Predicts 2020: Analytics and Business Intelligence Strategy

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Over the next five years, the way analysis is produced, managed and delivered will change. Data and analytics leaders must ensure that an integrated governance program covers self-service, Internet of Things and decentralized analytics programs.

Overview

Key Findings

- Unless there is planning for change, the default status of several key aspects of analytics will result in failure because:
  - Growing vendor interest in selling analytic capabilities risks producing fragmented analytic end-user initiatives driven by tactical opportunities rather than optimal strategy.
  - The Internet of Things (IoT) will require different skills from those used for traditional analytic projects. Failure to establish a strategy for acquiring these skills will prevent organizations from using IoT data or to create the next generation of smart devices.
  - The attempt to substitute technology for training by delivering “easy to use” or “intuitive” tools to business users so that they can do their own analysis will not deliver business benefits.
- Analytic governance will become increasingly important for success, but analytic governance cannot be separated from data governance.

Recommendations

Data and analytics leaders supporting analytics and business intelligence (BI) solutions should:

- Focus training associated with the deployment of analytic tools on understanding when and why to use these tools and the analytic process, rather than on how to use specific tools.
- Evaluate incumbent data and analytics, as well as business process, applications to see if they include sufficient machine learning (ML) capabilities for targeted use cases.
- Work with business strategists or enterprise architects to understand likely IoT scenarios for your organization and their analytic implications. Most commonly, the issue will be how to deal with streaming sensor data, but more complex requirements will require embedding analytic capability into edge devices.
- Extend data governance with the inclusion of analytics governance, and avoid instituting analytics governance as a stand-alone initiative. They should start by prioritizing an agreed business outcome (with a business case) or objective.

Strategic Planning Assumptions

By 2022, augmented analytics technology will be ubiquitous, but only 10% of analysts will use its full potential.

By 2022, 40% of machine learning model development and scoring will be done in products that do not have machine learning as their primary goal.

By 2023, 90% of the world’s top 500 companies will have converged analytics governance into broader data and analytics governance initiatives.

By 2025, 80% of consumer or industrial products containing electronics will perform analysis on the device.

Analysis

What You Need to Know

Once, analytics was linked to but distinct from operational business. Reports were compiled about organizational performance, scores were calculated and then inserted into a business process. But for maximum impact, analytics is done for the business, not about it. Scores are calculated in real time as part of the process. Business analysts have, as it were, changed from a high priesthood of data to a participatory democracy.

But the increasing need for analysis throughout a business means decisions that were once somewhat independent — where analysis should be done and how analytics should be deployed — are now inseparable from the broader data and analytic ecosystem and business strategy. There now arises the question, for example, of whether analysis should be done in a data management tool (in association with a data-driven decision-making process close to the IT department) or delivered as part of a business application (probably from a cloud provider selected by the part of the business performing analysis in the context of a specific business process). Additionally, as the IoT expands, the ability to “smarten” devices with onboard analytic capability raises issues ranging from how to ensure competitive differentiation in a variety of physical product markets to security and privacy concerns. This unstoppable trend for embedding analytic capability into tools that are not primarily designed for analytic purposes (whether consumer electronics, industrial equipment, business applications or data management and integration tools) raises governance questions that are not simply about analytics. They are about the intertwined nature of data governance and analytics governance — it becomes inconceivable to discuss one without the other.

But even as we plan for a future of embedded analytics throughout the value chain, we must acknowledge the limitations of the market’s move toward analytic tools augmented with ML capabilities. Ongoing developments promise that analytic tools will become storytellers of insight, not just tools for its creation. This change will further expand the potential audience for analytic capabilities. But it will also expose us to an uncomfortable truth — that even though analytics tools have become easier to use, there has not been as much progress in terms of changing what people use them for. All the potential of smarter tools, embedded in devices and processes that people need, and with the required governance and oversight, will fail to be realized unless we ensure that users know *why* they should care.

Figure 1 shows the relationship between typical organizational circumstances and the likely or best-practice outcomes.

Figure 1. The New Equations for Analytic Success

Strategic Planning Assumptions

Strategic Planning Assumption: By 2022, augmented analytics technology will be ubiquitous, but only 10% of analysts will use its full potential.

