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Using Targeted Analytics to Improve Talent Decisions

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Abstract

Analytics and metrics offer great potential to improve the quality of decision making on HR and human capital issues in organizations. Despite conventional wisdom, strong statistical skills are not necessarily a barrier to applying analytic ways of examining and solving organizational issue. The bigger barrier to applying analytics is the time and resources needed, and an understanding of what types of analytics to apply, when to apply them, and how to do so. I review the “what,” “where” and “how” of analytics, including proven frameworks that anyone in a business partner or generalist role can master to improve daily decision making and business impact.

1. Introduction

The past decade saw the emergence of analytics as a potential force for driving data-based decision making in HR (Lawler, Levenson, and Boudreau, 2004; Levenson, 2005). At the beginning of the decade, "human resources analytics" was not part of the language of business. Today, at the end of the decade, a Google search for the same term produces over 1.5 million results. When the topic of HR analytics was raised at the Center for Effective Organizations annual sponsors meeting in 2003, it was not part of the formal agenda and there were no established courses or seminars on the topic in the HR consulting and training space. Today there is an ever-expanding array of providers and content to train and certify practitioners in HR analytics and automate HR analysis.

Yet despite the apparent progress, there still is much uncertainty regarding how best to design, apply and integrate analytics into the daily workings of the HR function. The challenge lies in understanding what analytics to apply where, and the time and resources needed to achieve true insights. In this article I first discuss the "what" and "where": the variety of analytics and skills that can be used to achieve business insights related to HR and talent. Case study examples illustrate the importance of matching the analytic method to the issue under study. A key point related to "what" and "where" is that simple analytics sometimes are the most appropriate way to identify business-relevant insights. This is important because the statistical skills needed to do technically sophisticated analysis (a) tend not to be located in HR, and (b) when they are located in HR, tend to be concentrated in HR analytics centers of excellence, not more broadly throughout the function, which limits how often and widely they can be applied. The good news, and the second key point, is that the limited availability of advanced statistical skills does not necessarily restrict HR professionals' ability to do meaningful analytics. What matters is knowing what analytics to apply and where to apply them.

From there we move to the "when" and "how": the time and resources needed to conduct analytics, and the best way to use analytics to improve decision making and organizational effectiveness on a daily basis. Some of the best examples of analysis-driven deep insights come from very involved projects that require a large amount of time, energy and resources to complete, though not necessarily the most technically advanced statistical methods. The challenge is how to improve decision making in everyday settings when very involved analytics projects are not feasible. To answer that, I review three proven frameworks that can be applied to make better on-the-spot decisions, even in situations where there is little time for extensive data collection: (a) the Capability-Opportunity-Motivation model for diagnosing behavior and productivity on the job that can be used for job design, (b) a labor markets model of external opportunities and career development to analyze the cost-benefit of job design, staffing and talent management decisions, and (c) an organization design model for diagnosing structural barriers to enterprise-wide collaboration and performance. When HR professionals master these models and apply them to everyday decision making, two things happen: (a) the path to identifying which analytics to apply becomes clear, and (b) when there is no time for intensive analytics, the models – their logic and the empirical evidence behind them – are effective substitutes that improve the accuracy and impact of talent and organizational decisions.

2. Analytic competencies in the HR function

Human capital analytics are most powerful when they help tell and validate a story that illustrates the driving forces behind individuals' and groups' behaviors and performance. As Boudreau and Ramstad (2006) point out, the analytics need to be embedded within a logic framework that is linked to the business, and a (change) process is needed so they are used in a way that ensures maximum impact. The logic framework ensures that the analytics are focused on the right issues and are set up to maximize the discovery of data and analysis results that are actionable. The process for using the results of the analytics ensures the data is turned into action.

The first challenge in applying analytics is the wide array of statistical and analytic techniques that are available from which to choose. Providing an exhaustive list of techniques would be overkill. Instead, Table 1 lists categories of analytic competencies divided by type and level of complexity. The categories are drawn in part from Rothwell and Sredl's (1992) competencies for a Human Resource Development Researcher, and in part from my personal experience conducting and training others in human capital analytics and statistical analysis.

The top panel of Table 1 contains analytical competencies related to statistical techniques; the bottom panel contains other analytic competencies. The second column provides examples of techniques and concepts; the third column provides a rough approximation (my own calculations) of the coursework and on-the-job experience needed to become proficient for each competency, as well as the general education level associated with people who are proficient. Note the latter does not imply an educational requirement; instead it can be thought of as a proxy for the population characteristics that an organization might target when recruiting for a role that required that competency.

