in part by the hype around big data analytics, which has demonstrated the power of data and analytics to transform companies, better serve customers and implement new, more competitive ways of doing business. Moreover, the general public is now familiar with predictive analytics thanks to Edward Snowden who unlawfully revealed the scope and nature of the National Security Agency's (NSA) "data mining" program that taps into the metadata about consumer phone calls made between U.S. citizens and people overseas.

In addition, many BI professionals are leading the charge into predictive analytics. These professionals have helped their organizations master data warehousing, reporting, OLAP and dashboarding. They now see predictive analytics as the next wave of technology that can help their organizations leverage their investments in data. Many are starting analytical centers of excellence to complement their BI programs or are working more closely with analytical teams to coordinate efforts. The fact that more than 3,000 people took our 2014 predictive analytics survey (compared to 800+ respondents in 2006) testifies to the interest in the topic among BI professionals.

A new wave of self-service predictive analytics is just starting to form.

Stagnant deployment. Ironically, despite the hype around predictive analytics, the percentage of companies that have implemented the technology has remained flat. This is hard to explain.

Perhaps, the stagnant deployment rates are due to the fact that most companies don't know where or how to get started with predictive analytics. I am often asked, "Which applications should we apply predictive analytics to?" and "Will it be worth the investment?" Also, the technology is esoteric and historically has required highly skilled and richly paid craftsmen. Executives often ask me, "Do we need to hire a statistician?" and "Do we have enough work to keep a statistician busy?"

Given the confusion, most executives might decide to place high priority on other data-oriented initiatives, such as data cleansing or data governance. Nonetheless, there is palpable interest in predictive analytics that I believe will eventually translate into higher adoption rates. I suspect that many companies are ready and eager to join the predictive analytics movement, but just need a nudge and some guidance about how to proceed.

Self-service. Fortunately, there are many vendors eager to provide that nudge. To capitalize on the interest in predictive analytics, many vendors are releasing self-service tools that make predictive analytics accessible to mere mortals—namely, business analysts or Excel jockeys. Our recent survey shows that business analysts, not statisticians, constitute the largest percentage of people applying predictive models.

This new wave of self-service predictive analytics is just starting to form, and many new products and vendors are trying to disrupt the stodgy and expensive world of traditional data mining and analytics. For example, some vendors I talked to for this report are already closing large six-figure deals for self-service predictive analytics tools geared to power users.

Applications. A final trend is the breadth of applications that companies implement or support with predictive analytics. Although predictive analytics has been around for more than 20 years, its adoption had always been limited to large firms with the resources to hire statisticians with machine-learning skills on a full-time basis. Specifically, credit card firms drove most of the early use because the techniques could improve their rate of return on expensive marketing campaigns and detect fraud in real time.

Today, however, companies use predictive analytics to address a wide range of problems. For instance, improving budget forecasts and demand planning are the top two applications today. And there is now a long tail of niche

applications, including everything from predicting engine or machine failure to optimizing schedules and dispatching.

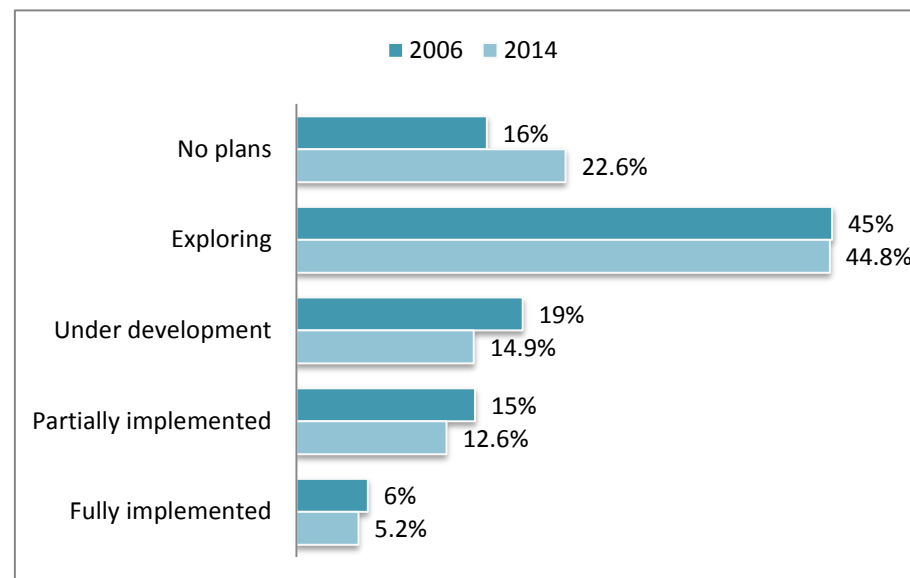
There are many other trends in the deployment of predictive analytics, but these are the most prominent. The remainder of this report describes additional trends using the results of our 2014 survey.

Trends from our Survey

Status. There is a lot of interest in predictive analytics these days. The trade press is full of articles about analytics and the predictive powers of big data. We are seeing a rise in the number of conferences focused on the power of analytics to optimize business processes and give organizations a competitive edge.

Despite the buzz, our data suggests that not much has changed in the past eight years. Virtually the same percentage of organizations is exploring predictive analytics (45%) as eight years ago. Slightly more organizations (21%) had partially or fully implemented predictive analytics eight years ago than today (18%), and more organizations (23%) today have no plans to implement the technology than in 2006 (16%). (See Figure 1.)

Figure 1: Status of Predictive Analytics Implementations—2006 versus 2014



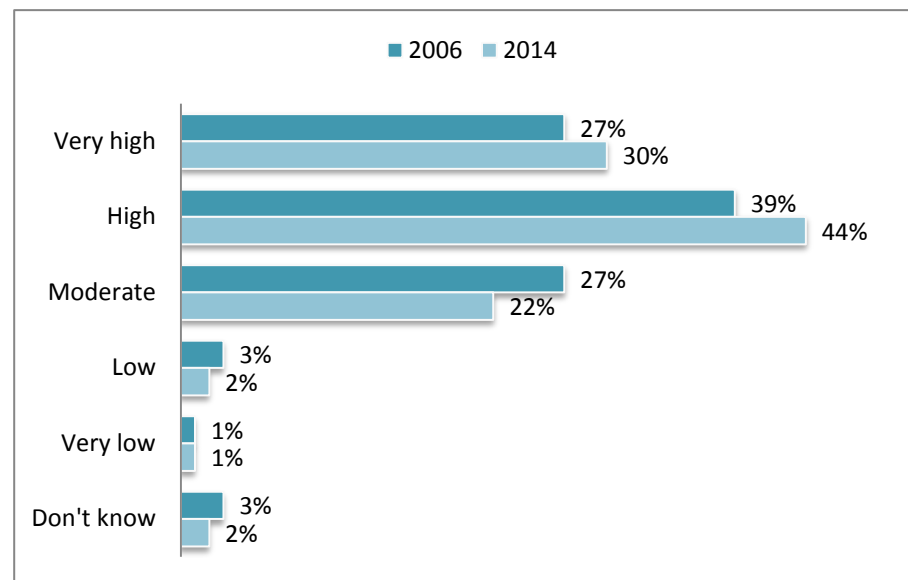
Based on 3087 respondents to a 2014 TechTarget survey and 833 respondents to a 2006 TDWI survey. The 2006 results are found in a report I wrote titled, "Predictive Analytics: Extending the Value of your Data Warehousing Investment."

These results are very odd. I would have expected much greater penetration of predictive analytics by now. The population for both surveys is quite large so I'm confident the numbers are accurate. The only major difference between the two surveys is percentage of non-U.S. respondents. In 2006, 60% of the respondents came from the U.S.; in 2014, only 29% came from the U.S.

So, at first blush, it appears that the rest of the world is at the same stage of adoption as companies in the U.S. were eight years ago. However, if we filter the 2014 data by just U.S. respondents, we don't see much of a divergence from the greater population of survey takers. The percentage of companies that have partially or fully deployed predictive analytics is virtually the same (18% for U.S. only respondents versus 17.8% for all respondents.) So, it appears that companies everywhere are still exploring predictive analytics more than implementing it.

Business value. One thing that has grown slightly since 2006 is the percentage of companies reporting that predictive analytics delivers strong business value. Among companies that have either partially or fully deployed predictive analytics, almost three-quarters in 2014 (74%) say it delivers either high or very high business value. That's an 8% increase from 2006 when two-thirds (66%) said predictive analytics delivers high or very high business value. It's clear that organizations are gaining more benefit from predictive analytics as time goes on. (See Figure 2).