Analysis by: Carlie Idoine

Key Findings:

- Augmented analytics technology has become mainstream, with new vendors focusing on an augmented approach, while traditional vendors incorporate augmented capabilities into their current offerings.
- Data literacy and business acumen are key requirements for exploiting augmented analytics. Easier-to-use, automated approaches, while making the process of creating analytic assets much easier, do not remove these key requirements.
- Augmented capabilities offer automated approaches at specific points across the end-to-end analytic process. Often, however, these capabilities do not carry through to the deployment and operationalization of analytic assets, and thus limit their ultimate impact on business value.

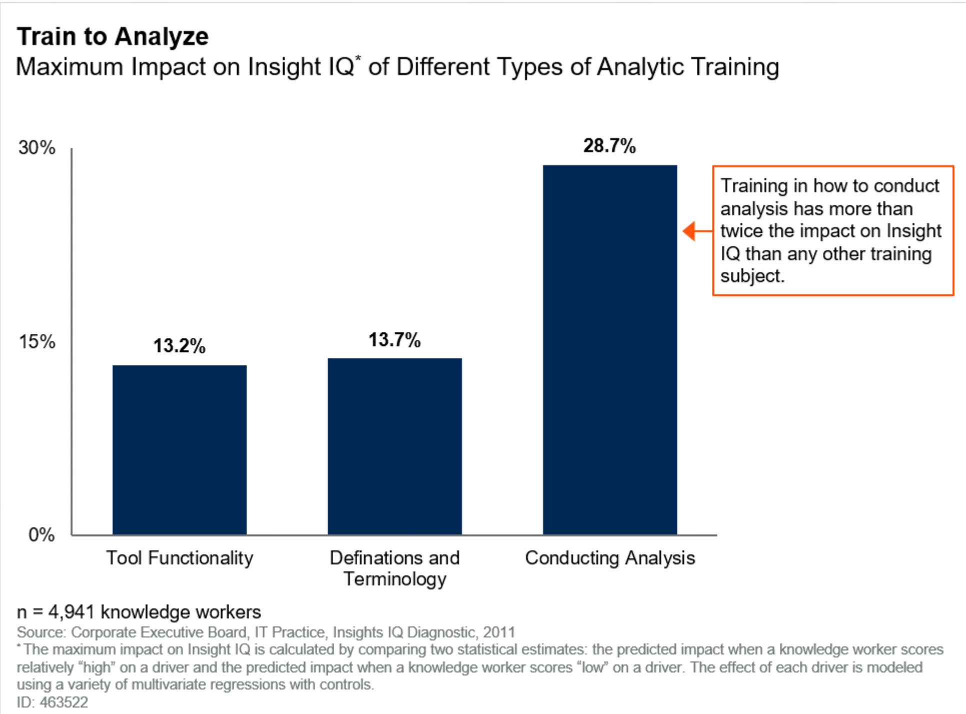
Market Implications:

Augmented analytics technology is well on its way to ubiquity. In addition to specialized tools that focus on an augmented approach, well-established “legacy” vendors are increasingly adding augmented capabilities within their toolsets. This is increasing support for users throughout the analytic process, from accessing data and developing analyses to collaborating and sharing results.

But providing easier-to-use tools does not eliminate the need to help with the application of tools and resulting analytic assets within a business context. Implementing augmented analytics technology without an ecosystem to support its use within the context of the end-to-end analytic process can limit or even eliminate its value.

Figure 2 shows the value of different types of analytic training.

Figure 2. The Value of Analytic Training



Data literacy — learning both to “talk data” and to apply and interpret it with a business context — is paramount for successful use of augmented analytics. Gaining the ability to easily create a visualization or model is a good and powerful first step. An understanding of the quality of the underlying data and of the suitability of the analytic technique, as well as knowledge of how to interpret results (and recognize potential bias) is also required to validate results and ensure their use. The ability to “lift the hood” in order to see, verify and audit automated steps is necessary when taking an augmented approach.

Gartner’s research shows that more than 65% of data science projects are not operationalized, even though it is easier than ever to access data and create analyses. There are many reasons for this, including a lack of a process for required hand-offs to other teams for operationalization and a lack of technology to support operationalization steps (including their management over time to verify continued accuracy and relevancy). With the introduction of citizen data scientists who potentially lack insight into the complete analytic process and the technical prowess to support activities on their own, potential for analytic assets to be created but never embedded into a business increases. As a result, the value that citizen data scientists ultimately provide to business processes can be diminished or altogether lost.

