OPERATIONAL ANALYTICS: Putting Analytics to Work in Operational Systems

BeyeNETWORK Research Report
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# Table of Contents

**EXECUTIVE SUMMARY**  
1

**INTRODUCTION**  
2

**ANALYTICS IN OPERATIONAL SYSTEMS**  
3  
- **Overview**  
3  
- **Key Concepts in Operational Analytics**  
4  
- **The Business Motivation for Operational Analytics**  
6  
- **Which Decisions Will Show a Positive Return on Operational Analytics**  
7  
- **How Operational Analytics Can Change Business**  
10

**Operational Analytics Techniques and Technologies**  
14  
- **Analytic Model Development**  
15  
- **Analytic Model Deployment**  
17  
- **Analytic Model Evolution**  
20

**Customer Experiences with Operational Analytics**  
22  
- **Case Study Summaries**  
22  
- **Keys to Success**  
24

**Implementing Operational Analytics**  
26  
- **Critical Success Factors**  
26  
- **Best Practices**  
28  
- **Challenges**  
31  
- **Journey**  
33  
- **Conclusions**  
34

**Appendix I – Operational Analytics Survey Results**  
35  
- **Model Development**  
37  
- **Model Deployment**  
39  
- **Model Evolution**  
41  
- **Key Features**  
42  
- **Challenges**  
43  
- **Results**  
44
EXECUTIVE SUMMARY

Analytics, and the use of analytics to make organizations more effective, have become an increasingly hot topic over recent years. With books like *Super Crunchers*, *Competing on Analytics* and *Analytics at Work* promoting the approach, analytics have begun to move into the mainstream. There are many ways to use analytics to improve an organization’s effectiveness and efficiency, and many different ways to apply analytics. This report is about how to use analytics to improve day-to-day business operations.

When you apply analytics to business operations, especially when you apply analytics to operational systems, not every analytic technique or technology is appropriate. Improving the decisions in operational systems is the primary objective of applying analytics in those systems. This requires a focus on executable, operational analytics.

Those applying operational analytics are focused primarily on business process improvement and competitive position, though customer centricity also drives adoption. With a focus on decisions that involve identifying opportunity or assessing risk, customer decisions dominate the operational analytics landscape. In this study, case examples tackle scoring the value of prospective customers to improve targeting, improving customer satisfaction, effectively developing prospects, targeting direct-to-consumer marketing, and optimal scheduling and resource usage – all classic operational analytics problems.

A variety of technologies and approaches can be used to deliver operational analytics, and these can be broken down into different ways to build operational analytics, deploy them and evolve them over time. Whether building analytic models manually or automatically, no matter how those models are deployed into operations and whether those models adapt automatically or are updated manually, the value is clear – better decisions, more accurate decisions and thus more effective business operations.

The technology required for operational analytics is well established and proven. Yet challenges remain. To be successful in operational analytics, organizations must be clear about the decisions they are improving, must start small and expand systematically, and must invest in the management of organizational change. A focus on key performance indicators or metrics and how analytics impact them as well as a vision that is matched with a systematic plan are likewise essential.

Organizations can receive tremendous value from operational analytics and the success stories are becoming more numerous and more compelling. For most, however, there is real work to do if they are to successfully adopt this exciting set of technologies and approaches to changing their business for the better.
INTRODUCTION

This report discusses the role of analytics in operational systems and the technologies and approaches involved. It introduces the concepts of applying analytics in operational systems, differentiating these concepts from others such as business intelligence or operational business intelligence. It discusses the benefits of analytics in operational systems and shows how to get a return on the investment required to adopt them. It also discusses core techniques and technologies and best practices for using these. A summary of the results of an informal survey of BeyeNETWORK members on how they are using analytics in operations is included. This custom report has been developed for Oracle, one of the five sponsors of this research.
ANALYTICS IN OPERATIONAL SYSTEMS

OVERVIEW

Terminology in the analytics space is often confusing and overlapping. For some, the general term “analytics” subsumes business intelligence (BI) while for others analytics is distinct from business intelligence, representing a different and perhaps higher order set of technologies and techniques. Meanwhile, some users of the term business intelligence are seeking to expand it to include newer techniques and technologies, up to and including data mining and predictive analytics. Still others use business analytics as an overarching phrase that includes business intelligence, analytics, performance management, data management and more.

For instance, business intelligence can be defined as:

* A set of applications, technologies and techniques – including fixed and ad hoc reporting, querying and OLAP – designed to monitor, report on, analyze and help understand the performance of an organization.

Business intelligence technologies and techniques answer questions such as what happened and when, how often and where is there a problem. Business intelligence can be applied at many levels in an organization – at a strategic or executive level, at a tactical or managerial level and at an operational level. This last touches on business operations, the same context in which we will be discussing analytics.

* Operational business intelligence has been defined as:

* A set of applications, services and technologies for monitoring, reporting on, analyzing and managing the business performance of an organization’s daily business operations. (Davis, White, & Imhoff, 2009).

Analytics, it has been said, simplify data to amplify its meaning. As such, a wide range of techniques and technologies can be grouped under the banner of analytics. This report concentrates on the use of analytics in operational systems. It focuses on approaches and technologies that help put data to work in operational systems to make better, more effective decisions. Because operational systems are high-volume, low-latency systems and because they often involve straight-through processing rather than human intervention, not every approach or technology works.

In this report, we will extend the definition of operational BI to include the use of data mining, predictive analytics, optimization and simulation. We will define operational analytics as:
Applying insight and foresight into the drivers of performance

A set of applications, techniques and technologies for gaining insight and foresight into the drivers of performance in an organization and for driving fact-based decision making in that organization's daily business operations.

While some technologies and approaches, such as performance management and dashboards, have a role in both operational BI and operational analytics, our definition brings in more insight orientation as well as those approaches more suitable for automation.

Operational analytics use the same historical data as business intelligence systems, but focus on extrapolating trends, making predictions and driving decision making based on actionable insights.

**KEY CONCEPTS IN OPERATIONAL ANALYTICS**

Understanding operational analytics requires an understanding of some key concepts, particularly around the various kinds of analytic models possible and some related technologies such as business rules.

**Analytic Models**

Operational analytics, the application of analytic techniques in operational systems, involve the development, deployment and evolution of analytic models. An analytic model is typically a mathematical representation that can be executed to create a new piece of information – a piece of insight derived from data fed into the model. The result of executing an analytic model is often a number, known as a score.

Building an analytic model typically requires historical data and involves the application of analytic techniques such as linear regression analysis, decision trees or genetic algorithms. Those interested in the details of these techniques should consult the references in the bibliography. Suffice it to say that quantitative techniques and historical data are combined to develop analytic models that can then be executed against live, transactional data to create a score for subsequent use in decision making.

It can be useful to break these models into three broad categories – descriptive analytic models, predictive analytic models, and optimization and simulation. These categories represent increasingly prescriptive and sophisticated approaches as shown in Figure 1. Moving from the knowledge and historical perspective of business intelligence approaches, analytic models classify and describe data, predict outcomes and ultimately optimize decisions.
Descriptive Analytics

Descriptive analytics are used to analyze and describe historical data and trends – to give you insight into your data. Examples include clustering parts into groups or categories based on historical patterns of failure, segmenting customers based on the historical relationships they have had with the company or finding the association rules among product purchases to see which products have historically been purchased together. These descriptive analytic techniques can result in the creation of a set of business rules.

Predictive Analytics

Predictive analytic models and techniques turn uncertainty about the future into usable probability. A predictive model is built using historical data but is designed to make a prediction about the future – to give you foresight. Predictive models include neural networks that predict how likely an insurance claim is to be fraudulent and credit scores that predict how likely a customer is to pay his bills on time. A predictive analytic model typically calculates a score that shows how likely something is to be true in the future, and these scores are often used to rank order customers or transactions – from most likely to least likely.

Optimization

Optimization is a mathematical approach to determining the best outcome to a problem given a set of constraints and a definition of an objective. Linear and non-linear programming are approaches to optimization commonly used where multiple conflicting objectives must be traded off against each other. Optimization models identify the actions that will result in the best outcome for a particular problem.

Adaptive Analytics

Most analytic models are built offline and then deployed so they can be used to score or classify transactions or other data. Once deployed, they continue to operate in the
same way until new models are developed and deployed to replace them. An adaptive analytic model, in contrast, continually adapts based on the results it achieves. As it operates, it measures the results of decisions based on its output and, using definitions of success provided by the developer, changes its model to continuously improve its results.

**Business Rules**

Business rules are not an analytic technology per se, but they have an important role to play in operational analytics. Some descriptive analytic techniques result in models that can best be represented as a set of business rules. In addition, the need to act on analytic models, especially those deployed in operational systems, means that organizations must define the actions to be taken when the models return scores in a particular range or when a customer has a particular score and other attributes in particular ranges. Business rules allow these actions to be defined declaratively, rather than in code, making them easier to change and manage alongside the model.

**Adaptive Control**

In operational analytics, it is important to continually challenge and update the models being used. The most effective way to do this is to develop an adaptive control methodology. This approach is also known variously as champion/challenger testing, test and learn or A/B testing. In the approach, a set of models and rules is identified as the champion, the preferred or default set. Alternative models and rules are then developed to see if they might perform better for some or all of the transactions being processed. These “challengers” are then tested on a small percentage of the transactions and results are compared. Those challengers that outperform the champion are generally promoted to be the new champion, and the process repeats with new challengers being developed and tested. This might be done manually by a modeling team or it might be handled automatically by the model itself as in the case of adaptive analytic models.

**The Business Motivation for Operational Analytics**

In the survey, business process improvement was the biggest driver for adopting operational analytics with 70% of respondents identifying it as an impetus for their use of analytics in operational systems. (See Figure 9: Impetus for Operational Analytic Projects.) Followed by improved competitive position and customer service as well as a better return on investment, respondents clearly saw business-changing potential in operational analytics.

