SHRM-SIOP Science of HR White Paper Series

Trends and Practices in Talent Analytics

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ABSTRACT

Increasingly, organizations are investing in or upgrading their efforts in talent analytics. Based on 22 interviews with academics, consultants and practitioners at 16 corporations and other talent analytics experts, this paper offers a review of key approaches, competencies and tools. Examples of sophisticated talent analytics projects to address human resource challenges and organizational dynamics are also provided. We find that successful talent analytics depends on mandates, structure and operationalization, and responses to obstacles. By classifying talent analytics work into three broad categories—data infrastructure and reporting, advanced analytics, and organizational research—we offer a high-level roadmap for building and growing the talent analytics function.

Executive Summary

What kind of work is being done in talent analytics? What is required to set up and run an effective talent analytics function? These are the questions that we sought to answer through 22 interviews with academics, consultants and practitioners from a mix of industries (technology, banking, automobile and pharmaceutical).

What kind of work is being done in talent analytics? Recognition of the value of talent analytics is accepted by both business leaders and the human resource (HR) community. Some fundamental practices are widespread: reporting infrastructure, dashboard for HR metrics and employee surveys. About half of the organizations in our sample also perform statistical analysis and modeling of data, and a few have exceptional practices worth emulating. However, most organizations have a fragmented or inconsistent approach to talent analytics. Existing problems include a lack of adequate skills and resources and competing priorities that hold back practitioners from more advanced analytics.

Advanced technologies such as machine learning and artificial intelligence (AI) are still in an experimental phase in HR. Apart from skills and resources, obstacles include the unavailability of clean data, which, in turn, results from spotty quality control or legacy HR systems.

What is required to set up and run an effective talent analytics function? Talent analytics teams, especially when serving organizations of more than 1,000 employees, tend to have in-house or borrowed data analysis skill, knowledge of industrial/organizational (I/O) psychology and good IT support. The most successful talent analytics teams tend to report directly to HR leadership and centralize research and analytics. It is also important for analytics to be a visible part of the HR strategy of the chief human resource officer (CHRO). Centralized analytics enables an organization-wide view, which leads to greater impact. However, even with a centralized talent analytics function, close partnership with line HR is imperative. It enables better contextualization of data and improves the data-oriented mindset throughout HR. Finally, HR practitioners must consider ethical and legal considerations of data collection and decision-making.

Based on a snapshot of the 16 companies, together with the content of our interviews and literature review, we reveal potential trajectories for building and growing a talent analytics function. Our analysis finds three components of a mature talent analytics function: 1) data infrastructure and reporting, 2) advanced analytics, and 3) organizational research. Data infrastructure and reporting are the obvious place to start for most companies. It is difficult to do more advanced analytics or research without a clean, well-organized body of data on which at least basic statistics and trend analyses can be performed.

Advanced analytics refers to the use of more sophisticated analytical tools often applied to a more diverse set of data to arrive at deeper insights. For example, correlations between employee satisfaction surveys and standard HR data (such as salaries and promotion rates) may allow predictive modeling of employee retention and attrition.

Organizational research refers to scientific studies about HR issues that often have implications beyond a single company. It seeks to answer questions such as these: What are the distinguishing traits of effective teams? Why are women underrepresented in leadership? What are the best methods for recruiting new hires?

We find that after data infrastructure and reporting, the next step can be either advanced analytics or organizational research. Either way, additional data analytics capacity that is beyond traditional HR training is required. Some mature talent analytics functions concentrate resources on just one or the other (advanced analytics or organizational research); others eventually opt for the full complement of talent analytics capability.

While there is no one-size-fits-all solution for building a high-performance talent analytics function, an understanding of strong models and recent trends can inform next steps for any organization.

Introduction

Talent analytics—also known as "people research," "workforce analytics" and other labels—is the attempt to understand patterns in an organization's workforce through analysis of employee-related data. It has a decades-long history, though not necessarily in the form we know it today. In 1984, Jac Fitz-enz wrote the seminal book *How to Measure Human Resources Management* in which he emphasized the need to measure the impact of HR's work. And if talent analytics is about measurement, then it has been around for at least as long as the field of industrial/organizational psychology, which has its roots in the early 1900s (Landy, 1997). Starting in 2010, talent analytics became a buzzword, piggybacking on the excitement around "big data"—digital data defined by its tremendous volume, velocity and variety. A spate of articles and literature heralded the entry of big data in HR and the ways in which it would change the HR landscape. However, no such revolution took place in HR. In his 2010 white paper "Are We There Yet? What's Next for HR," Dave Ulrich contended that HR functions are still lamenting their status as administrative and compliance functions. He advised HR to embrace talent analytics to elevate the function as a full partner to the business.

Change is coming, but in most companies talent analytics is still a fledgling activity. Deloitte's *Global Human Capital Trends* (2015) pointed out that "talent and people analytics are a high priority and a tremendous opportunity, but progress is slow." The study found that only 8% of the companies surveyed claim to have a "strong" talent analytics function. The firm's 2016 study found that only 8% of the companies (up from 4% in 2015) surveyed were "correlating HR data to business outcomes, performing predictive analytics, and deploying enterprise scorecards," and the 2017 study revealed almost no change.

With this context in mind, we sought to understand what companies with a focus on talent analytics are actually doing. We sought answers to two questions: First, what kind of work is being done in talent analytics? Second, what is required to set up and run an effective talent analytics function? The answers reveal effective practices and provide models for emulation.

Methodology

We gathered information through interviews and a literature review. We conducted 22 interviews over a span of three months (December 2016 through February 2017). Out of 22 interviews, 16 interviews were held with practitioners in a variety of companies in terms of size (revenue and number of employees) and industry. Where we have permission or refer to published information, we use actual company names; otherwise, we have used a consistent masking scheme: Company A, Company B and so on. These companies are not a random sample of organizations, and they do not include all organizations that are doing talent analytics work. Our participating companies were chosen because they are known to have a strong focus on talent analytics. The six subject matter experts whom we interviewed were either academics, consultants with deep experience in talent analytics with their client organizations, or part of cutting-edge HR-tech product development companies.

We used a semi-structured interview approach starting with a standard set of questions and improvising follow-up questions according to context and response.

The literature review focused on surveys conducted by consulting firms, white papers written by the industry thought leaders and research papers published in peer-reviewed journals.

The qualitative data from our study were distilled into three broadly defined categories of work, a list of technologies and tools used, and several classes of common challenges. We were then able to construct coarse-grained trajectories for growth of talent analytics by sorting our study participants in rough order of the maturity of their talent analytics functions.

Definition of Talent Analytics

Talent analytics is known by different names: people analytics, HR analytics, workforce analytics, people research and analytics, and HR business intelligence. And just as with the name, there is no standard definition (Marler & Boudreau, 2017). On the one hand, Lawler, Levenson and Boudreau (2004) suggested that HR metrics and HR analytics are different. They wrote that HR analytics involves "statistical techniques and experimental approaches" to show the impact of HR activities on the organization's performance metrics. According to them, HR metrics by themselves are simply measures of outcomes emanating from the HR function. On the other hand, Bassi (2011) reported that HR analytics "is an evidence-based approach for making better decisions on the people side of the business; it consists of an array of tools and technologies, ranging from simple reporting of HR metrics all the way up to predictive modeling."

For the purposes of our study, we used Bassi's definition in which any work spanning the gathering of HR data and decision-making about talent constitutes talent analytics. We identified three categories of work: a) developing the infrastructure for tracking HR data and metrics—we will refer to this as "data infrastructure and reporting"; b) statistical analysis, model-building and application of data science techniques—"advanced analytics"; and lastly, c) developing and deploying experimental approaches to solve business problems in the short and long run—"organizational research."

Findings

Kathryn Dekas, the head of the People and Innovation Lab at Google, summed up the objective of talent analytics as a means "to elevate problem-solving by making it evidence-based." This description nicely captures the goal.

CATEGORIES OF WORK

Work done within HR analytics falls into the following three broad subfunctions:

- **Data infrastructure and reporting** to capture, store and report HR-relevant data and metrics.
- **Advanced analytics** focused on data exploration, analysis and modeling primarily at the enterprise level.
- **Organizational research** comprising scientific studies related to specific organizational problem statements.

