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Increasingly, organizations are using data analytics to improve performance across business functions, including procurement. Our examination of 15 Fortune 500 companies' procurement practices found that most are not using data analytics fully. To understand why, we investigated the challenges procurement functions face in moving up the analytics hierarchy. From our analysis, we provide five best practices that executives can follow to get more out of data analytics, and describe the actions to effectively implement them.[1,2,3]

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Rich Opportunities for Applying Data Analytics to Procurement

Increasingly, organizations are using data analytics to extract insights from data and inform decision making both within business functions and across business processes.[3] This article describes a set of best practices that can help managers get the most out of their efforts through functionally dedicated data analytics initiatives. Though the best practices were developed in the context of the procurement function, they are equally applicable to other business functions. In particular, these best practices are highly relevant to information systems (IS) because their implementation requires the active involvement of the IS function to enable every major capability of data analytics (drill down, real-time dashboards, visualization, etc.).

We chose the procurement function both because every company has to acquire goods and services from external sources for its business operations, and because procurement is an area where there are rich opportunities to apply data analytics. Like IT, procurement is an essential support activity in the value chain to make primary activities more effective and efficient. Typically, procurement involves making critical purchasing decisions while dealing with

1 Iris Junglas is the accepting senior editor for this article.

2 The authors thank Iris Junglas and members of the review team for their insightful comments and guidance throughout the review process. We also gratefully acknowledge the funding support provided by the Center for Advanced Procurement Strategy (CAPS) Research for the project "Data Analytics Teams and Procurement: Who and What" from May 2017 to December 2018. The survey and interviews carried out for the project form the basis of the findings presented in this article.

3 See, for instance: 1) Handfield, R., Choi, T., Venkatraman, J. and Murthy, S. *Emerging Procurement Technology: Data Analytics and Cognitive Analytics*, Center for Advanced Procurement Strategy (CAPS) Research, 2017; and 2) Laursen, G. H. N. *Business Analytics for Sales and Marketing Managers: How to Compete in the Information Age*, John Wiley & Sons, 2011.

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Table 1: Characteristics of Participants' Organizations

Industry	Gross Revenue	Region
Instruments and Related Products Manufacturing	$98 billion	Europe
Financial Transactions Processing	$12 billion	U.S.
Petroleum and Petroleum Products Wholesalers	$8 billion	U.S.
Miscellaneous Food Manufacturing	$16 billion	U.S.
Automobile Manufacturing	$243 billion	U.S.
Electric Power Generation	$17 billion	U.S.
Semiconductor and Related Device Manufacturing	$6 billion	U.S.
Computer Systems Design Services	$79 billion	U.S.
Petroleum Refineries	$244 billion	U.S.
Hydroelectric Power Generation	$3 billion	U.S.
Other Individual and Family Services	$3 billion	U.S.
Grocery and Related Products Wholesale	$8 billion	Europe
Aircraft Engine and Engine Parts	$41 billion	U.S.
Industrial Valve Manufacturing	Less than $1 billion	U.S.
Research and Development	$3 billion	U.S.

the constraints of scarcity. Using data analysis methods based on statistics and econometrics, procurement ensures that a firm acquires goods and services at the best possible price while considering factors such as quality, quantity, time and location.

Data analytics can yield insights into key procurement operations. First, data analytics can help chief purchasing officers (CPOs) keep track of how much is being spent, when and where, avoiding the hit-or-miss outcomes caused by human assumptions and biases. Second, data analytics assists CPOs with strategic sourcing by identifying the appropriate times, areas and stakeholders for sourcing decisions. Third, applying data analytics to category management enables CPOs to recognize opportunities for savings, prioritize suppliers, alleviate supply risks and exploit innovations. Fourth, data analytics can help CPOs assess the accuracy of payments, find opportunities for rebates, correct errors and detect frauds. Fifth, data analytics can inform CPOs about when contracts with suppliers need to be renegotiated and what terms to focus on. Finally, data analytics can support CPOs in evaluating the environmental and societal impacts of procurement practices and discovering more sustainable and resilient alternatives.