Underlying all motivations for operational analytics is a need to make better, more fact-based and future-focused decisions. Better decisions can improve the processes of which they are part, make customer interactions more rewarding and profitable, and put data to work.
Most organizations have large quantities of data: data about their customers, their prospects and their products; data about marketing offers made and accepted; loans that were and were not paid off; claims or tax returns that turned out to be fraudulent. This data often goes back years, and organizations have historically tried to find ways to use this data to improve the way they operate. However, most organizations still merely store this data and report on it, making little or no use of it to systematically improve operations.

In particular, the systems that store this information make no use of it to improve their interactions with customers, partners, suppliers or employees. This contrasts strongly with how good employees operate. Consider a new employee working with customers. The first interaction they have with a customer will be based only on policies or procedures provided to them. But over time, as they interact with more customers, they will develop a sense of what works and what does not. They will become familiar with established, repeat customers and use this familiarity to improve the experience for those customers. They will learn about the customers they interact with. Contrast this with a typical information system that will store information about all the customers, all the interactions, and yet continue to treat every customer just the way it was programmed – applying only the policies and procedures coded into it. There is no learning going on.

Trident Marketing and the post-secondary education company in the case studies are great examples of this. Both had large amounts of data about what worked and what did not, who was a valuable prospective customer and who was not. Yet only when they applied operational analytics were they able to put this data to work in their day-to-day business.

In a system that takes advantage of operational analytics, however, the data collected drives improved interactions. Each interaction creates a richer dataset, and that data is used to drive analytic models so that the system can treat customers more appropriately, learning from the data it collects. The ability of operational analytics to turn stand-alone enterprise applications and repetitive processes into smarter, learning systems is the key motivation for adopting operational analytics.

### WHICH DECISIONS WILL SHOW A POSITIVE RETURN ON OPERATIONAL ANALYTICS

**Little decisions add up**

Organizations of any size make vast numbers of decisions. These decisions range from strategic decisions related to business direction right down to individual customer treatment decisions made in the call center or branch office. It is useful to categorize decisions into three broad categories: strategic, operational and tactical (Taylor & Raden, 2007). Strategic decisions are those high-value decisions that determine business direction and that are either uniquely individual or made so rarely that they can be considered individually. Tactical decisions, those of medium value
and some repeatability or volume, are those related to managerial control. Operational decisions, shown at the bottom right of Figure 2, are those low individual value yet high-volume decisions that relate to operational execution.

![Figure 2: Different Types of Decisions](image)

Because organizations of any size make large numbers of these decisions – for instance, a customer base of just 100,000 generates 5,000 monthly statements a day, each of which might involve multiple decisions – the impact of these operational decisions can be very high.

Consider this example: a once-a-year contract for a distribution channel worth $1 million in profit next year versus the decision to retain customers worth $50 each in profit next year. It might seem clear that more time and money should be spent getting the channel renewal decision correct than on customer retention decisions. Yet a company with just 26,000 customers on an annual contract must make 500 renewal decisions each week. As Figure 3 shows, the multiplicative effect means that this operational decision has much greater value when the total value for a year’s worth of renewal decisions is considered. On an annual basis, even for a small customer base like this, the value of retention exceeds that of the apparently more important channel renewal decision.
In general, strategic and tactical decisions tend to require decision support applications – software designed to help individuals with analytic skills make better, more informed decisions. In contrast, operational decisions tend to require decision management applications, designed to make decisions (often analytically informed decisions) on behalf of their users and either present a specific action or a limited range of viable actions. These decision management applications are sometimes known as action support systems.

Several things must be true of a decision if analytics are to be helpful making it. First, there must be some degree of freedom in the outcome – a completely regulated decision, for instance, cannot be analytically enhanced as the rules for making the decision are completely defined. Second, there must be a reasonable amount of information available at the time the decision is to be made. Without some information about the customer, transaction or product involved in the decision, it will not be possible to link any analytic models to the decision. Typically some amount of historical data must be available: descriptive and predictive analytics rely on previous results, whether outcomes were good or bad, in order to improve future decisions. If there is no historical data, then optimization and simulation must be applied.

For all these reasons, operational decisions are generally the most amenable to the use of analytics. Because operational decisions are repeated, they accumulate a large historical record of what works and what does not. Even when this historical data is missing, the repeatability of operational decisions lends itself to experimentation and testing to acquire data about what works and what does not. Operational decisions are
part of the day-to-day operational execution of an organization and, as such, are integrated with the enterprise applications and business processes that run the business. This means they have data available to them about customers, orders, products and transactions. Operational decisions that involve an assessment of risk (whether credit risk, delivery risk, fraud risk or any other kind of risk) and those that involve an assessment of opportunity (can this customer be up-sold or cross-sold, for instance) are particularly appropriate because there is a fair number of degrees of freedom in those decisions: the organization must make pricing, offer or other selections from a finite but non-unitary list.

Survey respondents identified customer service, customer retention, customer acquisition/sales and marketing as the top areas for operational analytics as shown in Figure 10. Given that, for most organizations, it is customer-facing decisions that are most numerous and most operational, this is not a surprise.

**HOW OPERATIONAL ANALYTICS CAN CHANGE BUSINESS**

Operational analytics have the potential to change the underlying assumptions of many businesses. For instance, an insurance company might have assumed in the past that more business meant hiring more underwriters – after all, each new policy must be assessed for risk and price, and that requires a review by an underwriter. The use of analytics to predict the likely risk of a policy, combined with business rules to automate legal requirements and to calculate prices based on the likelihood of risk, would allow a percentage of policies to be underwritten automatically – in practice perhaps 80-95% of home or personal auto policies, for example.

In this new world, the underwriters will not spend their time approving individual policies. Instead they will be spending their time on exceptions and on managing the book of business: working with agents to grow their local business, identifying products that are selling poorly, analyzing claims patterns to see if risk models should be changed and so on. As a result, the number of underwriters is no longer proportional to the amount of new business being written – the assumption of dependency from new business to underwriters has been changed.

**Reducing the Need for Manual Decision Making**

Analytics help make this kind of change by reducing the range of decisions for which a manual decision-making process is required. As Figure 4 shows, there are simple decisions (low complexity, low value) that are easy to automate and expert decisions (high complexity, high value) where decision support technologies make sense and where companies are simply not going to trust automated decision making. In between is the realm of manual decision making. The use of analytics to predict risk or opportunity to correctly segment or cluster customers or transactions expands the realm of automation and squeezes the “no-man’s” land between easy automation and expert decisions. There are two primary reasons for this:
First, operational analytics take large volumes of information and, instead of relying on a person to analyze it, use analytics and other techniques to analyze the data, find patterns in it and present the results of the analysis. Instead of presenting an underwriter with the complete history of a particular applicant so that an assessment can be made of the riskiness of the applicant for instance, operational analytics are used to calculate a risk score that an automated decision can consume. This score represents the likely riskiness of the applicant as extrapolated from the data.

The use of analytics to score leads in the post-secondary training company is a classic example of this. Instead of routing every lead similarly, the company was able to score and rank leads so that those likely to be more productive could be prioritized.

Secondly, operational analytics can replace, at least to some extent, the experience of an individual with a particular decision with an analysis of the history of many such decisions. Thus, loan officers might have dealt with many customers and observed which ones do and do not make their payments. Based on this, they may be confident that they can assess a new applicant in terms of how likely he/she will be to make his/her payments. Operational analytics, in contrast, considers all previous customers and their payment history to make this same assessment – replacing a person’s direct experience with the collective wisdom of all previous decisions.

Figure 4: Operational Analytics Can Increase the Range of Decision Automation

The result of using operational analytics in this way is often to free up those who were handling the decision manually to consider the overall business of the organization, to move up and right in Figure 4 toward higher value, more complex decisions. The ability to automate these decisions can also result in changes to
business processes, as when a customer can enter a claim on a website and have it be automatically approved and paid without manual review.

**Operational Analytics and the Customer Experience**

This illustrates one of the most powerful aspects of using operational analytics in operations – the ability to change the customer experience. Today many customers are frustrated in their interactions with companies:

- They want to serve themselves, yet companies insist on having them speak to staff members to get many things done.
- They want to be treated as individuals, yet most companies treat their customers as a largely undifferentiated mass.

**Operational analytics can help address both these aspects of the customer experience.** By enabling more decisions to be automated, operational analytics allow self-service applications to do more. Decisions about product eligibility that include a risk assessment, for instance, can be automated. Decisions about claims payment that include a fraud or abuse assessment can be made based on data entered through the website and so on. Customers get a better experience because their self-service options expand. This can include more options on a website, more options at a kiosk or an ATM, or more options on a mobile device.

Operational analytics also allow more targeted marketing and a more personalized customer experience. Customers respond to the decisions companies make as though those decisions were personal and deliberate. Operational analytics help segment customers so that offers and treatments can be targeted to the customer more precisely, making the decisions feel more personal and more relevant. The customer experience is improved because a blanket decision is replaced with one more targeted to the customer.

**The ROI of Operational Analytics**

Operational analytics can generate a return on investment (ROI) for organizations in many different ways. To be sure that an operational analytics project will show a positive ROI, organizations should understand their own metrics and key performance indicators (KPIs) and how the decisions being impacted by operational analytics relate to those measures. If a company, for instance, is tracking customer retention as a key performance indicator, then it is likely to know exactly what the return will be on any improvement in this number. When operational analytics are applied to decisions that impact customer retention, the value of improvement will therefore be clear.

