Big Data and the Future of R&D Management

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OVERVIEW: *Beginning in 2015, IRI undertook a study to explore the concept of "Big Data" and to test whether, and to what extent, this new domain might affect R&D management in the future. We conducted extensive discussions to dissect the nature of Big Data and to achieve a common understanding of what it represents. We then constructed a research framework that analyzes Big Data based on its potential to inform, enable, and transform/disrupt R&D management across four dimensions: strategy, people, technology, and process integration. Through a literature review, interviews with experts, and case studies of organizations using Big Data, we show that this phenomenon will have significant implications for innovation management and capabilities in the future, although progress and impact is somewhat uneven among different industry sectors.*

KEYWORDS: Big Data, Digitalization, R&D, Management

Big Data is a term that is widely used, often described but with no commonly-agreed definition. The absence of consensus contributes to gaps in research and findings relevant to R&D managers. Large quantities of published information is available on the technical developments in Big Data creation, acquisition, storage and analysis. Another set of literature looks at the operational impact of Big Data on companies, primarily in customer-facing functions such as marketing and customer service. Publications on the impact of Big Data on R&D activities, to the extent that they exist, generally come from government research institutions and academia. While this suggests that most applications of Big Data in R&D are found in the public sector, we suspected that the private sector also provided emerging indicators of how this new capability will transform innovation in the future.

In the early phases of the *Digitalization and its Implications for R&D Management* project ideation phase there was broad input from IRI members to elicit areas of interest. We uncovered a wide range of questions uncovered, reflecting a very broad spectrum within the IRI membership for the understanding of and involvement with Big Data in their operations. Members reported that their explorations of Big Data ranged from large research programs and groups focused on Big Data to those still trying to determine the meaning of Big Data and why they should be concerned with it. With this diversity of understanding and utilization of Big Data the first challenge was to identify a common language to discuss the impact on R&D.

What is Big Data?

One of the first questions addressed by the working group was, "What do we mean by Big Data?" This proved difficult to answer, as much has been written about "Big Data" but with many different meanings, interpretations, and implications. Early discussions made it clear that IRI members held diverse opinions about Big Data and its importance. So, our first question became, "Is it actually helpful to define Big Data?"

Our conclusion is that Big Data is going to mean different things to different organizations. For those organizations accustomed to working with massive datasets, Big Data implies a scale far beyond state-of-the-art data management technologies. For other organizations, Big Data may be any dataset that cannot be handled by Microsoft Excel. Or, as Dr. Bill Pike of the Pacific Northwest National Laboratory puts it, "Big Data is data of sufficient size and complexity to challenge contemporary analytical techniques." The more useful approach is to look at the characteristics of what we call Big Data, and how those characteristics relate to the way that organizations are accustomed to using data.

Discussions within the working group and at IRI meetings demonstrated that there is no single set of criteria that defines Big Data across all organizations. In fact, one problem with the term Big Data is that it does not describe a particular technology or approach. As noted by Stephen Hoover, CEO of the Palo Alto Research Center (PARC) in his remarks at the 2015 IRI Annual Meeting, "Big Data isn't a solution—it's a problem." What is clear, however, is that all R&D organizations will need to deal with Big Data sooner or later. In fact, the market research firm Gartner Group recently removed Big Data as an item on its annual "hype cycle" chart of emerging technologies, arguing that Big Data is so pervasive and well-established that it is no longer "emerging" (Sharwood 2015). Organizations are no longer asking whether or not they should exploit Big Data for competitive advantage—they are determining what to do with the Big Data that is already part of the operating environment.

Instead of using the term "Big Data," participants at the 2015 IRI Winter Meeting suggested that the term "Uncomfortable Data" might better reflect how this trend affects R&D management. Uncomfortable Data refers to any set of data so large and unwieldy that it defies analysis using the tools and methods normally employed by an organization. Apart from sheer volume, these types of data come from sources in too many different formats to be handled by existing tools, and may be generated too rapidly to be ingested and managed with existing systems. The point is not the absolute size of the dataset, but rather its size and nature relative to the data processing capacity and expertise of the organization. Uncomfortable Data emphasizes the challenge posed by Big Data—it requires new technologies and new approaches to enable organizations to use data effectively in improving decision-making and operations.