Table 2 provides data on the proficiency of two different groups of HR professionals: people who work in HR analytics groups, and others in HR (outside of HR analytics groups). The data in Table 2 are from Levenson, Lawler, and Boudreau (2005), and were collected in 2005 from a survey of HR analytics professionals and people who work with them; there were 47 respondents from 40 companies. Given the relatively small sample size, the results in Table 2 are useful for identifying potential patterns in the HR profession. They should not be taken as the final word – for that we need more comprehensive data.

Despite the limitations of the data, the patterns in Table 2 are consistent with conventional views of the HR function, particularly the gap between the analytic skills of HR professionals versus what their organizations ask of them. For example, HR professionals outside of analytics groups are often called upon for basic analytics tasks such as conduct root cause analysis, calculate univariate statistics (means, percentiles, etc.), and communicate the results of statistical analyses in a clear and understandable way. Yet only a minority of HR professionals have the skills needed to perform those tasks. The good news is that the skills gap for HR analytics group members for those tasks is much smaller: the vast majority of analytics group professionals can do those basic analytics tasks. Yet the gap persists for more advanced, multivariate analytics tasks, with less than half of analytics group members possessing at least an intermediate ability to execute them. This suggests a fundamental gap for the HR function overall: conducting multivariate analyses is not a core competency, even for HR analytics groups. This presents a challenge for conducting HR analytics in some cases but not, as we will discuss below, a barrier to insightful analysis in all cases.

Analytics group members' skills in another key area match up well with the demands put upon them: identifying the data needed for analysis and obtaining it from others. In contrast, HR professionals outside the analytics groups are twice as likely to be called upon to demonstrate these competencies as they are capable of doing them. Does this make the glass half empty, or half full? It depends on how you look at it. On the one hand, analytics group members, in organizations where such groups exist, tend to have the skills needed to get the requisite data. On the other hand, analytics group members are responsible for acquiring the data only some of the time. Non-analytics groups members are also often called upon to identify and acquire the data needed for analysis (about two-thirds of the time), and yet are typically not proficient at these tasks. This presents a key challenge because the HR business partners typically have the best access to identify and obtain the right data. Even in organizations with HR analytics groups, the small size of such groups, relative to the total number of HR professionals in the organization, greatly restricts their ability to engage the organization in analytical analysis in the broad array of issues that are ripe for examination. The inability of HR professionals outside of analytics groups to define and guide the path forward for analysis is a major impediment to deeper insights.

3. Which human capital analytics and analytics strategies have the greatest potential to impact business results?

Table 3 reports on analysis applications for a number of HR processes. Most functionally-driven processes are subjected to data-based analysis with a high degree of frequency, including both intermediate and advanced analysis. Yet despite this apparent abundance of analysis, Table 4 shows that analytics is much less commonly applied to decision making where it matters the most: (i) to aid decisions that reflect the organizations' competitive situation, (ii) to identify where talent has the greatest potential for strategic impact, (iii) to connect human capital practices to organizational performance, (iv) to assess and improve the human capital strategy of the company, and (v) assess the feasibility of new business strategies. Thus the problem for HR is not a lack of analysis, but the targeting of that analysis to insights that matter most to the organization.

An example illustrates these challenges. Turnover reports are commonly used as a type of "temperature gauge" for what is happening with employees. High turnover at face value is usually interpreted as bad because talent is being "lost." Yet turnover is a function of both job fit and job demands. If a role is staffed by people who are average to below-average ability for the job responsibilities, both voluntary turnover and productivity will be low. If the job demands are raised, then both turnover and productivity should increase. And if the time to productivity in the role is short (i.e. very little on-the-job training is needed for a new employee to become fully productive), then high job demands and high turnover may be the right choice, depending on the pool of people available to be hired.

Indeed, for certain roles, the only way to attract high productivity people may be to hire them with the knowledge that they will leave after a specified period of time (and thus have higher turnover than lower-productivity people who are happy to stay): they might only choose to come work for you if there is a clear career path to other jobs they can move on to that build on the skills and experiences gained while working in the role. For example, early-career school graduates are often willing to trade lower compensation and job security for the reward of building skills and experience they need for higher level positions. Thus "low" turnover can signal that productivity is low and "high" turnover can signal that productivity is high. Turnover reports alone cannot provide the full picture of how human capital contributes to business performance. For that a deeper understanding and more targeted analysis is needed.

