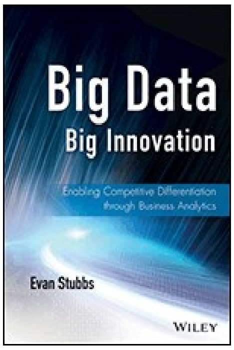

Big Data, Big Innovation: Enabling Competitive Differentiation through Business Analytics

by Evan Stubbs
John Wiley & Sons (US). (c) 2014. Copying Prohibited.

Chapter 4: The Intelligent Enterprise

Overview

Organizations are, by and large, pretty dumb. Shows like *The Office* and comics like *Dilbert* are funny not because they're absurd but because at times they hit a little too close to home. Steering an organization can sometimes seem like a constant fight against chaos— there's political intrigue, competing points of view, and sometimes even an active desire to subvert the system. One of the most stunning cases I've come across involved a business that actually ran an entire shadow IT department. They were eventually caught when they migrated their customer engagement system off their (already deployed) isolated network onto the cloud.

Culture is essential. So is capability. Culture might enable the vision, but without supporting skills, processes, technology, and data there's only good intentions. The goal in making it real is to try to tame the chaos inherent in managing highly complex systems and transform into an intelligent enterprise.

Most organizations are united in a common objective. Despite this, people still act independently. Everyone knows their role but all too frequently people act in isolation. It works, but only to a degree; faced with instability or a changing market, the organization struggles. Quality suffers, cost increases, and inefficiencies abound.

A truly intelligent enterprise operates like our nervous system. It's adaptive, agile, and flexible, able to respond quickly and appropriately to external stimuli. Faced with a threat, it mobilizes quickly and takes appropriate action. Interactions are sophisticated and tailored to opportunities and threats. On encountering either, *everything* that's needed is quickly deployed and engaged. Action and response is seamless, instantaneous, and automatic.

This chapter covers the *intelligent enterprise*, as shown in Figure 4.1. The five levels it describes are progressive; they represent the path usually taken by organizations that focus on building capability. Real value starts at level three and continues from there.