Our Research into Data Analytics Best Practices in Procurement

To improve procurement practices through data analytics, CPOs need their own dedicated data analysts, but they face myriad unique challenges and issues in hiring, training, managing and using data analysts effectively. To understand both current and best practices for leveraging data analytics in procurement, we conducted a survey of 15 CPOs of major corporations (all Fortune 500 companies). We then followed up with in-depth interviews that shed light on how procurement analytics is staffed and structured, how procurement can be facilitated by analytics, and how procurement analysts should interface with corporate-level data analytics teams. The survey and interviews[4] yielded valuable insights into what type of support CPOs can get from their data analytics initiatives, who needs to be hired to provide that support, how data analytics personnel need to be structured within both the procurement function and the larger corporate organization to deliver the needed support, and how to enhance the types of analytics being used as an organization becomes more mature in analytics. Table 1 provides an overview of the 15 organizations participating in our study.[5]

Procurement Managers' Expectations for Data Analytics

Our first objective was to understand procurement managers' expectations of data analytics. Not surprisingly, the high-level goal shared by every CPO was to improve business performance by supporting business strategy. We asked how data analytics could help them achieve this goal.

Though an individual CPO's expectations of data analytics were often industry specific, there were five common threads:

1. Providing data integration, drill down, real-time dashboards and visualization
2. Determining should-be pricing
3. Identifying opportunities to drive down the spending on major cost components such as transportation, fuel and labor, as well as the ability to home in on these opportunities during negotiations
4. Improving risk management
5. Integrating internal information with external information to create more dynamic insights into the business.

However, we discovered that most of the CPOs' organizations had not progressed beyond data integration, drill down, real-time dashboards and visualization. Moreover, many were uncertain about how to do more with data analytics.

These expectations for data analytics are in line with the findings of a recent Deloitte survey of CPOs.[6] This survey found that operational efficiency and cost reduction remain at the top of CPOs' priorities, but the focus now is on digital transformation and innovation through data analytics to make their organizations more agile and capable of coping with increasing complexity. According to the Deloitte survey, leveraging data analytics and digital technologies is the key to this agility initiative: "Analytics is quite simply the most exciting and impactful digital area happening in procurement and value chains." Moreover, many CPOs view data analytics as the best way of gaining actionable insights to support procurement practices related to negotiations, demand planning and risk management. The Deloitte survey also found that the top barriers to analytics-driven procurement agility are inadequate data quality, poor integration and lack of funding. The findings from our study will help CPOs to overcome these barriers and get their digital house in order.

Understanding the Hierarchy of Data Analytics Capabilities

Having identified procurement managers' expectations for data analytics, we then set out to gain an understanding of the data analytics capabilities required to meet those expectations. McAfee and Brynjolfsson discuss the managerial changes that must take place in an organization to effectively leverage data analytics.[7] They say that with big data, "managers can measure, and hence know more about their businesses, and directly translate that knowledge into improved decision making and performance." According to McAfee and Brynjolfsson, however, without the needed leadership, talent, technology, processes and culture, data analytics cannot achieve its full potential.

4 Details on how the surveys and interviews were conducted can be found in Shao, B. B. M. and St. Louis, R. D. *Data Analytics Teams and Procurement: Who and What*, Center for Advanced Procurement Strategy (CAPS) Research, 2018. All of the direct quotes in this article, except for a few otherwise noted, are from this report.

5 These organizations include six (30%) of the 20 major industry segments covered by the North American Industry Classification System (NAICS), and those six segments include 35% of the business establishments tracked by NAICS. Thus, the participating organizations provided a broad perspective on where organizations in different industries are situated with respect to the use of data analytics and how they arrived there.

6 *Agility: The Antidote to Complexity*, Deloitte 2021 Global Chief Procurement Officer Survey, available at https://www2.deloitte.com/content/dam/Deloitte/at/Documents/strategy-analytics/at-cpo-survey-2021.pdf.

7 McAfee, A. and Brynjolfsson, E. "Big Data: The Management Revolution," *Harvard Business Review* (90:10), October 2012, pp. 60-68.