That deeper understanding comes first from knowing how to assess the job design, economics, and organization design factors that drive behavior in a system; it does not necessarily come from conducting highly technical statistical analysis. Before defining and interpreting the relevant statistical analyses, whether basic or advanced, the more important first steps require analyzing the context and engaging directly with key stakeholders and decision makers. If advanced statistical analysis is needed, the number crunching tasks can be assigned to internal and/or external statistical experts, and that is a straightforward task. The real challenge lies in defining what should be analyzed and turning the analysis results into meaningful information for the stakeholders and decision makers.

a. Financial services case study

Consider the following two examples, both from a financial services firm. The first case was a multivariate statistical analysis of the relationship between the characteristics of an incentive pay scheme and sales performance for a key role in the organization. The analysis was conducted by a dedicated HR analytics person whose statistical approach was impeccable. The insights derived by the analysis questioned a large number of assumptions about the pay plan and what drove behavior in the role. Yet the general manager (GM) responsible for that part of the business was not engaged in the investigative process from the beginning, and was presented only with the "gift wrapped" results at the end of the analysis. The response was a complete rejection of the analysis and questioning of the analytics behind it. The key mistake of the HR analyst was not engaging with the GM at the start of the process to ensure that there was alignment around the potential need for the analysis and interest in receiving and potentially acting on the results.

The second case was a straightforward employee survey conducted in the midst of a large amount of organizational change and upheaval. The survey was viewed by the senior leaders as an important vehicle for monitoring the employees' responses to the changes, and the leaders' success in mitigating the negative impacts of the changes. The analytics used to analyze the survey responses were very basic, including only means and frequencies. But because the questions were designed to directly address employee responses to a critical transition period, the survey results were given great weight in the leaders' process of assessing and adapting their approach to managing the changes.

So advanced statistical techniques are not necessarily a prerequisite for deep insights and actionable information. They are, however, often a key part of a comprehensive set of analyses that may be needed for the deepest insights. Two case studies illustrate this point. Both started as problems that appeared related to compensation. After conducting extensive analyses meaningful insights to the limits of compensation as a solution were achieved, and actions were taken that led to lasting positive impacts. In both cases there were (a) advanced statistical techniques for one part of the work, (b) simple data analyses for other parts of the work, and (c) introspective, thoughtful consideration of causal factors using logic only and virtually no (new) data analysis for the remaining parts of the work.

b. PricewaterhouseCoopers case study

The first case comes from a talent management and retention challenge faced by PricewaterhouseCoopers (PwC). Extensive details of the case are described in Levenson, Fenlon and Benson (2010). Here I discuss briefly the issues addressed and focus on the types of analytics used and insights derived from them.

PwC had relatively high turnover for a key talent pool: senior associates, the second stage in the career ladder that starts at entry-level associate and ends at partner. A solution that was under consideration to improve retention was deferred compensation: offer the promise of greater pay in the future for those who stayed longer with the firm. The firm also had anecdotal evidence that people who left the firm at later career stages (after achieving manager or senior manager status), had better career outcomes in the long run, such as achieving CFO, compared to those who left at earlier career stages (associate or senior associate). What the firm needed was evidence on whether a deferred compensation program would work as a retention tool, and whether more accurate information – data-based, not anecdotal – on career outcomes after leaving the firm might cause people to choose to stay voluntarily without the additional incentive of a deferred compensation program.

Data was collected by surveying current and former employees on their experiences at the firm and, for those who left, career progression outside the firm. Some of the most difficult parts of the project included identifying the right samples of people to survey among the former employees, getting them to respond, and figuring out which responses were best to use for the analysis – none of which required doing any advanced statistical analysis. To start, this required deep knowledge of the firm’s culture and relationships with former employees. That led to identifying offices that were representative of the firm’s business which had stronger networks among the former employees. It also required knowledge of how to get the former employees to respond, by appealing in part to their ongoing goodwill with those relationships, and in part to the former employees’ satisfaction with their developmental experiences at the firm and what those experiences delivered in terms of career success.

Basic statistical techniques were used to estimate the total number of former employees to survey, based on typical responses rates for comparable surveys, and to determine which responses to use in the analysis. The final analysis sample focused on former employees who had left the firm more recently (within the prior fifteen years) because their response rates were higher and more representative, and because their recollection of their experiences at the firm was subject to less recall bias (versus those who had left more than fifteen years prior to the survey). Advanced statistical techniques – multivariate regression – was used to compare (a) the career outcomes among former employees who left at different career stages, (b) work-life balance for former versus current employees at comparable career stages, and (c) drivers of retention for current employees. For all of the analyses, multivariate regression enabled an "apples-to-apples" comparison by controlling for factors that might otherwise have led to perceived differences among the groups and between individuals (level of education, whether the person had a CPA or other professional certification, gender, race, office location, total years of work experience, and the line of service in which the person worked at PwC before leaving). For the retention models, multivariate regression further enabled an analysis of which factors were more important in driving employee decisions to leave; this was key to identifying non-compensation factors, such as work-life balance, that figured prominently in the process.