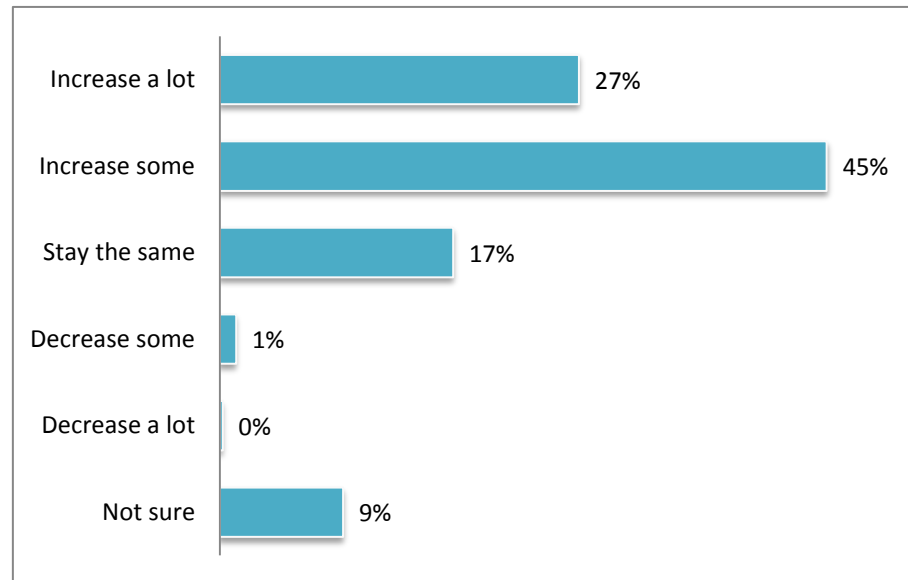
Figure 2: Value of Predictive Analytics—2006 versus 2014



Based on 168 and 430 survey respondents in 2006 and 2014, respectively, who have partially or fully deployed predictive analytics

Investment. Given the high value most organizations experience with predictive analytics, it's not surprising that almost three-quarters (72%) plan to increase their investments in predictive analytics in the next 18 months. Only 17% say they won't invest additional money during this timeframe, and only 1% said they would decrease their investment, while 9% weren't sure. (See Figure 3.)

Figure 3: Expected Investment in Predictive Analytics

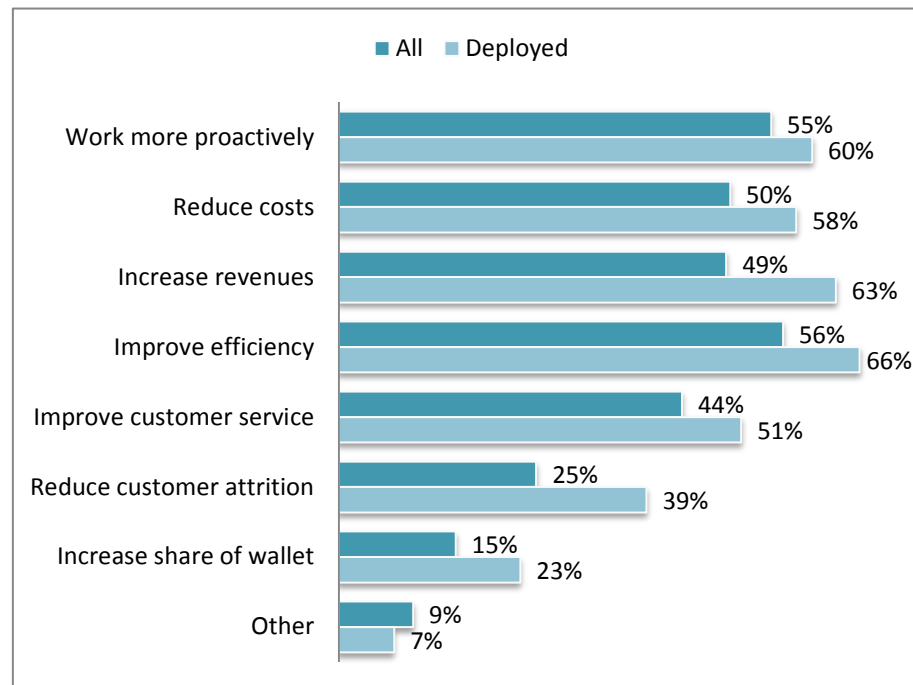


Based on 430 survey respondents, who have partially or fully deployed predictive analytics, 2014

Benefits. There are many benefits to predictive analytics that deliver business value. A majority of both those who have deployed predictive analytics and those who haven't say the discipline brings improved customer service, increased revenue, more proactive work and reduced costs.

Those who have deployed predictive analytics cite more benefits than those who have yet to implement the technology. Thus, we can extrapolate that predictive analytics provides a higher degree of return than companies originally anticipate. The biggest unexpected returns come in customer churn (14% reduction), increased revenues (14% gain) and improved efficiency (10% gain). (See Figure 4 on next page.)

Figure 4: Benefits of Predictive Analytics

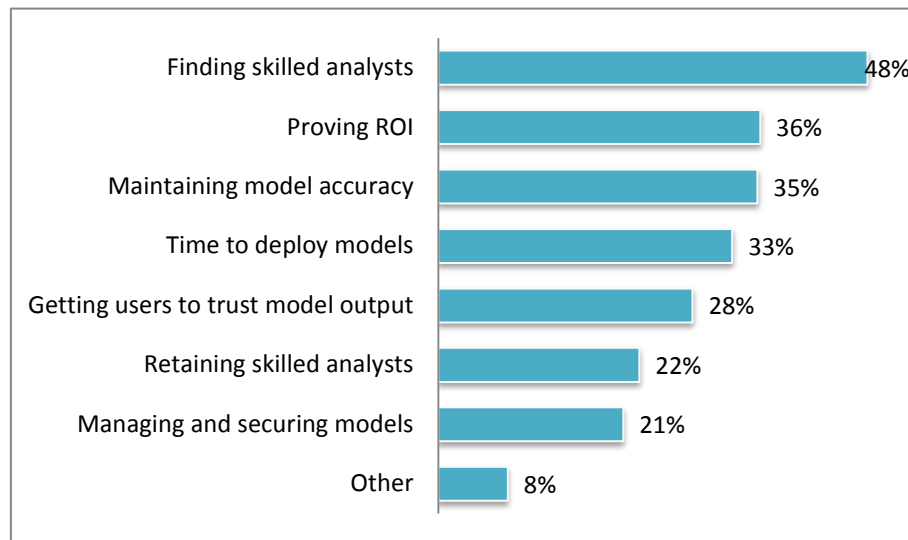


Based on (3087) survey respondents (all) and 430 respondents (deployed) who have partially or fully deployed predictive analytics, 2014

Challenges. The chief challenge cited by almost half (48%) of respondents to the 2014 survey is finding skilled analysts. This puts a premium on self-service predictive analytics tools geared to data-savvy business analysts with minimal training in statistics and machine learning. Traditionally, predictive analytics has been the province of statisticians and data scientists, who are highly trained and spend years refining their expertise.

Given the high value that predictive analytics offers, it's surprising that more than one-third (36%) said "proving ROI" is a challenge. A nearly identical percentage (35%) said "maintaining model accuracy" is a challenge, followed by the "time to deploy models" (33%) and, my favorite, "getting users to trust model output" (28%). (See Figure 5 on next page.)

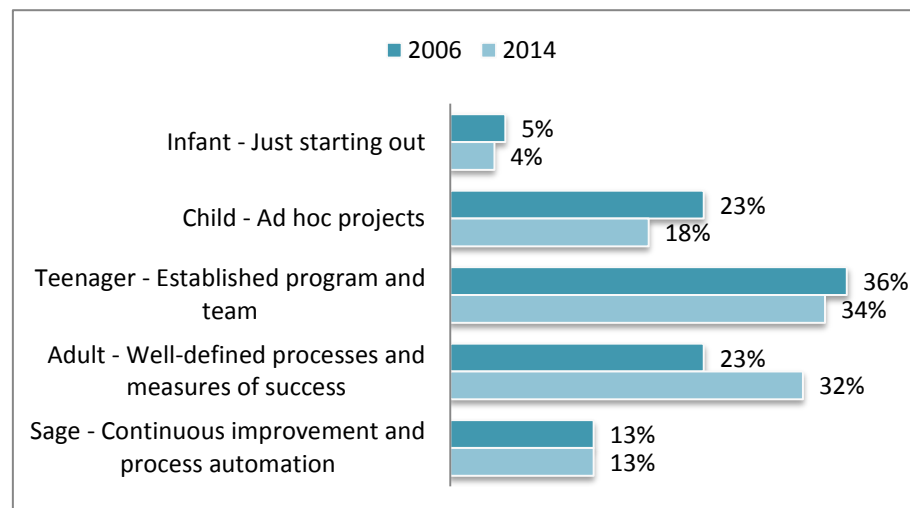
Figure 5: Challenges in Deploying Predictive Analytics



Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Analytic Maturity. The increased value of predictive analytics correlates with the growing maturity of implementations. Compared to the 2006 survey, almost 10% more organizations in 2014 claim their predictive analytics deployments are in the *Adult* phase characterized by well-defined processes and measures of success. In both surveys the same percentage (13%) says they are in the *Sage* stage reflected by continuous improvement and process automation. Conversely, fewer organizations in 2014 say their predictive analytics deployments are in the *Infant*, *Child* or *Teenager* stages. (See Figure 6.)