Figure 1: The Analytics Hierarchy

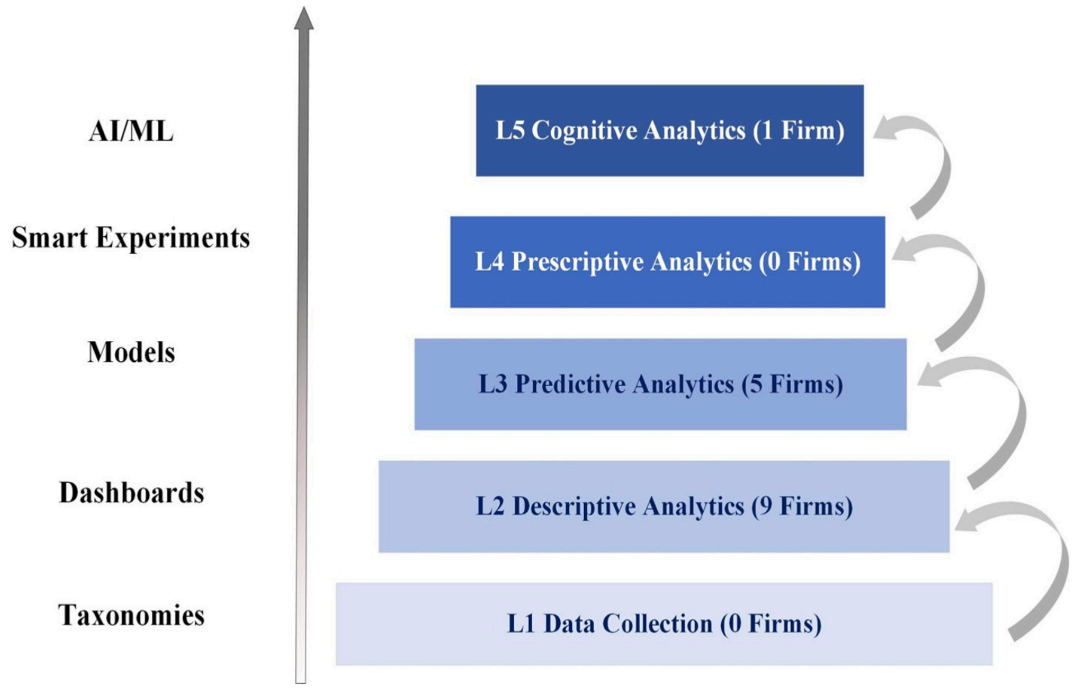

Figure 1 shows that data analytics can be divided into a hierarchy of descriptive, predictive and prescriptive levels,[8] with data collection (Level 1) at the bottom and cognitive analytics (Level 5) at the top.[9] (The figure also shows the number of firms in our research that were at each of the five levels.) The foundational Level 1 consists of sound processes for data collection. An organization cannot analyze data it does not have, and the quality of analytics depends on the quality of data. Robust procedures for data collection, cleaning, integration, governance and retrieval must be put in place before an organization can move up to the next level. Poor data governance would result in granularity that cannot support the analyses or makes it impossible to integrate data into a data warehouse.

Once an organization has sound processes for collecting, cleaning and organizing data, it can proceed to descriptive analytics (Level 2), which involves building dashboards, pivot tables and data cubes. Dashboards enable managers to monitor key performance indicators in real time, while pivot tables and data cubes enable them to drill down into the data to better understand what drives performance. The ability to monitor and track performance broadly and promptly, as well as to understand what drives performance, is essential to performance improvement.

The next level in the hierarchy is predictive analytics (Level 3) where models are developed from past data to predict future actions, behaviors and outcomes. In procurement, for instance, predicting the actions of buyers and suppliers is key to predicting supply chain flows, reducing inventory-carrying costs and preventing stock-outs. Loshin[10] argues that predictive analytics should be deployed as a cycle where as soon

8 The analytics hierarchy depicted in Figure 1 is based on a model formulated by Diana Shealy. See Shealy, D. *The Analytics Hierarchy of Needs*, DZone, March 2016, available at https://dzone.com/articles/the-analytics-hierarchy-of-needs.

9 Blum, B., Goldfarb, A. and Lederman, M. "The Path to Prescription: Closing the Gap between the Promise and the Reality of Big Data," *Rotman Management Magazine*, September 2015, pp. 45-49.

10 Loshin, D. *Five Steps to Build Better Predictive Analytics Applications*, TechTarget, December 2017, available at https://searchbusinessanalytics.techtarget.com/tip/Five-steps-to-build-better-predictive-analytics-applications.

as a new model is embedded in the operations, the model refinement starts again in a cycle for continuous improvement.

Level 4 is prescriptive analytics. Compared with descriptive and predictive analytics, prescriptive analytics is more context-specific and action oriented.[11] It provides insights into the consequences of actions by uncovering cause-and-effect relationships. By identifying the factors that determine outcomes, an organization can quantify the effect of future decisions and advise on possible outcomes before those decisions are made. Prescriptive analytics not only predicts what will happen but also explains why it will happen and hence recommends desirable actions. A key tool used for prescriptive analytics is smart experiments.[12] The goal is not to conduct perfect experiments, but to inform and make better decisions.