Recommendations:

Data and analytics leaders should:

- Recognize data literacy as a required, core competency for using analytics, and establish a program to support it.
- Establish a collaborative environment, pairing expert data scientists with nonexperts across the analytic life cycle in a way that capitalizes on the skills of all parties. The collaborative approach could also include others, such as ML operations (MLOps) staff, to complete the life cycle. Data science is a team effort.
- Use augmented analytics not only to support new and less expert analytic users, but also to shorten time to insight for more expert users. In addition, ensure that the augmented approach is fully transparent and auditable, and that a process is established to review and certify analyses created.
- Build an ecosystem that includes not only tools but also data, people and processes to support the use of augmented analytics.
- Establish a process, supported by technology, for operationalizing analytic assets within business processes, as well a process for monitoring and managing the impact from a business perspective.

Related Research:

“Augmented Analytics Is the Future of Data and Analytics”

“How Augmented Analytics Will Transform Your Organization”

“Build a Comprehensive Ecosystem for Citizen Data Science to Drive Impactful Analytics”

“Leading Upskilling Initiatives in Data Science and Machine Learning”

“Four Real-World Case Studies: Implement Augmented DSML to Enable Expert and Citizen Data Scientists”

“How Augmented Machine Learning Is Democratizing Data Science”

“How to Operationalize Machine Learning and Data Science Projects”

Strategic Planning Assumption: By 2022, 40% of machine learning model development and scoring will be done in products that do not have machine learning as their primary goal.

Analysis by: Adam Ronthal and Svetlana Sicular

Key Findings:

- Although there is no shortage of dedicated products focused on enabling data science and ML capabilities, these capabilities are also being included in adjacent product offerings in the data and analytics space. Data management solutions for analytics (analytic DBMSs), data integration platforms, analytics and BI platforms, and enterprise applications are all incorporating these kinds of capabilities.
- The concept of embedding advanced analytic algorithms that can support data science activities inside an analytic database has been widely accepted for over a decade. Now we are seeing embedded advanced analytics expand beyond their core product constituencies.
- Data, analysis and actions are the building blocks of analytic solutions. Data management vendors are adding ML capabilities, so that ML can be close to data. Analytics vendors are adding ML, so that they can extend their analysis with new capabilities. Enterprise application vendors are adding ML capabilities, so that ML will be close to the end users who are taking actions.

Market Implications:

Organizations’ appetite and readiness to improve decision making and become data-driven are resulting in ML crossing the boundaries of data science. It is expanding to platforms that are more familiar to mainstream IT staff. As a result, data management and analytics platforms are acquiring ML capabilities.

This expansion beyond the data and analytics core has significant long-term market implications, such as the prospect of simplified data and analytics architectures and accelerated delivery of data science and ML-based insights into production environments. Closer synergies and ties between ML innovation and operationalization will result.

The commoditization of ML capabilities will lead to widespread adoption beyond traditional data science teams and deliver increased business benefits. ML will be explicitly accessible for model development in various platforms, such as DBMSs, and BI and enterprise applications. It will be implicitly accessible in offerings that provide off-the-shelf ML solutions, such as those used for IoT analytics, marketing campaigns, customer churn and antimoney laundering, as well as chatbots, virtual assistants and many others. Although predictive maintenance is the No. 1 priority for many organizations with expensive capital equipment, it will take years for vendors to create off-the-shelf solutions with the right combination of data, analytic techniques and deployment model for each use case.

Recommendations:

Data and analytics leaders should:

- Evaluate whether incumbent data management and data analytics products have sufficient ML capabilities for targeted use cases.
- Use dedicated ML and data science tools for use cases when they can deliver significantly more value than the capabilities of incumbent offerings may offer.

Related Research:

“Magic Quadrant for Data Management Solutions for Analytics”

“Magic Quadrant for Analytics and Business Intelligence Platforms”

“Magic Quadrant for Data Science and Machine Learning Platforms”

“Hype Cycle for Data Management, 2019”

“Hype Cycle for Data Science and Machine Learning, 2019”

Strategic Planning Assumption: By 2023, 90% of the world’s top 500 companies will have converged analytics governance into broader data and analytics governance initiatives.