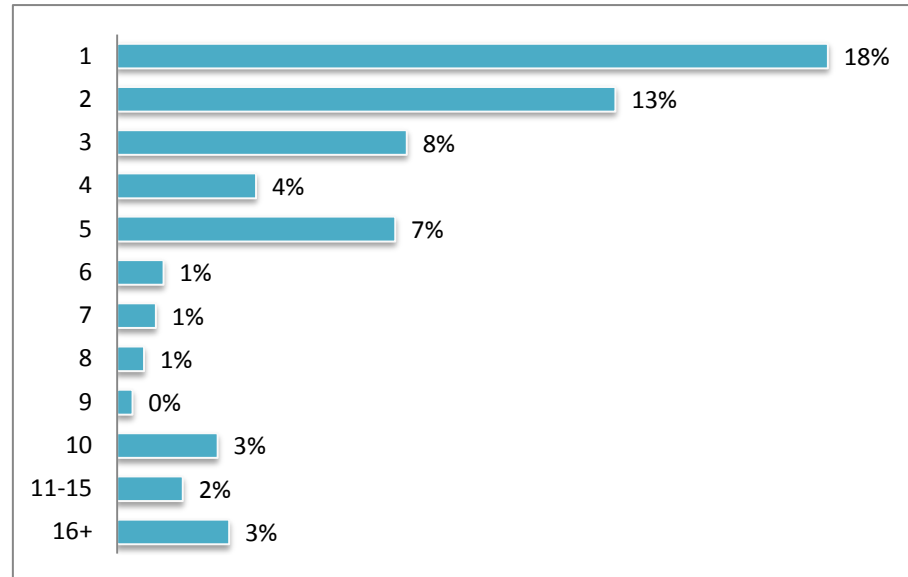
Figure 6: Analytic Maturity—2006 versus 2014



Based on 168 and 430 survey respondents in 2006 and 2014, respectively, who have partially or fully deployed predictive analytics.

Longevity. Most organizations that have deployed predictive analytics are relative newcomers to the discipline. Almost one-third (31%) have used predictive analytics for less than two years. And half (50%) have used it less than five years. (See Figure 7.)

Figure 7: Years of Deployment—2014

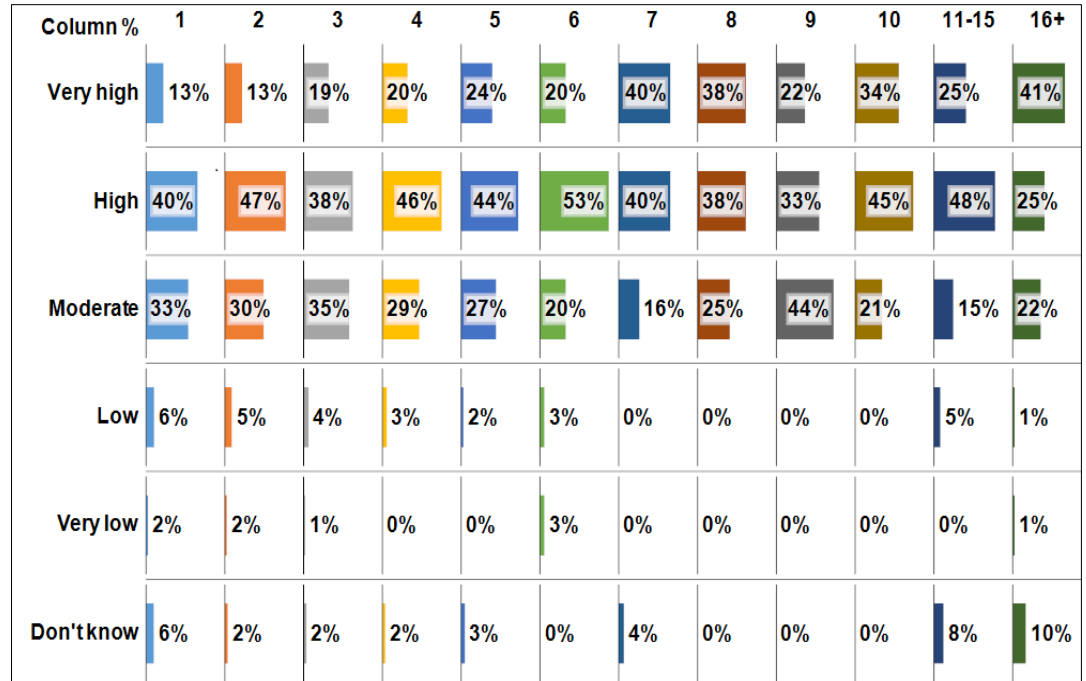


Based on 430 survey respondents in 2014 who have partially or fully deployed predictive analytics.

Value versus Years. When we examine business value by years of deployment, we see that organizations quickly attain high value from their predictive analytics deployments. This is quite a testament to the power of predictive analytics to optimize processes and performance when deployed in targeted ways. (See Figure 8 on next page.)

Moreover, more organizations reap very high value from their predictive analytics deployments over time. About 18% of organizations receive very high value from predictive analytics during the first five years. This percentage almost doubles to 31% from years six to 10 and then increases slightly to 33% for organizations that have deployed predictive analytics for more than 10 years. Moreover, the average percentage of organizations reaping very high and moderate value inverses across these time frames, suggesting that organizations move up the value chain as they gain experience with predictive analytics.

Figure 8: Business Value by Years of Deployment



Based on 3087 respondents, 2014

Years and Maturity. Although most organizations reap significant value when they first deploy predictive analytics, they gradually increase the value of those deployments over time.

A logical explanation for the gradual rise in value that organizations gain from predictive analytics is that they become more mature in the way they deploy the people and technology. This correlation is displayed in Figure 9 on the next page. In the first five years of deployment, the majority of organizations inhabit the first three stages of maturity: *Infant*, *Child* or *Teenager*, although a surprising percentage (45%) cite they are in the *Adult* or *Sage* stage in year five. From year 10 onward, almost half (47%) of organizations cite they are in the *Sage* stage.

Figure 9: Maturity of Deployments by Years of Deployment

Column %	Infant - Just starting out	Child - Ad hoc projects	Teenager - Established program and team	Adult - Well-defined processes and measures of success	Sage - Continuous improvement and process automation
1	56%	18%	13%	4%	2%
2	13%	35%	17%	13%	7%
3	0%	16%	16%	6%	5%
4	0%	8%	13%	10%	4%
5	0%	10%	16%	24%	21%
6	0%	3%	6%	5%	4%
7	0%	1%	2%	4%	5%
8	0%	0%	1%	2%	4%
9	0%	0%	1%	1%	0%
10	0%	1%	7%	10%	13%
11-15	0%	4%	1%	10%	9%
16+	0%	1%	5%	10%	25%

Based on 430 respondents who have partially or fully implemented predictive analytics, 2014

(Note: Respondents who said they have deployed 0 years were filtered out so row percentages do not equal 100%.)

Applications. The types of applications organizations are supporting with predictive analytics has changed slightly in the past eight years. In 2006, the top applications for predictive analytics were all marketing related: cross-sell/upsell (47%), campaign management (46%) and customer acquisition (41%). In contrast, the top application in 2014 is budgeting/forecasting (47%), with the next nearest trailing by 8% or more: campaign management (39%), demand planning (38%) and quality improvement (38%). (See Figure 10 on next page.)