Level 5 of the hierarchy, cognitive analytics, is more nebulous. At this top level, sensor data, machine learning, artificial intelligence and robotics are used to optimize end-to-end workflows with little to no human intervention.[13] Although machine learning can be applied to predict the impact of manipulating different inputs on performance, managers cannot automate a process until they truly understand the business process and get it under control.[14]

Different skills are required for the distinct activities performed at each level of the analytics hierarchy. To move up the hierarchy, the skill set of existing data analysts must be expanded or analysts with the new skills must be hired. Managers must therefore understand where their organization lies in the analytics hierarchy before acquiring data analysts with the needed skills. Moreover, because each level depends on the levels below it, managers cannot assess the feasibility of analytics activities without first knowing where their organization is in the hierarchy.

Challenges of Moving Up the Data Analytics Hierarchy

In our survey and interviews, we investigated where firms were in the data analytics hierarchy in terms of leveraging data analytics for procurement and what was preventing them from moving up the hierarchy. Although nine of the 15 organizations we interviewed had not progressed beyond Level 2 (data integration, drill down, real-time dashboards and visualization), all had instituted best practices intended to enable them to move up the hierarchy.

Given that all of the organizations we studied are Fortune 500 companies, we were surprised how few had progressed beyond Level 2. Closer examination showed that progress did not depend on organizational size or on how long the company had been undertaking data analytics initiatives. Instead, progress depended on how well they responded to the challenges, described below, associated with moving up the analytics hierarchy.

Just one firm in our research had reached Level 5 and provides an exemplar of how to respond to the challenges. In the next section, we describe the best practices that were developed by this firm (which we call Firm L5) to respond to each of the challenges. Although we cannot reveal the identity of Firm L5, we note that it was at the median size for our group of firms and did not begin its data analytics initiatives any earlier than the other firms.

Challenge 1: Inappropriate Data Granularity

One of the most frequently mentioned challenges identified by the CPOs we interviewed was the inappropriate granularity of the data captured and stored. When data governance is weak and CPOs are not strongly involved with data governance, data usually is not collected at the level of granularity that is needed for spend analysis and contract management. The solution to the data granularity problem is to change the governance process for collecting and storing data. For example, procurement analytics can deepen the fundamental data collected from the

11 Vorhies, B. "Prescriptive versus Predictive Analytics: A Distinction without a Difference," *Machine Learning Times*, November 2014, available at https://www.predictiveanalyticsworld.com/patimes/prescriptive-versus-predictive-analytics-distinction-without-difference/4259/.

12 Anderson, E. T., and Simester, D. "A Step-by-Step Guide to Smart Business Experiments," *Harvard Business Review* (89:3), March 2011, pp. 98-105.

13 Goul, M., Raghu, T. S. and St. Louis, R. D. "APC forum: Governing the Wild West of Predictive Analytics and Business Intelligence," MIS Quarterly Executive (17:2), 2018, pp. 157-183.

14 Liker, J. *The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer*, McGraw-Hill Education, 2014.

finance function by integrating detailed supplier invoices into the ERP system, thus preserving a fine level of granularity on the type and quantity of goods and services purchased and adding new dimensions to spend analysis.

Challenge 2: Data Cleansing and Integration Difficulties

A second challenge identified by nearly every CPO was the difficulty of cleansing and integrating data. From the interviews, it is clear that many companies are struggling with data cleansing and integration because they do not have standardized processes and taxonomies for creating the data in the first place. As a result, they do not collect all of the needed data and much of the data they do collect is either inaccurate or inconsistent across systems. Many of them still use manual or semimanual approaches to data cleansing and integration, with the result that it can take weeks or months to generate reports. These approaches are costly and time consuming, and prevent procurement analytics from being scaled to more sources and varieties of data. Given this constraint, procurement analytics is often limited to the analysis of only a fraction of available data.

Challenge 3: Reluctance to Move Up the Hierarchy

A third and unexpected challenge that we found was the reluctance of CPOs even to attempt to move up the analytics hierarchy. Several CPOs simply were not comfortable with the idea of using advanced analytics. Although only one CPO explicitly stated an unwillingness to adopt advanced analytics, the majority of CPOs said that the bulk of their efforts were devoted to gathering data and descriptive analytics (i.e., Levels 1 and 2 of the hierarchy), with only one CPO stating that their organization had progressed beyond the predictive analytics (Level 3) of the hierarchy. We believe that the CPOs were reluctant to move up to the prescriptive analytics (Level 4) because they think this would involve complicated models rather than simple, easy-to-explain experiments.