_Deltacom did a great job of this, linking all their operational analytics back to a formal model of their KPIs. Day-to-day operations were strongly aligned with corporate objectives at every level._
Operational systems, at their core, improve the *efficiency* of operations. They make it possible to issue checks faster, eliminate paper forms, minimize handoff delays and so on. Analytical systems, systems that embed operational analytics, focus on the *effectiveness* of operations. They make it possible to target the best prospects, price risk more accurately, route customers to the most effective call center staff and make better use of available resources. In general, operational analytics translate this effectiveness into a positive ROI in one of several ways:

- **Improved revenue.** More targeted acquisition effort, more personalized up-sell or cross-sell and other analytically enhanced decisions can often show an increase in revenue, with customers being more likely to accept analytically targeted offers.

- **Decreased costs.** The use of operational analytics to focus resources where they will have the most success can reduce costs. For instance, analytically focusing the acquisition efforts of a company can reduce costs by identifying those prospects that are unlikely to convert and avoid the expense of marketing to them.

- **Resource utilization.** When analytically enhanced decisions free up resources to work on higher value problems, this can add tremendous value to an organization. While harder to calculate than the more direct benefits, this is often the most valuable. Being able to focus auditors on those tax returns most likely to be fraudulent and recoverable, for instance, an organization can use a limited resource (auditors) much more effectively.

Often a single operational analytics solution can combine all these aspects. For instance, consider the use of analytics to more effectively target customer acquisition by identifying those prospects most likely to convert to customers. This can increase revenue by focusing limited pre-sales resources on those leads most likely to convert. It can decrease costs by allowing an organization to pay less for poor quality leads or even stop paying for leads completely when a lead source consistently generates poor quality leads. The way commissions are paid and the performance expectations of those handling the leads can be determined, in part, by the quality of leads they work on. Ultimately, the most experienced and expensive resources can be assigned where they will make the most difference, further adding to the value of the solution.

*GE Rail’s use of analytics to optimize the scheduling of repair facilities, analytically enhancing the assignment decision, resulted in exactly this kind of improvement in resource utilization, reducing waste and boosting results.*
Operational analytics are additive to existing systems

Analytics, especially when applied to operational decisions in operational systems, require a particular set of technologies. Shown in Figure 5, these technologies must be able to execute on top of a standard enterprise IT platform and use service-oriented architectures (SOAs) to integrate with enterprise applications and business process management technologies.

In the survey, respondents identified dashboards, operational reporting, query/drill down and standard reporting as the analytic technologies most likely to be used. In those applications reliant on advanced analytics, predictive scoring and business rules were also widely used. Operational analytics, to the respondents at least, are clearly additive to existing BI and performance management technology.

Decision services and analytic deployment containers

The best way to think about these technologies in an operational context is to consider decision services, services that answer questions or make decisions, as the deployment container for these technologies. Business rules, predictive models and optimization technologies can all be mixed and matched in the context of a specific decision service to make the best possible decision. Because decision making requires experimentation and continual learning, adaptive control approaches must be able to work on these decisions services. Finally, the whole decision-making infrastructure must be able to use the information architecture of the enterprise (its databases, data warehouses and information exploration technology) and integrate with the performance management infrastructure to ensure that results are being properly tracked.
ANALYTIC MODEL DEVELOPMENT

There are three basic approaches to developing models – have specialist analytic experts, typically statisticians, develop them; empower business analysts and BI professionals to develop them through the automation of the mathematically complex tasks; have the model be built automatically once deployed. In addition, it is important to consider the overall degree of automation of the model creation process and how models are validated, simulated, tested and managed.

Model Development by Analytic Professionals

Perhaps the most common approach to developing analytic models, and the approach chosen by nearly 50% of the survey respondents, generally involves the analysis of data by statisticians or other quantitative analysts using a variety of techniques including, but not limited to, linear and logistic regression, nearest neighbor, clustering, decision trees, neural networks and rule induction. Optimization and simulation techniques may also be applied that do not analyze historical data but create a mathematical representation of reality that can be used to make predictions or manage tradeoffs between alternatives.

The models are built using a tool specifically designed for developing models or a scripting language with strong support for quantitative and statistical operators. These tools help the user access, clean, integrate, explore, understand and analyze the data available. Multiple techniques are typically applied and compared or combined to find a model that is “best” for a given problem.

For some organizations these analytic professionals are employees; for others they are a contract or outside resource applied to specific problems/projects as needed. Most providers of analytic tools also provide analytic professionals to build models for their customers and have relationships with specialty consulting firms that often combine analytic modeling skills with domain expertise.

Model Development by Business Analysts

As organizations adopt operational analytics more broadly, many find that a reliance on specialist analytic professionals is constraining – that they simply cannot build enough models. Other organizations find that they cannot justify the investment in specialists because they have too few models to develop or their use cases are not of sufficient value. Organizations then often look for tools that would allow less quantitatively skilled business analysts to develop models in a self-sufficient manner. The typical candidate is someone who understands the business and the data available and who is familiar with using business intelligence tools to report on and describe the available data.

Tools for these users apply many of the same techniques as those used in tools for statisticians and expert modelers, but do so in a more automated way, asking the user
to apply less judgment or experience in selecting constraints or parameters, for instance, or running large numbers of similar analyses to see which works best. The results tend to be less explicable than those built by experts, with more data being used in a less obvious way than when a professional analytic modeler has been involved.

These tools sometimes require that the data will be moved from the database or other data management environment so that the business analysts can work on it. This can, obviously, cause problems with data freshness and security. If the business analysts are disconnected from the analytic team, these risks can be serious.

**GE Rail used internal analytic experts to develop its models, while Trident Marketing outsourced model development and used in-database analytic routines to develop them.**

**Automated Model Development**

The third option is not to have someone build the model at all, but to allow software to build the model automatically. Typically this involves the business owner defining the constraints on the decision, determining how a good decision can be measured and then using the software to build a model through experimentation. Essentially, the model tries different approaches for different customers/decisions and determines which work best (given the definition of success provided). Over time, it establishes the characteristics of customers or transactions that make one decision preferable over another and builds a model of this that is then used repeatedly. This approach is typically combined with automated model evolution as part of a single, integrated model development and evolution process.

**The North American financial services company used this approach to successfully embed analytics in its website to improve its initial interactions with customers.**

**The Model Development Process**

Regardless of who builds a model, there are many options for automated support of the model development process. The process can be completely automated with just manual oversight, largely automated with a few manual steps or largely manual with automated steps being interspersed at the modeler’s discretion. Generally, the use of less analytically sophisticated users in the model development process requires a higher degree of automation, but many tools offer a high degree of automation even for those models being developed by analytic experts.

**Model Validation, Simulation and Testing**

Finally tools must provide ways for those involved in the model development process to validate models and to simulate/test the impact of those models in operations. A variety of business-centric and statistics-centric approaches are often used, with the more statistical ones being used only when an analytic professional is involved in the
Increasingly, it is the ability to simulate the business impact of a model or of a new version of a model that matters.

**Analytic Model Deployment**

Analytic models have value only once deployed

To be effective, models must be deployed into operational systems. A wide variety of options exist for the deployment of models including batch updates, code generation, in-database analytics, the manual recoding of models, the use of business rules or business process management systems, and the use of domain-specific decisioning applications. The role of standards, especially of the Predictive Model Markup Language (PMML) also needs to be considered.

**Batch Database Update**

The easiest and most common way that models are deployed is through the use of batch database updates. In this approach, the database has additional columns in which it can store the scores calculated by the various analytic models being used. On some regular schedule, typically overnight, the models are executed for every record in the database and the results stored in the database. Once the results are stored, any application or process can access the model in the same way it accesses any other data in the system.

This approach is not complex to implement and makes it easy to have multiple systems access the model. However, it is limited when new records are being created (these won’t have scores until the next time the batch process is executed) and when data changes in between updates.

*While this approach has long been considered the default, the survey showed that the deployment of models is increasingly moving toward real-time scoring with most models being calculated as needed (53%) rather than in batch (42%).*

**In-Database Analytics**

The execution of analytic routines “in database,” that is near the data and on the same machine that is running the database management system or data warehouse, is a rapidly developing trend. Several companies specialize in such in-database analytics, while others offer an option to do all or some analytic work on the database or data warehouse server. In-database analytics support both model creation and model execution. Model creation using in-database analytics means that some or all of the data preparation and modeling tasks are completed on the database server using routines that are in or near the kernel of the database. Model execution typically means that predictive scores are calculated by the server as the data is retrieved, ensuring the score uses up-to-date data as well as maximizing performance by keeping execution close to the data.
In both cases, the routines take advantage of the inherent parallelism of the platform on which they run, perform the analysis inside the database architecture and only move the results once processed. Performance improvements can be significant, though the additional load on the database/data warehouse must also be considered. Many in-database analytic vendors extend SQL to make it easy to include models in reports or other analytic tools.

*Taken together, these two approaches dominated in the survey responses with database and data warehouse servers each being selected by more than 40% of respondents.*

**Manual Recoding of Models**

Many models are turned into specifications for programmers, and a piece of code is then written to calculate the model/score in production. Programmers use the production environment data definitions and data access, and a programming language suitable for execution in the production environment to create a service or program that takes a record and calculates a score for it. These are typically used interactively, scoring a customer or transaction when needed. As a result, they are using data that is up to date, and this can include data being created during an interaction or conversation. The performance of these routines is typically good, as they have been custom coded for the environment in which the score is needed.

The key challenge with this approach is time to implement, with many models taking 6 to 12 months to be deployed in these circumstances. This is an issue because models degrade over time (new data has been collected that is not included in the model creation process) and because the time and cost of this approach often mean models don’t make it into production at all. Reuse of the score in multiple situations can also be problematic if the coding is too environment-specific.