Talent analytics priorities are often planned for a particular financial year with acknowledgement that some priorities may change. After the priorities are set, organizations employ different approaches to determine the execution plan.

One such approach is the *value-chain* approach, which considers talent analytics to be a sequence of discrete activities. For example, if talent retention is the priority to be addressed, an end-to-end talent analytics work flow would involve the following steps (Fink, 2017):

1. Asking the right **question**.
2. Identifying the right **method** to answer that question.
3. Locating or generating the **data** to answer the question.
4. Effectively and appropriately **analyzing** those data.
5. Developing **insight** based on the analyses.
6. Taking **action** based on that insight.
7. Measuring **results** to determine whether the action was effective.

Though some organizations, such as Companies A, B and C, have teams housing interdisciplinary skills that can deliver on the entire value chain consistently, most companies do not traverse the entire value chain for every class of problem. Many organizations commonly practice some aspects: gathering data, observing trends and patterns, and arriving at insights. Other aspects are rarer: building predictive models, performing experimental research and measuring long-term impact.

Examples of the work and problem statements that the talent analytics teams handle are shared below within the three categories. These examples have also been collated in a tabular format in the appendix.

I. Data Infrastructure and Reporting

Data infrastructure refers to the systems to source, store, maintain and query data at high quality and in a consistent manner. Though this infrastructure depends greatly on the information technology required for these activities, it is also about the policies, culture and practices of people who handle data. *Reporting* is the activity of providing summaries of the data in various forms, usually to business leaders. It may require simple statistics, such as means, standard deviations and hypothesis tests. Together, data infrastructure and reporting are the bread and butter of all HR analytics, without which other categories of analytics work is difficult to perform. In this section, we discuss infrastructure and reporting but also the closely related issues of data sourcing and dashboards.

Data Sourcing: The first step in talent analytics is to source data. For the most part, talent analytics appears to focus on data generated and maintained by the HR function. This is a good place to start, but the true potential of talent analytics emerges when data across functions are combined. Rasmussen and Ulrich (2015) wrote that "analytics typically only yields truly new insights when multiple fields and perspectives are combined (investors, customers, technology, human capital, safety, etc.), so any functional denomination prior to 'analytics' is really just a sign that it has not yet matured enough."

Few talent analytics teams include cross-functional perspectives, and even fewer teams use data from functions beyond HR, such as finance, sales, procurement, facilities, marketing or engineering. The reason seems to be in part because the teams are at a nascent stage and have not yet organized their own HR data, or they are still trying to break through organizational silos.

However, the exceptions are indicative of vast future potential. Company D used sales performance data combined with network information to show that high-performing teams were typically the ones that were better connected as a group (either a specific function, or geography, etc.). Similarly, Company E used both internal HR data and external market data to build a predictive model for where compliance issues may emerge in the future. For developing the talent sourcing strategy, several companies in our study use external data (like labor market reports and cost-of-living indices) to identify which locations to target. And Company A ensures that talent analytics project teams have representation from HR, employees, managers and cross-functional teams. Using this approach not only brings in holistic perspectives but also facilitates acceptance and implementation of solutions. In addition, inclusion of project team members from outside of the HR function can help reduce organizational barriers in accessing cross-functional data.

Data cleaning is a vexing chore for most data analysis tasks, and this is just as true for talent analytics. Typically, data are housed in multiple systems. Combining datasets and validating data are time-consuming and can be error prone: There are flawed data in legacy systems, quality issues in data gathering processes, mundane human errors, and the proliferation of multiple spreadsheets and local files—all of which increase error and conflicting bodies of data. Some organizations proactively create their own data lakes, extracting, transforming and loading multiple feeds into a single, queryable database. This method can reduce time spent managing the data themselves and free up time for analysis, insight and action.

Reporting: Every company we spoke with has institutionalized reporting of HR data. In nine out of 16 companies surveyed, the reporting function is part of talent analytics. For other organizations, however, reporting is intentionally kept separate from the talent analytics function. Amit Mohindra, head of talent analytics at Apple, explained that "due to the ever-increasing demand for HR reporting, the analytics work often gets crowded out." He added that reporting tasks can be readily distributed across HR operations, but analytics benefits from centralization or centralized coordination. Lorenzo Canlas, head of talent analytics at LinkedIn, suggested that to protect talent analytics from the incessant demands of reporting, "the success criteria are defined before the work begins or even the data is collected." In other words, reporting itself must happen with an end objective in mind.

Regardless of the structural relationship between analytics and reporting, all of our study participants agreed that talent analytics must have access to all relevant data and the power to influence the type and quality of data that the reporting team generates.

Rick Guzzo, co-leader of Mercer's Workforce Sciences Institute, partners with companies to architect their talent analytics function. He told the story of a company that wanted to create a more diverse workforce and expected its hiring team to address the issue. However, reporting and data analysis suggested that the hiring team was already inducting a very diverse talent pool and that retention was the problem. The conclusion led the organization to direct resources more appropriately. Guzzo said, "Baseline reporting and exploratory data lends immediate baseline credibility for the analytics function."

Dashboards: The next step up from reporting is dashboards that comprise critical HR metrics. In all the companies surveyed, talent analytics participates in designing and communicating dashboards for the executive leadership level. Here, defining clear metrics is crucial. How exactly is good or bad attrition calculated? What costs does cost-per-hire include? When and how do we measure quality of hire?

Dashboards can allow for exploratory analysis wherein undesirable scores and trends immediately flag a need for further investigation.

IT Infrastructure: The infrastructure used for reporting and creating dashboards can be developed in-house or bought from vendors. Reporting is usually generated through the human resource information systems (HRIS). Often, since the HR IT systems are not integrated, HR reporting is supplemented with customized software or manual work that integrates data from different sources.

Dashboard infrastructure ranges from Excel and online dashboard tools to in-built dashboard features in HRIS systems and customized dashboard software. Often, HR partners with the IT team to implement IT infrastructure or hire external vendors. In some companies, like Companies A, B and F, the talent analytics teams are more directly involved in the building of infrastructure that generates data for reporting, dashboards and advanced analytics. Their goal is to control end-to-end data management and data quality for analytics. While the primary focus of HR IT infrastructure development is to integrate internally generated data, there may also be value in data integration with external HR service providers such as those that conduct assessments, provide talent development and manage employee giving.

II. Advanced Analytics

Advanced analytics—beyond reporting and basic statistics—is the category of work in which much of the new promise of HR analytics lies. Below, we discuss a few examples.

Decoding Employee Engagement: A key concern of any enterprise is employee engagement and retention. Every company in our study conducts an employee satisfaction survey at least once a year. Some companies, like Companies I and J, conduct the survey twice a year—one full-fledged survey and one shorter pulse survey. A few even have more frequent assessments with smaller samples of employees to gain feedback on a monthly or even daily basis. Very often, companies outsource the administration and even the analyses of such surveys.

There are three main types of analyses with employee survey data: a) basic statistical analysis of numerical scores, b) text analytics on open-ended data and c) predictive analysis. All our companies use basic statistical analyses, especially to compare scores across demographic groups.

Text data, however, are treated in a variety of ways. Every company sees its importance in providing color commentary to the numerical scores, but how they analyze text data varies. Some companies manually label data to understand key themes. Companies A, D, F and K optimize their text analysis work by asking employees to tag their comments with one or more of a discrete set of labels (e.g., career, training, manager). This kind of tagging eliminates the need to manually classify comments and simplifies the identification of topics. A few companies have also tried sophisticated computing technologies to do topic clustering and sentiment analysis, but with less than satisfactory results.

Companies A, D, E, G, I and K tie employee responses back to other data to build predictive models. For example, correlations of past employee satisfaction and manager ratings with employee exit dates may show trends that could predict future attrition. There is a tension, however, between powerful models and employee confidentiality, because such correlations are easier to draw if individual data from one source can be matched to the same individual's data from another. When surveys are anonymous, many forms of deeper analysis cannot be conducted. In any case, proper communication to employees about the degree of confidentiality is essential to maintaining trust, increasing participation and ensuring honest responses.