They could learn from Firm L5, which has been actively involved in running simple experiments and using machine learning. Its CPO described this practice as follows:

> *"We're looking at reducing the process steps in the organization by doing experiments in different ways with two or three different suppliers in terms of reviewing contracts. We have two experiments online at the moment. First, rather than everything having to go to a person like it does today, we see if machine learning can react to the terms of the contract and autonomously deal with different scenarios. Second, we're only just starting to do an experiment with scraping tools on the Internet. I suspect we're going to pull a lot of information down from there to fill in the gaps in how we manage small spend and areas like that. At this moment in time, our roadmap is just to keep on piloting, and once we are absolutely happy with everything, then [we will] industrialize the activity and [bring it] in-house to our shared service team."*

Challenge 4: Showing Return on Investment for Data Analytics

CPOs also flagged the challenge of showing the return on investment (ROI) for data analytics. Two general themes were evident. The first was that demonstrating the ROI from investments in Level 2 (descriptive analytics) activities is relatively easy, but this ease hinders organizations from moving up to the predictive and prescriptive levels because demonstrating ROI for these higher levels is perceived to be much more difficult. The second theme was that when investment decisions are centralized, projects with relatively low ROIs have difficulty getting funded, even if their potential returns are substantial. There are two possible approaches for addressing this nearsighted issue: 1) the portfolio approach that takes a broader view of evaluating analytics projects in aggregate to seek opportunities for synergies; and (2) the option-valuation approach that looks beyond the present to explore the long-term potential of an analytics project.[15]

15 Pearlson, K. E., Saunders, C. S. and Galletta, D. F. *Managing and Using Information Systems: A Strategic Approach*, 6th ed., John Wiley & Sons, Inc., 2016.

Table 2: Summary of Data Analytics Challenges

• The level of data granularity tends to be inappropriate when data is captured and stored.
• Data cleansing and integration are difficult because of the lack of standardized processes and taxonomies.
• Manual or semimanual approaches to data cleansing and integration are time consuming and make it difficult to scale data analytics.
• Managers are reluctant to move beyond descriptive analytics to predictive or prescriptive analytics.
• Reliance on ROI to fund analytics projects can be misleading and can trap the organization at the descriptive level of the analytics hierarchy.
• Managers often do not see or acknowledge the benefits of data analytics.

Challenge 5: Finding and Hiring Analytics Personnel

Surprisingly, only one CPO felt that it was challenging to find analytics personnel with the required skills, and the majority did not feel that it was challenging to get the budget required to hire such personnel. Perhaps this is due to the recent high profile of data analytics attracting people into this emerging field and motivating organizations to allocate resources to analytics projects. However, it also may be because most of the organizations were at Level 2; finding personnel with the right skills will likely become more difficult as they move up the analytics hierarchy. Interestingly, it was the CPO of Firm L5 who said that finding people with the right talent was the greatest challenge, giving credence to this view.

Challenge 6: Persuading Procurement Staff of the Benefits of Data Analytics

The challenge that seemed to surprise CPOs most was the difficulty of getting staff within procurement, let alone the rest of the organization, to see the benefits of data analytics. The CPO of Firm L5 said:

> *"The hardest thing was getting the procurement team to recognize the benefits of the information. It allowed them to break down costs and have visibility. Getting them to buy into that was a huge challenge. Everybody likes to create their own little bit of magic and not share their own intellectual property."*

Other CPOs also echoed this sentiment.

The six data analytics challenges identified from the feedback provided by CPOs are summarized in Table 2.

Best Practices and Actions for Moving Up the Analytics Hierarchy

All of the CPOs that we interviewed had been developing best practices and taking specific actions to overcome the challenges identified in Table 2. In the words of one of the CPOs, "In procurement, we're early in the journey there. That was one of our objectives with bringing in a tool like Tableau, to give us the ability to start doing predictive analytics and some of those more advanced analytics." Below, we describe the five best practices we identified from our interviews with CPOs and the actions taken to implement them. Many of these best practices come from firm L5, the only one in our research to have reached Level 5 of the hierarchy.