The combined efforts of the analysis and subsequent retention initiatives by the firm had a clear impact. The analysis revealed that adding a deferred compensation program would have had a much smaller impact on retention than addressing work-life balance and concerns about career development and progression. The actions the firm took included strengthening relationships between partners and staff, focusing on coaching and development, and providing new tools for leaders and HR to manage workload balance issues. The end result was a marked decrease in voluntary turnover that met the firm's operational and strategic goals.

c. Frito-Lay case study

The second case also involves a talent management and retention challenge, faced by Frito-Lay, a division of PepsiCo, and detailed in Levenson and Faber (2009). The key talent pool in this case was the Route Sales Representatives (RSRs), who perform three tasks: (a) take the company's products from the distribution centers to the stores (driving / delivery), (b) manage the in-store inventory and placement on the display shelves (merchandising), and (c) take orders and negotiate for additional display shelf space, which drives incremental sales volume (sales). The company was experiencing low productivity and high turnover in the role. They knew that compensation was a potential issue because some regions had fallen behind the company's local benchmarks for target compensation.

An initial regression analysis revealed that regions with larger compensation gaps tended to have higher turnover. Yet the statistical relationship was stronger for new hire turnover and weaker for longer-tenured RSRs who have greater productivity and sales. So closing the compensation gap would have positively impacted the talent supply of RSRs but not necessarily productivity. To better understand the situation, a study was launched that included surveys of both the RSRs and their supervisors.

The employee survey collected information on years of experience before joining the company in jobs that required the three different skills related to the job's components (driving/delivery, merchandising, sales), along with many attitudinal measures. The supervisor survey collected ratings of each RSR's ability to execute the three different job dimensions, and a measure of how much time the supervisors spent covering RSR routes and the estimated lost sales as a consequence: covering routes takes away from supervisors working directly with the accounts to increase sales above what the RSRs can do on their own. This represented one of the most difficult parts of the work because an extremely high response rate from the supervisors was needed to ensure that a large and sufficiently representative sample of the RSRs would be rated. The high response rate was achieved by close coordination between the analysis leaders and the senior and mid-level executives who communicated throughout the supervisor ranks the importance of contributing to the study.

Simple statistical analysis (means) of the supervisor data on time spent covering down routes and the estimated lost sales provided the economic justification for investing in closing the compensation gaps to reduce new hire turnover. Adding to this evidence was a logic argument based on deep understanding of the external labor market and changes in the job over time. The job candidates traditionally came predominantly from the pool of high school graduates (i.e. non-college graduates). Over thirty years time this pool had shrunk from being three quarters of the U.S. population to half, making it harder to attract job applicants. At the same time the job demands had increased with a growing number of products and greater channel and retailer competition. These two trends provided additional logic behind keeping pay at the intended targets. Acting on the analysis and logic, the company made a significant investment over three years to bring RSR compensation to the market targets.

Multivariate regression analysis of the supervisor ratings matched with employee performance revealed a second path for improvement. The analysis enabled a comparison of the importance of task execution across the three job dimensions, both relative to each other, and in the context of different route types. The results demonstrated that sales skills were the bottleneck on smaller volume routes, and that driving/delivery skills were the bottleneck on higher volume routes. The former further highlighted the importance of sales task execution in driving incremental sales volume, an issue well known within the organization. The latter was less expected, but was consistent with concerns people in the organization had about restrictive delivery windows at large format retailers and the RSRs' ability to effectively serve those accounts. The study results helped crystallize the decision to move forward with a job design change for those routes that added a dedicated hourly merchandiser while increasing the number of stores, route volume, and capital utilization.

Finally, a separate regression analysis of the role of different types of work experience before joining Frito-Lay revealed that prior sales experience contributed to sales volume on both types of route. This led to a modification of the hiring profile to put a greater emphasis on prior sales experience.

4. What can analytics and logic contribute when there is not enough time for in-depth analysis?

The case studies in the previous section provide rich examples of the range of analytical and statistical techniques that often are needed when conducting analysis that leads to meaningful business insights. The good news is that advanced statistical procedures *can be* part of the tool kit needed in a given situation but *are not required* in all situations. Yet it is not the sophistication of statistical techniques that typically poses a barrier to meaningful analytical insights. What often consumes the most time and creates the greater challenges is identifying and collecting the new data required for the analysis that is most likely to reveal the deepest insights. Once the data has been collected, the time needed to carry out statistical procedures – even the most advanced ones – tends to be shorter and sometimes much, much shorter.