*Manual recoding was only used by 28% of the survey respondents, much lower than would have been expected even 12 months previously.*

**Code Generation**

Some (most) analytic modeling tools now provide some code generation options. These take a finished model and generate code for it so that the model can be calculated in production. Quicker and cheaper than recoding the model, this approach is typically limited by the range of models for which it is available – often only simple models can be generated, while the more complex and multi-technique models that are required in most circumstances must still be recoded.

*Despite the limitations in this approach, over 40% of survey respondents said they used code generation at some level.*
Business Rules Management Systems

Many organizations deploying analytic models do so into a business rules management system. Some analytic techniques, such as rule induction or decision trees, explicitly create business rules, making this an easy process. The accessibility of the business rules management system to non-technical users often helps with usage as the business experts can read and edit the rules more easily than they could in the analytic environment. Finally, the business rules management system allows definition of the rules within the model and proscribes the actions to be taken.

The use of a business rules or business process management system to deploy models showed up in many responses to the survey, each technology being identified by more than 25% of respondents.

Decisioning Applications

Many organizations use vertical applications that manage critical decisions such as a marketing application that handles cross-sell or up-sell decisions or a customer relationship management (CRM) solution that takes care of customer retention decisions. These applications increasingly allow the integration of analytic models and the automated deployment of these models. Sometimes the models must be created using tools designed for the purpose; sometimes they can be imported from a wide range of tools.

25% of responses in the survey showed a predefined decisioning application as a deployment option.

Access Paradigm

It is also worth noting that different model deployment options offer different access paradigms. Some analytic models are designed to be accessed directly using extensions to SQL. This can make it easy to integrate the models with other elements of the architecture – SQL being widely used in reporting, operational systems, etc. – but can also be more technical and more tightly coupled with the information model than is entirely appropriate. Extending SQL means that anyone consuming the model must write SQL to access it. Other approaches provide simple interfaces with an abstraction layer. These enable a wider set of knowledge workers to specify decision logic that uses the output of the model. The suitability of the access approach for an organization is important to consider as it will determine who can access the models and how they do so.

Predictive Model Markup Language

PMML is an XML format designed originally to make it possible to move models from one analytic modeling tool to another. Increasingly, this is used to move models from analytic development environments to production deployment without the need to generate code or manually recode the models. A number of decisioning
applications and business rules management systems support PMML for this purpose. PMML has some limitations, however. It does not support certain kinds of models or model encryption. In addition, elements of PMML that handle data preprocessing are not widely supported by vendors, and there is limited documentation and guidance for its use. Finally, the variability of vendor support (different versions are supported with various proprietary extensions) makes true interoperability difficult to guarantee.

**PMML adoption had not made much progress among respondents, with almost no responses mentioning it or any other standards as being important to survey respondents.**

**Analytic Model Evolution**

Once models are deployed, they must be evolved and maintained. This might be managed manually or automated. Closing the loop, tracking results and managing experimentation are all issues to consider. If models are not evolved, they will gradually become less effective. The world in which the models are being used continues to change once the model is complete. Some of these changes may undermine the assumptions of the model or require that the model be changed to take advantage of them. As new data is gathered, it must be fed into the models, and they must be updated so that they do not become stale and ineffective.

**Adaptive Analytics**

Adaptive analytics are a branch of operational analytics designed to automate the model evolution process. Often combined with the automated creation of analytic models, adaptive analytics ensure that models will stay up to date with changing data and that experimentation will be conducted automatically to keep the model fresh. For many adaptive analytic models, the separation of development and evolution is an artificial one, with the same process being used to continually test and refine a deployed model as was used to create the initial structure of the model.

**Nearly 40% of respondents used models that adapted or modified themselves automatically.**

**Manual Refresh of Models**

When models are not built using an adaptive approach, they must be manually refreshed. Many analytic modeling tools make it easy to do this, storing and managing the process by which a model was originally developed and allowing a user to rapidly rerun the same modeling process against new data to see if the model should be updated or refined. Obviously, the more automated the development and deployment process, the more easily this refresh can be accomplished.
Only one-third of respondents relied solely on manual refreshing of models, with most using an automated or semi-automated approach for updating models.

Tracking Results

One of the advantages of using automated deployment and evolution technologies is a clearer linkage of the model to business results. When models are recoded or deployed to a new environment, the developers must ensure that the results of the model are tracked relative to the overall business results. Regardless of the approach, it is important that the scores/decisions used in every transaction are recorded so that the results achieved can be mapped back to them.

Less than 20% of respondents had not linked model performance to their overall performance reporting.

Adaptive Control

Because the environment in which models are being used changes all the time and because new data and new situations must be included, most analytic models must be constantly challenged to see if they remain the best possible approach. This adaptive control process (sometimes called test and learn, A/B testing or champion/challenger) involves creating multiple new models/decision-making approaches and comparing them. Either all transactions are fed through several equally valid alternatives (A/B testing) or multiple “challengers” are identified and executed on a small subset of all transactions to see if they outperform the current default or “champion” approach that is executed on the majority of transactions (champion/challenger). Automated model deployment approaches sometimes build in support for adaptive control, and adaptive analytic approaches apply it automatically while manual deployment approaches need to allow for it explicitly. Regardless of the approach used, organizations need to plan for adaptive control and for tracking and managing results so that the relative performance of different approaches can be analyzed.

The more experienced responders were more likely to use adaptive control to improve models, with over 48% of those who had already deployed operational analytics using some form of experimentation or adaptive control.
CUSTOMER EXPERIENCES WITH OPERATIONAL ANALYTICS

Five companies, each a customer of one of the sponsors of the report, were interviewed for this report. The objective was to understand how they had used analytics in operational systems, how that had improved their business and what the critical success factors were for those projects.

This section contains a brief overview of each case study and a summary of the keys to success across all these projects.

CASE STUDY SUMMARIES

Adaptive Technologies, Inc. (ATi) Case Study – A For-Profit Technical Education Provider

The company is a national for-profit provider of post-secondary technical education. The company specializes in training those who wish to become technically qualified as motor mechanics. The company’s new student acquisition strategy relied on a large lead generation effort to ensure a pipeline of prospective students. A KPI – cost per lead – was trending negatively. The company saw a need to identify the potential value of leads when purchased or generated. This would help them to purchase the right ones, route and treat them correctly, and convert them effectively.

The company adopted ATi’s technology and worked with ATi to develop a custom model for scoring leads. This model was plugged into the existing lead distribution process and lead incubation system. Based on the propensity calculated for the lead, it would be distributed and prioritized for follow-up. The company saw that the leads scored as high propensity were much more likely to convert to paying students, improving enrollment and attendance numbers. Leads that scored in the top 4 deciles showed a positive ROI, whereas leads in the bottom 6 deciles showed a negative ROI. The cost savings from not following up on low propensity leads were significant as were savings for leads not purchased when low-quality lead sources were eliminated.

Aha! Case Study – Deltacom

Deltacom is one of the largest business communications providers in the Southeast, providing a robust facilities-based network and innovative integrated communications and equipment solutions. One of Deltacom’s measures for success is increasing customer revenue through an ability to grow and retain customers, and by delivering a customer experience that works. Deltacom saw operational analytics as core to creating an enterprise solution for an excellent customer experience. Aiming
to increase the visibility of the unseen factors that drive an improved customer experience, the project was predicated on a belief that small improvements in customer experience have a big impact on operational results.

Using Aha!’s Axel analytics services platform, Deltacom set out to build and capture the key KPIs related to customer satisfaction and extend and relate this to other areas of the business. The project was designed to capture the business knowledge of the organization and represent it back consistently, delivering a single source of truth to everyone when it came to customer service. The system delivers a new level of understanding and analysis not based on a snapshot that ages, but one that is current and actionable. Deltacom was not only able to retire the cost of reporting and redeploy reporting analysts to more important priorities, but also could take action to improve customer satisfaction through near real-time models of the customer relationships and touchpoints.

**Fuzzy Logix – Trident Marketing**

Trident Marketing is a customer acquisition, sales and marketing company that blends traditional and nontraditional direct marketing channels to deliver profitable results and customers for its clients. First and foremost, Trident Marketing’s focus is on using analytics to improve marketing programs. Trident Marketing commits millions of dollars to these programs and often runs literally thousands of programs at one time. Measurement and analytics are critical if Trident Marketing is to be effective as its scale is less than a quarter of its next nearest competitor. Being effective in many specific niche markets is the key. To thrive, Trident Marketing must deliver high-yield marketing programs.

Trident Marketing’s move to adopt analytics was not a single project. Instead, it has used Fuzzy Logix technology in a wide variety of analytics projects – some truly predictive analytics and some more general quantitative analytics. Trident Marketing management had begun to ask complex, more sophisticated questions that its general purpose BI tools could not answer. A desire to answer these questions led the team to analytics and to Fuzzy Logix.

**Oracle – North American Financial Services Company**

This company is a major North American financial services company. One of its business priorities is the effective adoption of potentially disruptive technologies. It sells its products primarily directly to consumers, through its website and call center, rather than through agents.

The company adopted Oracle Real-Time Decisions (RTD) to manage offers made and content displayed to website visitors. Beginning with analytics driven only from the visitor’s likely location and getting increasingly sophisticated as more information is collected, Oracle RTD constantly experiments and learns what works with customers as they use the website. The analytically driven decisions of RTD
focused on the right product at the right price and broke even just 3 months into the pilot – the increased results in those 3 months covered the planned 3-year cost for installing and running the platform. Besides this stronger bottom-line performance, the system builds customer loyalty earlier in the process and quickly becomes very accurate at predicting what will work best for a given person.