Analysis by: Guido De Simoni, Saul Judah

Key Findings:

- Digitalization initiatives are often impeded by disconnected silos of data and analytics across an enterprise. Without governance of data and analytic assets, decision making is more complex, time-consuming and expensive.
- Analytics governance has enabled consistent, organizationwide oversight of analytic assets such as decision models and algorithms. However, where analytics governance is separated from data governance, achieving business outcomes becomes more resource-intensive and carries higher risk.
- Where data governance and analytics governance form a combined capability, data and analytics leaders are more able to start with business outcomes and then more effectively govern data and analytics assets and decisions across business domains and within central functions.

Market Implications:

Governance enables business outcomes via an effective decision and accountability framework. Business leaders don’t think in terms of analytic outcomes or data outcomes — these are constructs that have traditionally been created for the benefit of organizing IT roles. Treatment of analytics governance as a capability separate from data governance can be a conscious decision or an outcome of gradual organic growth. Often, we have seen the two emerge as distinct areas, following organization models that separate center-of-excellence practices for analytics and data. But with the acceleration of digital transformation initiatives, data and analytics leaders are increasingly exploring how combined data and analytics governance practices can encourage the much-needed dialogue about the balance between centralization and localization.

Analytics governance focuses on the viability, relevance, transparency, reproducibility, legitimacy and appropriateness of the analytics applied. Data governance focuses on the quality, consistency, lineage, curation and trustworthiness of data. Insight gained from analytics cannot be truly meaningful unless the data from which it came from can be trusted. Data governance and analytics governance, therefore, must work in tandem with effective integration.

In 2019, interest in data and analytics governance grew (we recorded over 2,100 customer interactions involving this topic). Subjects of interest include AI model governance, analytics governance in data warehouses and lakes, IoT data governance, ethics as a discrete policy, and the bringing together of multiple policy disciplines for unified governance of quality, privacy, security and other matters. The scope remains all data: application data, content, records, external social data, master data, metadata, algorithms and AI models, analytic models, and key performance indicators or other metrics.

A conversation about the convergence of data and analytics governance is underway, but this convergence is still a work in progress in most organizations (see “The Role of Technology in Data and Analytics Governance”).

As organizations break down the organizational and technical silos between data and analytics, we expect full convergence of data and analytics governance. Organizations should always approach data and analytics governance as a discipline, using an adaptive framework that enables different governance styles to suit the business context.

Recommendations:

Data and analytics leaders should:

- Extend data governance by the inclusion of analytics governance. It is important not to attempt to institute analytics governance as a stand-alone initiative.
- Get started on data and analytics governance by aligning your data and analytics strategy with clearly prioritized business outcomes.
- Identify key stakeholders to cosponsor the data and analytics governance initiative, such as the chief data officer or chief data scientist.
- Focus on the least amount of data that will have maximum impact on business outcomes as this will help embed the work of data and analytics governance into a business context, by the business, for the business.
- Link data and analytics governance to corporate governance and enterprise digital governance initiatives.

Related Research:

“Building a Comprehensive Data Governance Program”

“Toolkit: Build the Business Case for Data and Analytics Governance”

“Toolkit: Data and Analytics Governance Role Descriptions”

“Adopt SMART Information Principles for Effective Data and Analytics Governance”

“Use Adaptive Governance for Data and Analytics to Drive Digital Business Success”

“Hype Cycle for Data and Analytics Governance and Master Data Management, 2019”

Strategic Planning Assumption: By 2025, 80% of consumer or industrial products containing electronics will perform analysis on the device.

Analysis by: Carlton Sapp and Ted Friedman

Key Findings:

- It is often of greatest value to react to event data at the source. This is particularly so in cases where it enables a device to behave autonomously — real-time connection to a central data and analytic processing environment being impracticable for self-driving cars and devices on the ocean floor, for example.
- Most data and analytics teams are not well-equipped to deploy and support edge-based analytics workloads — including their monitoring, change management and governance.