Both the PwC and Frito-Lay cases are examples of the kinds of analytics that can be conducted when there is a large organizational commitment in terms of resources and the study participants' time. The timeline needed is also often quite lengthy, requiring typically four to six months to do the work when surveys have to be designed, administered and matched to other data sources. That does not necessarily include the upfront time needed to get stakeholder alignment and support for the work, which can significantly lengthen timelines.

Because of these time and resource commitments, the larger-scale initiatives represented by the PwC and Frito-Lay cases often are more the exception than the rule when it comes to HR analytics. For the vast majority of HR processes and decisions to be made about them, the time and resources are not sufficient for a comprehensive data analysis. This raises the question, Can analytics be applied in these cases to improve decision making and, if so, how? A comprehensive answer to this question cannot be provided in one article. The foundation of knowledge needed to do so can be outlined, and that is what I now do in the remainder of this paper.

a. The Capability-Opportunity-Motivation model

Figure 1 contains a version of the Capability-Opportunity-Motivation (COM) model that has strong roots in both the research and practice traditions (Blumberg and Pringle, 1982; Boudreau, Hopp, McClain and Thomas, 2003). It was a core part of the approach used to conduct the PwC and Frito-Lay case studies. The main point of the model is that each of the following is a potential causal factor behind individual motivation and performance. Usually, more than one, if not all three, factors are involved:

- Capability: knowledge/skills/abilities (KSAs); how they are built through on-the-job learning, training and development; the time it takes for someone to get to full (average) productivity in the role
- Motivation: all the factors that influence motivation in the role, including relationship with supervisor, fit, satisfaction, rewards, and work-life balance

- Opportunity: the structure of the role and organization that enables and/or impedes performance in the role, including both formal and informal processes

As a diagnostic tool, the COM model is a standard for identifying the complete range of factors that impact individual performance, and the collective performance of the entire group of people in a role. As in the PwC and Frito-Lay cases, it can be used to define the domains of data to be collected for an in-depth analytics project.

In cases where there is not sufficient time for in-depth analytics, the COM model can serve as a map for checking whether the appropriate questions are being asked about what is driving behavior, and testing alternative scenarios beyond what is initially identified. Many functionally oriented HR people consider only their own area of expertise and influence when determining a course of action to take. This typically means only the “capability” angle or only the “motivation” angle; it rarely ever means only the “opportunity” angle, as that is a key aspect often ignored when HR assesses possible solutions to productivity challenges. The COM model can help HR professionals to break the cycle of only inwardly-looking diagnosis and consider other factors. For example, a compensation and benefits person presented with the Frito-Lay RSR challenge might easily have chosen to focus on closing the regional gaps in compensation while ignoring other possible causal factors. Using the COM model, diagnostic questions that could be asked include:

- Could a lack of skills, including sales skills, contribute to low productivity? If we close the compensation gap but do not address recruiting profiles, would that ensure we get the right mix of sales skills in the role?
- What happens to the supervisors when turnover is so high? Do they have to compensate for RSR absences in ways that hurt overall sales performance?

It is no guarantee that asking these questions without extensive survey data collection and analysis would lead to the exact same insights found by the study. But asking them and engaging with the other experts in HR and the line organization would greatly increase the chances of identifying the sales recruiting profile and supervisor lost sales opportunities issues.

b. Labor markets model

Figure 2 embeds work design at the job, team and organization levels inside a framework that addresses both external labor market and career issues, and business model issues as follows:

- External labor market and career issues, including:
  - External job opportunities
  - Alternative career paths available to each person and differences across people in their chosen career paths
  - Job dynamics as people transition through different career stages, including trading off compensation today for development that can lead to greater compensation tomorrow
- Business model issues:
  - What are the P&L assumptions behind the work design, including options for paying more (less) to attract and retain higher (lower) productivity workers?
  - How to evaluate the buy versus build decision for a given skill set, including options for outsourcing individual jobs/roles or entire segments of the production process?

Using both the COM and labor markets models is important for evaluating the full set of options available to an organization related to increasing profitability; the COM model alone addresses only productivity, not the bottom line impact.

For example, in the Frito-Lay case, the labor markets model was critical for identifying the option of adding a dedicated merchandiser to the higher volume routes as a cost effective solution for dealing with the challenges of low productivity on those routes. The labor markets model in both the PwC and Frito-Lay cases was important for evaluating the role of alternative jobs as drivers of motivation and productivity. A big benefit of the labor markets model is that careful consideration of common sense factors is possible using logic only, when there may not be sufficient time for extensive data collection and analysis. For example, the conclusion reached about Frito-Lay RSR compensation gaps based on the historical trends in college attendance and changes in the job design used elements of both the labor markets and COM models without time-intensive data analysis.

c. Organization design model

Figure 3 presents the classic organization design model pioneered by Galbraith (1977). Since then there have been many other organization design models, yet the essence of the models is the same in the fundamental way that is relevant for our purposes: there must be alignment among all the key organization design elements, and both formal and informal processes are needed to ensure successful operations across the entire enterprise.