Uncomfortable Data also brings out how Big Data challenges the role of data in organizations. Due to their attributes of variability, (questionable) veracity, etc., high-velocity datastreams are inherently *uncertain*. Data is being collected and transferred at such high rates and in such volume that an analyst may not have the time, resources, or ability to understand all the structural properties of those datastreams. The data may be biased, for example, or it may be corrupted. The pace of business will not always allow analysts the luxury of cleansing and validating those data. In a world of Uncomfortable Data, decisions become probabilistic—the data tells us what we *think* we know to be true, but we cannot be completely sure. Organizations need to decide what level of uncertainty they are comfortable in managing, and calibrate their use of Big Data to match their preferences, if possible.

Analytics: Answering Big Data Questions

If Big Data is the defining challenge of a data-rich environment, what is the solution? The answer is advanced analytics—new techniques that apply machine learning to glean insights from complex datasets. Advanced analytics will identify latent relationships between variables, uncovering patterns that are not discernable by humans alone. This interaction between data, models, and analysis are the core of the promise of Big Data for applications such as R&D. The IRI 2038 Study (Farrington, Crews

2013) noted the expectation that artificial intelligence (AI) systems will play increasing roles in both project and portfolio management, leveling the field in terms of R&D's execution and value proposition.

INFORMS (the Institute for Operations Research and the Management Sciences), in 2010, commissioned a report (Robinson, Levis, Bennet 2010) by the consulting firm Capgemini to study the rise of analytics and its implications for the society. The study sought to confirm whether or not the field of analytics was a new successor to what had been labeled as "operations research" (OR), and to what extent it differs from OR. In what is now a seminal work in understanding this new field, Capgemini argued that analytics in many ways superseded OR to become a broader phenomenon, in large part because advanced analytics is driven not just by methodologies and techniques but by business concerns.

The report adopted the definition that *Analytics facilitates realization of business objectives through reporting of data to analyze trends, creating predictive models for forecasting and optimizing business processes for enhanced performance.* Capgemini drew further distinctions among a set of progressively more sophisticated forms of analytics:

- *Descriptive analytics:* using data to find out what has happened in the past.
- *Predictive analytics:* using data to find out what might happen in the future (i.e., forecasting and estimation).
- *Prescriptive analytics:* using data to identify the courses of action that are likely to produce the best outcomes under given conditions.

In one framework for comparing these approaches (Delen 2014), descriptive analytics is comparable to traditional business intelligence solutions—the compilation of statistics and major findings about past activities and conditions in a given time period. Predictive analytics takes traditional forecasting but applies new techniques to create very sophisticated models of an environment, typically leading to classification problems. The work of quantitative hedge funds in modeling the stock market is one example of predictive analytics at work. Modern approaches use advanced statistical methods and machine learning algorithms to isolate and study thousands of variables simultaneously in a predictive model. This enables organizations to construct very complex models of an environment and observe the interactions of those many variables to determine which ones drive the emergence of a potential future result.

Prescriptive analytics applies techniques such as optimization, simulation, and heuristics-based decision-making to test the potential consequences of pursuing alternative strategies or courses of action. This type of analysis provides an organization with a means of understanding trade-offs between decisions, and may improve the quality of decisions by integrating factors beyond the capabilities of human cognition. One area of prescriptive analytics, for example, is in computer-assisted diagnosis, where a physician can enter in observations about a patient and rapidly scan the entirety of the medical literature to identify diseases or disorders that might be generating those symptoms, rather than relying solely on memory to generate those diagnoses (Haftner 2012). The system can then use those inputs and its analysis of the literature to identify the procedures or treatments most likely to be effective in that particular case.

What is certain is that the use of Big Data analytics will have an impact on management. The Economist Intelligence Unit (2012) stated that "management decisions based purely on intuition or experience are increasingly regarded as suspect." Another study, conducted by the *MIT Sloan Management Review* (LaValle 2010) suggests that "top-performing organizations use analytics five times more than lower performers." The challenge to management is apparent as strategies and operations will become more complex (Zhao, Fan, Hu 2014). The question is whether R&D management has prepared adequately to cope with this changing environment. The observation that "Innovators are rising to the challenge of Big Data" (Gobble 2013) is a warning that as R&D we need to understand the changes occurring.