**SAS – GE Rail Services**

GE Rail Services is one of GE’s independent businesses and handles leasing, servicing and financing railcars for use in freight trains. GE Rail offers full-service leases, basic leases where the client operates the railcar and financed leases where GE Rail also provides financing. GE Rail’s customers are railroads and shippers as well as the companies whose goods are being transported. GE Rail customers with full-service leases can call customer service whenever they have a problem with a railcar. GE Rail must then make arrangements to send the railcar to a shop to have it repaired. This apparently simple problem is actually complex from GE Rail’s perspective as it has to pay transit/freight costs and network switching fees to get the railcar to the repair shop, select the appropriate repair shop, and then return the railcar to a location specified by the customer.

GE Rail’s analytics team built an application using SAS and web enabled it so that the call center could use it. The application was also integrated with the legacy system used to manage repairs and facilities. The new system decides where to send the car for repair and where to send it when it is fixed, railcar by railcar. The solution is currently estimated to save more than $1 million per year for GE Rail and took less than 6 months to show a return on a fairly modest investment.

**Keys to Success**

Across the various case studies, each using different technologies and working with different vendors, there were a number of common keys to success:

- All the case study companies highlighted the importance of “letting the data speak.” The importance of a corporate culture that values experimentation, collection of data and data-driven decision making in general cannot be underestimated. Some of the case studies had executive leadership pushing a more data-driven approach. Some aggressively replaced gut decisions with data-driven ones, while some allowed manual overrides of the decisions but reported on how well this worked. Organizational change, time for experienced staff to revisit their assumptions in the light of new data, and even changes to bonus and compensation plans are all part of making this work. Regardless of the approach taken, it was always vital to end with a commitment to data-driven decisions.

- All the projects had a strong element of organizational change. The case study companies all felt that the technological challenges were much less than those
related to adoption and organizational change. Operational analytic technologies work, and the vendors involved were all able to provide the technical support the companies needed. Organizational and people issues were the ones that required the most focus. And they required this attention on an ongoing basis, not just at the beginning. Constant education about the approach and its effectiveness is highly recommended.

- The initial scope of each project was very focused. Each team picked a single, well-defined problem to solve. This matches the best practices seen in other research where a decision-first approach works much better than a horizontal or platform approach. Pick a decision area, get the analytics working in that area, show results and only then expand the scope.

- Once initial projects showed success, however, companies reported strong benefits from investing in making it easier to add new projects. Investing in the technology, platform and skills made rolling out the approach to multiple projects easier and made it possible to run many projects in parallel. This last was important as most of the projects reported that initial success resulted in an ever-increasing set of opportunities being identified.

- Understanding how the analytics and the resulting decisions impact the company’s overall metrics and KPIs was often identified as critical. Without this linkage to the performance management environment of the company, it was hard to keep momentum and manage the organizational changes involved. Understand how and why the decisions being analytically improved matter to the organization’s objectives and measures.

- Flexibility and adaptability were key to long-term success. Almost all the projects reported that the initial deployment and use of analytical decision making had to evolve and be changed, often quite rapidly. Sometimes flexibility was required to respond to changing circumstances, sometimes to take advantage of additional analytic opportunities that became clear once the project was underway. Ongoing learning, well beyond the initial deployment, was common to many of the projects.

- Thinking a little outside the box and considering all the ways in which one might experiment was often suggested by those interviewed. The sense is that a broad view of what can and should be used to drive decision making improves the likelihood of finding the best solution.

- Invest in making it easy for those who run the business to use the analytic models and in making it easy to update and evolve those models. Every case study emphasized that the real value came not from a one-time analytic improvement but from the creation of a closed-loop, learning environment.
IMPLEMENTING OPERATIONAL ANALYTICS

There are many ways to adopt and successfully implement operational analytics in operational systems. A focus on decisions and a plan/vision for analytics are both critical, and some common threads of best practice are apparent as are some common challenges. Recent research also shows that there is a common journey that organizations make to adopt operational analytics.

CRITICAL SUCCESS FACTORS

A Focus on Decisions

One of the two critical success factors in the adoption of operational analytics is a focus on the business decisions that are to be made with the analytics, to begin with the decision in mind.

There is an unfortunate tendency among those who are the custodians of data to adopt analytics by focusing on the data they have, seeing what information and insight can be derived from this data using analytic techniques and then trying to find decisions that can be influenced by this as shown in Figure 6.

Figure 6: One Approach to Influencing Decisions Begins with the Available Data
It is much more effective to begin with the decision in mind, and organizations that do so have much better success in adoption of operational analytics and in applying analytics in a way that shows a positive result.

In this approach, shown in Figure 7, an organization identifies the decisions it wishes to improve or automate. Working together and based on an understanding of the decision(s) involved, analytic and business teams determine what kind of analytic insight might be useful. The analytic staff then works with the IT department to see what information and data are available and to integrate and source other data required to build useful analytic models. This decision-first approach is more likely to successfully influence the results of the business and is less constrained by the data that happens to be in the data warehouse or already integrated.

The post-secondary technical education company illustrates this well, with a ruthless focus on a particular decision (what is the appropriate follow-up for this particular lead) that drives the success of the overall project.

Vision and Plan

The second critical success factor is a clear vision of the analytic future to which the organization is heading. While local use of operational analytics can be achieved without a grand vision, the systematic use of pervasive, predictive, actionable analytics to change the business of an organization will only be achieved if such a vision is clearly articulated. Adopting operational analytics widely is a significant organizational change and can be very disruptive. Without a clear and compelling vision, it will not be possible to sustain the kind of change management and investment that will be necessary.

While a vision is key, a plan to achieve that vision in manageable steps is also critical. No organization is going to make it to pervasive, predictive and actionable
operational analytics in one fell swoop. They must take a series of steps, each of which adds value, and have those steps lead them toward the end-state vision.

*Trident Marketing’s systematic and gradual expansion of its use of analytics to improve marketing programs and GE Rail’s increasingly broad use of analytics in multiple business processes are both excellent examples of this plan/vision combination.*

**BEST PRACTICES**

In working with organizations that have adopted operational analytics, especially those that have successfully adopted operational analytics in multiple operational systems, a number of best practices have become apparent.

**Implement Decision Services**

By far the most effective way to embed operational analytics in operational systems is to develop what are known as decision services. A decision service is defined as:

_A self-contained, callable service with a view of all the conditions and actions that need to be considered to make an operational business decision._

Or, more simply:

_A service that answers a business question for other services and processes._

Embedding operational analytics, analytic models, into such services enables multiple processes and applications to access not just the analytic model, but the business logic that makes the analytic model actionable.

These decision services generally should not have any side effects. That is to say that calling them returns an answer – what to do next – without actually changing the state of any system. The calling application or process can then take the actions required. By keeping the decision service side-effect free, an organization can be sure that it can be called from any system or any process without restriction. As soon as the decision service itself takes an action, then it can only be called when that action is appropriate. For instance, if a decision service to determine the right offer to make to a customer actually sends them an email with that offer, then it cannot be used to determine which offer should be printed on a monthly statement or displayed in the call center. If it simply identifies the appropriate offer and leaves sending the email to the email system, then it is reusable across these different environments.

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1 In an event-driven architecture the phrase “decision agent” is often used as services are not perceived as sufficiently event-centric.
GE Rail’s enhancement of its legacy system through the creation of an external decision service is a classic illustration of the power of this approach.

Cross-Channel and Batch/Online Integration

Using decision services, analytic decision making can be easily delivered across channels and in both batch and online or interactive systems. This is important as decision making, business decision making, is not generally constrained to a specific channel or to a particular processing paradigm. However, it is also important that the models being developed also use information from multiple channels and systems. For instance, a model to determine the churn risk of a customer should consider data from the website as well as the CRM system and transactional applications. While the customers’ use of a service (recorded in the transactional application) might be the key driver of churn, what pages they look at online might also be predictive (checking pricing, terms and conditions or cancellation requirements for instance) as might calls to the service desk. Analytic models that integrate data from multiple channels are likely to be superior to those that do not.

Deltacom uses a common KPI model across all channels and systems to ensure that its operational decisions are driven by analytics regardless of the channel involved.

Store, Cleanse and Integrate Transactional Detail

Analytic models are built from detail-level data and not from summaries. For instance, a model to predict customer churn in telecommunications is likely to use the actual calls made by someone, not just the total number of minutes of calls made in a given week or day. When this level of detail is not stored in an organization’s data warehouse, the analytic modelers will go straight to the operational systems’ logs. Similarly, if data cleansing an integration effort works off summary data, then analytic modelers will cleanse and integrate the data they need themselves, repeating this process. Organizations that can cleanse, integrate and store data at a level of granularity that matches the needs of analytic modelers will save time and money by avoiding having multiple groups conduct very similar activities while making it easier to report, execute and model using the same data.

Report, Execute and Model Using the Same Data

When business users are asked to approve analytic models for use in operational systems, they will want to see what the impact of those models will be. They might, for instance, want to understand how many customers end up in each of the analytically derived segments. When the results of their analysis do not match those of the modelers, they will often reject or question the model. This is a challenge for many organizations as the data being used by the modelers is not the same as that made available to business users for their reporting and ad hoc analysis.
Similarly, when analytic models are being deployed, the IT department may find that the data available to the operational system, the decision service, is not the same as that used in modeling. This may result in implementation delays while the data is assembled in the operational environment and may also mean that testing is painful as the IT department cannot get the test data and test results to match those achieved by the modelers.

Organizations that wish to develop and deploy multiple analytic models will find it much easier to do so if they can ensure that all three groups – business, IT and analytics – share a common data definition/data structure and that the data available for reporting, testing and modeling is consistent. This need not mean all three groups have to look at the same exact data source, but it does mean effective synchronization is important.

**Real-Time Conversation Information in Decisions**

As analytic models are used in more interactive operational systems, not just batch, it becomes important to consider the conversation of which they are a part. For instance, if an analytic model for collections risk is being used in a decision service that supports a collections agent as he/she talks with a customer, then the conversation to that point – what the customer has said about the delays in their payments, what payment plans have been offered and rejected and so on – is likely to be important. Ensuring that this kind of data flows into the model and that the model takes account of it, not just the data available before the conversation, has been shown to make a big difference to the effectiveness of the model in improving decision making.