Building Staffing Plans: The most prominent use of data analysis in staffing involves workforce plans and models to forecast hiring needs and identify quality talent pools. Mohindra cautioned that robust workforce planning requires a range of conditions, including trust between HR and finance, a disciplined approach toward planning, a way to track talent supply and demand, and integrated systems. He suggested that even while these conditions are being built, organizations are well served by investing in analytics, because it can provide decision-makers relevant information about employees and the external labor market.

LinkedIn offers a concrete example of workforce analytics augmenting recruitment efforts: During a period of rapid growth, the talent analytics team gathered information about all key positions and the hiring need for those positions. The team built a 12-month forecast model. One of the outcomes was a clear recruiting capacity forecast, which led to an allocation of recruiters aligned with business need. The exercise saved the company 15% of its recruiting budget in its first year.

We also came across other kinds of analytics that enhanced recruitment strategy. For example, Company I regularly uses labor market data to identify where it can find relevant talent. This influences which college campuses it visits and where it sets up new offices. Similarly, Company E analyzes airport traffic patterns, hotel use, education migration and other macroeconomic factors to determine where the talent is.

Strengthening Management Excellence: Employee engagement survey data are also used to understand managers and good management practices. Company J uses employee survey data to look for combinations of practices that make for good managers, defined as those who oversee high-performing teams, have low turnover and whose employees express high job satisfaction in surveys. After conducting a variety of analyses and referencing external best practices, the team at Company J identified a set of 13 characteristics. This index has been used as the basis for a peer-led program for building manager capability.

Another example is Project Oxygen, started by Google in 2009 and containing 10,000 rows of employee data and more than 100 variables (including performance reviews, award nominations and employee feedback surveys). Statisticians began "looking for patterns" (Bryant, 2011) and arrived at eight characteristics of good managers. Google then used these eight characteristics to guide management development programs.

Measuring Training Impact: Most companies do not measure training impact, or if they do so, it is on a one-off basis. For example, Company P's talent analytics team was asked to assess the effectiveness of a set of employee wellness trainings. The team used an experimental design with control groups to evaluate the impact of one set of trainings over five years. It measured statistically significant impact on promotions and performance.

Some companies, however, do regularly asses training impact. Company H considers impact measurement of employee and leadership development programs to be a core part of its work. It regularly reviews employee behaviors and performance indicators and measures the impact of programs over time. The company goes beyond simple measures like employee feedback and uses more objective data to make comparisons across employee groups.

Enabling Talent Movement: Talent Analytics can enable talent movement. For example, Company P compiled historical data about internal mobility (like promotions, lateral movement, and cross-geography and cross-functional transfers). Analysis of these data suggested that talent mobility led to higher employee engagement and improvement in employee turnover. The company then chose to facilitate such talent movement across the company.

Dawn Klinghoffer, general manager of HR Business Insights at Microsoft, shared a similar example. Her team analyzed talent mobility data to understand its impact on employee engagement and retention. After looking at an array of data, the team discovered that employees who had made a recent job transfer within Microsoft were more positive about their career and more engaged than those who did not experience similar mobility. This finding led the company to simplify the process of job transfers.

Developing Predictive Models for Hiring, Retention and Attrition: All the companies in our study have either built or are in the process of building predictive models for issues such as hiring, retention and attrition. On their own, it is not clear that these models significantly affect HR decisions. However, when combined with broader business problems like workforce planning, diversity and internal mobility, some companies experienced meaningful changes. Company L clarified that its predictive models are used to better understand root causes of attrition but not necessarily to make decisions about model outcomes. In other words, models inform but do not dictate decision-making. Even the predictive models themselves can sometimes be difficult to understand. Fred Oswald, professor in the Department of Psychology at Rice University, noted that "some predictive models cannot pinpoint the individual variables responsible for predicting attrition, because all of the predictor variables end up being used in complex ways."

Oswald continued, "This complexity makes predictive modeling more effective, but potentially more challenging to defend legally." Even if models are built on data, if they are the reason for decisions that discriminate based on race or gender, for example, the company may run afoul of Title VII of the Civil Rights Act. This is a challenging issue because avoiding possible discrimination in predictive modelling is not as easy as leaving out race, gender and other variables. Hidden correlations may lead to inadvertent discrimination even when the variables in question are not explicitly incorporated. Here, it is critical that groups whose membership understands both law *and* data science have a say in how analyses are used. (Further ethical and legal considerations are discussed later in this paper.)

Designing Employee Benefits: Compensation and benefits teams have traditionally used a variety of data like external benchmarking, labor market reports and internal HR data to inform the design and continuous improvement of its offerings. As a result, these teams immediately see the value of talent analytics.

An example is Company M, which undertook careful analysis of its employee demographics, qualitative feedback and attrition trends to determine that a one-size-fits-all approach for benefits is suboptimal. This outcome led to the company making its parental leave policy more flexible.

III. Organizational Research

Organizational research is our third category of HR analytics work. It includes studies or experiments conducted to address a specific, one-off organizational question. Usually, these efforts involve sophisticated data science and considerable advance planning, and while they may be led by an HR analytics team, they can also be run by teams whose primary focus is research, not HR. Some of the work already described in the previous section on advanced data analytics is often performed as a component of organizational research. Below are other examples.

Understanding Team Dynamics: Team satisfaction, collaboration and performance are important issues. Duncan Watts is a Microsoft researcher widely known for his pioneering work on social networks. He used company data to understand what predicts team satisfaction. Watts and his team conceived a multiyear project called Organizational Spectroscope that combines data generated from productivity software (e-mail, calendar, document, authorship and similar digital traces) with more traditional forms of data like "job titles, office locations, and employee satisfaction surveys" and used a variety of statistical modeling techniques to predict team satisfaction. There were many detailed findings, but one example was that 93% of the time, "email response time between the manager and direct reports (longer is worse)" could predict the bottom 15% least-satisfied teams.

The workforce research team at Eli Lilly tried to understand a different aspect of team dynamics by studying the enablers of successful partnerships. In a project called the Voice of the Alliance, the team measured what Lilly employees thought about external partners (alliances) and the success of the products (both technical and commercial) they worked on. The study showed that the more conflict the groups felt, the stronger the outcomes were. Conflicts emerged from the group members needing to defend their rationale and thus engaging in healthy debates, which pushed them toward more substantial learnings.

Google's project Aristotle, which started in 2012, sought to understand what makes some teams more successful than others. The project team gathered data over two years through "200+ interviews with Googlers (our employees) and looked at more than 250 attributes of 180+ active Google teams" (Rozovsky, 2015). After reviewing data like employee education backgrounds, interests, hobbies, personality traits, out-of-office socialization and technical skills, the project team could not find any obvious patterns that distinguished high-performing teams from others. The team eventually recognized the importance of group norms or unwritten rules, and further research revealed specific norms that were critical—with "psychological safety" ranking at the top.

Improving Diverse Talent Representation: Several companies are designing studies to surface hidden biases and behaviors in hiring. For example, Company C first gathered data across the company and created a visualization to highlight representational gaps. Then, the company led an experiment in which the control group received resumes in their original format, and the treatment group received resumes in which the names and other information identifying race and gender were obscured. Differences in the hiring patterns of the two groups revealed how implicit biases worked against diversity.

At Eli Lilly, the workforce research team sought to understand the variables that led to leakage in the women's talent pipeline. Leakage was explored from the perspective of a combination of leadership decisions (both beliefs and assumptions) and individual employee decisions (both original intent and unintended withdrawal). The team collected a variety of qualitative and quantitative data, including network data from a previous organizational survey. The conclusions that emerged highlighted the importance of dispelling long-standing myths—such as that women don't desire higher positions or that women don't have what it takes —and of focusing on the actual areas that seemed to affect leakage, including barriers related to delaying family decisions, dual-career spouses, lack of senior leader networks, household obligations and assumptions from supervisors about capacity (not capability) that produce a damaging cumulative effect over time. Just as there is no magic bullet, there is no one solution that could be identified—instead, many small interventions proved to be key in helping prevent pipeline leakage, such as addressing misconceptions about women, promoting a more inclusive culture, enhancing work/life balance and providing support to overcome barriers.