Research Framework

The working group realized early in our deliberations that we needed a framework to understand how Big Data might affect R&D management, and especially how R&D organizations might need to change to operate effectively in a world of Big Data. With a broadened view of Big Data and analytics, the working group defined our hypothesis: "Big Data will impact R&D management through changes in how R&D is informed, how R&D is enabled and how R&D will be disrupted or transformed."

We constructed a research framework (Figure 1 – Research Framework) to guide our tests of this hypothesis. In that framework, the working group defined questions to pursue for how Big Data would inform, enable and disrupt/transform R&D across four dimensions: Strategy, People, Technology and Process Integration. This framework allowed us to characterize more precisely the impact of Big Data on R&D management. We could then minimize the confusion stemming from the dynamic nature of Big Data, as it continues to pose new technical and operational challenges.

To test our hypothesis, our approach was to review the literature, interview thought leaders, examine case studies and to collect input from the IRI membership during 2015 and 2016 in workshops at the Annual Meeting and Member Summit.

Applying the research framework made clear that to address the broad spectrum of understanding of this topic in the R&D community, we needed to establish our common view of Big Data as a topic as well as define four dimensions of the framework. Our first deliverable to address this was *A primer on big data for innovation* (Alexander, Blackburn, Legan 2015). The central message of the primer emphasized that Big Data will have an impact on R&D management, and that organizations need to appreciate both the short-term and long-term implications of that impact (Holden 2016).

Findings

A summary of our findings is found in Figure 2 – Study Results. We sought to provide a basic idea of the relative maturity of different organizations in how they handled and utilized Big Data, and to suggest an overall approach to comparing levels of maturity. We considered the examples collected by industry segments of Industrial Manufacturing, Consumer Goods, Food & Beverage, High Tech, Energy, Chemicals, and Health Care & Pharmaceuticals as well as Government. We classified each of these segments based on whether we identified "many examples," "examples," or "few/no examples" of Big Data applications for R&D management in that segment. Table 1 summarizes quantitative responses from participants in the 2016 IRI member summit, showing a snapshot of Member views on impact within the research framework.

The types of examples observed were diverse. Examples represented analysis of large data sets, cheminformatics (Bunger 2015), advanced analytics using the approaches such as Machine Learning (Li 2011) or Artificial Intelligence (Wigley, et.al. 2016), pattern recognition, image analysis, text analytics

(Markham, Kowolenko, Michaelis 2015), virtual experimentation & simulation, forecasting (Huang, Schuehle, Porte, Youtie 2015), bioinformatics & genomics (Stephens 2013), and general practices for managing Uncomfortable Data.

Case Study: Big Data in the Pharmaceutical Industry

Figure 2 illustrates that the pharmaceutical industry is one of the sectors where Big Data is having most impact on R&D and where examples may be found of informing, enabling and disrupting R&D.

For many years this industry has run clinical trials with thousands of patients (May, 2014) and encountered an inherently variable response because of the genetic and physiological diversity across the patient population. The industry developed very sophisticated capabilities in data analysis to deal with this challenge. However, the historically successful pharmaceutical research enterprise has become increasingly less effective over the past two decades, at least in part because of "lack of data or lack of appropriate analysis of the available data" (Tormay, 2015).

Availability of certain kinds of data has rapidly gone from being inadequate to overabundant in the past 10 years, with advances in genome sequencing and reduction in cost. The global Human Genome Project announced its first draft sequence in 2000 and its first finished genome in 2003. This was the result of over 10 years' work and cost approximately $2.7 bn. It took collaboration between 20 different institutions to sequence the roughly 3 billion base pairs in one genome (Human Genome Project). Now a human genome can be sequenced for around $1,000 in a matter of hours and one high throughput sequencer can deliver 400 bn base pairs per day and up to 12 human genome sequences and 1.5 terabytes of data per 3.5-day run (Illumina, 2015).

<u>Informing pharmaceutical R&D</u>. This power has been harnessed in the UK's 100,000 Genomes Project, which is sequencing entire genomes from a diverse set of subjects, including those from patients with rare diseases and cancers. The resulting knowledge and insight should help clinicians to improve diagnosis and outcomes (Genomics England). This is but one organized project using such new approaches. The resulting torrent of data, when linked with information on medical conditions and disease states will provide insights to identify new potential drug targets.