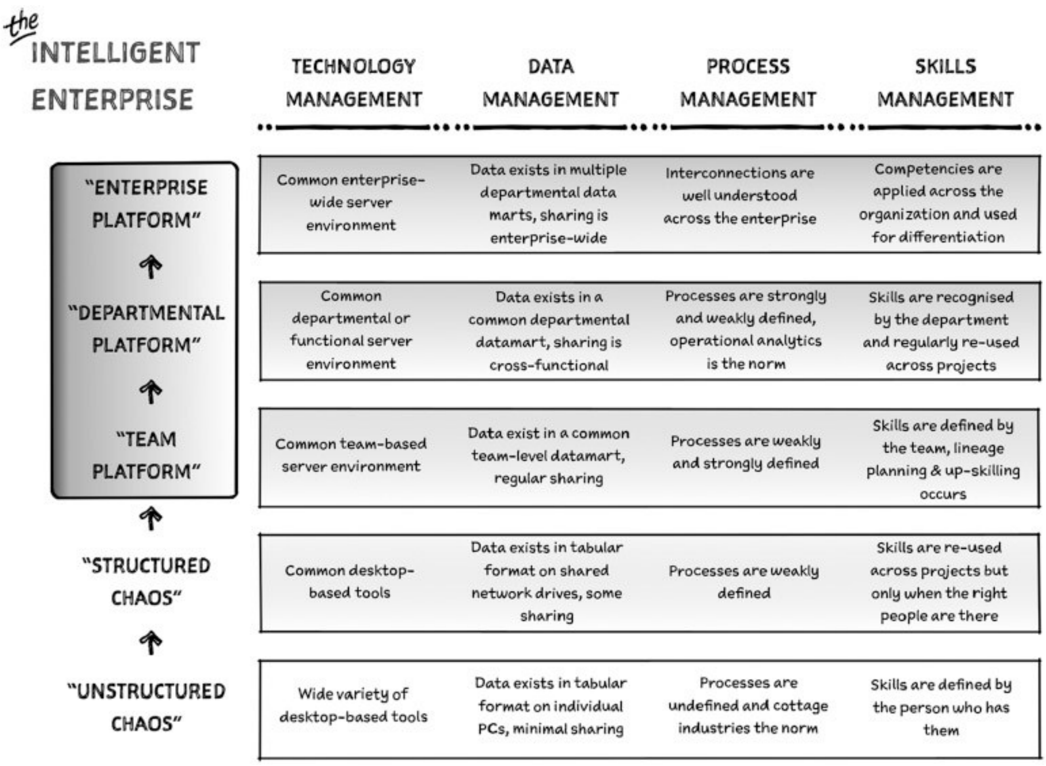

Figure 4.1: Intelligent Enterprise

Level 1: Unstructured Chaos

Every organization has to start somewhere. Typically, that "somewhere" is rarely where the organization actually *wants* to be. To paraphrase, every beginning starts with darkness and chaos.

Organizations at the lowest level of capability are best described as "confusing." They're characterized by *unstructured chaos*. Everyone is working hard; it's just not always clear how or why they're doing it. Like the proverbial sausage factory, no one really wants to think too hard about what's being used to make the final decision. Because of this, quality is hard to measure. When decisions work, no one wants to know how they were made. When they don't, no one knows why. Because of fragmented processes and data, unpicking the final result is almost impossible.

At this level, people get the job done. However, they also do whatever it takes to get the job done, often leading to highly variable quality and efficiency. Processes are almost consistently ad hoc, bespoke, and usually reactive. Firefighting is more than just a quick fix; it's business as usual. Things succeed not through planning or design but usually through the heroic effort of motivated individuals.

Freedom Can Be Constraining

One of the clearest examples of an organization in this state was one that started with the right foundations but somehow ended up somewhere they really didn't want to be. They started by doing everything right. The interest in business analytics came from the top down. They built the company around information and even went so far as to establish a broadly defined center of excellence. They understood the difference between discovery and operational analytics. Whether through sanity or serendipity, they even managed to solve many of the structural issues that inhibit delivery.

Unfortunately, they got one thing wrong. They gave every data scientist the almost total freedom to select his or her tool of choice. Intuitively, this made sense; it was hoped that it would promote access to best-of-breed capabilities, align tools to existing skills, and make it easy to onboard people by giving them the ability to choose their own working environment. Superficially, the theory was sound.

Unfortunately, practice diverged from theory. Giving people choice also means having to accept that people *will* exercise their right to make choices. What started out as a handful of tools rapidly exploded into a veritable laundry list of every possible tool under the sun, most of which were invisible to their unfortunate IT department.

This was great for the analysts. They had freedom and control. Empowerment is empowering—what's not to like? Strategically though, it led to countless integration and execution issues. Because tools were dependent on the person, it became extremely difficult to create repeatable processes. Filling a role required not only domain knowledge but specific technical and tool knowledge. In the worst cases, some roles were so tightly coupled to individuals that when people were sick, everything would stop. Because no one else knew how to use the missing person's tools, no one else could do his or her job.

Alone, this operational risk was unacceptable. However, their real problems ran deeper. Because everyone was using different tools, modules, and coding standards, it also became extremely difficult to take action on insight. In one case, the discovery team had deep experience in using Python and R. Sadly, no one in the operational team knew how to turn what were largely untested processes into production-grade routines. Even worse, these same data scientists were in high demand. When they eventually left for other opportunities, the intellectual property they had built stagnated and eventually died a grim death because no one else knew how to use it.

After a few years of operating like this, their leadership team knew they had a problem. Unfortunately, the system they had designed had grown so organically and chaotically that they no longer knew how it worked. Every time they tried to make a change their analysts almost revolted. And so they became stuck, trapped in the monster they'd unintentionally created.

Common Characteristics

Organizations do function at this level. They just carry far more cost and operational risk than they need to. They also rarely manage to coalesce their latent capabilities into any real form of differentiation.

Some indicators of an organization operating at this level are:

- **Personal tools.** Analysts use a wide variety of desktop-centric tools with choice largely defined by personal preference.
- **Data-focused effort.** Analysts spend significant amounts of time trying to source, manage, and exchange data between semi-compatible tools.
- **Fragmented data.** Data is fragmented and centered around product, process, or at best, organizational silos.
- **Perpetual reinvention.** Team-members each create their own repository and usually start from scratch every time

they have a new project.