Improving Staffing Processes: While some studies and experiments may be a one-time process, others are part of an ongoing effort to improve core HR functions. Company I regularly tests its staffing processes by comparing candidate responses to different approaches. For example, to evaluate the best way to approach candidates in terms of the language or medium used (e.g., LinkedIn, e-mail, phone), Company I evaluates the candidate response to different approaches and adopts the one with the best response for the target demographic.

Determining Organization Design: One of the companies we studied wanted to see if teams should be manager-led or self-managed. The company's talent analytics team undertook a two-year experiment with control and experimental groups. Pre- and post-data about business results (customer satisfaction, costs, revenue) and people results (engagement, retention) showed self-managed structures to be superior.

TALENT ANALYTICS METHODOLOGIES

Our interviews revealed several categories of analytic methodologies in use across talent analytics practitioners, including some emerging practices.

Basic Statistical Analysis and Modeling: Basic statistical analysis is commonly used across organizations. These techniques include sampling (using data from only a subset of a larger population), hypothesis testing (e.g., t-tests, ANOVA), factor analysis (a method for identifying the most significant contributors to some outcome) and regression analysis (estimating relationships among variables). Though a basic understanding of statistics is needed to use these techniques properly, their output can be intuitively understood even with little formal training.

Visualization: Data visualization involves intentionally designed graphics to represent data. It can involve everything from simple pie charts and bar graphs to interactive animations that allow in-depth data exploration. All the companies in our sample use data visualizations at varying degrees of sophistication.

Evan Sinar, chief scientist and vice president of the Center for Analytics and Behavioral Research at DDI, said that data visualization skill is "essential in exploring, explaining and most importantly, engaging an audience in the outcomes of an analytics project." He pointed out, however, that "as a discipline, visualization has been so far underutilized in HR; despite its strong potential to influence stakeholders and decisions." He recommended that talent analytics teams should familiarize themselves with various forms of visualizations and the type of data that they are most suitable for to enhance their communication effectiveness. Most HR professionals are familiar with bar charts, scatter plots, histograms, pie charts and line graphs, but other visualizations are worth investigating: alluvial diagrams, sunburst charts, streamgraphs, slopegraphs, circle packing, horizon charts and parallel coordinates, among others.

Artificial Intelligence and Machine Learning: There is no single definition of either *artificial intelligence* (AI) or *machine learning*; both phrases represent entire fields of study. What they have in common is an attempt to perform intelligent analysis by computer—to mimic the human brain and even to surpass human intelligence. Though the underlying techniques of contemporary AI and machine learning often boil down to statistics, their level of sophistication goes far beyond regressions and factor analysis, and they are designed to identify patterns in extremely large, complex bodies of data.

In our study, we found very few companies using machine learning for talent analytics. The exceptions were large companies with more than 25,000 employees. The limited use of machine learning technologies in HR is explained both by the difficulty of hiring for these skills and by the fact that the infrastructure and resources to process vast amounts of data are not yet in place. Simply understanding what the tools do requires considerable formal training. Furthermore, domain understanding is still required both to apply machine learning tools and to interpret their output. It is difficult enough to attract data scientists to work in talent analytics, but data scientists with HR domain knowledge are even scarcer. From a technical perspective, the precondition for using these algorithms is large amounts of relatively clean data; otherwise, there is the risk of "garbage in and garbage out." Finding clean data, however, in HR can often be extremely challenging.

Intel (Saffron) and IBM (Watson Talent) have their own AI-based "cognitive computing" products, and they use these products within HR. Over time, it seems likely that AI and machine learning will have powerful impacts on the full range of HR decision-making.

Automated Text Analysis: One AI subdiscipline is *natural language processing* (NLP) or *automated text analysis*, in which computations on regular prose text allow for classification and some degree of understanding of the content.

In our study, we found that most companies rely on manual text analysis. But there are attempts toward more automation. The talent analytics team at Company B, for example, built its own system for *sentiment analysis* of text data generated in the HR team. Sentiment analysis automatically labels chunks of text (usually a paragraph or less) according to its polarity on some dimension: Is this employee comment positive or negative toward the company, and by what degree? Company B is currently adapting the technology into an application for the HR team. Two other companies in our study are using third-party tools like Kanjoya (now acquired by Ultimate Software), which provide sentiment analysis and pattern finding tools.

Because NLP is still immature as a technology, some practitioners express dissatisfaction with automated text analysis. Text analysis components like *topic clustering* (identifying dominant topics in a large body of text) and sentiment analysis are not robust yet because of the inherent challenges of digitally processing human language. The results are not always reliable. Company I used ready-made software for text analysis and was disappointed with the results.

But if state-of-the-art NLP is still far from perfect, there are many use cases in which moderate accuracy is good enough and less expensive than having someone pore over thousands of employee comments. The best current uses of text analysis appear to be when human beings remain in the process. As noted earlier, employee satisfaction surveys, for example, increasingly introduce a tagging step by which employees self-select the topic of their comments. This method allows for the topic of the comments to be determined by hand; after which, automated sentiment analysis could be used to assess aggregate feelings about the topic. Another use is for text analysis to serve as a flagging mechanism for further human processing. One example is IBM's internal social networking platform, Connections, which is available to its 380,000 employees across 170 countries. According to an *Atlantic* (2016) article, it functions like Facebook, Dropbox and Wikipedia bundled into one package, allowing employees to publish posts, comment on posts and collaborate in smaller groups. The company developed a sentiment analysis tool called Social Pulse to monitor posts and comments to flag trending issues.

Network Analysis: Network analysis seeks to understand social relationships, flows of information and dynamics involving network interactions among multiple entities. It has the potential to answer questions such as these: How many people are involved in an average e-mail conversation? How can information diffusion best be enabled within a particular group or the organization as a whole?

The most common method for acquiring data about networks is through surveys that ask about whom employees interact with. Company D, for example, used a survey-based network analysis two years in a row to examine organizational patterns and uncovered important learnings from the exercise. Although such surveys can produce valuable information, they are often time-consuming and not real-time. Watts (2016) suggested that "digital traces can be used as proxies for social networks and their associated information flows." Several companies we spoke with expressed interest in using such digital data but are approaching the issue with caution due to employee trust and privacy issues. Watts noted that data must be “combined in ways that respect privacy and ethical considerations” for companies to use digital data for network analysis. In his Organization Spectroscope project at Microsoft, for example, only e-mail metadata was used (i.e., the information in From, To, Date and other fields, but not the main body of text), all identifiers were encrypted, data were aggregated to the manager level, and only managers with at least five reports were included.

Uhl-Bien and Arena (2016) highlighted the importance of organizational networks to understand forms of social capital such as “group cohesion” and “brokerage.” They said, “HR professionals need to more strongly consider social capital strategies in driving both performance and innovation within complex organizations.” According to their study across 30 companies, it is social capital that helps create an “adaptive space” between formal and informal networks in the organization, which in turn sparks new ideas and fosters collaboration. Based on our interviews, network analysis at corporations is still rare. However, existing talent analytics teams seem eager to incorporate it.

Research Experiments: Research experiments involve the use of active interventions differentially applied to subsets of employees within a company, as with the treatment and control groups used in a medical clinical trial. This kind of experimentation is part of the high end of the talent analytics value chain. The five companies in our sample that conduct experimental research on a regular basis follow methodologies involving hypothesis generation, research study design and hypothesis testing through experimental trial.

We came across very few other examples of HR problems being solved by experimental studies. One possible reason for this is explained by the talent analytics head for Company I. He said, "The challenge for conducting A/B testing for HR processes is both the scale of experimental group and the timeline to see the results," and recommended that experimental methods are appropriate only when "the experimental group is larger scale and the outcomes occur in a shorter time frame." This person has considerable experience with companies in which *A/B testing*—the common name for experimental research conducted on online platforms—is a constant practice. Companies that employ A/B testing use their customers as unwitting guinea pigs—for example, half of a website's visitors see Layout A, and another half sees Layout B; if Layout A demonstrates a statistically significant, higher rate of clicks on ads, the company has learned something about its customers that it can use to business advantage. But this sort of experimentation is more difficult in HR contexts in which employees are fewer in number—unlike the millions who flock to a website—and HR-related outcomes may require years to uncover.