Figure 10: Applications for Predictive Analytics—2006 versus 2014

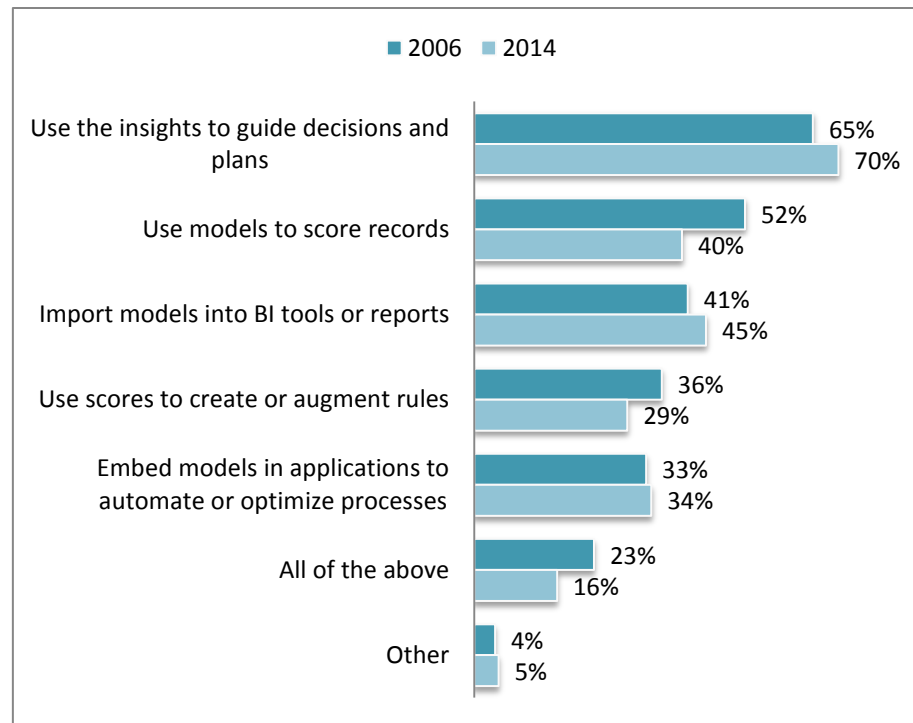


Based on 168 and 430 survey respondents in 2006 and 2014, respectively, who have partially or fully deployed predictive analytics

Deployment Options. There has been a slight shift since 2006 in the way organizations use predictive models. The majority still “use insights to guide decisions and plans” (65% in 2006 and 70% in 2014). But there has been a sizable drop off in the percentage that “use models to score records” (52% in 2006 and 40% in 2014).

Most of the remaining options have held fairly constant, including “embed models into applications to automate or optimize processes” (33% and 34%, respectively). Many consider automating process with analytical models the holy grail of predictive analytics since it can have the biggest impact on business value. (See Figure 11 on next page.)

Figure 11: Deployment Options for Predictive Models—2006 versus 2014

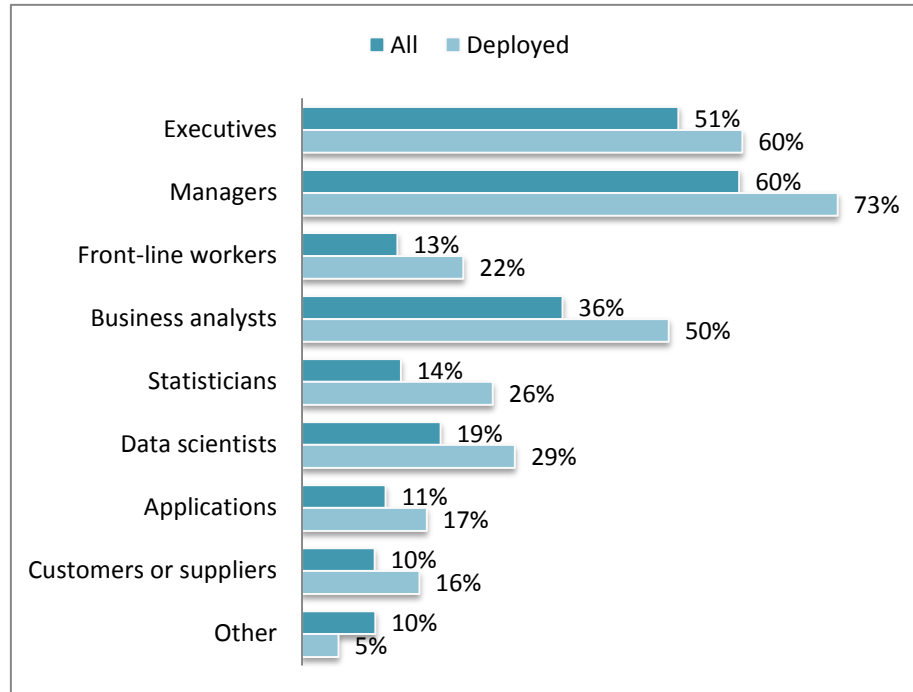


Based on 168 and 430 survey respondents in 2006 and 2014, respectively, who have partially or fully deployed predictive analytics

Users. There are many users who use the output of predictive models. The two biggest groups by far are managers and executives, cited by more than 50% of all survey respondents. This shows that predictive modeling is not low-level or solely an operational endeavor. Rather, top-level business people are keenly interested in predictive modeling.

When we filter the data by those organizations that have implemented predictive analytics, we see that those companies cite a wider range of users than those who have yet to deploy predictive analytics. (See Figure 12 on next page.)

Figure 12: Users of Predictive Analytics Output—2006 versus 2014

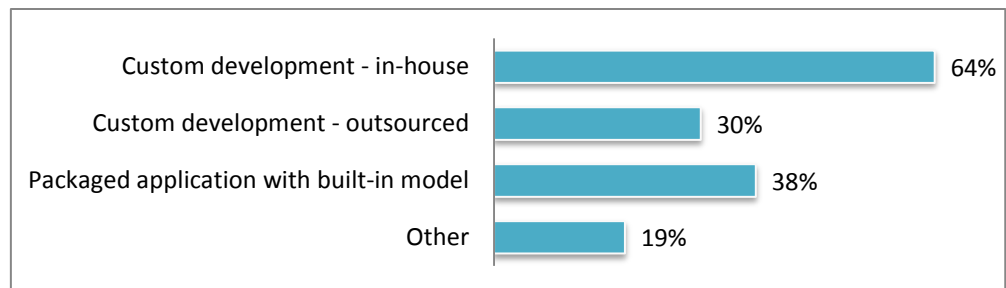


Based on all (3087) survey respondents and 430 respondents who have partially or fully deployed predictive analytics, 2014

Model Development. Analytic modeling has traditionally been the domain of the highly skilled statistician or data scientist. However, since most companies can't afford to hire these highly paid analysts or don't have enough work to keep them busy full-time, many have turned to service bureaus or applications to meet their analytical requirements.

According to our survey, almost two-thirds (64%) of respondents build analytic models in house. Another 30% outsource the development to a third party, while 38% leverage models embedded within packaged applications. (See Figure 13.)

Figure 13: Sources of Predictive Models

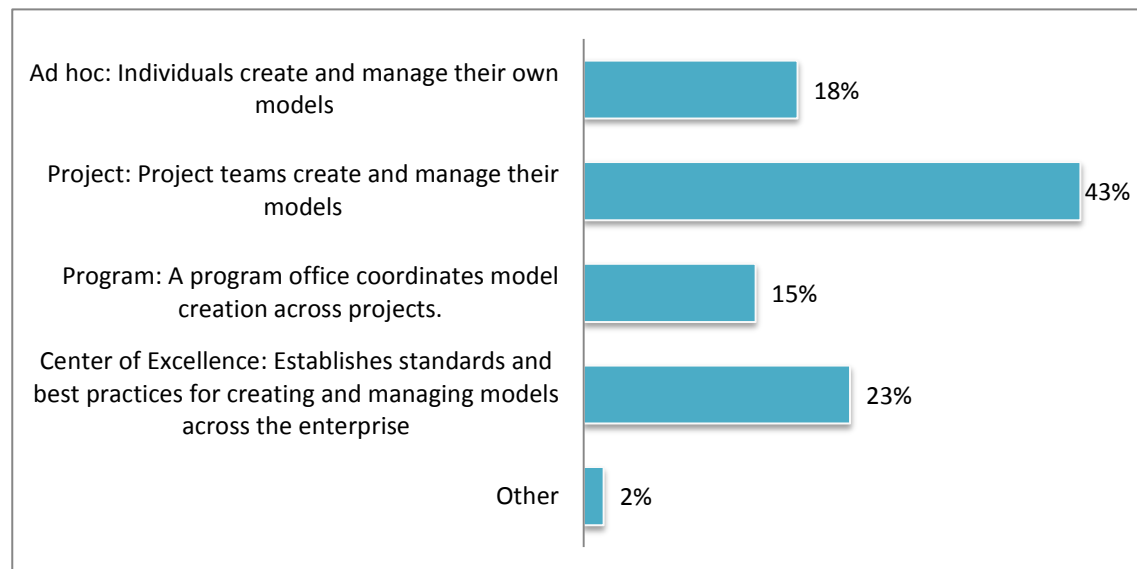


Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Analytic Projects. As organizations gain more experience with predictive analytics, the way they staff and manage analytic projects evolves from individuals doing work on their own to ultimately a center of excellence that establishes standards and best practices for creating models across the enterprise.

Today, the largest percentage of organizations (43%) build models on a project-by-project basis, using a team of people to create models. The remaining are fairly evenly split between ad hoc development by individuals (18%), a program office that coordinates model development across projects (15%) and a center of excellence (23%). (See Figure 14.)