*The North American Financial Services company uses the ever-expanding set of information gathered during a conversation with a prospect to constantly refine and improve its decision making, ensuring the website feels like it “knows” a visitor.*

**Tie to Performance Management**

Organizations that successfully adopt operational analytics in their operational systems understand how those analytics models and the decisions that will be made from them impact their KPIs and their overall performance management system. Not only does an understanding of the relationship between analytic decisions and performance metrics allow users to see the positive impact of analytic decisions, making adoption and change management easier, but also it helps focus analytic effort where it will make the most difference.

*Deltacom’s model of its KPIs and its use of this model to manage its operational analytic approach is the most comprehensive of the cases in the report, but all of the companies involved understood how their operational analytics impacted their key metrics and performance indicators.*
CHALLENGES

There are, of course, challenges in deploying analytics in operational systems. These typically fall into six broad categories (based on Taylor & Raden, 2007).

Organizational Change

The biggest challenge in adopting analytics in operational systems is almost always that of organizational change. Analytic decisions will often replace manual decisions, causing concerns among those who used to make the decision that they are being replaced by a system. Analytic decisions might also enable customer self-service or empower junior staff to “make” decisions that used to be referred to supervisors, changing internal dynamics and responsibilities. While analytic decisions may be better for the business, they may clash with the incentives currently in place for staff who are being impacted. For some organizations, new insights may require significant change to generate value.

For all these reasons and more, the organizational implications of operational analytics must be kept front and center in any adoption plan.

Business, IT and Analytic Cooperation

Many IT departments have what can only be described as an adversarial relationship with their business users – trust is short and positive experiences of working together on a project are rare. Analytic teams do not typically have a poor relationship with their business colleagues, but they are often unaccustomed to working closely with IT, often regarding their job as done once the model is built regardless of whether it gets deployed or used. Getting these three groups – business people, IT people and analytic people – to work together on the effective application of analytics in operational systems is both critical and difficult. Any successful adoption will have to address this challenge and come up with ways to drive better working relationships between these three groups.

GE Rail particularly focused strongly on this aspect of its project, making sure the roles of the different groups were clear and ensuring they could work together for success.

Data Readiness

As noted, it is important that analytic teams work from the same data that business and IT folks are using, both in terms of structure and historical records. Broad adoption of operational analytics can be hamstrung by master data management or metadata projects that are focused only on reporting, for instance, or by data sourcing strategies that make it hard to bring third-party data into an organization.

Thinking through all the data-related projects and ensuring that they are integrated with and supportive of the effort to adopt operational analytics is a challenge that
must be met. At the same time broad, horizontal efforts to integrate and cleanse data can be too broad and lack the necessary focus. Organizations need a blueprint for data readiness across the organization but need to deliver on that blueprint one business area, one collection of decisions at a time.

Deltacom had been investing in its data before beginning its operational analytics project and found this investment to be enormously beneficial as it embarked on using analytics to improve day-to-day business operations.

**Analytic Understanding**

For many organizations, there is simply not much analytic expertise outside of a small group of “quants.” Analytic modeling techniques, statistical terms and measures, the math behind an analytic model – all these may be confusing and threatening to business and IT people who must collaborate with analytic modelers if operational analytics are to be adopted broadly. Some business intelligence competency centers can help with this, but too many are focused on reporting infrastructure and technical details rather than on supporting a more data-driven decision-making approach (Schlegel, 2008). Organizations need to invest in sharing analytic understanding and the basic building blocks of data-driven decision making, leveraging those in risk management, marketing or supply chain optimization that have experience in this area.

**Executive Interest in Operations**

The final challenge for many organizations is that some executives simply do not spend enough time focusing on operations. While some executives understand that the organization must execute on a strategy for it to be effective and regard it as part of their job to ensure this happens, too many prefer to stay at the strategic level and simply wave their hands at operations, hoping that someone else will make sure their strategy gets implemented. The use of analytics in operational systems must be tied to effective strategies and to effective operations.

One great example of this was the post-secondary technical education company whose CEO led the focus on operations and on data-driven decision making. This kind of executive leadership is very powerful.

**Customer Focus**

Many operational analytics projects focus on improving customer decision making. Often companies have no history of real managing at the customer level – if, indeed, they can even agree on a definition of “customer.” Clear ownership of the customer experience is often missing. A channel-specific customer experience might be owned by IT, controlling the website for instance, while product-specific offers and pricing drives a product-centric customer experience that is owned by different lines of business. A customer experience executive or chief customer officer may be needed
to get the company to pull together and accept sub-optimal product line results to get optimal company results through a genuine focus on the customer.

*Trident Marketing, Deltacom and the North American Financial Services company all put the customer at the center of their operational analytics projects. All three got strong results as a consequence, improving their interactions with customers and boosting results.*

**JOURNEY**

A series of steps can ensure widespread adoption of operational analytics

It has become clear in recent research that there may be a series of steps on the journey to widespread, systematic use of operational analytics. The two sequences revealed by these research efforts are shown in Figure 8. On the left is the ladder of analytical applications (Davenport, Harris, & Morison, *Analytics at Work: Smarter Decisions, Better Results*, 2010), while on the right is the conclusion of the author’s own research.

Both sequences start with getting data organized – sourcing it, integrating it, cleansing it – but doing so with a purpose, a decision, in mind rather than as a broad horizontal effort. Understanding this data, making it available to those operating the business and segmentation followed by the analytic allocation of resources and differentiation round out the first three steps.

The latter steps are less of a sequence or rather the sequence is more variable. Many organizations move to a focus on predictive analytics and then institutionalize these predictive analytics in operational processes, while others find they must adapt their operational systems to allow for fine-grained analytical decision making before progressing to predictive analytics. Regardless, these two steps taken together ensure that organizations have predictive, pervasive, actionable analytics. The final stage is to optimize the trade-offs in analytical decision making, ensuring that multiple models and multiple perspectives can be balanced effectively.
Organizations wishing to adopt operational analytics broadly should consider where their starting point is on this journey and use these steps as a guideline for their future development.

**CONCLUSIONS**

We are clearly in the early days of operational analytics. While some industries and some companies are broadly adopting analytics in operational systems, much opportunity remains. The power of analytics to improve decision making has huge potential when applied to the large numbers of decisions in operational systems.

Companies can and should be thinking about applying analytics to their operational processes and operational systems. This requires new thinking about the analytic techniques and technologies required to maximize the value of their data and a new level of cooperation between business, IT and analytic experts.

As the case studies show, the payoff is real. Better customer experience, more effective use of limited resources, a targeted and personalized customer experience and more are all possible when analytics are put to work in operational systems.
APPENDIX I – OPERATIONAL ANALYTICS SURVEY

RESULTS

Respondents to the survey came from many industries, with retail/consumer branded goods (12%), computer software/hardware (20%) and banking/insurance/financial services (15%) being the most common. Organizations mostly had more than 100 employees (79%) with nearly half (47%) of all responders coming from organizations with more than 2,000 employees.

Forty-six percent (46%) of the responders were planning an operational or transactional system that uses analytics, 42% had already implemented one and 12% were currently implementing. Figure 9 shows the impetus for operational analytics among the respondents. The biggest driver by a clear margin, with more than 70% selecting it, was business process improvement with better ROI, improved competitive positioning, improved customer service and increased revenue all scoring above 40%. Interestingly, staffing reduction and other cost reductions were hardly ever the focus – with just 14% and 15% respectively.

![Figure 9: Impetus for Operational Analytic Projects](image-url)

Operational Analytics: Putting Analytics to Work in Operational Systems
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As can be seen in Figure 10, customers are the focus of operational analytics applications with customer service (which includes customer experience and loyalty) as the top focus area followed by customer retention and customer acquisition.

![Figure 10: Business Areas for Operational Analytics](image)

Figure 11 shows dashboards are by far the most common analytic element in these operational systems, with 78% of implementations using them. Other common elements were business rules, operational reporting, predictive analytic scoring, OLAP/drill down and standard reporting – all of which show up in more than 50% of all implementations. Somewhat surprisingly, neither advanced visualization (30%) nor segmentation/clustering (38%) scored very highly.

Interestingly, both statistical extrapolation and forecasting and descriptive models scored more highly when only those applications targeting operational staff were considered, reflecting the need to embed more intelligence in the system for these users. In systems that used some form of advanced analytic or statistical model, business rules and predictive scoring overtook every technology except dashboards, reflecting their role as “backbone” technologies in these kinds of systems.
The users of the analytics in these systems fell into several categories. VP/Director, middle management and analysts all scored highly with around two-thirds of all respondents saying that the analytics in these operational systems were aimed at these categories. Operating staff was also a target in over half the response, as you would expect given the focus on operational systems.

Ninety percent (90%) of the respondents used data mining or predictive analytic models in their solution. Half the respondents had 10 or fewer models under management, but 17% had more than 100 and 6% more than 1,000 so clearly some are really systematizing this. Those with 100 or more models were more likely to use business rules, much more likely to use adaptive analytics and generally used more automation in both development and deployment, as you would expect.

**MODEL DEVELOPMENT**

Considering only those that did, by far the most common scenario was that these models were developed by data mining/analytic professionals in a central team, with one-third of all respondents picking this option as shown in Figure 12. Interestingly, only 5% had internal data mining/analytic professionals who were not in a central team, a surprisingly low number. Internal BI professionals at 23%, domain experts (14%) and external analytics professionals (11%) rounded out the major categories.
Forty-two percent (42%) used specialist commercial workbenches such as SAS Enterprise Miner or IBM SPSS Modeler with another 12% using products such as Base SAS. Open source, business user modeling tools, adaptive technology and automated in-database routines all scored around 5%.

