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Introduction

Data and data analytics have generated a lot of hype. Hype brings the danger that people jump on the bandwagon without proper planning. The result is failed projects, wasted money and missed opportunities.

In a recent study, Gartner stated that big data deployments had only increased by 1% during the last year. This is a somewhat underwhelming result for an industry with so much transformational potential.

The reality is that data is as varied as it is complex; often transcending company silos, barriers and traditional ways of working. To release the business value locked within, data analytics expertise is needed within the context of clearly defined business goals.

Successful data projects are open, empowered partnerships that bring together the right people, with the right skills and domain expertise to bear down on your data problems: to release value, ensure that the needed insights are acted upon to drive business decision-making forward.

Underestimating this challenge, or taking a bet on data without a strategy, is a fast route to the failure of a company's data programmes. But getting data analytics right has massive and transformational business potential.

The following five rules will help ensure that your analytics investments deliver transformational value and avoid the pitfalls that lead to failure.

Focus on business outcomes - decisions first, data last

Many instances of data failing to deliver its promised value stem from initial focus on the data itself. Successful analytics programmes start by identifying the decisions needed to advance the business or solve problems, and only then focus on the data needed to inform those decisions.

They should ask how those decisions could benefit from greater insight and what that insight might be. Decisions should not be restrictive: Asking 'What decisions do I need to make to create the most profitable line of research?' is far better than 'Should I pursue research programme A or research programme B?'.

Only then should the data to make those decisions and the systems to capture and process that data be identified. Each data project must be deployed strictly according to the strategic analytics plan, and data collection and analysis must be driven by the decision being supported, not by the data already captured. We call this the "Decisions First, Data Last" planning chain.

This is where the collaborative data partnership starts. Identifying decisions means bringing together the business decision makers with domain experts, data scientists and IT to understand what is needed and how it can be achieved. Critical to the success of the project is ensuring it is led by someone who understands data and technical functions, but whose primary drive is to deliver business outcomes.

Data exploration is an important aspect of successful analytics. It identifies new opportunities and uncovers the possible. However, data exploration needs to be controlled and aligned with the analytics programme plan; any new opportunity refined early to feed back to the analytics programme, prioritised and progressed.



Too many failures stem from having technically focussed people dive in and play with data. This data is often the easiest to collect or already exists, rather than specifically the data the business needs.

The data itself, is vital, but context is king. Which is why questions relating to data come at the end, not the beginning. Until you know which decisions to improve, you can't plan to generate the insight to support them. Until you know the insight required, you can't plan the analytics to deliver it. And so on, back through the planning chain until one ends up identifying exactly what data is needed.

What am I trying to achieve?

What am I trying to achieve?

What decision do I need to make or improve to do that?

What new information do I need to know?

What are the factors involved and how do they relate to one another?

What does that mean for how I gather, manage and deliver the data?

What data do I need to drive

THE DECISIONS FIRST, DATA LAST:
PLANNING CHAIN

this process?

LAST

Have a big vision but focus on quick wins

Data is increasingly seen by senior executives as a valuable business asset. This opens up more opportunities to do more with data. But it also brings greater scrutiny and more pressure to deliver measureable results.

Meeting this challenge requires a careful balance. Those leading analytics initiatives must sell big picture, visionary data programmes which speak to their sponsors' desire for business transformation. But they have to demonstrate that the projects are delivering value and ROI at scale before senior teams lose interest.

The solution is to frame the opportunity in business friendly language that speaks directly to solving the most pressing issue- or industry-challenges on the agenda of senior teams. This should then be backed up with a pragmatic execution plan, with early milestones for demonstrating success.

The initial plan should focus on multiple, smaller projects, executed with agility to deliver the fast actionable results and rapid value that will win over senior teams. Launching a number of parallel analytics projects generates significant analytics momentum internally, but can be a resourcing and skills challenge. Projects which can be easily repeated should also be an early focus while data projects are gaining acceptance.

