JAMES C. SESIL

APPLYING ADVANCED ANALYTICS TO HR MANAGEMENT DECISIONS

METHODS FOR SELECTION, DEVELOPING INCENTIVES, AND IMPROVING COLLABORATION

Applying Advanced Analytics to HR Management Decisions

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James C. Sesil

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To Kathy and Al

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About the Author

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Sesil's work has won three best paper awards from the Academy of Management and the Labor and Employment Research Association and has been covered in *The New York Times, BusinessWeek,* and *The Financial Times*. He spent eight years in HR roles at Control Data, Honeywell, and Cargill, Inc., and he holds a Ph.D. from the London School of Economics.

Preface

Written for anyone in any organization making human capital management (HCM) decisions, including C-level executives and all managers, this book does several things:

- It provides a summary of implications associated with new research on how decisions are made and what motivates us.
- It develops an evidence-based approach using advanced analytics to assist organizations with developing a collaborative workplace and with selecting and motivating people.
- It applies the new thinking associated with advances in behavioral economics, psychology, and machine learning to the decision-making process and refers to this as "The New Human Science."
- And it further recognizes the value of human experience and expertise and provides a mechanism for applying both advanced analytics and intuition or expert knowledge.

Here is how the book is structured.

Chapter 1, "Challenges and Opportunities with Optimal Decision Making and How Advanced Analytics Can Help," provides the overall framework and discusses how it is to be applied to human capital management (HCM) decision making. This framework builds on the work of Nobel Prize winning social psychologist Daniel Kahneman, along with others, to provide strong evidence that we do not decide rationally. The chapter discusses the role biases play in decision making and how the use of advanced analytics can help eliminate bias from decisions.

Chapter 2, "Collaboration, Cooperation, and Reciprocity," focuses on the role of collaboration, information sharing, and decentralized decision making. In this chapter, some of the old thinking about what motivates us is dispelled, and new findings are applied. Economic science has long held that we are generally self-centered, selfish, inherently lazy, and largely interested in only income maximization. This assumption about our natures has had a substantial impact on the way in which the employment relationship has been structured and has generally led to mistrust and noncooperative behaviors. Recent evidence finds that we are actually unselfish, cooperative, altruistic, and potentially very self-motivated. This has substantial implications for how we ideally organize ourselves. The role and importance of collaboration and cooperation is also discussed.

Chapter 3, "Value Creation and Advanced Analytics," covers evidence where value is found within organizations and how getting the right mix of human capital, HCM practices and policies, and technology will ultimately lead to better performance outcomes. The loss associated with high employee turnover is discussed, as is how human science can help reduce the loss of expertise associated with human capital leaving the organization.

Chapter 4, "Human Science and Selection Decisions," covers how advanced analytics can reduce and eliminate discriminatory hiring and promotion decisions. The focus of the chapter is on the use of bio data to make better hiring predictions.

Chapter 5, "Human Science and Incentives," focuses on how advanced analytics can assist with decisions associated with developing incentive contracts. New evidence on what motivates people is discussed, as well as how a focus on tournament compensation is sub-optimal. Application of human science including advanced analytics to practical incentive contract challenges is made.

Introduction

The New Human Science and HCM Decisions

I am a runner. I have completed 23 marathons and more half-marathons, 10k, and 5k races than I can remember. So in 2010 when I went in for my annual physical and was told that I had the loudest heart murmur the examining physician had ever encountered, I thought she had a seriously faulty stethoscope. Nonetheless, I took her advice and went in for an EKG and discovered I did indeed have a seriously faulty heart. I had mitral value prolapse with flail (MVPWF)—essentially, one of my values was not closing and I needed surgery to have it repaired or replaced. So, being a research-oriented type of person who really wanted to keep running, I learned everything I could about MVPWF and starting looking around for a great cardiovascular surgeon. I sent the video of my faulty heart value to surgeons around the country and discussed my options with a number of them. I examined and evaluated all the data I could find on my condition and what could be done about it. I also did a lot of due diligence when choosing a surgeon. The one I finally chose had all the right numbers, but what sealed the deal for me was his office walls were covered with pictures of all the hearts he had fixed. When I saw the way his face lit up when he started to talk about his wall of hearts, I knew I had the right guy, and I did.

My choice of a surgeon was a selection decision, plain and simple. Though I did not realize it at the time, it was also a case study in data and intuitive decision making. I am a fact guy; it is really important to me to make as optimal a decision as possible, but I also have learned to trust my instincts. The data analyzed and research I did was critical for making an optimal decision, but just as important was my own intuition. There is still no software application, supercomputer, or A.I. tool that can touch our ability to assess certain intangibles.

The use of analytics has a long history associated with human capital management (HCM) decisions, but far too many organizations continue to use these tools for reporting simple descriptive statistics and correlations. Advanced analytics has been adopted by other business functions such as finance and marketing; however, it still has a long way to go to be fully utilized for HCM decisions. According to research conducted by IBM in which 700 chief human resource officers were interviewed, less than 25% are using sophisticated analytics to predict future outcomes and for decision making.[1]

The underutilization of advanced analytics associated with HCM decisions is a problem because the jury is in: There is a real and direct bottom-line impact associated with getting these decisions right. If an organization wants to deliver the highest quality goods and services, superior customer service, and the most innovative products, effective HCM is required. Getting HCM right boils down to making many decisions and making them correctly.