Figure 14: Characteristics of Analytic Development Projects

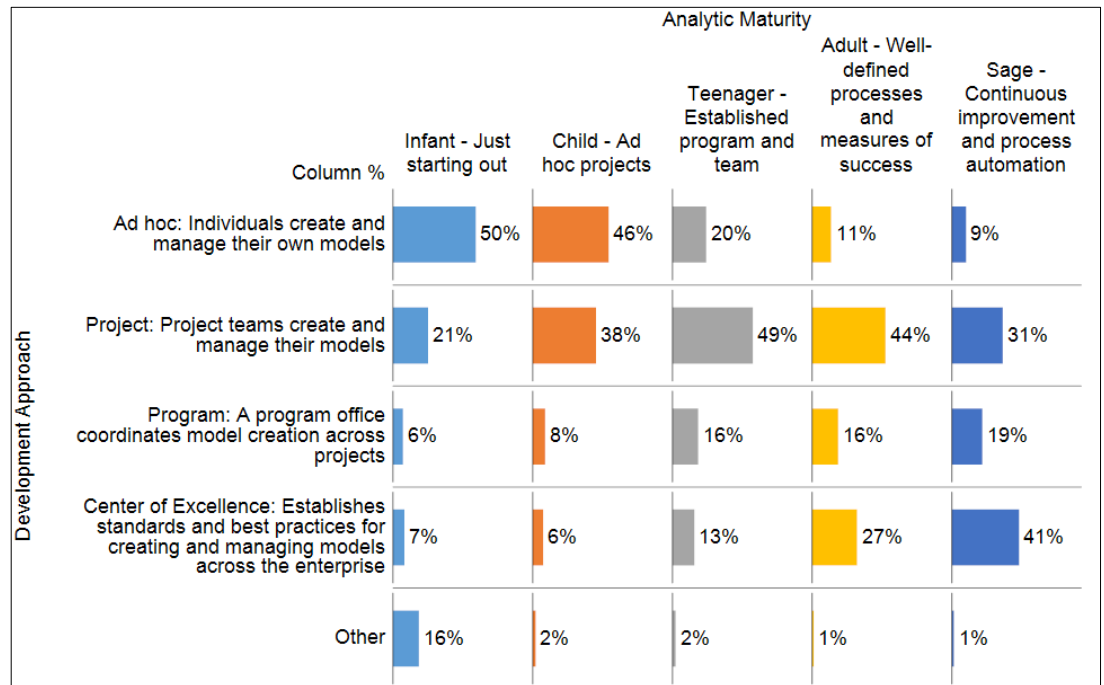


Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Maturity Impact. Not surprisingly, the more mature a company is in its deployment of predictive analytics, the more likely it will adopt a more mature approach to developing analytic models.

Figure 15 on the following page shows that most organizations in the early stages of deployment take an ad hoc or project-based approach to analytics, while those in the latter stages of deployment and maturity take a programmatic approach, including implementing a center of excellence.

Figure 15: Project and Deployment Maturity



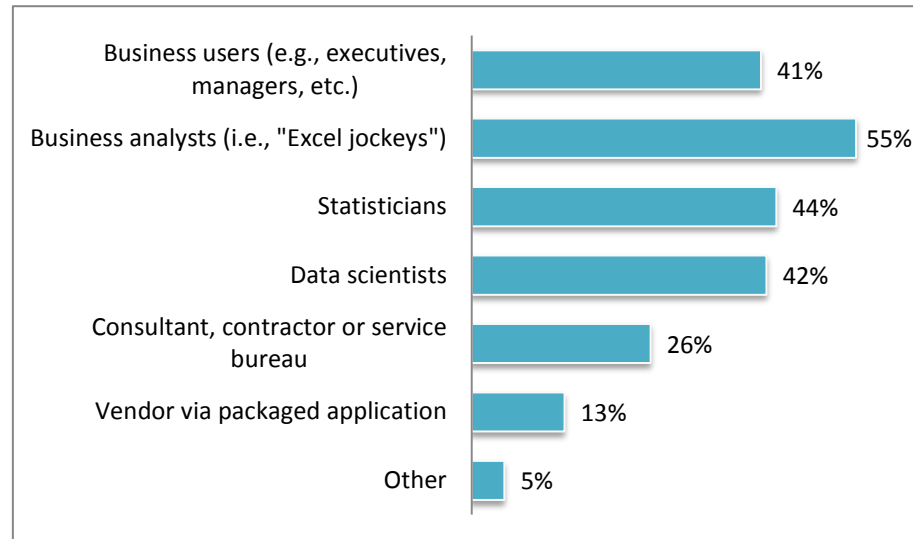
Based on 430 respondents who have partially or fully implemented predictive analytics, 2014

Developers. Traditionally, statisticians and data scientists with machine-learning backgrounds build analytic models. But new tools and platforms make it possible for more types of users with less formal training to create predictive models.

These new tools, some of which are Web- or cloud-based, provide visual workbenches and wizards to step users through the process of creating models. In addition, support vector machines with associated learning algorithms and new approaches, like ensemble modeling, take a lot of the guesswork out of developing models. If an organization runs its business on analytical models (e.g., credit card companies) and requires a high degree of accuracy, transparency and compliance, it might still want to hire a bank of statisticians and data scientists to create models.

Our research shows that a majority of organizations (55%) use business analysts to create models and another 41% use business users. So the era of self-service predictive analytics has arrived. Another 44% use statisticians, 42% use data scientists, 26% use a contractor or consultant, and just 13% use packaged models (although you could argue some users don't realize there is a model embedded in a package). (See Figure 16 on next page.)

Figure 16: Developers of Predictive Models

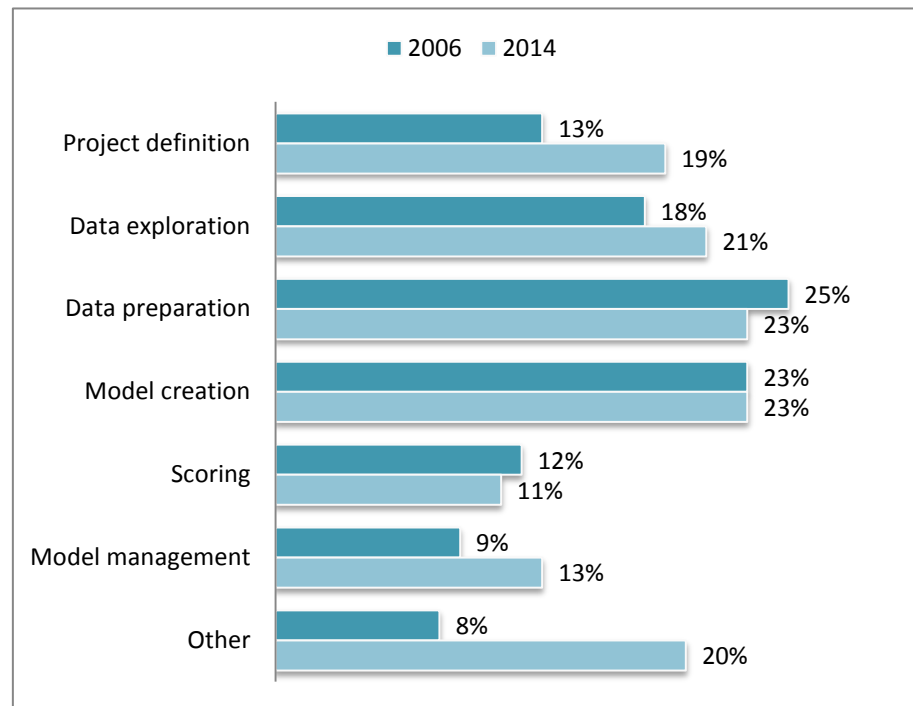


Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Methodology. Although there are many less-skilled users creating analytic models, the time spent on each phase of the classic model building process (definition, exploration, preparation, creation, scoring and management) has remained relatively constant. (See Figure 17 on next page.)

Today, companies spend about 19% of time defining the project, another 21% exploring data, and almost a quarter (23%) preparing the data. They spend 23% of their time creating the model, 11% scoring it, and 13% managing models for compliance, accuracy and reusability. The only real deviation is the percentage of users checking "other." Since we didn't provide an open-ended response, we aren't sure what motivated people to select "other." Possibly they spend time operationalizing models (which is part of the scoring process) or visualizing results (which is an important vehicle for disseminating results more broadly to more users), two choices we didn't include in the survey.