As you would expect, and as shown in Figure 13, transactional data dominated, with 77% of models using it. Account and demographic data were also widely used (55% and 48%, respectively). Real-time interaction data, the use of which is widely considered fairly state of the art, showed up in over a third, suggesting that this has become an increasingly mainstream activity.

Models were developed mostly offline, with only 23% being developed in real time or on demand. Of those developing models offline, however, 56% updated and refined models in real time. The combination of offline development and real-time updates/learning was the most common development approach.

Figure 14 shows that, as expected, relatively few respondents (just 7%) had completely automated the development of models. Besides those with completely automated development, the results split evenly between mostly automated processes with some manual intervention, automation in support of a manual process and a largely or completely manual process.
MODEL DEPLOYMENT

Generating code and deploying to a database or data warehouse server were the three most common deployment options with about a third of all those deploying models using each approach (respondents could pick several approaches each). Manually recoding models, deploying to packaged applications, business rules management systems or business process management systems all showed up in about a quarter. See Figure 15.

Despite the widespread use of technologies to ease deployment – only about a quarter, for instance, talked about recoding models manually – time to deployment remains an issue as shown in Figure 16. While 40% were managing to deploy models in 3 months or less and 6% in less than 1 month, 40% were taking more than 6
months and 23% more than 9. With the value of a model degrading more or less from the time it is completed, these results are a little concerning.

### Time to deployment remains an issue

<table>
<thead>
<tr>
<th>Time to Deployment</th>
<th>Percentage</th>
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<tr>
<td>1 - 3 months</td>
<td>30%</td>
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<tr>
<td>More than 9 months</td>
<td>25%</td>
</tr>
<tr>
<td>3 - 6 months</td>
<td>20%</td>
</tr>
<tr>
<td>6 - 9 months</td>
<td>15%</td>
</tr>
<tr>
<td>Less than 1 month</td>
<td>5%</td>
</tr>
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**Figure 16: Time to Deploy Models**

Models were deployed to a wide range of systems and channels as shown in Figure 17. More than half of those deploying models did so to an enterprise application, the most common response. Thirty percent (30%) used their models on registered websites, inbound call centers or in email generation. Neither kiosk/ATM or mobile systems scored very highly (7% and 11%, respectively) and branch/store systems only scored 19%. Clearly models could be more widely used at customer touchpoints.

**Figure 17: Deployment Channels**

As can be seen in Figure 18, nearly 40% only deployed their models to a single channel. But over 60% deployed them to multiple channels, with significant numbers deploying to 4 or more.
Most models were calculated as needed (53%) rather than in batch (42%), another sign of the evolution of model usage in operational systems. Not so long ago, the assumption was batch updates of scores with the database or warehouse being updated overnight. Clearly this has changed.

**MODEL EVOLUTION**

Models become stale and must be updated. As previously noted, most respondents were updating deployed models automatically. Nearly half used a semi-automated refresh while nearly 40% had models that adapted, modified themselves, automatically. A third manually refreshed their models as and when they felt was appropriate. Twenty-seven percent (27%) used some form of experimentation, adaptive control or multifactor experimental design.

If only those who have already implemented such systems were considered, however, there was more manual model updating (40%) and much greater use of experimentation (48%). Clearly those with actual experience deploying these systems use experimentation more heavily than those who are still working on developing their solution – they see the value and are more willing to try new, competing techniques and approaches to get further improvement.

When it comes to measuring performance of deployed models, real-time monitoring had less than 20% of respondents and daily monitoring had a similar score as shown in Figure 19. Weekly monitoring was the most common, at around 35%. Among those already in production, there was a significant drop in those not monitoring performance, from 24% to just 17%.
Weekly monitoring most common

Figure 19: Measurement Timeframes for Model Performance

This reporting was largely integrated with other performance reporting (53%) with 73% mapping to KPIs or a balanced scorecard as shown in Figure 20.

Figure 20: Mapping of Model Reporting to Other Performance Metrics

**KEY FEATURES**

**Accuracy and quality of decisions is key**

The relative importance of some key features is shown in Figure 21. As you would expect, accuracy or quality of decisions is top. The ability to leverage existing data and performance slightly outperformed consistency and timeliness.
Figure 21: The Relative Importance of Key Features

CHALLENGES

Data quality continues to be a challenge for most organizations

Figure 22 shows the various challenges respondents faced. Data quality and cleanliness topped the list of challenges with 81% of respondents identifying it as a challenge. Data integration at 62% and availability at 47% put data in the top 3 slots. Integration with operational systems at 38% was lower than expected, reflecting the higher than expected use of automated deployment tools, while the organizational change/adoption problems at 32% were much lower than expected.
Interestingly 64% rated prebuilt data management capabilities as somewhat or very important in their selection of an analytics solution, reinforcing the importance of data management challenges.

RESULTS

One-third thought it was too soon to make a judgment

Of all respondents who have implemented a solution, 35% felt it was too soon to make a judgment (see Figure 23). Of those that have a result, 51% thought their solution was working well and met their needs/realized an ROI while 17% had exceeded their expectations. Fifteen percent (15%) had found implementing the solution more difficult than expected and a similar number were failing to meet their expectations.

![Figure 23: Results Achieved](image)

The number-one measurement is improved business results

Figure 24 shows the various approaches respondents used to measure ROI. Improved business results were the number 1 measurement, with 42% of respondents, but competitive advantage ran a close second at 38%. Reduced business costs (26%) and to a lesser extent reduced IT costs (15%) were also important. Nearly 20% were targeting profitability improvements of over 5% while nearly a quarter were looking to explicitly make an ROI in two years or less. Twenty-two (22%) were not measuring the ROI at all.
Looking forward, in Figure 25, most were focused on these same areas with 47% focused on improved business results, 32% on reduced business costs. For future projects, more were focused on reducing IT costs (29%) and on measuring adoption by the business (27%) while nearly 20% were going to explicitly make build versus buy calculations. These results showed, perhaps as a result of the recession, a greater focus on cost reduction in the future and a less optimistic approach to ROI and profitability with lower results and longer time to value being accepted.

Improvement in organizational performance, at 42%, outpolled improvements in organizational processes (33%) or insights into the customer base (32%) as a focus area going forward.
ORACLE SUMMARY AND CASE STUDY

COMPANY BACKGROUND

Oracle Corporation provides complete, open and integrated business software and hardware systems to more than 370,000 customers that represent a variety of sizes and industries in more than 145 countries around the globe.

Oracle provides database technology and applications to enterprises throughout the world and is the world's leading supplier of information management software and the world's second largest independent software company. Oracle technology can be found in nearly every industry and in the data centers of 100 of the Fortune Global 100 companies. Oracle has developed and deployed 100% Internet-enabled enterprise software across its entire product line: database, business applications, application development and decision support tools.

Oracle Corporation was founded in 1977 and is headquartered in Redwood Shores, California. Oracle employs more than 100,000 people and had sales of more than $23 billion in 2009.

OPERATIONAL ANALYTICS PRODUCTS

Oracle provides enterprise-class business intelligence (BI) and analytic tools and technologies that are designed to provide comprehensive reporting and analysis capabilities for organizations with heterogeneous systems and applications. Oracle’s primary BI tools and technology products include:

- Oracle BI Suite Enterprise Edition Plus, (OBIEE Plus), an enterprise BI platform
- Oracle BI Publisher, an enterprise reporting solution for generating high-fidelity pixel-perfect reports
- Oracle Essbase, an OLAP server for multidimensional analytic reporting, “what-if” scenario modeling, forecasting and management reporting
- Oracle Real-Time Decisions

Oracle also offers a broad portfolio of analytic applications that leverage Oracle’s BI tools and technology. These include packaged BI applications that integrate with Oracle E-Business Suite, PeopleSoft, JD Edwards, Siebel, and SAP. These modular applications span multiple business functions, including sales, services, marketing, loyalty, price, financials, HR, procurement and spend, supply chain and order management, and projects analytics. The applications feature content that based on functional and industry-specific best practices. Each BI application conforms to an
enterprise data model and features prebuilt ETL integration with the relevant application source system, subject area data model, metadata (metrics, KPIs, calculations, definitions) and a library of interactive dashboards. In addition, Oracle offers performance management applications that span strategy management, planning and forecasting, profitability management, and financial close and reporting.

In addition to Oracle’s core BI technology and application offerings, Oracle also offers native analytic capabilities within the Oracle database, such as data mining and OLAP.

Oracle's Real-Time Decisions (RTD) platform combines both business rules and predictive analytics to power solutions for real-time decision management in operational systems. It enables real-time intelligence to be instilled into any type of business process or customer interaction. A high-performance transactional server delivers real-time decisions and recommendations based on sophisticated analytics. This server automatically renders decisions within a business process and reveals insights, creating actionable intelligence from data flowing through the process in real time.

**OPERATIONAL ANALYTICS STRATEGY**

Oracle’s business analytics strategy is built around Oracle Business Intelligence System Enterprise Edition, Oracle Essbase, Oracle Real-Time Decisions and the Oracle Business Intelligence and Performance Management applications. The Oracle Fusion Middleware stack, particularly the SOA Suite with its Oracle Business Rules component and the BPEL business process management product are also relevant as companies move to real-time, action-oriented systems.

The foundation for the Oracle business analytics strategy is the Oracle Business Intelligence System Enterprise Edition, which allows access to heterogeneous sources, manages metadata, controls security, etc. It also supports and is integrated with Oracle Essbase (the OLAP server is tightly integrated with metadata, for instance) as well as Oracle Real-Time Decisions. All these analytical products can work on top of multiple databases and data warehouses as stand-alone products or an integrated fashion. Customers using Oracle Database can also use Oracle Data Mining to provide in-database analytics.