TOOLS AND TECHNOLOGIES

The top five tools and technologies used in the talent analytics world, based on an open-ended question in our interviews, are R (used by 94% of our interviewed companies), Tableau (83%), Python (50%), SPSS (44%) and Excel (44%). Though we did not ask interviewees to enumerate every single tool used by the talent analytics team, they spontaneously highlighted the most oft-used tools. Although some companies mentioned their HRIS or HR management systems (HRMS), we do not discuss those platforms here, because they were largely not chosen by talent analytics teams.

The most common tools our interviewees reported using were those that enable statistical analysis and data visualization, and R was the most widely cited. Still, its primary use seemed to be for basic statistical analysis and visualization. R also has several machine learning packages, but we did not hear many of the participating organizations using them. R is a favored tool because of its compatibility with a wide array of data formats, file formats and other tools such as Tableau. R is also open source and free to use.

Other frequently used tools include Tableau, P, Python, SPSS and Excel. Tableau offers powerful visualization tools, dashboard creation and a relatively simple user interface. For the most part, companies use Python for statistical analysis, data cleaning, data management and, in some cases, machine learning. Company L also uses Python to develop internal talent analytics applications. SPSS and Excel are traditional tools that analytics professionals continue to favor because of tried and tested capabilities. Stata, SAS and SQL databases were also mentioned.

Newer tools and technologies include those permitting cognitive computing and AI (such as IBM's Watson Talent, Intel's Saffron, HireVue's video analytics platform), network analysis (TrustSphere, Innovisor, UCInet), text analysis (Kanjoya, the Python NLTK library), distributed computing, machine learning (Weka, the Python scikit-learn library), surveys (Qualtrics, SurveyGizmo, Sirota), statistical analysis, and business intelligence and analytics (Cognos, Visier).

Two conclusions can be drawn from this analysis of tools used: First, the talent analytics community is quick to adopt new tools; many of the tools mentioned are only a couple of years old. Second, the long list of new HR technology tools confirms that talent analytics is engaged in a lot of experimentation. Teams seemed to lean toward free or open-source tools for budget reasons. Among paid tools and technologies, the established tools (like Tableau) tend to be adopted. As the fields of AI and machine learning advance over the years, we foresee new HR tools entering the market as well as more consolidation to enable end-to-end talent analytics.

OPERATING MODEL

Our interview participants offered opinions about the structure, skills and processes that enable effective talent analytics. *Structure* refers to how the talent analytics team is organized, where it sits in the overall organization and how it engages with its clients, particularly HR partners. Our findings on *skills* relate to the profile of people on the team. And finally, *processes* cover data governance and operating models for prioritization.

I. Structure

Team Structure and Size: Our study identified three organizational structures for talent analytics:

1) Companies A, B, C, F and I perform all three categories of work (infrastructure and reporting, advanced data analysis, and organizational research) and have all of the activity reporting into a single talent analytics team.

2) Companies D, E, G and P limit their talent analytics team to advanced data analytics and organizational research. Infrastructure and reporting occur in other parts of the organization.
3) Talent analytics at the remaining companies focuses on reporting and advanced analytics. These companies are typically consolidating organizational data and laying the foundation of talent analytics for the long term.

Across all companies, there are ongoing efforts to systematize and automate reporting to enable self-service by various users.

Citing LinkedIn data, Canlas said that "there are over 5,000 companies with talent analytics employees on LinkedIn. Over 70% of these companies have only 1-2 people." Our study suggests that the number of employees within the talent analytics team varies according to its responsibilities and the size of the organization. In large companies, analytics teams vary greatly in size, but five to 35 people is common, with the larger teams taking on reporting and IT infrastructure.

Functional Reporting: For most of the companies in our sample, the talent analytics function sits within the larger HR function. In about half of the companies, the function reports directly to the CHRO. In others, the analytics team reports to a level or two below the CHRO to the leader of a center-of-excellence team like talent management, HR operations, or compensation and benefits. Participants felt that the closer the talent analytics team is to the CHRO, the more impactful it is because the team is able to focus on the right enterprise priorities, receive stronger sponsorship and access necessary resources.

Companies N and O were the two exceptions in which talent analytics does not report into the HR function and is instead part of a broader data analytics group. There seem to be pros and cons to this model. Being part of the data science team means access to a wider range of data experts, cross-company data and talent that would not take up positions focused only on talent analytics. The cons are that more work must be done to understand the HR context: building trust with HR teams and getting access to HR systems and databases.

Supporting the latter model, Rasmussen and Ulrich (2015) suggested that companies should eventually "take HR analytics out of HR." To build an end-to-end story using data from across the organization, talent analytics "must transcend HR issues and become part of existing cross functional business analytics, just like the analytics from other functions must transcend their functional areas." But Rasmussen and Ulrich also cautioned that their ideal state cannot be reached immediately. Talent analytics functions "need to be matured to some extent within the HR function first," and organizational IT systems must be more integrated before making this transition. For the reasons that Rasmussen and Ulrich shared, Ian O'Keefe, managing director of workforce analytics at JP Morgan Chase, agreed that talent analytics needs to be part of the larger companywide analytics work in the future but that the work needs to be incubated within the HR function first. We also foresee additional challenges if HR data analytics is moved outside of HR prematurely: dilution of HR context and issues of employee confidentiality. These may have legal and ethical implications on a par with intellectual property and trade secrets.

Engaging with HR partners: For enterprise-wide projects, talent analytics teams consider the business to be their primary client. In the case of specific business projects, however, talent analytics teams may see their HR partners as clients. This is a mutually beneficial partnership in which line HR amplifies the work of talent analytics by providing business-specific contexts, and talent analytics teams bring their data and research expertise to tackle HR challenges.

As in the cases of Companies A, J, K and P, it is not uncommon to see an "account model" in which members of the talent analytics teams are assigned to focus on specific lines of business. These account managers serve as a liaison to HR partners, for whom they act as something like consultants. One positive of this model is that it encourages an analytics-focused culture and builds expertise in the HR organization.

II. Skills in Talent Analytics

Meghan R. Lowery, I/O psychologist in the Workforce Research group at Eli Lilly, said that "effective talent analytics requires a triangulation of research, data science, and IT skills." We saw this sentiment expressed in the way talent analytics teams hire. Companies A, B, C, D, F, I, K and P have talent analytics teams comprising Ph.D.s (in social sciences like I/O psychology), MBAs, data scientists, engineers and IT professionals. The required skills include consulting, business analytics, HR expertise, research design, statistical analysis, visualization and storytelling. Some companies also look for skills in survey design and administration, and data warehousing. Company H additionally values user experience design and usability testing to ensure that employees have a positive experience when using the tools developed by the talent analytics team.

Skill in data visualization, used both for exploratory analysis and for communication, was cited in several interviews as a skill that was much needed but hard to find or difficult to make an internal case for.

In the largest organizations (>25,000 employees), roles tend to be more specialized, which means that employees within a specific category, like research or reporting, focus primarily on that slice of work. For smaller organizations, however, a generalist approach seems to be more common. Company F, for example, focuses its talent analytics work on informing, insights, and actions and accountability. There are specialists for each of these activities, but every member performs work in all three areas and partners with HR to scope the work.

Smaller organizations (<1,000 employees) appear to struggle with meaningful talent analytics. But Mohindra stressed the importance of laying a talent analytics foundation early on to ensure that data are captured for meaningful analytics in the future. For example, are the onboarding forms capturing qualifications and skills of new hires in a systematic way? Is the information being added to a database accurately to ensure clean data for the future? We believe that smaller organizations will also benefit from two things: regular employee feedback and an HR dashboard that captures key HR metrics (e.g., hires, offer acceptance rate, good attrition, bad attrition). Smaller organizations setting up a talent analytics team should prioritize hiring expertise in data analytics, business and HR. More advanced technical capabilities can always be added later.