Figure 17: Time Spent on Each Step in the Model Lifecycle Process—2006 versus 2014

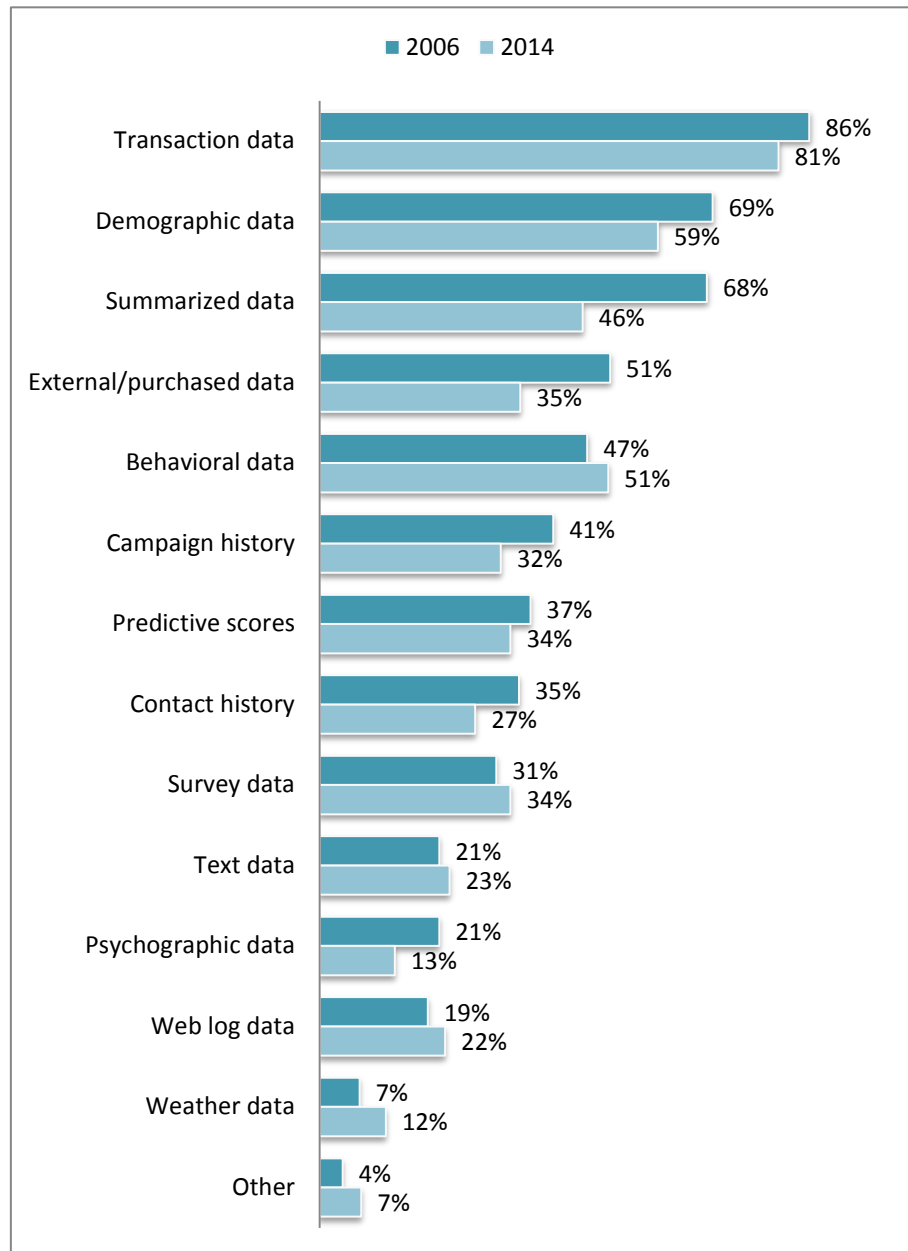


Based on 168 and 430 survey respondents in 2006 and 2014, respectively, who have partially or fully deployed predictive analytics

Data. Organizations are mining the same types of data as eight years ago with some differences. There has been a sharp 22% decline in the use of summarized data since 2006, probably owing to the influence of big data, which emphasizes the importance of collecting and analyzing detailed data.

Also, there has been a 16% decrease in the use of external data from eight years ago (51% to 35%) and a 10% decline in the use of demographic data (69% to 59%). Conversely, there have been slight increases in the use of behavioral, survey, text and Web log data. Given that the big data movement started by analyzing Web log data, I'm surprised we didn't see bigger gains in that data type in this survey. (See Figure 18 on next page.)

Figure 18: Data Used to Create Predictive Models—2006 versus 2014

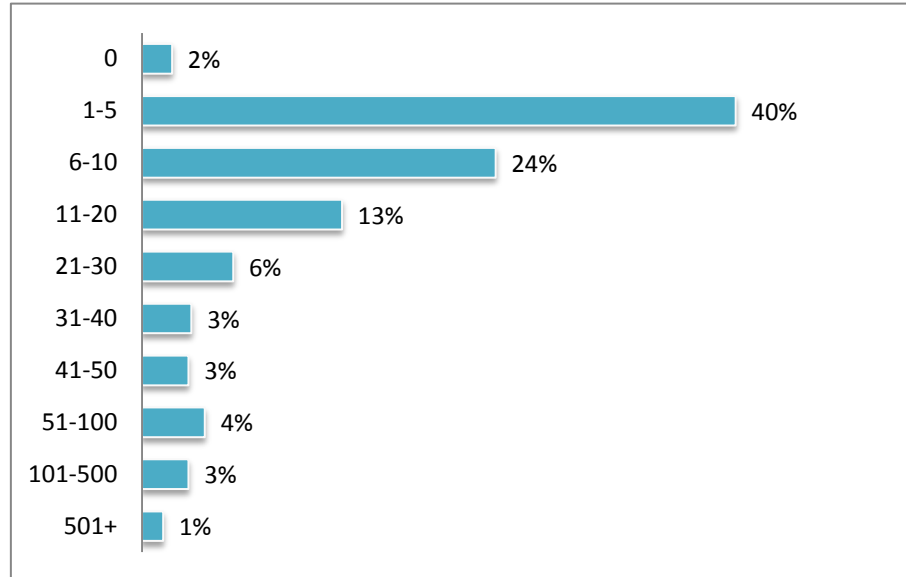


Based on 168 and 430 survey respondents in 2006 and 2014, respectively, who have partially or fully deployed predictive analytics.

Models per Year. Most companies don't produce a lot of models. Two-thirds (66%) produce less than 10 models a year, and another 13% produce between 11 and 20. However, 3% of companies produce between 101 and 500 models a year and 1% produce more than 500. The latter companies are typically credit card, retail and Internet organizations that rely heavily on target marketing.

Some also require heavy duty modeling to detect fraud and support recommendation engines. (See Figure 19.)

Figure 19: Number of Models per Year

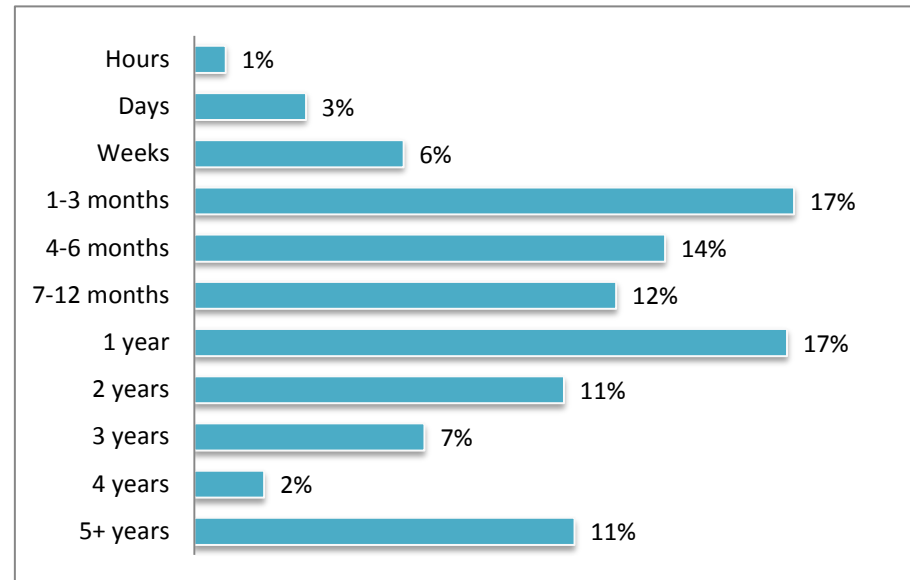


Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Life Span. Most models have a limited life span. Slightly more than a majority of companies (53%) report models lasting less than a year, while 28% have models that last from one to two years and 11% report having models that last more than five years. (See Figure 20 on next page.)

The reason for the short life span is that many of the things that models predict—especially human-centric behavior processes and behavior—change over time, which means the models gradually become less accurate and useful. Analytic modelers are constantly tweaking their models to keep them as accurate as possible. Some algorithms use self-learning techniques if continually fed with data, eliminating the need to manually update models to reflect new market conditions.