- **Undefined processes.** Processes are largely undefined, extremely manual, and require substantial effort to execute.
- **Unaware and overpaid.** Vendor management for analytics tools is limited and largely ineffectual, forcing higher-than-necessary licensing costs.
- **Selfish hoarding.** Analytical data is stored on individuals' personal computers and very little (if any) reuse occurs between analysts.
- **Big-chief syndrome.** Competencies are linked to the individual and skills are a source of job protection.
- **The haystack method.** Competencies are rarely applied across projects in a consistent way and finding value is as difficult as searching for a needle in a haystack.

Taking the Next Step

Getting past this point requires acknowledging that sometimes structure is necessary. Somewhat counterintuitively, it's about limiting choice, reducing flexibility, and improving repeatability.

Flexibility encourages innovation and agility. However, too much of a good thing can hurt. Without a way to commercialize good ideas, all the benefits of innovation are lost. Organizations operate in a different context from individuals. What may work brilliantly for one person rarely scales to a larger system without some deliberate design and planning.

The starting point is usually to start profiling current activities across people, process, data, and technology. Are there too many tools? Conduct an audit and start rationalizing them. Are there undefined processes? Understand what people do and what outputs their customers are expecting. Are there PC-based data structures? Consolidate them onto a shared environment. Is there limited reuse of skills across projects? Profile existing skills and start thinking about capabilities rather than individuals.

The objective at this level is simply to create some structure, even if it's limited in the first instance. More than anything else, it's about exposing current practices and simply *understanding* them. Trying to *fix* things is often a step too soon and too far in these cases. Without knowing where the problems are, where attention is being focused, or even how effectively people are doing their jobs, every "fix" carries the risk of making things worse.

Level 2: Structured Chaos

Chaotic systems aren't necessarily random. That might sound strange, but consider a Lorenz attractor. Within a truly chaotic system, it's impossible to predict the position of any element at any particular point in time. That doesn't mean that the system itself doesn't follow higher-order patterns. When this happens, one has hit a point of *structured chaos*. While individual elements might still behave randomly, their overall behaviors might just be random around a broader pattern.

Organizations at this point have started to tame the chaos. Rather than try to force structure, they take a softer approach, balancing local choice with global requirements. They set constraints, establish an intended functional or divisional strategy, and try to get the entirety of the organization to comply with it. As is probably unsurprising, this is where most organizations sit. Standards are meaningless if they're not complied with; the true test as to whether an organization is at this level or the next is real-world compliance with guidelines and strategy. Having a standard operating environment is one thing. Having the business *comply* with that standard operating environment is another.

The biggest barrier to success at this point is unconscious ignorance. These organizations are usually sophisticated enough to know that information is valuable. They've taken the first steps toward turning what's usually an ad hoc, undefined activity into a core, if still somewhat basic, competency. However, their lack of awareness of what's possible and what "good" looks like inhibits their ability to scale or create tangible value. Often, their belief that they've solved the problem by defining a governance model is a major inhibitor. They become self-deluded and convince themselves that they've succeeded without taking the time to check whether their strategy and intent is actually happening.

Total Agility Can Be Costly

A prime example of this type of organization discovered this almost unintentionally. As an outsider looking in, they appeared to be a real leader in their sector. They deeply understood the value of information. Almost to the last, their analysts were extremely capable and intelligent. They had rationalized their analytics tools, they had an internal structure which made it easy to engage with data scientists, and their key performance indicators were cleanly aligned with tactical and strategic objectives.

Despite this, they had some rather strange quirks. For one, they lacked a central processing or data storage environment. To most of their leadership team, this wasn't seen as a problem. They simply bought big PCs and lots of local storage. In practice, they even sometimes held this up as an example of their ingenuity and innovation; by taking the road less traveled, they felt they had created a highly innovative, flexible, and agile business.

Another was their apparent lack of structure. Where most of their competitors were struggling with overly defined governance models, they had highly flexible support and delivery frameworks. More than just "getting" agile methods, they practically lived them. This was again held up as a prime example of their ability to innovate. However, while the milestones they had to work through were always clear, what wasn't was how they'd generate insight or act on it. Everyone did things differently.

For a long time, everything seemed to hum like a well-oiled machine. Unfortunately, one year they experienced a perfect storm of three things that shook the status quo.