Market Implications:

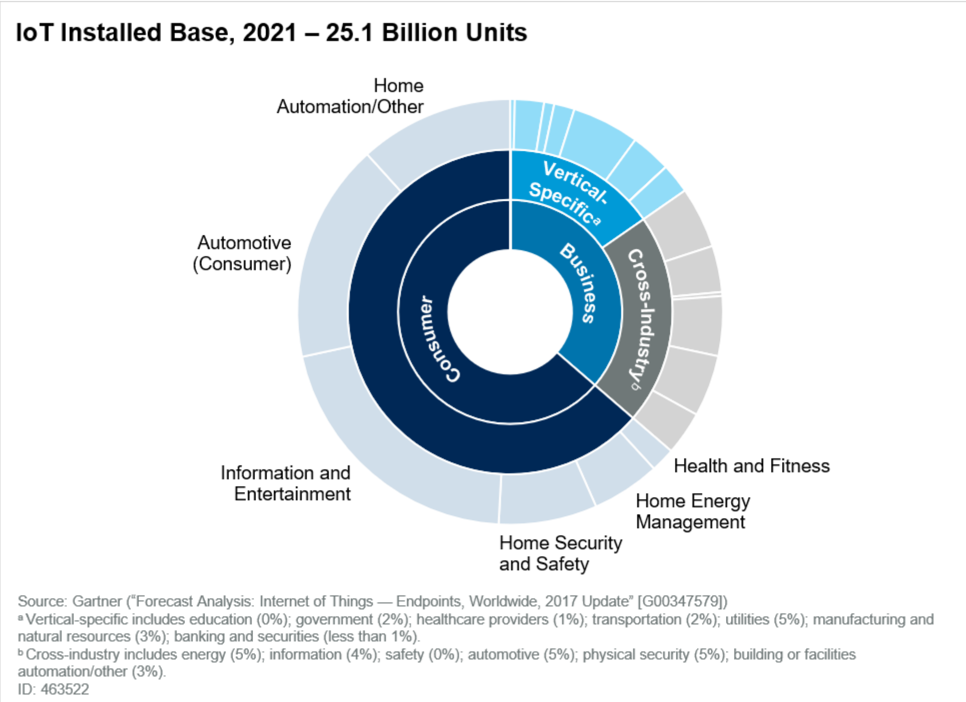
The rapid proliferation of infrastructure, applications and data will continue to force organizations to provide analytics and BI solutions far more widely. This will include the use of embedded analytics and BI solutions in consumer and industrial products containing electronics.

There are many reasons why analytic processes will take place in edge or on-device environments. In some cases, privacy concerns will limit the ability of organizations to bring data from devices back to a central location for analysis. In other cases, data will be relatively inaccessible — as, for example, with devices in remote field locations or other relatively inaccessible places such as an ocean floor. In other use cases, the reaction time between a sensor and a response will preclude real-time communication — as, for example, with self-driving vehicles.

As demand for more context-sensitive decisions increases, and as organizations look to improve profit margins by making devices smarter, sensors will be added to the vast majority of devices. This means that analytics and BI strategies must expand to include diverse deployment strategies across proliferated infrastructures that are concerned with lightweight consumer and industrial digital products and the IoT. Business demand for automation and rapid decision-making support will require modernization of analytics and BI strategies to include a spectrum of diverse analytics, from the edge to the enterprise.

Figure 3 shows the estimated volume of IoT devices in different categories. These will provide large quantities of data for organizations to analyze, as well as potential consumers of analysis.

Figure 3. Device Categories for the Internet of Things



Although organizations face numerous organizational and technical hurdles to IoT adoption, analytics is identified as a top-three concern by 14% of organizations (data and information management is a top-three concern for 22%).[1] In many cases, organizations have yet to address their analytics problems. Immediate concerns about topics such as security and privacy are conceptual stumbling blocks that organizations must overcome before they begin an IoT initiative. If they do not prepare now, by the time they reach the analytic component of an initiative, they risk discovering that they lack the relevant skills to deliver a solution. This is particularly true in situations that will require deployment of analytic capabilities within devices, as model deployment — already an area of weakness in "normal" analytic projects — is even more complicated in devices with limited memory, processing and updatability.

Just as cloud computing paradigms drove substantial changes in technology providers' delivery and licensing models, so too will edge computing. Vendors of analytics capabilities of all types will begin investing heavily in both native and containerized deployment capabilities in order to support the demand for onboard analytics on edge devices. Buyers should plan for such capabilities to be of generally low maturity in the short term, which will mean greater implementation and support costs for early adopters in this area.

Recommendations:

Data and analytics leaders should:

- Evaluate analytics requirements, based on the desired speed of delivery and the computational resources available.
- Determine where to provision analytic solutions, based on new consumer or industrial product enhancements.
- Make the cost of transporting data an important factor when evaluating and assessing analytic delivery strategies.
- Update their deployment strategy to include lightweight embedded analytics, if the plan is to use consumer or industrial digital products.