<u>Enabling pharmaceutical R&D</u>. Once new drug targets have been identified, the drug development process looks for a compound that can interact with the target in a desirable way. Historically this has been through wet chemistry and biological screening. More and more, this process is moving to virtual screening in which computer models examine millions of compounds for potential interaction with targets and only a small subset undergoes traditional biological screening (Storrs, 2015). Taking this approach allows potential molecules to be identified more quickly and at lower cost.

<u>Transforming & disrupting R&D</u>. Extrapolating a little, it is not hard to see how the revolution in availability of genomic data and data analysis changes the nature of pharmaceutical discovery by permitting identification of compounds with high efficacy in targeted genetic groups, even if that efficacy cannot be determined from placebo when compared across the general population. During the interview stage of our research, Bernie Meyerson, Chief Innovation Officer at IBM and one of the pre-eminent thinkers on big data, suggested that healthcare is the field where big data will have the greatest societal impact (at least in the U.S.) and the opportunities in R&D just mentioned would ultimately be a contributor to that outcome.

Big Data in R&D Management: Other Examples

For Big Data to inform R&D, the IRI Member Summit survey showed that new types of skills and competences are needed to apply Big Data to R&D management. In particular, Big Data is most effective when the analysts are very familiar both with data analytics and the underlying business or research question that is being addressed (Clay Heaton, Interview), calling to mind the "pi shaped" skill set described in Alexander et al (2015). These observations both point to a need for changes in hiring and training in R&D organizations. In turn this puts an emphasis on organizational willingness to invest in infrastructure and human capital (Clay Heaton, interview).

In one case-, Eastman Chemical Company engaged in a collaboration with North Carolina State University to apply Big Data to gain insight to the 3D printing technology and market environment, enabling R&D by identifying lucrative, underserved spaces which could be addressed by Eastman capabilities. Applying Big Data analytics early in the R&D process enabled more rapid opportunity assessment as compared to traditional means. Building on this activity, Eastman informed its R&D strategy by using unstructured text data to gauge public response to particular products, noting trends, concerns, and opinions of products made with Eastman or competitors' materials. This Big Data use spanned the boundary between marketing and R&D. To keep costs down, the company built its own advanced analytics software, as the available commercial solutions were more expensive to implement. This indicated that applying Big Data analytics early in the R&D process was generally more valuable than waiting until the market had completed developing off-the-shelf tools.

In another example of informing R&D, a small consulting company, Newry, uses a combination of Big Data and traditional consulting skills to identify valuable new product opportunities. One very interesting aspect of their approach is understanding that as the world changes, new opportunities emerge for existing products and services and these might be missed because they were not part of the original target market. Newry now has many examples of identified opportunities, including some where applications were provided to clients in as little as a few weeks from making the connection. Important observations from Newry include that the approach works better with relatively technologically sophisticated companies and not so well with more consumer-oriented companies, and that people remain important in the process to guide and validate exploration.

Another consulting example at the intersection of informing and enabling R&D was from Decernis. That organization operates a very large regulatory database of worldwide regulations pertaining to food, cosmetics, over the counter pharmaceuticals, medical devices, packaging and more. All materials are uniquely identified and translated across 40 languages. This permits R&D to formulate for new markets with greater confidence that final products will be accepted by regulatory agencies in the target market, and gives insight into potential regulatory changes before they cause operational difficulties. Again the need for humans skilled in both the big data and the product/technical areas came through very strongly. Another observation was that people in client R&D departments have become more proficient in computer skills and data analysis over the past 10 years, at the cost of some loss of product/technical skills.

Consumer products companies have invested in Big Data capabilities in their sales and marketing organizations. One leading consumer packaged goods company reported using Big Data to inform sales and marketing teams through, for example, monitoring of social media feeds. When added to consumer calls (complaints or suggestions) and external databases such as patents and scientific literature, the data analytics group generates insights for product improvements and "quick fixes" which form a large part of the work of a consumer products R&D group. This is an example of informing leading to enabling R&D. Here, again, we heard a strong message that data analytics does not replace the need for existing knowledge and interpretation skills, rather that the skills profile of R&D teams will need to evolve for greatest effectiveness.