Going in too big, too early can undermine long term data projects. High costs in early stages also tend to generate poor returns: the large price tag for a big data platform inevitably scales the expectation of ROI, but such platforms often fail to deliver value in the short to medium term. Not having the right range of skills in place also causes problems with delivery; identifying insights but lacking the scale and focus to exploit them in practice consistently leads to projects being quietly dropped.

For examples of how to get this right, look to the pharmaceutical industry. It has long used vast complex data sets to identify profitable areas for new research. Although still far from perfect, their maturing combination of data analytics and clarity of vision of what they want to achieve, across multiple, clearly defined projects, puts them ahead of the game.

$\to \mathsf{OVUM}$

Ovum Paper: Trends to Watch: Analytics Services: Diversifying requirements demand a flexible approach "The most successful users of analytics services are those with a clear and well-understood idea of the business problem they are trying to solve. Enterprises should adopt a tactical approach (smaller, more numerous projects) to engaging services, thereby reducing overall risk.

With a clear view of required business outcomes comes the opportunity to select vendors capable of meeting requirements. We strongly urge careful consideration be given to those vendors who can offer both business and technology capabilities; both are required to successfully operationalize analytics."



Master the how, when and who of business insights

Producing analytical insight requires not only a mastery of advanced mathematical and computational techniques but also an understanding of their limitations. In addition, how insight is presented is a question of appropriateness rather than simplicity: it may be a data visualisation that speaks to expert understanding of drug chemistry or oil well drilling. Or it may be a mobile app which presents complex analytics of multiple health metrics as a simple text recommendation.

The point is this, success requires clear understanding of the audience, who, the way they engage with the insights being provided, how, and when the information is needed. These three components are vital to understanding and trust, and there can be no action without trust. Analytics projects must combine deep problem solving and the ability to translate this to clear business action. This is a key challenge facing the commercial use of data science over the next decade.

One of the big reasons for the success of self-service tools is that the approach naturally simplifies the how, when and who equation. "The who", ie the user, is responsible for delivering the insight they need when they need it. It is one of the reasons that Gartner's figures show that quick and easy data visualisation is currently winning out over sophisticated modelling and that many entrants to the analytics platform market concentrate on accessibility and ease of use, over depth of capability.

However, not all business transformation can be achieved using self-service tools. A successful data project is not just about understanding data, it is about making data solve problems. Once data becomes a critical part of the business, the outputs from that data will need to be used by all sorts of people, from scientists in different fields, to engineers, to business people, to consumers. Some will have no understanding of data, and even those that do will want any system to be as easy to use as possible so they can focus on their own job.

Ensuring data projects deliver the value promised means considering the nature of the business insights generated: how they are presented, how and when they will be acted upon and by whom. Presenting the output of analytics is a delicate balancing act between power and ease of use. Judging it wrong can mean angry staff or customers, and of lots of idle technology and another failed big data use case.



Replace silos and barriers with translators and collaboration

Data is no longer confined to technical departments. Data projects transcend traditional organisational boundaries, many of which typically do not work well together. As our previous rule states: the success of a project depends on people actually using data to drive action. This often leads to considerable confusion as to where exactly it should sit within the organisation.

Organisational silos often hold data back from its transformative potential. These silos can be fatal to the development of data analytics maturity. As data becomes bigger, both in volume and complexity, it increasingly needs to move beyond organisational boundaries.

Successful data projects must be partnerships between lots of different groups with different goals, mindsets, levels of understanding, and ways of working. So design of data analytics and the insight generated that must work across these different worlds, means modern analytics projects must be highly collaborative.

Where analytics teams are "owned" by one part of the organisation and not made available more widely, their potential to impact the whole business is limited. Equally, data that could be of value across an organisation is often locked within a localised system. Even knowledge and insight - either that generated by analytics, or that which could help improve analytics programmes - is often closely guarded by small groups of experts.

Companies need to adopt new evolved structures, which create a culture where data scientists are in direct contact with the business functions, the IT department and the section of the business to which they are providing insights. Broadly cross-functional groups are the way to consistently realise rapid value from data science.