Organization design is listed as a design element in the COM model in Figure 1, so it may seem repetitive to address organization design as a standalone model in Figure 3. The reason for doing so is to highlight the different levels of aggregation that must be addressed when analyzing organization behavior and performance. The COM model focuses exclusively on an individual or on groups of people who occupy the same role. It can be applied to different groups of people in different roles, but its accuracy diminishes greatly as the roles become more and more dissimilar and/or the people in the roles become more and more dissimilar.

The organization design model, in contrast, addresses the aggregate organization behavior issues that exist enterprise wide, including, most importantly, where processes work well versus break down across divisional and functional lines. Neither the COM model nor the labor markets model addresses those critical determinants of organizational performance and success. Moreover, from an analytics perspective, the organization design model is “data light,” meaning that organizational diagnoses often can be made through qualitative assessments of decision rights and the formal and informal processes by which work gets done in the organization. Advanced statistical techniques such as network analysis certainly have the potential to improve organization design diagnoses; yet deep insights often are gained through a series of carefully designed interviews and a logical analysis of the way the work *should be conducted* versus the reality of the way the work *is conducted*. This is a type of targeted analytics that often does not require any statistical analysis at all, even basic statistics.

5. Conclusion

Analytics in the HR function to this point has been treated as an unusual competency, something to be applied more often by specialists residing in centers of excellence than the large mass of generalists who do the bulk of the day-to-day work in HR. In this article I have shown a number of ways that analytics can – and should – be adopted more widely throughout the HR function and targeted toward a much broader range of issues. Part of the problem until now may have been a lack of understanding of the barriers to conducting meaningful analytics. Through the case studies presented here I have shown that advanced statistical analysis is needed only some of the time to achieve the deepest insights. Moreover, even in those cases, the hardest part of the work typically consists of identifying, getting access to, and collecting the data needed for the statistical analysis. Those are tasks and competencies that must be mastered by HR generalists, not analytic specialists, in order to increase the overall level of insightful, analytically-based decision making in HR. Mastering them is doable for most people, so this is not an impossible challenge for today's typical HR generalist.

Another key issue is the time needed to do deep analysis. The models discussed here – COM, labor markets, organization design – all have elements that can be applied as diagnostics using logic exercises when time is insufficient for intensive analytics. If HR professionals can master these models and other like them, that will raise the level of analytic competence throughout the function. This will not diminish the role of statistical analysis in HR decision making and, to the contrary, likely will enhance it because many more opportunities for applying advanced statistics to diagnose HR issues will emerge from applying good analytics more broadly.

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Table 1: HR analytical competencies		
Analytical competencies related to statistical techniques		
Category	Examples	Level of statistical expertise required (and approximate educational equivalent)
Basic data analysis	• Mean • Median • Minimum & maximum; range • Percentiles	• Beginning course in basic statistics • Minimal on-the-job experience applying the techniques • High school / undergraduate level education
Intermediate data analysis	• Correlation • Statistically significant differences • Standard deviation	• One to two courses in basic statistics • 3-6 months on-the-job experience • High school / undergraduate education
Basic multivariate models	• ANOVA / ANCOVA • Regression • Factor analysis	• Course in advanced statistics • 1-2 years on-the-job experience • Undergraduate / MBA education
Advanced multivariate models	• Structural equations models • Hierarchical linear models • Bivariate / multivariate choice models • Cross-level models, including adjustments for grouped and non-normal errors	• Degree or concentration in statistical methods • Substantial experience applying the techniques on-the-job (multiple years) • Graduate degree (Masters or Ph.D.)
Other analytic competencies		
Data preparation	• Identify data for analysis • Prepare / clean the data for analysis (transform, identify outliers, etc.)	• One to two courses in basic statistics • 3-6 months on-the-job experience • High school / undergraduate education
Root cause analysis	• Identify causal paths • Six Sigma analysis	• One to two courses in basic statistics • 6-12 months on-the-job experience • High school / undergraduate education
Research design	• Treatment vs. control groups • Experimental design (exogenous variation created by researcher) vs. "natural" experiments (exogenous variation that already exists in the data)	• Course in advanced statistics • 1-2 years on-the-job experience applying the techniques • Undergraduate / MBA education
Survey design	• Sample selection • Survey item design; validity; reliability	• Course in advanced statistics • 1-2 years on-the-job experience • Undergraduate / MBA education
Qualitative data collection and analysis	• Interview techniques • Interview coding • Content analysis	• Course in research design • 1-2 years on-the-job experience • Undergraduate / MBA education