The best practices are presented in the order in which they must be implemented. Best Practice No. 1 is concerned with capturing and storing data, without which there can be no data analytics. No. 2 ensures the right people are in place to turn the data into useful information and use that information to improve operations. No. 3 is for defining the vision that is required to guide people to create and use information to improve operations. No. 4 concerns interactions with data analysts, who must act to support the vision. And No. 5 ensures that organizational resources are leveraged, so that the vision can be accomplished.

Best Practice No. 1: Define Taxonomies and Processes for Capturing Data

The most commonly mentioned and fundamental best practice is to develop taxonomies for capturing procurement data. A taxonomy is a way of consistently organizing data for easier retrieval. It also provides a framework to help guide the storage of new data. An example of a taxonomy is The North American Industry Classification System (NAICS), the standard used by federal statistical agencies in classifying business establishments for the purpose of collecting, analyzing and publishing statistical data related to the U.S. business economy. All the CPOs recognized that, without taxonomies, it is impossible to get clean data or integrate data across platforms. Perhaps the most relevant comment on taxonomies was made by the CPO of Firm L5: "One of the best decisions we made was using the U.N. classifications for all our indirect spend." This action enabled Firm L5 to analyze its expenditures at a very granular level, identify the best vendors, prices and terms for each specific expenditure category, and make the risks transparent. Other firms developed their own taxonomies using machine learning or purchased software such as SpendHQ.

Although having a taxonomy is a necessary condition for success, it is not sufficient by itself. Unless a process is put in place to enforce the taxonomy, data will not be collected and entered correctly. The most salient comment from a CPO regarding taxonomies was: "In order to really standardize data and get it to a high level of quality and integrity, standard processes common throughout all the businesses are very important." Without clean data, an organization cannot reach even Level 2 of the analytics hierarchy. Hence this is the first best practice that must be implemented.

Best Practice No. 2: Get People with the Right Skills and Provide Them with the Right Tools

While CPOs noted that it was possible to find people with the needed analytics skills, they also believed that procurement analytics people should have both the technical skills (e.g., C++, Python and R) needed to collect and analyze data and the business skills necessary to explain analytics results and help make better decisions. The CPO of Firm L5 commented:

> *"They fall into three types of people. The first is what we call 'accountants' whom you call data analysts. They are trained to make certain that one plus one equals two. Second, we have IT software people who understand all of our internal systems and who are able to extract information from the systems and get it into a format that users want. The third is the data scientists who build the predictive models and create the automatic classifications."*

CPOs also stressed the importance of having dedicated analytics people within the procurement function. One said:

> *"We have a central team that is supposed to be doing data analytics, but if you want anything customized then they won't do it. That is why I had to hire a few people in my group to figure out what data is available and what can be done with it."*

Another told us:

> *"Logistics has been a black hole for us for many years because we don't manage that spend data ourselves. We have an outsource partner that pays our invoices and is responsible for auditing those invoices to our rates. They get the data and normalize it from all the different carriers, and put it into a data warehouse for us. By the time we get it, it's so summarized that it's almost not usable."*

Because of its size, Firm L5 went further and had dedicated data analysts in the procurement function and regions. Its CPO commented:

> *"The organization [has] a couple hundred data analytics people in total, but in procurement we have about eight people in the center and then from two to six in each of the four regions. We perform our own business intelligence on our functions in terms of spending."*

It is also important to equip data analytics personnel with the right tools (e.g., Tableau, SAP HANA, Oracle, Hadoop, Salesforce, Riva, QlikView, Hyperion, etc.). Some tools put information into the data lake,[16] some get information out of the data lake, and others create dashboards and

16 Data lakes and data warehouses are both widely used for storing big data, but they are not interchangeable terms. A data lake is a vast pool of raw data, the purpose for which may not be defined yet. A data warehouse is a repository for structured, filtered data that has already been processed for a specific purpose.

visualizations. Many of the CPOs in our research indicated that these tools are not as user-friendly as they should be. One commented: "Vendors who are divorced from the end-user experience can never speak the language to explain what it is their tool can do. They always talk about it from a technology perspective."