These teams must encompass data scientists and analysts who can understand the data, and business people who can frame the problems that need solving. It needs IT people who can put it all to work, and domain experts to ensure the insight is clearly presented. Teams should be led by someone with a strong understanding of the business. A leader who can deploy effectively all of these parties, give clear direction to ensure everything links back to the business' objectives, and that the insight is delivered in a practical way that can be easily and reliably acted on.



Critically, such teams much include specialists to bridge the gap between these different parties. A key factor that is missing in underperforming organisations, and present in successful ones, is the role of translators. These are people with real influence whose views will be respected by both sides. They are people who can talk both the language of the business and of that of the data scientists, and who understand the business's strategic goals and how data will help it reach them.

The world's most successful organisations use data science very effectively: energy companies use it to know where to drill for resources, pharmaceuticals to identify the best research routes, cosmetics to formulate new skin creams, rail to optimise rolling stock. They succeed because they take a strategic approach to data science, identifying which parts of the organisation need to work together and the right teams to manage and deliver data projects within a strategic context.

$\to \mathsf{MCKINSEY}$

McKinsey, How to get the most from big data

"Simply collecting big data does not unleash its potential value. People must do that, especially people who understand how analytics can resolve business issues or capture opportunities. Yet, as most executives know, good data people are hard to come by. According to a McKinsey survey, only 18 percent of companies believe they have the skills necessary to gather and use insights effectively. At the same time, only 19 percent of companies are confident that their insights-gathering processes contribute directly to sales effectiveness. And what if number crunchers aren't enough? After all, if a great insight derived from advanced analytics is too complicated to understand, business managers just won't use it.

That's why companies need to recruit and cultivate "translators"— specialists capable of bridging different functions within the organization and effectively communicating between them."





Take a scientific approach to data science

It is received wisdom amongst many 'data gurus' that correlation equals insight. And supporting them in their quest are plenty of analytics platforms to spot these correlations and hidden relationships and additional tools to blend data and identify further relationships.

The reality is that most data interrelationships are not that simple. Many correlations are based on false assumptions or ignore key factors. And as data gets bigger, more of these opportunities for error are introduced.

For inspiration on how to design data projects that actually can deliver, we should look to more complex, higher stake environments. Life science leads the way in the intelligent use of data. Where the output is a drug or treatment that could either make millions or be a costly failure; there is an absolute imperative to not just get it right but to get it right as soon as possible.

What life sciences appreciate, that many other domains perhaps don't, is that there is a difference between observing correlations and actually understanding what the seemingly simple observations are telling you.

The copious amount of research data used in drug discovery and development is approached in the same manner as a scientific experiment. People who understand the subject matter and the information currency, design experiments which test how different decisions affect the outcome, then test whether there is a direct causal link.

Having people who understand the meaning of the data, what it is you are looking for, and who can, therefore, design experiments to find meaningful, proven insights, not just spot correlations, will ensure that you are taking the best and most informed decisions. A black box data analytics platform will just see a pattern unless it is part of a project set up by subject matter experts to understand the relationships they are looking for.

Data has implicit knowledge but if you don't understand what the data represents then any knowledge, and potential value, may go squandered.



Conclusion

Good decisions are well informed. Establishing causal links between data and the outcome allows you to move from intuition-based to evidence-based decision making. The right links can only be established if you begin your data project by identifying those decisions at the outset, and setting up your data team in a way that ensures the work is constantly linked back to business outcomes.

Having the right partnership between the right people with the right range of skills and clear reporting lines to the business is key to bringing all of this together. It will ensure the project stays focussed on business outcomes, the

results are presented clearly and can be acted upon, and those responsible for the project's budget stay informed and supportive. The data itself is just one part of a successful data project; the five steps captured in this document are all necessary if you want an investment in collecting and analysing data to deliver real business change.



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Five rules to deliver value from data analytics:

An executive's guide