III. Processes

Prioritizing Work: Companies A, D, E and K base their priorities on an annual HR strategy and operating plan. Besides some core processes that take place every year (like employee surveys and dashboards), talent analytics work involves specific projects that are based on organizational priorities. In reality, however, ad hoc projects sometimes come up that force the teams to either reprioritize their work or add additional resources. Company E specifically pointed out that its business priorities mandated a readiness for ad hoc projects. For Companies H and O, very often the prioritization occurs based on estimated returns on investment (ROIs) for each proposed project.

Company P uses a 2x2 matrix of effort and impact to prioritize work. “Effort” captures variables such as data availability, data readiness and time involved in resolving legal and privacy issues. “Impact” captures the footprint of the work in terms of local versus global, enterprise-wide versus specific businesses, and criticality of the business. Visualizing work in this matrix immediately identifies the high-impact, low-effort projects as “slam dunks” and causes de-prioritization of low-impact, high-effort work. The remaining projects are evaluated further on a case-by-case basis.

As in the case of Companies N and O, in which HR analytics resides outside the HR function, the onus lies on both the analytics and the HR partners to arrive at the right priorities to work on. This process requires the analytics teams to use HR to develop a better contextual understanding of HR and for the HR partners to ask the “right” questions—questions that help the business move toward its short- and long-term goals.

Data Governance—Legal and Ethical Considerations: *Data governance* refers to the formal procedures that ensure that quality data are gathered and used in a legal and ethical manner. Though in many contexts data governance tends to focus on data quality, we start with legal and ethical considerations, as these are particularly important in HR. In fact, talent analytics faces a potential minefield of legal and ethical problems, given that powerful technology can magnify both strengths and weaknesses in existing HR processes and culture.

Kentaro Toyama, author of *Geek Heresy* and an expert on digital technology's impact on society, suggested that "the first sin of AI is to allow machines to make ethically sensitive decisions on their own." HR activity is almost always ethically sensitive, so this is a stern warning for talent analytics. Toyama recommended that the best use of advanced analytics is as just another input into a holistic process of decision-making that is ultimately owned by human decision-makers. This approach ensures not only that legal and ethical issues are weighed by people but also that those people know they are responsible—a fact that can be easily forgotten if decisions are made by algorithms. Predictive modeling might be most useful, then, as a way to alert decision-makers to individuals or overall trends who might require attention, but not as a way to arrive at final decisions.

The full range of legal concerns remains just as critical with analytics as it is without analytics. But these issues may manifest in subtle and unexpected ways. For example, it may seem obvious that decisions should not violate laws such as Title VII, the Age Discrimination in Employment Act (ADEA) and the Americans with Disabilities Act

(ADA), but ensuring that data analytics avoids the corresponding biases is not always simple. As a baseline, for example, it would seem clear that models should not incorporate variables such as age, race, gender or disability that may influence hiring decisions. But biases for these characteristics can creep in unwittingly, even if they are deliberately left out. For example, using hours worked during the year as part of a measure of performance may seem reasonable, but such a variable may be correlated with gender and age (e.g., if mothers take more parental leave), leading to unintentional—and possibly illegal—biases in decision-making. These kinds of issues will require deep thinking among HR, data analysts and legal counsel to resolve adequately.

Employee trust and confidentiality are other issues. Many employment contracts give corporations the rights to all work-related data, but contracts are one thing—employee trust is another. Lazlo Bock, Google's former SVP of People Operations, in an interview with the *New York Times* (2013), said that the company gives "people an option to participate in anything either confidentially or anonymously." As advice to people working in talent analytics, he said, "You need to construct this really powerful tent of trust in the people gathering the data and how they use it."

Apart from legal and ethical concerns, good data governance principles also ensure that data are *clean*. In the language of data science, clean data are that which are accurate, complete and well organized. Due to legacy systems as well as short-term decisions made under constraints, HR data are often either incomplete or inaccurate. Ensuring clean data is therefore one of the topmost concerns for talent analytics teams. But data cleanliness is not a black-or-white issue. Some practitioners argue that HR should be satisfied with data, for example, that are "90%" clean, even if they contain a few errors. Statistical tools and machine learning algorithms can easily address issues if unclean data are proportionately limited. However, the reality is that for most companies ensuring mostly clean data is an uphill task.

Imperatives for Effective Analysis

In this section, we share what our experts considered to be the key imperatives for making talent analytics effective.

HR Mindset: HR professionals are criticized for not being data-savvy and for lacking analytical skills. O'Keefe said that "despite the focus on measurement in the HR profession, day to day decisions have traditionally been gut-driven." For talent analytics, however, it is important for HR as a profession to rally around a culture of data-informed decision-making. How might this occur? We heard four types of solutions in our study.

First, it is important to have an HR leader who values quantitative analysis. This is not to say that qualitative information should be ignored, given that many HR decisions require judicious strategic decisions that cannot be fully captured by numerical data. But a leader who is afraid of analytics or who neglects the potential of data is unlikely to cultivate a strong talent analytics function.

Second, ongoing partnership between talent analytics and line HR is crucial. O'Keefe advised that "we need to get HR used to seeing data. Get them used to making decisions based on bite-sized data and then scale up gradually."

Third, investments must be made to develop basic data analysis skills in HR itself, either through hiring or training. According to Oswald, "The goal here is not to make [HR employees] statisticians, but to build the skill of asking the right questions of the data, which can lead to better analyses and perhaps the collection of better data in the future." Google, for example, explicitly states in its job descriptions that one of the preferred qualifications for the role of HR business partner is to have "strong analytical and problem solving skills with proven ability to organize and analyze data, using HRIS systems for reporting." Similarly, Facebook expects HR business partners to "drive data-led decision-making through analysis of key people metrics." The idea is to foster a culture in which HR uses data to illuminate problems or bust corporate myths.

The fourth solution is for HR education to include basic data science. Scott Tonidandel, professor of psychology at Davidson College, reflected on the steps he is taking to ensure that his HR students graduate with data skills. He coaches his students to be interdisciplinary, especially by gaining more technical skills. In his classes, he has ramped up statistical training and data visualization skills.

Optimal Use of Technology: Rapid advancements in statistics, artificial intelligence and machine learning are increasingly packaged into software tools by open source developers and technology companies. Whereas functions like finance and marketing have been quick to adopt these technologies, HR has been relatively slow, likely because of missing data skills in traditional HR teams or budgetary constraints. Large companies have the luxury to hire the required talent into the team or borrow them from other parts of the organization. Smaller organizations should consult appropriately with internal or external experts, and engage vendors and consultants when necessary.

End-to-End HR Systems: To do data analysis you need data, and to collect data easily you need integrated HR IT systems. However, the reality of IT at most companies is that systems are not integrated in a way that makes extracting data from them easy. Nathan Mondragon, chief I/O psychologist at HireVue, said that "we are *still* consolidating . . . something I thought we'd be done with ten years ago." Vendors are striving to be one-stop shops for all solutions or to build solutions that talk with others seamlessly. Until such systems materialize, however, talent analytics needs to invest in data cleaning and systems integration technology to mine and use data.

Measurement: Rasmussen and Ulrich (2015) lamented about the "lack of analytics about analytics"—insufficient analytics to justify investments in talent analytics. This is a barrier to talent analytics' own credibility because it seems not to practice what it preaches. While nonfinancial metrics are common across our companies, we heard no instance of a company assigning ROIs for talent analytics work. This is a systematic challenge because HR impacts often occur in the longer term and on variables such as "culture" that are difficult to measure.