Oracle sees two approaches to applying business analytics in operations – one built around the use of the analytic applications to help those managing and executing business operations and one built around Oracle Real-Time Decisions to automate and manage operational decisions. These two approaches represent ends on a continuum, however, with the analytic applications on one side of an inflection point and Oracle Real-Time Decisions on the other. The Oracle BPEL/SOA Suite Fusion
Middleware environment connects both worlds, providing a common platform and allowing organizations to move seamlessly from one to the other.

As organizations use these operational management applications to apply analytics at an increasingly fine-grained level and in real time they reach an inflection point where the integration of analytics into the operational SOA/workflow environment becomes critical. At this point, many organizations adopt Oracle Real-Time Decisions which, although mostly used for e-commerce applications, has a general-purpose ability to manage and analytically improve operational decisions. Others use Oracle Business Rules (part of the Oracle SOA Suite) to bring analytics into the operational environment.

The increasing integration of analytics into business processes is a core element of Oracle’s Fusion Middleware and Fusion Applications. Business intelligence and analytics are core to the next generation of ERP and CRM applications built on the Fusion Middleware stack. The Oracle Real-Time Decisions and Oracle Data Mining technology will allow Fusion Applications to turn insight into action using the Fusion Middleware SOA technologies such as Oracle Business Rules.

CASE STUDY – MAJOR NORTH AMERICAN FINANCIAL SERVICES COMPANY

Company Background

This company is a major North American Financial Services company. One of its business priorities is the effective adoption of potentially disruptive technologies. It sells its products primarily directly to consumers, through its website and call center, rather than through agents.

Business Problem

The company does much of its business over the web, and its website is a critical element of the customer experience for almost every customer – 70% of its business originates on the web and over 50% is closed there. The company wants prospects, visiting the site while seeking products like those sold by the company, to get a relevant and useful experience from the very beginning. It also wants visitors to get an increasingly relevant experience as they provide more information to the company (explicitly by entering it or implicitly through their behavior). It wants to optimize the customer experience, and this means understanding prospects and their needs and then demonstrating that the company can provide products and services that best meet those needs.

This highly experiential approach involves demonstrating to a prospective customer that the company understands them, “gets” them, can tell them what they might want and help them find it. It involves giving customers a return on their attention. The website must be genuinely helpful, doing more than just passively providing information in response to requests.
The company has an ongoing effort to increase the level of customer engagement with its website. Some years prior to adopting the Oracle RTD solution, the company was looking at chat technologies. It found an interesting approach involving a heuristic engine to determine when to offer chat to web visitors. The potential of this approach was clear, but the company wanted to be able to apply it generally across its website, not simply to determine if chat was appropriate. As a result, it needed something that would dynamically and in real time use a closed-loop analytic approach to determine how best to treat people when they come to visit the site. It selected and purchased Oracle Real-Time Decisions (RTD) to deliver on this objective.

The focus of the initial deployment was purchase-oriented visitors – those who came to the site looking to make a purchase. To succeed in closing sales with these visitors, the site must be able to determine what aspects of a purchase are most important to each visitor. Some are cost sensitive, some risk averse and so on. The website already had a set of rules implemented in a business rules management system that were designed to match customers and products based on the company’s positioning as well as the customer’s location. The company wanted to do a better job of matching prospective customers with the products and product options they needed. It wanted a more fine-grained, customer-centric approach, and it realized a closed loop was essential for continuous improvement.

**Operational Analytics Solution**

Like most operational analytics project, there was an initial period identifying the best use case and getting executive support internally. The implementation, integration and deployment of the solution took just 3 months once the project kicked off. This project was very different from the company’s prior experience, and the company worked closely with Oracle and a third-party integrator recommended by Oracle on the initial deployment. This support was critical as this was not a typical BI project nor was it like the standard website experimentation projects the company was familiar with.

Oracle RTD uses analytics based on both site behavior data and personal data collected from site visitors. For instance, the engine starts with a visitor’s IP address, uses this to find their ZIP code and quickly approximates marketing demographic data for the visitor. Where visitors were referred from and what search terms they used are also considered as these are highly predictive.

Once the visitor gives his/her real ZIP code and fills out a sales application with basic contact information, the engine can drive information requests to public data sources. A combination of the RTD analytic engine and business rules make a decision to either ask the visitor to self-report or to pay for data from these sources. The cost of data and the value of it to the engine vary significantly depending on various factors such as location and demographics, so many things are considered before external
data fees are paid. As more data is gathered, from the visitor or from public sources, RTD makes increasingly accurate and granular decisions to target the visitor and allows the company to measure the value of the fees paid for this data at a very granular level.

Oracle RTD uses all this data and what it has “learned” from past interactions to personalize, in real time, the user interaction flow. It recommends relevant product features or highlights purchase options that are relevant to the customer and to the current interaction. This leads to fewer dropped shopping carts and higher average revenue per transaction.

Oracle RTD also reports on the analytic models involved, how they run and how they contribute to behavior. It provides a built-in analytic workbench – Decision Center – that allows the company to understand who is getting what experience and what is contributing to that experience. This set of reporting and analysis tools – aligned with Oracle’s OBIEE – reports on customer experience optimization metrics and helps the company find insights about the behavioral drivers of good customer experiences. This reporting and analysis extends the standard web analytic reports by linking web behavior to the underlying decision logic and analytics.

Besides reporting, Oracle RTD also handles experimentation. The support for experimentation offered by Oracle RTD has fundamentally changed the way the company thinks about experimentation. One of the challenges of doing experimentation as a standard practice, not as a one-off exception, is getting suitable data to all the various experiments being conducted. Oracle RTD removes this complexity by ensuring coverage, allocating prospects to experiments, tracking results, etc. The company runs many experiments, and only a small percentage of these cannot be handled automatically by Oracle RTD.

**Benefits**

The bottom-line result for this project was more business and more value from the customers won. Just 3 months into the pilot, the company broke even – the increased sales and revenue lift in those 3 months covered the planned 3-year cost for installing and running Oracle RTD.

Besides this stronger bottom-line performance and rapid ROI, the system builds customer loyalty earlier in the process because it enables the company to show it understands the customer at every stage. Oracle RTD quickly becomes very accurate at predicting what will work best for a given person – getting to a segment of 1 almost magically – and this is reflected in improved customer perception.

As a result of Oracle RTD’s automation of experimentation, the company runs many more experiments. Oracle RTD not only manages these experiments, but also solves the challenge of running more than 1 test concurrently. It is hard to tell what is contributing to a specific outcome when multiple tests are being conducted.
Traditionally, this requires either single threading (one test at a time) or multiple instances of the website, each running their own test. As a result, either complexity increases or time does. With Oracle RTD, multiple experiments can be managed on a single instance of the website, results of the experiments are gathered quicker and are easier to analyze.

The analytically driven decisions of Oracle RTD corrected a bias to marketing “low cost” instead of focusing on “the right product at the right price.” The company’s customers had long said that low price was the key. But addressing the “long tail” of opportunity requires best-fit offers not just low-cost ones. This best-fit approach means that the customer feels that they are being treated as an individual; but the system is, at the same time, generating more money for the company. With Oracle RTD, this is not just an analyst hypothesizing about a segment. Instead, Oracle RTD is actually determining what customers want from actual responses not just from what they say they want.

Marketing and analytics people can now focus on strategic analytics and creativity, not on the day-to-day details. They can find new creative content and campaigns and new permutations while the machine handles the mechanics.

**Critical Success Factors**

The company has had great success with Oracle RTD and recognizes that implementing and using Oracle RTD is different from traditional BI and web analytics projects. The project used the same team as previous web projects – a team experienced with web analytics rather than statisticians. Because Oracle RTD handles the whole decision, this team does not have to reverse engineer web presentation rules from analytic results and so no longer has to try to describe the universe. Oracle RTD shifts the focus to identifying where the fallow ground is, where the next opportunity lies.

This change in roles changes who is good at their job. The company found that staff members were able to spend less time in number crunching and developing effective SQL statements and more time interpreting the data. These interpretation skills – What do these factors and weights tell us? How can we apply what we learn here elsewhere in another medium? – become critical. Some people do well out of this transition, others less so, and this creates organizational dynamics that must be managed.

Good architecture serves the needs of the business, and the architecture of the project was critical. Oracle RTD is a very general decision framework not biased to any one channel (web, IVR, call center). It has good general interfaces so it can be integrated with anything. Despite this flexibility it is simple to integrate – it has just two APIs, one to provide context information to the engine and the other to ask for a decision. Despite this simplicity, a rigorous approach is required when integrating something...
like Oracle RTD. The implementation must be flexible enough to support different experiments and to allow new decisions to be added incrementally without technology dependencies. While the first implementation had to prove the business case, it had to do so in a way that allowed the company to build out additional decision engines as part of a long term decision-management strategy. If the implementation is hard wired to the first decision being managed, then this ability to evolve over time could be lost. Oracle RTD allows the business to control the user experience without putting the underlying website at risk.

Information architecture is also critical – it is essential to know what information could be available to the engine and what might change over time so that this can be considered as part of the overall design.

Finally, the development of models that show and explain causation is critical. For long-term success, you need to know what elements of the interaction are truly associated with closing business, asking for a quote, becoming a customer. These causative elements are critical.

**Future Plans**

Usage has expanded beyond the initial deployment with additional implementation in the service portal (determining, for instance, how best to get people to enroll in paperless billing using a choice of green-, savings- or convenience-oriented messaging), on static pages to determine what gets displayed where on the page and in email for subject lines, message, header and creative. Future plans include extending the use of Oracle RTD to customer retention, supporting internal sales agents as well as the website and to determine what will contribute, at initiation, to long-term customer retention.
BIBLIOGRAPHY


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