Figure 20: The Life Span of Analytic Models



Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Vendors. The market for predictive analytic tools is bifurcated: there are a handful of vendors whose products dominate the market and dozens of smaller players that compete for the remaining tidbits. With the exception of SAS, which specializes in analytic software, and R, which is an open source data mining tool, the major players also happen to be enterprise software vendors: Oracle, SAP, IBM and Microsoft. All except Microsoft have acquired one or more predictive analytics tools in recent years.

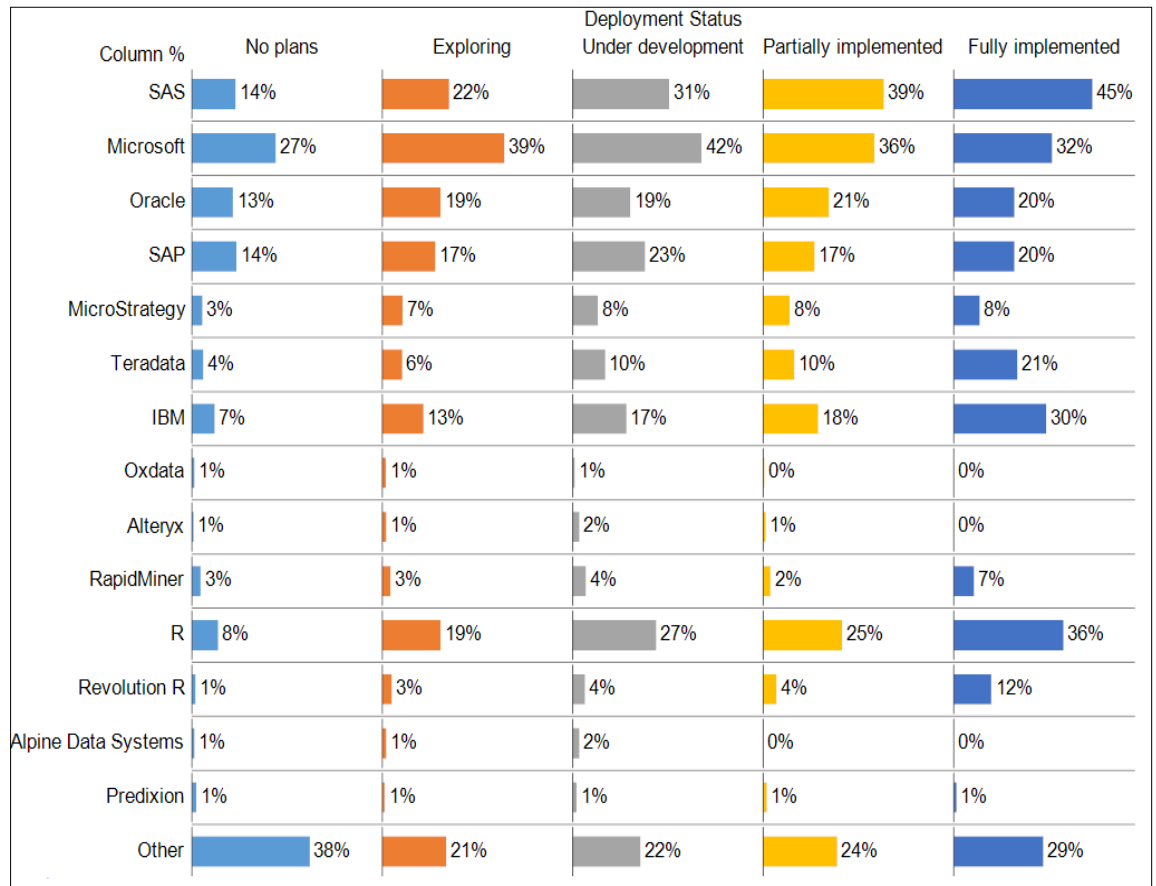
The R language has made significant inroads in universities because it's free and functionally rich. In addition, BI and analytics vendors are adding predictive capabilities into their toolsets in an effort to bring data mining to a wider audience. Finally, there are many new startups leveraging new Web, cloud, visualization and collaboration technologies and automated ensemble algorithms. All these trends are putting pressure on the enterprise vendors and starting to cut into their market share.

The changing landscape for predictive analytic tools is reflected in Figure 21. SAS dominates the market among organizations that have fully deployed predictive analytics with 45% market share, while it has a slight edge over Microsoft among those who are partially implemented (39% to 36%). Not far behind is R with 36% and 25% market share among organizations that are fully and partially deployed, respectively. Next come IBM, Oracle, SAP and Teradata.

But among companies that have no plans, are exploring or under development, Microsoft is the clear leader, even outdistancing R, probably because these companies already have Microsoft products and know about their data mining

add ins. SAS’ market share slips precipitously in these developing markets, while all the major players slip as well, but not as much as SAS. Finally, the “other” category has the biggest percentage among organizations that have “no plans” for predictive analytics, largely fueled by people who said “don’t know,” but not exclusively. The percentage of people checking “other” grows as organizations fully deploy predictive analytics, showing that companies are open to using other toolsets as they mature their deployments. (See Figure 21.)

Figure 21: Vendor Market Share for Predictive Analytics

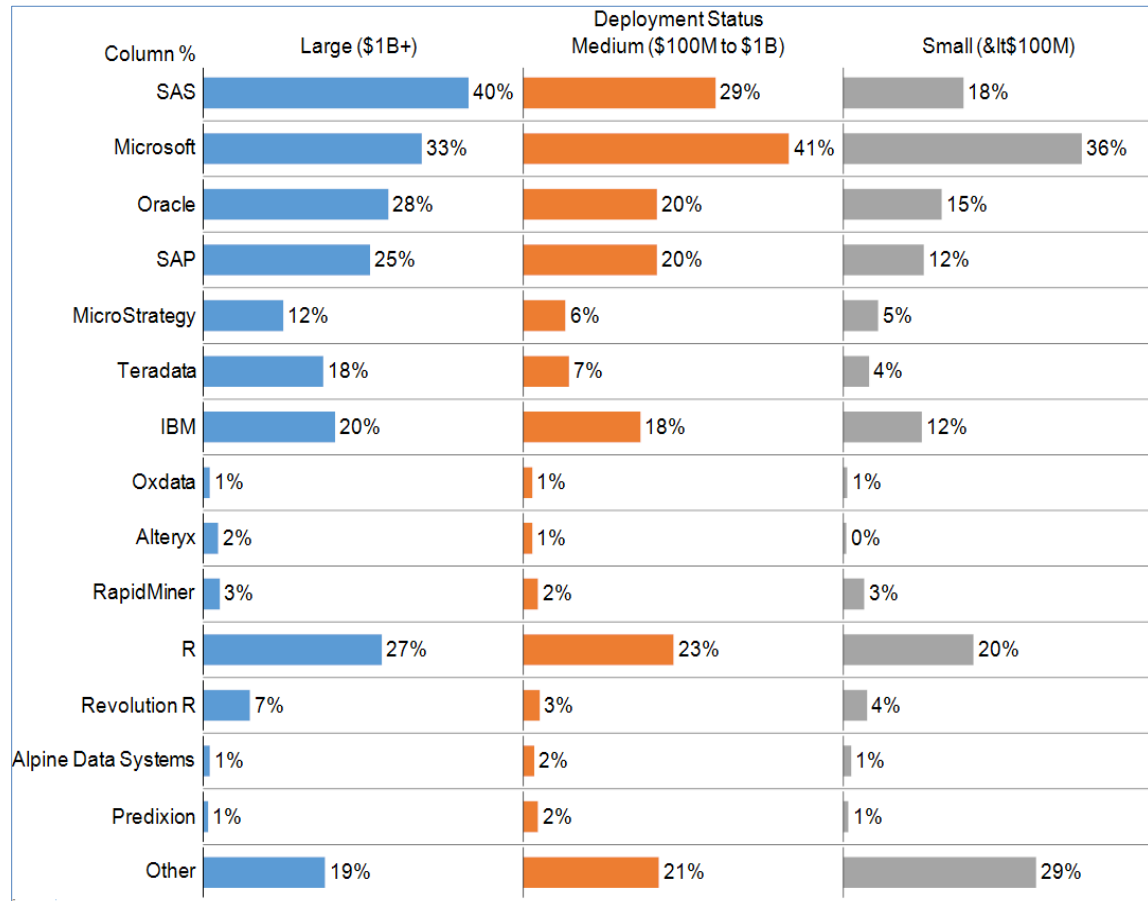


Based on all (3087) survey respondents, 2014

Company Size. When we look at product acquisition plans, several things stand out: SAS is the biggest player for large companies with \$1B+ in revenues (40%), followed by Microsoft (33%), Oracle (28%) and R (27%). Microsoft dominates the market for midsize companies with \$100M to \$1B in revenues (41%), followed by SAS (29%) and R (23%). Microsoft also leads the market for small companies with less than \$100 million in revenues, followed by “other” products (29%). (See Figure 22.)