Other CPOs commented that providing procurement data analysts with the necessary tools is at the top of their agenda because having the right tools is essential to both data quality and the effective use of analytics results. One insightful comment was:

> *"The level of tools that might be utilized has been a huge differentiator for us as users. To be able to load data into pivot tools rather than spreadsheets, and to click on something and answer questions right away, makes a big difference."*

The CPO of Firm L5 said:

> *"I spent last week with four suppliers of new kinds of software, and I was at five different providers of information from the outside world. The graphics and some of the work that they are doing are going to make procurement so easy. It will allow us to break down costs for visibility."*

Best Practice No. 3: Define a Vision for Data Analytics in Terms of Value Add and Competitive Advantage

Every CPO emphasized the importance of having a clear vision for data analytics, and communicating that vision within the procurement function, across the organization and to partners. The CPO of Firm L5 succinctly put it in these terms:

> *"If you haven't got a clear vision of where you're going, why you're going there and what are the benefits you want to get out of it, I think you'll end up going down cul-de-sacs. We have gone down cul-de-sacs in the past because we weren't absolutely clear what we wanted to do with the information, or we hadn't clarified what the benefits would be to the organization. Clarity of purpose is essential."*

Firm L5 even incorporated a value-adding component into its data-capture processes. Its CPO stated:

> *"We have a system now to define the processes. I prefer to define the outputs first, and then figure out the processes. I don't like going the other way around because it ends up being the tail wagging the dog. I always like to figure out: if we knew the answer to that, how would we drive value?"*

Focusing on whether and how the information is going to drive value was a key for this organization to reach Level 5 in the analytics hierarchy.

Another CPO commented: "[It's] been a struggle getting people to understand the value of the data. I didn't anticipate that. You must find ways to communicate in language that makes sense to them." The procurement function is tasked with some of the most critical business decisions, as emphasized by one CPO: "There's a strategic sourcing component from which a lot of the value comes, and that helps us identify marketplaces, identify spend and build strategies as we negotiate with our suppliers. The data provided allows us to put all that together and develop a strategy." The CPO of Firm L5 also stated: "I see a lot of work that my team and my colleagues have to do to get to an area where we have a strategic advantage on data analytics."

The CPOs of firms that were beyond Level 2 all believed that demonstrating how data analytics adds value and contributes to competitive advantage is the only way to get buy-in from commodity managers and top executives. Without that vision, and buy-in to the vision, useful analytics results either will not be produced or will not be used if they are produced.

Best Practice No. 4: Ask for Solutions to Problems, Not Data

Having the right data, the right people and tools, the right vision and buy-in to the vision are not sufficient to ensure the success of data analytics. An additional necessary condition is having the ability to interact appropriately with data analytics personnel. According to the CPOs we interviewed, the best approach is not to ask data analysts for data, but rather to ask them to help solve a specific problem. As one CPO stated:

> *"The issue is for us not to tell them what we need them to pull, but what we're trying to solve. This gets away from a tactical descriptive definition and allows them to become more of a team member. It's letting them be creative in coming up with a solution."*

The CPO of Firm L5 further commented: "I prefer to ask 'how's that answer going to help us?' And from that, you can figure out if it is worth investing in the process or a system or software—putting time into something to see if we can drive value."

CPOs believe that it is important to ask analytics personnel to deliver solutions and show how they drive value, and not just request data. Doing this helps cut down on wasted time as managers no longer need to go back and forth with the analysts about what data is needed. In addition, it allows CPOs to leverage the problem-solving capabilities of procurement analytics personnel, transforming them into business partners who are empowered to improve organizational performance rather than treating them as employees who simply fulfill requests for data.

It also is interesting to note that CPOs want to keep the focus of analytics on improving business operations, not on preparing scorecards. This seems like a productive way to use analytics. If CPOs do not interact with their analytics personnel in the most appropriate way, and if analytics is not used in the right way, then having the right data, people, tools and vision will not result in improved procurement.

Best Practice No. 5: Collaborate with the IT Department and the Enterprise Analytics Team

Every company has limited resources. Even when CPOs have collected the right data, hired the right people, provided the right tools, formulated the right vision, secured buy-in to the vision and interacted with analytics personnel in the most appropriate way, they still have to make the best use of the resources that are available to them. The CPOs we interviewed believe that procurement analytics personnel must collaborate closely with both the IT department and the enterprise data analytics team. Close collaboration with the IT department is necessary because: 1) procurement analytics personnel cannot do anything without data, which will most likely be collected through the IT department; 2) procurement data analysts must make data collection scalable, and this cannot be done without the help of the IT department; and 3) procurement analytics personnel need the help of the IT department to enforce uniform data quality standards, share infrastructure and adopt common analytical protocols. The CPO of Firm L5 stated: "Our relationship with IT is excellent. We have one person from IT at a strategic level when we go out evaluating new software or new capabilities, and that person is there to say whether it will work or not."