The first of these was the resignation of one of their most senior analysts. The talent loss was bad enough. Unfortunately, he was also the developer of their core customer insight engine. During his handover, it became frighteningly apparent that no matter how much he tried to bring others up to speed, no one else had any hope of understanding how his application worked in the time he had left. This lack of process suddenly created a massive operational risk.

It also led to the second event. Shortly after he left, the application stopped working. This in itself wasn't too surprising; despite their best efforts, they hadn't been able to maintain it. Unfortunately, they also found out that when the insight engine went down, so did their customer relationship management (CRM) system. Unknown to the team maintaining it, the insight engine had been feeding target lists to the CRM system every night. When the lists stopped coming, the CRM system produced an exception and halted *all* outbound marketing. The theoretical operational risk had just become actual losses.

The final blow was the complete and total loss of critical pricing data. A well-meaning but misguided junior analyst ran out of space on the network drive while doing some data mining. Knowing that the senior analyst was no longer employed by the organization, he thought it made sense to delete that analyst's folder. Unfortunately, the directories he deleted contained both archived as well as active data—active data that was still a direct input to a variety of other processes. When those directories disappeared, a number of pricing models stopped updating correctly. Even worse, these errors were subtle enough that they weren't identified for weeks afterward. While the final costs were never calculated, everyone knew they'd lost customers.

These losses in quick succession forced the executive leadership team to start asking questions. In a few short months, they'd lost money, talent, customers, and reputation. That same flexibility that had been such a strength had suddenly become a major liability.

Thankfully, they were self-aware enough to know not to replace everything wholesale. Their flexibility and agility *had* created a source of competitive advantage. Rather than getting rid of it, they rightly realized that they should instead *augment* it with structure in the right places. Shortly afterward they launched a transformation project to:

- Improve governance and structure for the operational use of analytics.
- Establish a focused model for human capital development and intellectual property retention.
- Identify and replicate best practices in operational processes through process management.
- Centralize information assets and ensure appropriate security/ privacy controls were in place.
- Establish a centralized computational platform that could support mission-critical uses of analytics.

Much to their surprise, what started as an attempt to mitigate operational risk actually turned into a source of significant value. Their efficiency levels increased. So did their ability to embed analytics into decision making. Their attention to culture and talent retention became a draw card for talent in its own right. And, the centralization of their information and analytics tools helped reduce their operating costs.

Common Characteristics

Organizations at this point "don't know what they don't know." They know analytics is important but their use is inconsistent. While it's not always the case, they're often guided by people who are familiar with using analytics mainly for research. They usually appreciate the need for a team approach.

More than anything else, they focus on insight. To their credit, they understand the importance of analytics. They try to encourage the use of common tools. And, they encourage data sharing. However, they rarely understand an extremely important concept: operational analytics.

Business analytics is more than just insight. Data science and exploratory analysis is important. Without action, however, all that insight is worthless. The most efficient way to act on insight is to embed those same analytics into operational processes. Improving one decision might add a little value. Improving *hundreds* of microdecisions can create tremendous value.[1] Of all possible applications, the use of operational analytics offers one of the greatest returns on investment.[2]

Organizations at this level are still fundamentally person-centric in their technology, process, and data design. While in principle they encourage sharing, their architecture is such that they simply *cannot* automate their analytical processes. And because of this, they inevitably constantly struggle to change their analysis from a collection of bespoke approaches into enterprise-grade processes.

Some indicators of an organization operating at this level are:

- **Team tools.** While analysts select their analytics tools from a predefined list or standard operating environment, these tools are still predominantly desktop-centric.
- **Search-focused effort.** Analysts spend most of their time trying to *find* data rather than recreate it.
- **Decentralized data.** Data is still centered on organizational silos but cross-referenced points are defined and understood.
- **Avoidable reinvention.** Team members share their data in common storage areas, even if reuse is still often low in practice.
- **Weakly defined processes.** Processes exist but are undefined outside inputs and outputs. When someone leaves, his or her replacement reinvents everything else from scratch.
- **Aware but uncertain.** Vendor management becomes aware of overpayment but is uncertain about what is necessary and what is sufficient.
- **Well-intentioned chaos.** Analytical data is stored on shared drives because of a belief in the value of information reuse. Unfortunately, little reuse happens in practice largely because of the complexity involved in trying to track down information.
- **Polymath syndrome.** While competencies are identified and applied across projects, the success of a project depends largely on who's working on it.
- **The cargo cult.** The path to value is based on subjective experience, and competencies, tools, and processes are selected based on what worked last time, not necessarily what makes the most sense.