Increasing amounts of open data create the opportunity for disruption by non-traditional players in any industry who can more rapidly or more effectively gain insights from the data (Dr. Bill Pike – interview). By driving down the "transaction costs" involved in innovation, Big Data can lessen many of the traditional advantages of conducting R&D in a large company. Hence, organizations need to look not only at what work is being done, but how it is structured. The intelligence community has responded by moving from a hierarchical organizational model to a network (John Ellenthal, interview). By aggregating large central data repositories, accessible through a secure network using a standardized suite of tools, agencies can perform multiple analyses simultaneously and collaborate organically, instead of routing all analytical work to one organization. Big Data offers a new mode of pursuing "open innovation," as Procter & Gamble pioneered in the early 2000's (Kastelle, 2012; Ozkan, 2015). Now, companies can form open networks of collaborators that can share information and respond rapidly to insights gleaned from widely-distributed Big Data resources.

A final, interesting observation is that R&D is not generally at the forefront of Big Data applications. Perhaps this is because applications began in fields where immediacy was highly valuable, such as e-commerce (led by companies such as Amazon), followed by sales and marketing in more traditional companies. Another early area of impact from Big Data is real-time operational decision-making, for example maintenance prediction and reliability improvement for aircraft engines or heavy equipment. GE's heavy investment in data analytics for its aircraft engine unit and other businesses exemplifies how companies are starting to exploit such capabilities (Winig, 2016). Looking at the evolution that took place in those fields can give us some sense for how the future might unfold in R&D.

Conclusion

Through this study, we confirmed our hypothesis that "Big Data" will impact R&D. The impact is seen in how R&D is informed, enabled and disrupted or transformed. Using Big Data technologies, analytics and skills of data scientists we have seen this impact in R&D across all industry segments as well as in government.

We have found many examples of R&D being informed by Big Data across all industry segments and in government. We found examples of R&D being enabled across all industry segments and in government and noted there were many examples in government and in the hi tech, energy and health care & pharmaceuticals segments. Examples of transformation or disruption of R&D can be found in government and in the hi tech, energy and health care & pharmaceuticals segments.

Our conclusion is that all R&D Management should be considering how Big Data will impact their business and operations. If there is a lack of awareness of potential impact to one's specific industry, then awareness needs to be built because there are others in your industry that are investigating, pursuing and implementing technologies, analytics and skills for the future. The view was expressed in one of our interviews (John Ellenthal) that organizations need to understand the most valuable decisions that they make, as that is ultimately where Big Data should be focused. But since all new ventures have some unknown risks, for those unfamiliar with Big Data it is probably more important to be doing something to build organizational capability now.