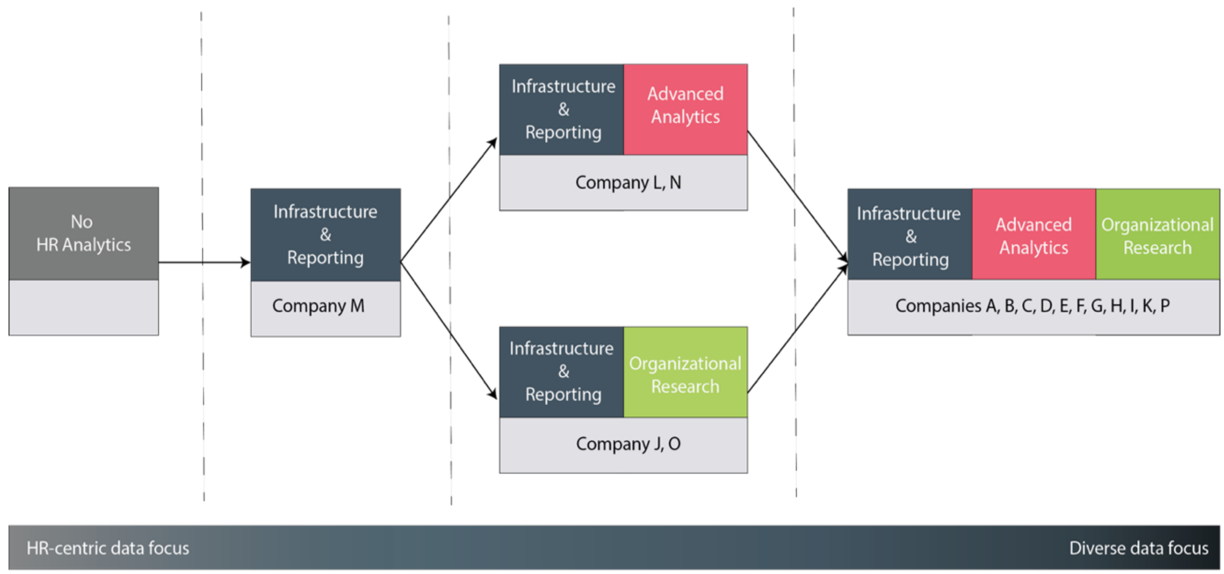
There are, however, some examples to inspire us. Companies H and O undertake talent analytics projects only when the ROI is clearly and credibly stated. Such policies can benefit the analytics team: At Company H, the talent analytics lead said that by using this approach, "we are able to weed out work that is being asked of the team just to quench curiosity with no business value." He noted that having a clear research statement and ROI help his team prioritize their work based on what is most critical to the business. This approach forces talent analytics teams to review historical data and external research to assign estimates of value to their work on a routine basis. Over time, data and experience accumulate, and estimates become more reliable. LinkedIn is another company that takes the ROI of talent analytics very seriously. After a start-up investment in 2014, it computed its ROI to be five times the talent analytics investment in 2015, and 7 times in 2016. The projected return for 2017 is more than 10 times the investment.

Conclusion and Call to Action

We have provided an overview of the work done in the talent analytics functions and the structures, system and skills that enable them. These findings and insights from practitioners, subject matter experts and literature review helped us arrive at the main conclusion of our study: a trajectory that companies can use to set up, grow and evaluate their talent analytics practices (see Figure 1).

We believe that organizations new to talent analytics should focus primarily on building their reporting capability and HR data infrastructures. These have immediate application and also lay the foundation for future talent analytics work. Clearly defined metrics and dashboards are indicators of strong talent analytics in this step. As a next step, a company could take on either advanced analytics or organizational research. Companies with a business need, adequate resources and an existing talent analytics program with a proven value could eventually add on the third category of work so that they have, in-house, the full complement of data infrastructure and reporting, advanced analytics, and organizational research.

Figure 1: Trajectory of Talent Analytics Function



A model for building talent analytics practices: The starting point is "Infrastructure & Reporting." Organizations then typically diversify into "Advanced Analytics" or "Organizational Research." The final stage involves integration of all three areas of work. Companies advance to the next stage of talent analytics based on their needs (like size, growth stage, talent issues) and readiness (skills and resources). As the talent analytics work evolves, the types of data sources (tangible data and perspectives) move from being HR centric to more diverse (cross-functional and external).

Our study is limited by a small sample that is not representative, but it does include companies spanning a range of revenue, employee sizes, industries and growth profiles. Some talent analytics functions in our study have evolved for over 20 years to assume their current structure and portfolio of work, and others have been in place for only the past two years. This contextual information about the participating companies helped us understand the choices that companies make in building and growing talent analytics over a period of time.

Create Your Talent Analytics Function

Our call to action for HR leaders is to identify their current placement on the talent analytics trajectory and to build up their talent analytics functions. These actions are essential to respond to the needs identified by CHROs and current demands for ROI from business leaders. We offer five key elements to consider:

1. **Identify meaningful problems:** As with many corporate fads, it is easy to get excited about talent analytics without being clear about its application and purpose. Review the appendix to gain ideas for how talent analytics can add value. Projects could range from identifying the right metrics to solving complex talent and culture problems.
2. **Get the right skills:** Ensure your team contains or has access to skills appropriate to the problems you hope to address. The core skills for talent analytics are in statistics, data analytics and research methodology. Other skills in data visualization, machine learning and distributed data processing can also be useful, but the need for these will depend on the nature of the problem. The right skills could be hired or borrowed from other parts of the organization. In some cases, HR staff with critical skills (e.g., Ph.D.'s with strong research backgrounds, data analysts fluent in data science) might be able to learn the necessary skills. Finally, because most of these are not skills native to the HR profession (yet!), it is critical to have trusted experts help decide exactly which skills are needed and whom to bring on board.
3. **Partner with other teams:** Accessing data from functions beyond HR is critical for advanced talent analytics. Establishing partnerships with business, finance and IT is essential. In addition to relationships with other business functions, a strong partnership with the IT team can ensure that the organizational systems are designed or modified to enable tapping into such data easily.

4. **Develop data governance principles:** To make talent analytics teams agile, ensure that there are well-established data governance principles related to quality of data and to the legal and ethical considerations for using the data. Here, too, a partnership with IT is helpful.
5. **Measure impact:** Identify the short- and long-term quantitative measures of talent analytics work and the team as a whole. If ROI can be established, it can improve the likelihood that business leadership will value the work.

These five key elements can serve as a scorecard to evaluate your existing team or as a framework to build out a talent analytics team. Talent analytics is a dynamic and fast-growing field, with potential to enrich people decisions in organizations in a profound way.

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Appendix: Table of Talent Analytics Practices

Category	Subcategory	Examples	Data Sources
Data Infrastructure & Reporting	Infrastructure	All companies in our study have institutionalized HR reporting and HR dashboards either through an automated HRIS system (often supplemented with custom software) or through a manual solution.	• N/A
		Companies A, B and F have their talent analytics teams more directly involved in the building of analytics-related infrastructure (whereas most other companies rely on their IT department or external vendors).	• N/A
	Data Sourcing [Includes tangible qualitative and quantitative data in addition to cross-functional perspectives]	Company D used *sales performance data* combined with network information to show that high-performing teams were typically the ones better connected as a group (e.g., either a specific function or geography).	• Sales (sales performance data) • HRIS data (employee demographics, e.g., location, function, performance review)
		Company E used both internal HR data and *external market data* to build a predictive model for where compliance issues may emerge in the future.	• External market data • HRIS data (e.g., employee location, function, performance review)
		Several companies in our study use *external data (like labor market reports and cost-of-living indices)* to identify which locations to target as part of developing their talent sourcing strategy.	• External market data (like labor market reports, cost-of-living index)
		Company A consistently ensures that talent analytics project teams have representation from HR, employees, managers and cross-functional teams.	• Cross-functional (viewpoints and perspectives)

Category	Subcategory	Examples	Data Sources
	Reporting and Dashboards	All companies in our study have processes in place to generate regular reports. Data from these reports contribute to the creation of dashboards comprising key HR metrics that are tracked periodically with HR leaders and the business.	• HRIS data (e.g., staffing, performance, rewards, location, function)
Advanced Analytics	Decoding Employee Engagement	All companies in our study conduct an employee satisfaction survey at least once a year and perform basic statistical analysis on the data.	• HR survey data
		Companies A, D, F and K optimize their text analysis work by asking employees to tag their comments with one or more of a discrete set of labels (e.g., career, training, manager). This kind of tagging eliminates the need to manually classify comments and simplifies the identification of topics.	• HR survey data
		Companies A, D, E, G, I and K tie employee responses back to other data to build predictive models. For example, correlations of past employee satisfaction and manager ratings with employee exit dates may show trends that could predict future attrition.	• Survey data • HRIS data (e.g., attrition, performance, location)
	Building Staffing Plans	LinkedIn's recruiting team gathered information about all key positions and the hiring need for those positions. Based on this information, it built a 12-month forecast model. One of the outcomes was a clear recruiting capacity forecast, which led to an allocation of recruiters aligned with business need. The exercise saved the company 15% of its recruiting budget in its first year.	• HRIS data (staffing)