Taking the Next Step

Getting past this point requires the commitment to start reengineering the way the organization works. It involves asking fundamental questions about why things are designed the way they are across people, process, data, and technology. In many cases, this is linked to a broader "lean design" or "transformation" initiative, tasked with making things simpler, more agile, and more efficient.

It's usually at this point where many organizations start to balk at the implications of becoming smarter in their operational decision making, largely because they start to appreciate the sheer scale of the challenge. At the extreme, it involves deconstructing every processes, one by one, and mercilessly hunting down and eliminating *every* non-value-added activity. The goal is to decouple the analytics from the individual, thereby turning it into a team competency. This is rarely easy; inevitably, it involves slaughtering more than a few sacred cows.

When starting out, most organizations find it difficult to do *any* analytics. Because the starting benchmark is so low, simply getting to the point of using analytics within a handful of operational processes is often enough to drive a surprising amount of value. This pales in comparison to the value offered through automated and operational analytics; rather than augmenting five or six decision-making activities, it becomes possible to have an impact on hundreds or even thousands.

Getting to this point means things need to change. And, making these changes happen is challenging. Of all capability improvements, this is arguably the hardest. People need to work differently, and behaviors need to shift from being "cowboy analysts" to team players. Making this leap is difficult. However, the benefits of doing so are significant.

While still a step short of transformation or differentiation, the major benefit of making these changes is operating efficiency and cost management. Consolidating technology increases purchasing leverage with a smaller set of vendors. With focus, this reduces vendor management and systems administration and maintenance costs.

These benefits also extend to developing people. By identifying and nurturing desired and valuable skills, organizations reduce the cost of hiring and retaining resources. Creating strongly defined processes also allows organizations to start automating non-value-added activities. This improves efficiency and often creates the opportunity to create a leaner, more agile organization.

The core objective at this level is to make things more efficient. More than anything else, it's about reengineering current practices to embody the basics of leading practice. The big step is moving beyond *understanding* what's wrong and actually *fixing* it. It's at this level where change management becomes the single most important factor in success. Without actually getting people to work differently, unlimited technology investment will nonetheless inevitably lead to "business as usual."

[1]James Taylor, *Decision Management Systems: A Practical Guide to Using Business Rules and Predictive Analytics* (Upper Saddle River, NJ: IBM/Pearson, 2012).

[2]Evan Stubbs, *Delivering Business Analytics: Practical Guidelines for Best Practice* (Hoboken, NJ: John Wiley & Sons, 2013).

Levels 3–5: The Intelligent Enterprise

Fixing things is excellent. Unfortunately, it's still not enough for organizations interested in repeatable innovation. The gap between "things working" and "best practice" is a broad one. Closing it requires achieving a certain minimum level of capability. They've become the *intelligent enterprise*.

Organizations at this level recognize that business analytics is a journey, not a destination. While their use might not be truly enterprise-wide, their platform architecture is such that they *could* eventually replicate those same capabilities across the organization if they needed to.

They have achieved a level of process-centricity, moving away from artisanal applications to mass-production methods. While there's a large gap between a single example of best practice and consistent use across the entire organization, they understand that there are benefits to replicating automated methods. Most important, they take constant steps toward best practice, slowly making it pervasive across as many business processes as they can.

Common Characteristics

Process automation and the use of operational analytics becomes, if not the norm, at least relatively common. Some of the biggest indicators of organizations at this point are:

- **Common tools.** Analytical tools are standardized at least within teams, usually across a department, and sometimes across the entire organization. They are predominantly server-centric with desktop-based tools being used almost exclusively to support niche R&D applications or to fill gaps where it would be uneconomical to deploy server-centric tools.
- **Leverage-focused effort.** Analysts spend most of their time trying to reuse data and assets rather than recreate existing assets.
- **Centralized data.** Analysts and data scientists share their analytical and value-added data in centralized repositories, whether they be appliances, traditional warehouses, distributed file systems like Hadoop, or NoSQL repositories like mongoDB.
- **Deliberate reuse.** Team members share their data in centralized marts and activity is centered around reusing what's already there.