Table 2: Application of HR analytic competencies				
Percentages	HR analytics group		Others in HR	
Analytical competency	Proficiency	Frequency	Proficiency	Frequency
Identify proper data for analysis	100.0	100.0	27.9	65.1
Data access / influence skills: obtaining data from others	78.9	89.5	38.5	64.1
Root cause analysis	84.2	73.7	30.7	51.3
Basic univariate statistics (mean, percentile, etc.)	79.0	79.0	23.7	51.3
Advanced univariate statistics (correlation, differences, etc.)	68.4	57.9	10.2	11.1
Basic multivariate statistics (ANOVA, regression, etc.)	42.1	38.9	8.6	8.6
Advanced multivariate statistics (structural equations, etc.)	27.8	11.2	2.9	0.0
Writing / communication (make statistical results understandable)	89.5	84.2	18.4	63.2
Presentation or public speaking (effectively present analysis to cross-disciplinary audience)	89.4	79.0	45.9	65.7

Proficiency = percent indicating “intermediate” or “advanced” skills; excluded categories: “none” and “basic”

Frequency = percent indicating “sometimes” or “frequently” used in work; excluded categories include “never” and “rarely”

Source: Levenson, Lawler, Boudreau (2005)

Table 3: Data analysis applications that organizations address with HR analytics					
Percentages	Data-based analysis conducted	Level of sophistication of data analysis:			Results used in reports, dashboards or scorecards
		Basic	Intermediate	Advanced	
a. Compensation	97.8	4.7	51.2	44.2	76.7
b. Employee attitude surveys	93.5	11.9	45.2	42.9	83.7
c. Recruitment	91.3	31.7	48.8	19.5	82.9
d. Diversity/affirmative action	86.7	20.5	46.2	33.3	89.7
e. Benefits	86.4	8.3	47.2	44.4	67.6
f. Selection	82.6	44.1	35.3	20.6	71.4
g. HR planning	82.6	24.3	56.8	18.9	71.1
h. Succession planning / leadership supply	81.0	45.2	38.7	16.1	53.1
i. Workforce planning	80.4	44.1	41.2	14.7	62.9
j. Organization development	80.4	31.3	46.9	21.9	48.6
k. Strategic planning	80.0	20.0	51.4	28.6	69.4
l. Employee training / education	80.0	52.9	23.5	23.5	66.7
m. Performance management	79.5	31.4	51.4	17.1	77.1
n. Promotions	69.8	30.0	43.3	26.7	76.7
o. Organization design	69.6	29.6	48.1	22.2	44.8
p. Competency / talent assessment	68.2	42.9	32.1	25.0	58.6
q. Management development	63.6	50.0	28.6	21.4	67.9
r. Change management	60.9	32.0	40.0	28.0	34.6
s. Downsizing layoffs	54.5	37.5	33.3	29.2	72.0
t. Career planning	52.2	45.5	36.4	18.2	43.5
u. Union/labor relations	27.9	80.0	0	20.0	45.5

Note: Percentages and Averages are computed with Not Applicable and Don't Know responses coded missing.

Source: Levenson, Lawler, Boudreau (2005)