Procurement analytics personnel also need to closely collaborate with the enterprise data analytics team because: 1) the larger enterprise data analytics team can hire and retain individuals with highly specialized skills that the procurement function cannot afford; 2) procurement data analysts need to have access to the specialized knowledge, tools, infrastructure and data lakes that belong to the enterprise data analytics team; and 3) the enterprise data analytics team can provide both training and mentorship for procurement analytics personnel. Firm L5 has several hundred people in the corporate data analytics team, but only 16 in the procurement function. The procurement data analysts initially define the processes for collecting, analyzing and presenting information, but once they are happy with how a process works, they standardize the activity and hand it over to the enterprise data analytics team.

Guidelines for Moving Up the Analytics Hierarchy

Our study shows there are no shortcuts to reaching the top of the analytics hierarchy. Instead, there is a set of best practices that need to be followed. To provide more specific guidelines for moving up the analytics hierarchy, we have divided the best practices into two paths that a company must simultaneously follow to assemble and organize high-performance analytics personnel for the procurement function. The first is a technical path and the second a cultural one.

Figure 2: Path of Technical Best Practices

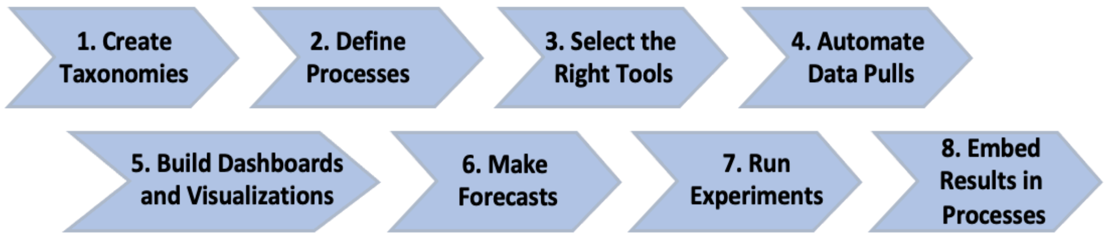

Figure 3: Path of Social Best Practices

Figure 2 outlines the path of technical best practices for moving up the analytics hierarchy. CPOs stressed the need to develop a data taxonomy and define a process that ensures the taxonomy is followed. They also emphasized that automation and machine learning can be used to scale data collection and categorization. Once the data is stored in a data lake, it needs to be made accessible to data analysts and managers. This will only happen if user-friendly tools are available that allow analytics personnel to create dashboards, enable drill down, construct data visualizations and provide self-service analytics capabilities to nontechnical managers and support staff. After the data is thoroughly understood, the organization can move on to forecasting so that it can better understand the demands, risks and opportunities in its business environment. Finally, to know what to change, organizations must run smart business experiments and use machine learning to embed the results of those experiments into their business processes.

Figure 3 outlines the path of social best practices for moving up the analytics hierarchy. First, as stressed by CPOs, it is important to get support from top management. It is very difficult to move up the analytics hierarchy if top leaders are not convinced of the value of data analytics. The CPO of Firm L5 got top management on board by showing that analytics could create something that "our customers see value in that is different, and where nobody can take us on in that space."

CPOs also noted the importance of close ties with the IT department. IT personnel understand what data is available, what problems exist with the data and how to extract the data. It is wasteful to duplicate that effort in the procurement and other business functions. However, the most important social factor relates to how functional managers work with analytics personnel. Managers should not tell data analysts what data needs to be pulled but rather what problems need to be solved. Finally, in the context of procurement, it is crucial to convince category managers of the value of data and promote successes that stem from the use of data analytics.

Concluding Comments

Many companies are employing analytics personnel to put structured and unstructured data to work in their organizations. In this article, we have described the analytics hierarchy and identified the best practices that have been developed by various organizations to move up the hierarchy.

Though our research focused on the procurement function, these best practices can be applied to other functional units as an organization works its way up the analytics hierarchy. In particular, data analysts in functional units need to collaborate closely with the IT department, because several of the best practices specifically need the help of IT personnel or rely on relationships with them. While each company has its own unique challenges to address, our study shows that, to improve organizational performance, there is a set of best practices that every company can follow to effectively build, structure and interact with data analytics personnel.

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