- **Strongly defined processes.** Processes are strongly defined where they need to be integrated with operational activities.
- **Aware and certain.** Vendor management becomes aware of overpayment and links investment to broader capability and value creation.
- **Optimistic sharing.** Analytical data is stored in common server-based environments and reuse happens functionally, departmentally, or even on an enterprise-wide scale.
- **The efficient machine.** Reuse of skills decouples project success from team participation. Projects succeed because of access to capability, not access to specific individuals.
- **The empire.** Competencies are explicitly recognized within the context of a formalized human capital development model.

Taking the Next Step

In many ways, there is no "moving past this point." Organizations that have built a platform to guide decision making no longer look for a finite series of point solutions. Instead, they appreciate that there are an infinite number of possible improvements that can be made. Their point of view shifts from one of "fix this, fix that" to one of continuous improvement where best practices are identified, nurtured, and replicated across the entire organization. They reuse their capabilities across people, process, data, and technology to drive maximum value. Their platform use progressively moves through "embedding" into "differentiating."

Getting to this point starts only from one of two locations. The *organic path* begins when a particular group within the organization is placed under such severe tension that they need to actively search for a new approach. Without this tension, "business as usual" remains the norm. As they develop their capabilities, they build a microculture within the organization that, if sustained for long enough, is eventually recognized by parties inside and outside the organization. Other groups learn from their successes and, given sufficient leadership and motivation for change, their culture ends up being replicated by other groups. Over a long enough period of time, this self-replicating culture ends up becoming pervasive.

This large-scale transformation through organic replication seems relatively rare. More frequently this cultural transformation halts either with the group in question or, in some cases, with the group they're part of. Without a clear commitment from the leadership team to sustain and replicate their positive culture, their approach frequently only exists for as long as the people driving the cultural change keep working for the organization. Given the high demand both internally and externally for people capable of creating value from big data and business analytics, their employment is typically far shorter than the time it takes to create a self-sustaining culture.

The *directed path* starts from the top and flows from there. Either through external tension or the unique opportunity to create a culture from scratch during the startup phase, the executive leadership team acknowledges the need for a particular culture and makes an explicit decision to create it. Due largely to the public nature of this approach, there are some well-known examples that highlight the impact it can have. Jack "Neutron" Welch reinvented General Electric and grew its revenues from $26 billion to more than $130 billion between 1981 and 2000. Despite starting as a monoline credit agency, Capital One pioneered a strongly data-driven decision-making culture, growing from a spunky startup to a Fortune 500 company.

It's important to remember that examples like this are rare. For every success, there are many examples of stalled or outright failed attempts. Changing an organization's culture is not for the faint of heart; it requires tremendous executive commitment and carries great risk. Change inevitably leads to discomfort and too much discomfort can lead to the loss of positive as well as negative patterns. At some stage the organic approach needs turn into a more direct approach, linking example with executive commitment.

From this point on, the goal is true differentiation. At the lower levels, organizations are usually playing catch-up with their competitors, simply trying to replicate what others have already achieved. From this point on, the organization has achieved a sufficient level of capability and intelligence to become unique. Rather than copying, they invent. Rather than repurpose, they create. And rather than start by looking externally for inspiration, they often start by looking internally; given enough competency, they recognize that their abilities surpass many of the examples that others provide. Equally though, they are self-aware enough to know that the boundaries are constantly expanding. As such they need to stay across leading practices both within and outside their particular industry sector.

This journey is a never-ending one. There are more opportunities for reinvention than there are hours in the day. Rather than being seen as an aspirational goal, *every* organization needs to achieve this level of capability at some point if it is to remain sustainable. In a world where big data is the norm and data offers a core competitive advantage, achieving this level of cultural focus and technical capability isn't optional; it's mandatory. This does not necessarily imply high investment costs. Whether it's through leveraging low-cost, cloud-based commodity infrastructure or through highly differentiated R&D development, the era of pure experience-based competition is over. Rejecting the power of data in a digital world and refusing to mature will inevitably lead to irrelevance.

Notes

1. James Taylor, *Decision Management Systems: A Practical Guide to Using Business Rules and Predictive Analytics* (Upper Saddle River, NJ: IBM/Pearson, 2012).

2. Evan Stubbs, *Delivering Business Analytics: Practical Guidelines for Best Practice* (Hoboken, NJ: John Wiley & Sons, 2013).