Related Research:

"Deploying IoT Analytics, From Edge to Enterprise"

"Design Your IoT Data Architecture for Streaming Edge Analytics and Platform Advanced Analytics"

"Start Moving Data Management Capabilities Toward the Edge"

A Look Back

In response to your requests, we are taking a look back at some key predictions from previous years. We have intentionally selected predictions from opposite ends of the scale — one where we were wholly or largely on target, as well as one we missed.

On Target: 2015 Prediction — By 2018, data discovery and predictive analytics offerings will converge, with most of the leading vendors of each capability offering both.

Since we first began to see mainstream adoption of modern analytics and BI tools and increased consumerization of data science and ML tools, there has been a gray area between analytics and BI platforms and data science and ML platforms. The basis for this prediction was the need for a single tool to deliver not only descriptive and diagnostic insights, but also predictive and prescriptive (something that was difficult to achieve due to the different personas needed to use tools in these areas).

Analytics and BI tools have increased the amount of advanced analytics delivered in visual or menu-driven ways for business users, analysts and citizen data scientists. At the other end of the spectrum, data science and ML platforms have made building predictive models an option for citizen data scientists and data scientists in similar ways (namely through menu-driven and visual options that automatically execute key steps of the model creation life cycle, rather than requiring the writing of code).

The rise of automation or augmentation was a key reason why this prediction came true, as these technological advances enabled organizations to automate some of the tasks for which skills were lacking. The convergence is ongoing. It is driven primarily by the addition to analytics and BI platforms of data science and ML features by means of augmented data science and ML capabilities that automate key aspects of the ML model creation process. Large providers like Microsoft, Salesforce and SAP, as well as smaller ones like Tellius, have each converged analytics and BI and data science and ML within a single product.

Related Research:

"Predicts 2015: A Step Change in the Industrialization of Advanced Analytics"

"Augmented Analytics Is the Future of Data and Analytics"

Missed: 2017 Prediction — By 2019, citizen data scientists will surpass data scientists in the amount of advanced analysis produced.

In our discussion of the preceding on-target prediction, we observe that technological advances can fill some of the skills gap in the field of data science. Citizen data scientists have increased in popularity significantly, but they are no replacement for expert data scientists. In some cases, such as when organizations are just beginning their data science journey or in a prototyping environment, citizen data scientists may produce more advanced analytics than the growing data science teams. However, citizen data scientists generating advanced analytics is not the same as utilizing a predictive model in a production environment — one of the biggest challenges in the field of data science and ML.

Citizen data scientists require an ecosystem of skills and technology to enable predictive and prescriptive analytics effectively within an organization. Data scientists, data engineers, ML developers and business analysts, among others, will be needed to derive business value from more advanced analytics at scale.

As technologies in this sector continue to gain augmented data science and ML capabilities, the transparency and openness of the models automatically produced will become increasingly important for interoperability across personas involved in the model creation life cycle.

Related Research:

"Predicts 2017: Analytics Strategy and Technology"

"How Citizen Data Science Can Maximize Self-Service Analytics and Extend Data Science"

"Maximize the Value of Your Data Science Efforts by Empowering Citizen Data Scientists"

"Build a Comprehensive Ecosystem for Citizen Data Science to Drive Impactful Analytics"

Evidence

[1] Gartner's Internet of Things Strategies Survey, for which there were 912 respondents to the following question: Please rank the three greatest technical barriers to the success of your organization's IoT activities.

The survey was conducted between July and August 2018 with 912 respondents in six countries: China, Germany, India, Japan, the U.K. and the U.S.

The survey's strategy module aimed to improve our understanding of organizations' strategies for the IoT overall, including measures of success, team structure and funding sources.

Participating organizations were required to have annual revenue of more than $50 million and to plan to pursue at least one IoT use case no later than 2019.

Respondents selected for the strategy module were required to have knowledge about their organization's IoT-related business objectives and strategy. They were also required to have a high level of responsibility for IoT decisions in relation to business objectives and the setting of IoT strategy.

The survey was developed by a team of Gartner analysts who follow this market. It was reviewed, tested and administered by Gartner's research data and analytics team.