We also see that most vendors do better with large companies than midsize and small firms. The only exception is “other” vendors whose percentages increase from 19% for large companies to 21% for midsize companies and 29% for small companies.

Figure 22: Product Share by Company Size



Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Applications. It’s also interesting to examine the types of applications that customers build with different products. For instance, the most dominant application for SAS users is fraud detection (45%), while for Microsoft it’s surveys (49%) and product obsolescence (49%) followed by quality improvement (47%). For SAP, the dominant application is supply chain (33%), while for IBM it’s surveys (25%), for R it’s fraud detection (37%) and for “other” it’s, ironically, “other” (54%). That suggests that companies use niche vendors to address niche or non-mainstream applications. (See Figure 23 on next page.)

Figure 23: Applications by Product

Column %	Campaign management	Cross-sell/upsell	Fraud detection	Promotions	Demand planning	Product obsolescence	Attrition/churn/retention	Other	Customer acquisition	Budgeting/forecasting	Pricing	Customer service	Quality improvement	Surveys	Supply chain
SAS	35%	36%	45%	30%	28%	33%	38%	20%	34%	26%	32%	29%	28%	32%	29%
Microsoft	39%	40%	37%	43%	42%	49%	39%	20%	43%	44%	46%	44%	47%	49%	42%
Oracle	18%	23%	27%	25%	24%	24%	25%	13%	23%	25%	26%	25%	22%	26%	26%
SAP	18%	20%	23%	23%	27%	25%	24%	9%	21%	24%	25%	24%	25%	25%	33%
MicroStrategy	9%	10%	15%	9%	9%	10%	12%	7%	9%	6%	9%	10%	9%	10%	11%
Teradata	12%	14%	13%	14%	9%	12%	11%	6%	10%	9%	11%	11%	10%	10%	12%
IBM	19%	19%	21%	21%	16%	22%	21%	15%	19%	17%	19%	20%	17%	25%	16%
Oxdata	1%	1%	1%	1%	1%	4%	1%	1%	1%	1%	1%	2%	1%	2%	1%
Alteryx	1%	2%	2%	1%	1%	2%	2%	1%	2%	1%	3%	2%	1%	3%	2%
RapidMiner	6%	5%	6%	4%	3%	5%	6%	3%	6%	4%	4%	4%	5%	6%	3%
R	23%	27%	37%	23%	21%	24%	32%	15%	25%	21%	23%	21%	23%	21%	27%
Revolution R	5%	6%	9%	6%	5%	7%	7%	4%	6%	4%	7%	4%	5%	5%	6%
Alpine Data Systems	2%	2%	2%	2%	2%	3%	1%	1%	1%	1%	2%	2%	2%	1%	2%
Predixion	1%	1%	1%	2%	1%	2%	1%	0%	1%	1%	1%	2%	1%	2%	2%
Other	21%	20%	24%	23%	21%	27%	23%	54%	22%	22%	20%	23%	22%	23%	20%

Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Other. An examination of a word cloud of “other” applications using “other” products shows that the dominant applications are management, development, maintenance and risk. (See Figure 24.)

Figure 24: Word Cloud of “Other” Applications Used by “Other” Products

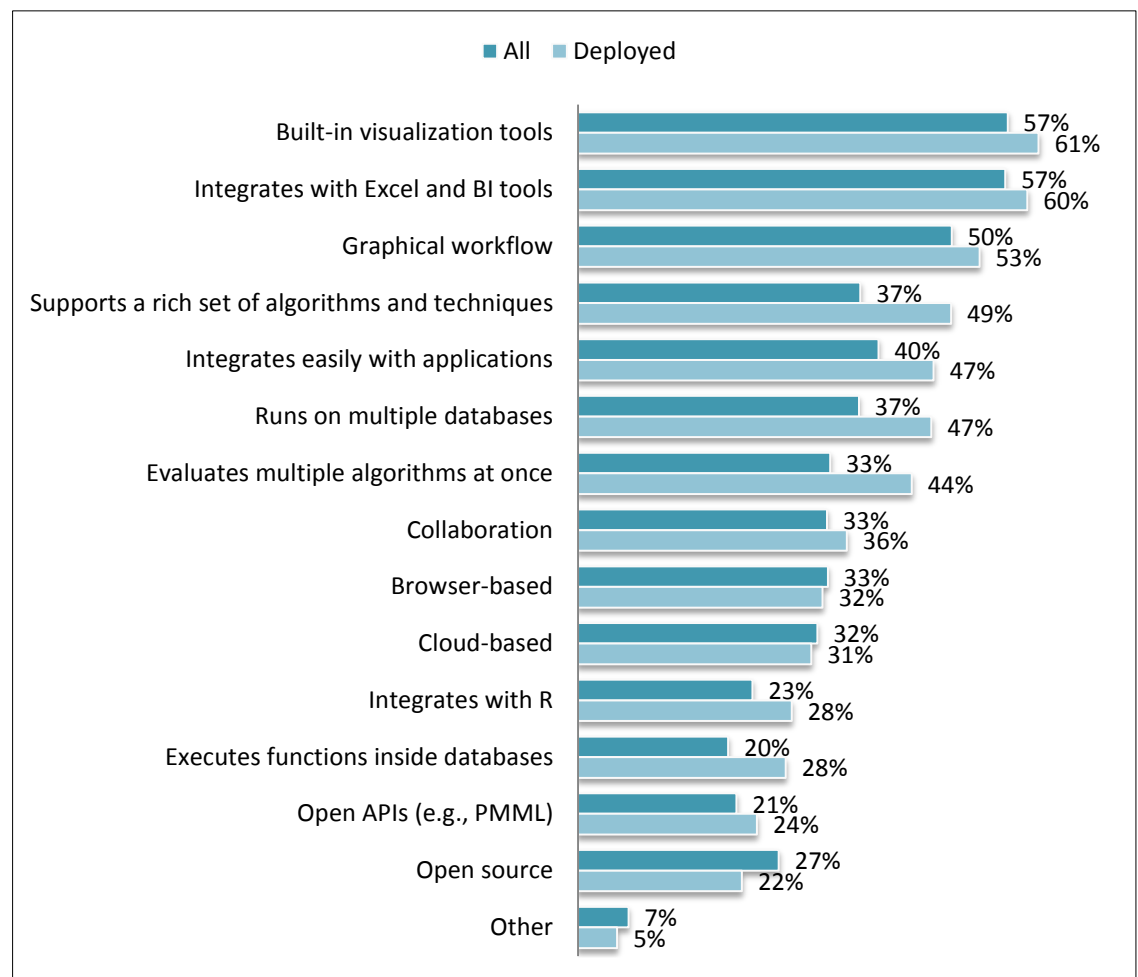


Based on 430 respondents who have partially or fully deployed predictive analytics, 2014

Features. Users want full-featured predictive analytics tools. At the top of the list, selected by a majority of respondents, are “built-in visualization tools,” “integrates with BI and Excel,” and graphical development, which eliminates or minimizes coding. Visualization and BI/Excel integration are increasingly important vehicles to communicate and disseminate model output to all employees. Graphical development is critical to support self-service predictive analytics since most business analysts don’t know how to code.

Desired features following graphical development are: “supports a rich set of algorithms and techniques,” “integrates easily with applications,” “runs on multiple databases,” and “evaluates multiple algorithms at once.” Those four features scored significantly more favorably among organizations that have deployed predictive analytics, suggesting that people value these features only once they begin using the tools. (See Figure 25.)

Figure 25: Important Features in Predictive Analytics Tools



Based on all (3087) survey respondents and 430 respondents who have deployed predictive analytics, 2014

Conclusion

Predictive analytics is a crucial part of any business intelligence portfolio. Most companies recognize the value of predictive analytics even if they haven't yet implemented it. Despite the fact that the technology has existed for more than 20 years, it is still an early adopter market. But the tides are changing. With the advent of big data, BI professionals are eager to help their organizations capitalize on the value of predictive analytics.



WAYNE ECKERSON has been a thought leader in the business intelligence and analytics field since the early 1990s. He is a sought-after consultant and noted speaker who thinks critically, writes clearly and presents persuasively about complex topics.

Eckerson has conducted many groundbreaking research studies, chaired numerous conferences, and written two widely read books: “The Secrets of Analytical Leaders: Insights from Information Insiders.”(2012) and “Performance Dashboards: Measuring, Monitoring, and Managing Your Business” (2005/2010). He is currently working on a book about data governance.

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