Category	Subcategory	Examples	Data Sources
		Company I regularly uses labor market data to identify where it can find relevant talent. This labor market data influences which college campuses it visits and where it sets up new offices.	• External data (labor market reports)
		Company E analyzes airport traffic patterns, hotel use, education migration and other macroeconomic factors to make determinations about where the talent is.	• External data (e.g., airport traffic, labor market data)
	Strengthening Management Excellence	Company J uses employee survey data to look for combinations of practices that make for good managers. After conducting a variety of analyses and referencing external best practices, the team identified a set of 13 characteristics. This index has been used as the basis for a peer-led program for building manager capability.	• HR survey data • Qualitative interview data
		Google's Project Oxygen, started in 2009, contained 10,000 rows of employee data and more than 100 variables. Statisticians started "looking for patterns" (Bryant, 2011) and arrived at eight characteristics of good managers.	• HR data (e.g., performance reviews, award nominations) • HR survey data
	Measuring Training Impact	Company P's talent analytics team was asked to assess the effectiveness of a set of employee wellness trainings. The team used an experimental design with control groups to evaluate the trainings over a period of five years. It measured statistically significant impact on promotions and performance.	• HRIS – Learning Management System data • HRIS data (including performance reviews)
	Enabling Talent Movement	Company P compiled historical data about internal mobility (promotions, lateral movement, and cross geography and cross-functional transfers). Analysis of these data suggested that certain types of talent mobility led to higher employee engagement and improvement in employee turnover.	• HR data (e.g., employee demographics, transfers, promotions, performance, awards) • HR survey data

Category	Subcategory	Examples	Data Sources
		Microsoft's talent analytics team analyzed talent mobility data to understand its impact on employee engagement and retention. After looking at an array of data, the team discovered that employees who had made a recent job transfer within Microsoft were more positive about their career and more engaged than those who did not experience similar mobility. This outcome caused the company to simplify the process of job transfers.	• HR data (e.g., employee demographics, transfers, promotions, performance, awards) • HR survey data
	Developing Predictive Models for Hiring, Retention and Attrition	All the companies in our study have either built or are in the process of building predictive models for issues such as hiring, retention and attrition.	• HR data (e.g., employee demographics, promotions, performance, awards, attrition) • HR survey data
	Designing Employee Benefits	Company M undertook careful analysis of its employee demographics, qualitative feedback and attrition trends to determine that a one-size-fits-all approach for benefits is suboptimal. This finding led to the company making its parental leave policy more flexible.	• HR data (e.g., employee demographics, promotions, attrition performance, awards) • HR survey data • Qualitative interview data
Research & Consulting	Understanding Team Dynamics	Microsoft combined data generated from productivity software with more traditional forms of data like "job titles, office locations, and employee satisfaction surveys" to predict team satisfaction. There were many detailed findings, but one example was that 93% of the time, "email response time between the manager and direct reports (longer is worse)" could predict the bottom 15% of least-satisfied teams.	• Organization IT systems (e-mail, calendar, document, authorship and similar digital traces) • HR data (e.g., employee demographics, attrition, performance) • HR survey data

Category	Subcategory	Examples	Data Sources
		Eli Lilly measured what Lilly employees thought about external partners and the success of the products they worked on. The study showed that the more conflict the groups felt, the stronger the outcomes were.	• HR survey data • HR data (e.g., employee demographics, performance) • Sales (performance data)
		Google's project Aristotle, which started in 2012, sought to understand what makes some teams more successful than others. The project team gathered data over two years through "200+ interviews with Googlers (our employees) and looked at more than 250 attributes of 180+ active Google teams" (Rozovsky, 2015) to reveal specific norms that were critical—with "psychological safety" ranking at the top.	• Qualitative interview data • HR data (e.g., employee demographics, attrition, performance)
	Improving Diverse Talent Representation	Company C led an experiment in which the control group received resumes in their original format, and the treatment group received resumes in which the names and other information identifying race and gender were obscured. Differences in the hiring patterns of the two groups revealed how implicit biases worked against diversity.	• HR data (e.g., candidate demographics, resumes, hiring decision)

Category	Subcategory	Examples	Data Sources
		Eli Lilly sought to understand the variables that led to leakage in the women's talent pipeline. A variety of qualitative and quantitative data was collected, including network data from a previous organizational survey. The conclusions highlighted the importance of dispelling long-standing myths—such as that women do not desire higher positions and that maybe women do not "have what it takes" (performance and potential)—and focusing on the actual areas that seemed to affect leakage. Many small interventions proved to be key in helping address pipeline leakage, such as addressing misconceptions about women, promoting a more inclusive culture, enhancing work/life balance and providing support to overcome barriers.	• HR survey data • Qualitative interview data • HR data (e.g., employee level, function, promotion, performance)
	Improving Staffing Processes	Company I determines the best way to approach candidates in terms of the language or medium used (e.g., LinkedIn, e-mail, phone) by testing and evaluating the candidate response to different approaches and adopting the one with the best response for the target demographic.	• HR data (e.g., candidate demographics, candidate feedback)
	Organization Design	Company A undertook a two-year experiment with control and experimental groups to determine if teams in a particular business group should be manager-led or self-managed. Pre- and post-data about business results and people results showed self-managed structures to be superior.	• Business performance data (e.g., sales, customer satisfaction) • HR data (e.g., performance, attrition) • HR survey data

Acknowledgments

We would like to thank the following people for generous support and valuable input in developing this paper: **Adam Myer** (Manager, Organizational Analytics at Johnson & Johnson), **Amit Mohindra** (Head, Talent Analytics at Apple), **Arun Chidambaram** (Global Lead of Talent Analytics at Pfizer), **Don Gray** (Director, HR Research & Analytics), **Evan Sinar** (Chief Scientist and Vice President of the Center for Analytics and Behavioral Research at DDI), **Fred Oswald** (Professor, Department of Psychology at Rice University), **Ian O'Keefe** (Managing Director of Workforce Analytics at JP Morgan), **Jackie Ryan** (Director, Watson Talent Analytics at IBM), **Jim O'Gorman** (Senior Vice President, Talent & Organization at Hulu), **J.J. Prescott** (Professor of Law at the University of Michigan), **Kathryn Dekas** (Head of People and Innovation Lab at Google), **Keith Zabel** (Workforce Planning & Analytics Specialist at Ford Motor Company), **Kentaro Toyama** (W.K. Kellogg Associate Professor of Community Information at the University of Michigan School of Information, a fellow of the Dalai Lama Center for Ethics and Transformative Values at MIT), **Lorenzo Canlas** (Head, Talent Analytics at LinkedIn), **Masanori Tokumoto** (Principal, HR Program Management at Hulu), **Meghan R. Lowery** (I/O psychologist in the Workforce Research group at Eli Lilly), **Michele Goldberg** (Director, People Insights and Innovation at Nestlé), **Nathan Mondragon** (Chief I/O Psychologist at HireVue), **Paul Tsagaroulis** (Director, Human Capital Analytics at GSA), **Rick Guzzo** (Co-leader, Mercer's Workforce Sciences Institute), **Sara Roberts** (Co-founder and Principal Consultant at Category One Consulting), **Scott Judd** (Director, People Insights at Facebook), **Scott Tonidandel** (Wayne M. & Carolyn A. Watson Professor of Psychology at Davidson College), **Stephen Lindia** (OD/OE Talent Executive at Bank of America), and **Susan Biancani** (Data Scientist, People Analytics at Airbnb).

How to cite this paper:

Kaur, J., & Fink, A. A. (2017). *Trends and practices in talent analytics*. Society for Human Resource Management (SHRM)-Society for Industrial-Organizational Psychology (SIOP) Science of HR White Paper Series.