Table 4: How extensively analytics is used for HR decision making								
Please indicate the extent to which HR analytics is used to:	Not At All (1)	Some Extent (2)	Moderate Extent (3)	Considerate Extent (4)	Very Great Extent (5)	*Don't Know*	***Average***	***Percent indicating "considerate" or higher***
a. Measure routine HR process execution (payroll, benefits, communication, etc.)	8.7%	23.9%	26.1%	21.7%	19.6%	2.1%	3.20	41.3%
b. Assess and improve the HR department operations	10.9%	19.6%	32.6%	15.2%	21.7%	2.1%	3.17	36.9%
c. Support organizational change efforts	10.9%	21.7%	23.9%	26.1%	17.4%	2.1%	3.17	43.5%
d. Measure the cost of providing HR services?	10.9%	26.1%	23.9%	17.4%	21.7%	2.1%	3.13	39.1%
e. Make recommendations and decisions that reflect your company's competitive situation	13.6%	22.7%	27.3%	22.7%	13.6%	6.4%	3.00	36.3%
f. Evaluate the effectiveness of HR programs and practices	6.8%	36.4%	27.3%	15.9%	13.6%	4.3%	2.93	29.5%
g. Contribute to decisions about business strategy and human capital management	15.2%	30.4%	13.0%	28.3%	13.0%	2.1%	2.93	41.3%
h. Measure the effects of HR programs on the workforce in terms of competence, motivation, attitudes, behaviors, etc.?	17.4%	26.1%	23.9%	13.0%	19.6%	2.1%	2.91	32.6%
i. Measure the business impact of HR programs and processes?	17.4%	26.1%	21.7%	17.4%	17.4%	2.1%	2.91	34.8%
j. Assess and improve the human capital strategy of the company	15.9%	31.8%	13.6%	22.7%	15.9%	6.4%	2.91	38.6%
k. Identify where talent has the greatest potential for strategic impact	20.5%	18.2%	31.8%	18.2%	11.4%	6.4%	2.82	29.6%
l. Connect human capital practices to organizational performance?	25.0%	25.0%	18.2%	25.0%	6.8%	6.4%	2.64	31.8%
m. Conduct cost-benefit analyses (also called utility analyses) of HR programs?	27.3%	25.0%	25.0%	9.1%	13.6%	6.4%	2.57	22.7%
n. Assess HR programs before they are implemented – not just after they are operational	25.0%	36.4%	18.2%	13.6%	6.8%	6.4%	2.41	20.4%
o. Evaluate and track the performance of outsourced HR activities?	26.7%	40.0%	13.3%	13.3%	6.7%	4.3%	2.33	20.0%
p. Assess the feasibility of new business strategies	39.5%	27.9%	11.6%	4.7%	16.3%	6.4%	2.30	21.0%
q. Pinpoint HR programs that should be discontinued	37.0%	28.3%	21.7%	8.7%	4.3%	2.1%	2.15	13.0%
Source: Levenson, Lawler, Boudreau (2005)								

Figure 1: Capability-Opportunity-Motivation model

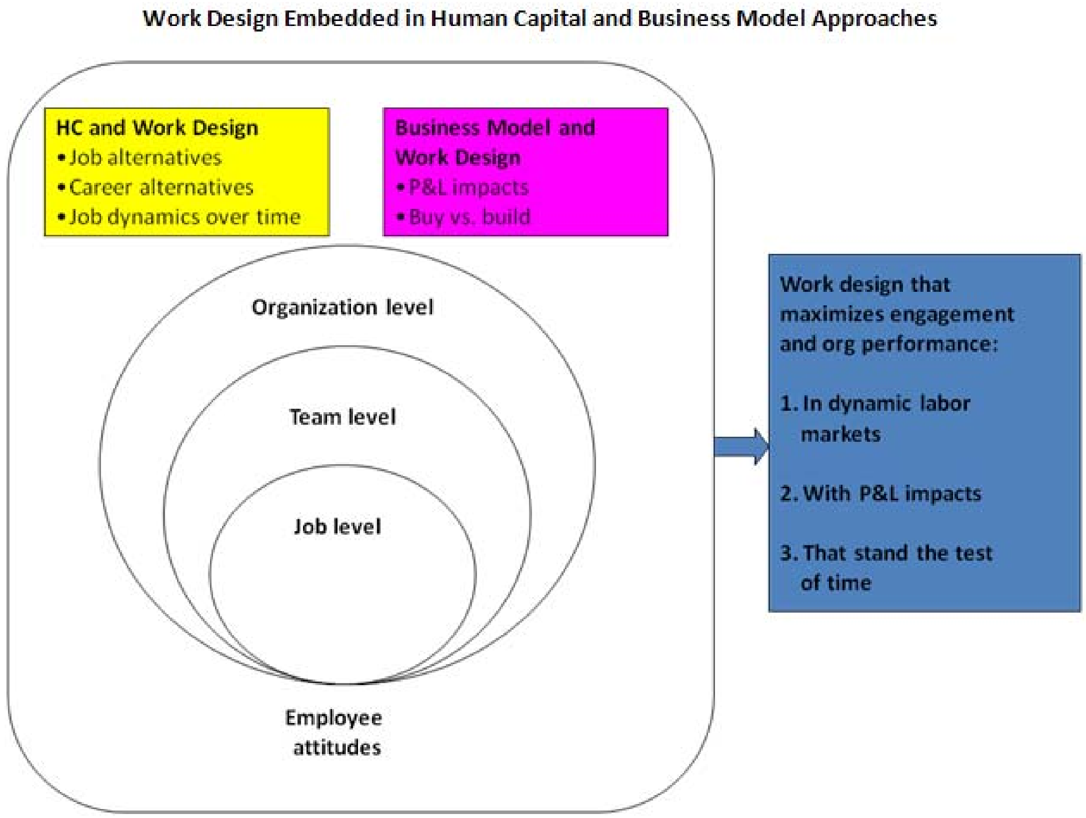

Figure 2: Labor markets model

Source: Galbraith (1977)

Figure 3: Organization design model