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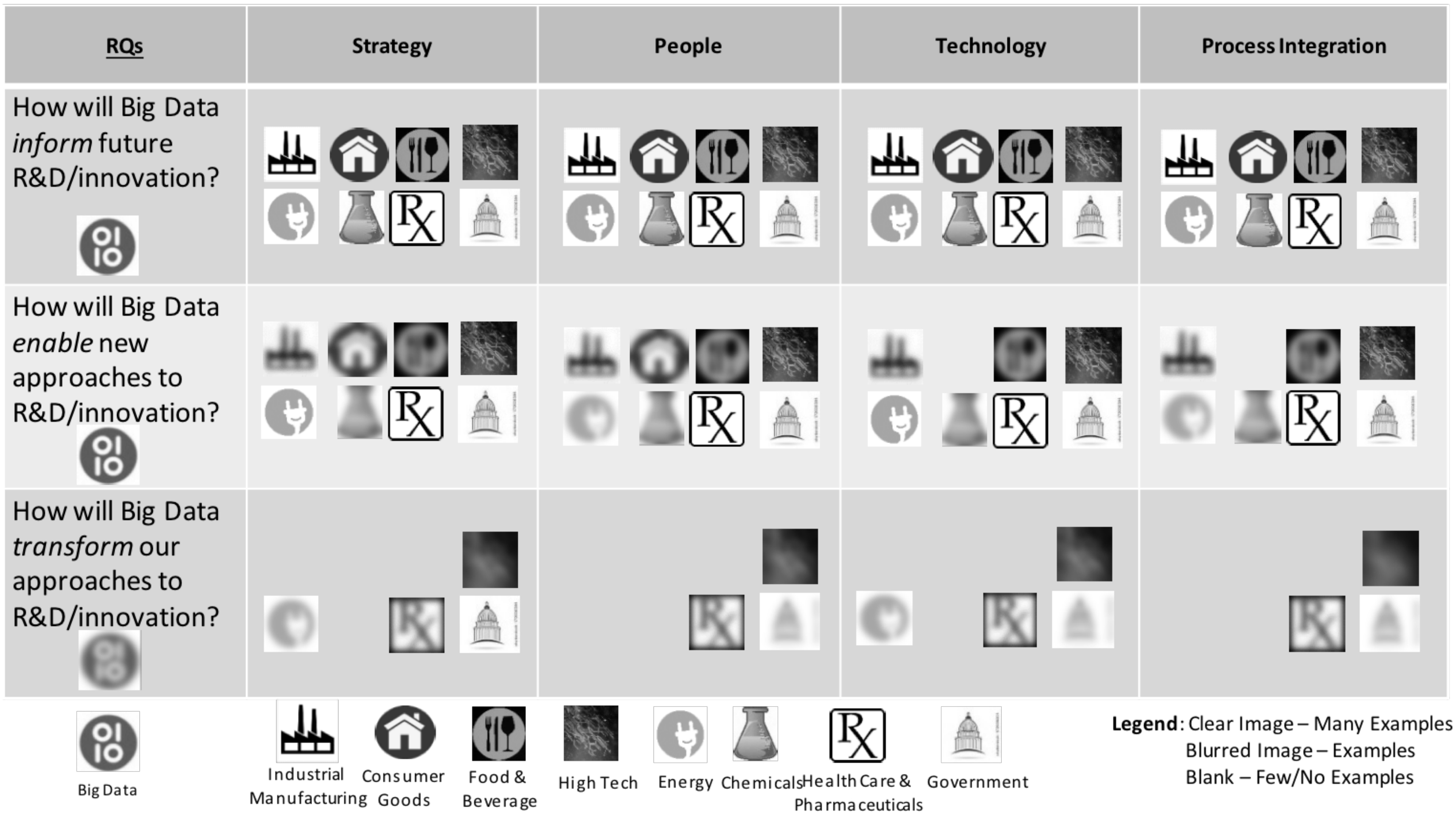
Figure 1 – Research Framework

RQs	Strategy	People	Technology	Process Integration
How will/does Big Data *inform* future R&D activities?	How could overall R&D management improve from the use of Big Data?	Who will be using Big Data to inform R&D management, and what will they need to know?	What Big Data technologies & systems will R&D management use to improve decision-making?	How will R&D management practices & processes change as Big Data becomes pervasive?
How will/does Big Data *enable* new approaches to R&D activities?	What new capabilities and approaches to innovation become possible thanks to Big Data?	How will the skills and knowledge of research teams change to make use of Big Data?	What Big Data technology and systems will become part of the R&D process?	How will R&D activities change as Big Data becomes pervasive?
How will/does Big Data *transform / disrupt* our approaches to R&D?	How can Big Data create/identify opportunities to disrupt markets and industries? How might competitors use Big Data against incumbents?	Who will use Big Data as a tool for disruption, and what will they look like?	What technologies on the horizon enable future disruptive opportunities?	What should companies do to predict/exploit disruptive opportunities using Big Data?

Figure 2 – Study Results



	Impact areas				
Research Questions	**Strategy**	**People**	**Technology**	**Process Integration**	**Total**
How will big data *inform* R&D activities?	40	18	21	14	93
How will big data *enable* new R&D activities?	31	9	25	14	83
How will big data *disrupt* traditional R&D?	25	18	16	6	65
Total	96	45	62	34	241

Table 1. Actual and potential impacts of Big Data on R&D identified by participants in the 2016 IRI Member Summit on Big Data. Individual impacts were listed, e.g. "new skills needed in R&D" and the listed impacts for each research question and impact area were counted and reported here.