The challenge and opportunity is that the entire range of HCM decisions (from where and how to recruit and hire, how to reward and motivate, and which policy and practice to use in a specific situation) is getting very difficult to make optimally. There are a huge number of different practices and policies and combinations to choose from and an ever-increasing amount of pertinent information useful for making these decisions. Fortunately, there is new research, insights, analytical tools, and processes associated with advanced analytics that can assist in making these decisions much more optimally. For example, companies like Xerox and Google are using predictive analytics to evaluate which characteristics are associated with good employees, and this information is used to help with employee selection.[2] The use of advanced analytics can help eliminate all forms of bias associated with selection and promotion decisions and also provide a mechanism for compensating and rewarding people in a more accurate and fair manner.

If biases are eliminated from the decision-making process, previously unconsidered possibilities will emerge. SAP, the German software giant, has announced that by the year 2020, 1% of its workforce will fall on the autistic spectrum. The company has found greater engagement and productivity in locations where they have adopted this hiring policy.[3] Some of the most productive and capable computer programmers fall on the autistic spectrum. By undermining any prejudice and bias associated with autism, SAP is potentially developing a previously unrecognized HCM competitive advantage. Advanced analytics can aid in the process of identifying these possibilities by eliminating all extraneous factors from decision making so that only merit and potential is taken into consideration.

A number of factors are converging that make this the right time to start using data and other information to make more robust decisions. Technology has become more accessible, user friendly, and powerful. There have been recent advances in machine learning, natural language, and deep Q&A expert systems (for example, IBM's Watson beating two former *Jeopardy!* champions). In addition, we know substantially more about what really contributes to organizational performance (for instance, balance scorecards and intangible capital), and we are also getting much better at modeling what is important to people and how people think and how they actually behave (for example, behavioral psychology, behavioral economics, and neuroeconomics).

Many of these paradigm-shifting developments have *not* been incorporated into our decision-making processes. It has long been held that we humans are rational decision makers who are very self-centered and selfish. Recent research has shown that we are rarely inclined to make rational decisions and that we are actually very cooperative, collaborative, and unselfish and want to be treated fairly and to see others treated the same.[4] These finding have tremendous implications for how we manage the employment relationship. Equity matters because it matters to the primary input in all organizations' output equation: human capital.[5] Humans want to be treated and rewarded fairly. If they are not, they withhold value-creating information and effort, are more likely to be absent, quit, and sometime actively conspire to undermine the goals of the organization.

I refer to all these recent findings as "The New Human Science." I integrate the recent findings on what motivates us, what influences our decision making, and what our natures are like, with recent advances in technology in order to assist us with making more optimal value-creating decisions.

This is not to suggest that advanced analytics will replace human expertise. Instead, I believe that it will complement it. In 1997, the chess master Gary Kasparov lost to the IBM computer Deep Blue. However, as Kasparov later reported, the most unbeatable champion is not a supercomputer. The most powerful computer can be beat by a good amateur chess player working with a standard PC. The optimal decision maker is not computer or human alone, but rather the combination.[6] That is the position taken in this book. When well-seasoned human expertise is combined with the right advanced analytics, the decisions made will be much more likely to create value for everyone.

There is data and there is data. I will be talking about techniques, but equally important is to get the questions right. The tools have gotten really cool and the types of analysis that are now possible were not even imagined ten years ago. None of that changes the fact that data is really about stories. In the case of this book, stories are about what is going on in your organization—what (and whom) is working and what is not. Everything that is discussed here is meant to help us become better and more accurate data story tellers.

Some might view big data, advanced analytics, and data science as being sterile and potentially dehumanizing. I argue the exact opposite. The use of these tools, when coupled with the right kind of human expertise, can help us become much more *humane* decision makers. By humane, I mean fairer, inclusive, and merit based—ultimately making our organizations more equitable, collaborative, and successful.

One final note. This book is meant to be used in conjunction with its associated website, DecisionAnalyticsInc.com. The focus of the book is on what can and should be done with advanced analytics and optimal HCM decision making. The website will provide tools and more detail on exactly *how* this this optimal decision making is accomplished.

1

Challenges and Opportunities with Optimal Decision Making and How Advanced Analytics Can Help

1.1 How We Make Decisions and What Gets in the Way

In their book *Nudge,* economist Richard Thayler and legal scholar Cass Sunstein describe homo economicus and homo sapiens. Homo economicus are humans as they are described in economics textbooks. They act and make decisions completely rationally, have the computing power of a hundred super computers, and they always know precisely what will make them happy. Homo sapiens, however, do things like jump out of perfectly good airplanes, forget significant others' birthdays, and occasionally drink or eat too much. Thaler and Sunstein refer to homo economicus as econs and refer to the rest of us as humans.[1]

Remarkably, until relatively recently, even in light of nearly unlimited anecdotal and empirical evidence, we *assumed* our decision making was almost always rational and optimal. It was not until the ground-breaking work of those like Thayler, Daniel Kahneman, Amos Tversky, Robyn Dawes, Daniel Ariely, and many others that this fundamental assumption of rationality was largely undone. Probably the fatal blow to the idea that we always decide rationally was delivered by

Kahnman and Tversky.[2] “Econs” have long been assumed to “maximize their utility”; this requires that they have a very clear idea of preferences. Work by Tversky and Kahneman provide evidence of a “framing effect.”[3] This finding shows that our preferences and subsequent decisions will be impacted depending on how the information is presented.

Relative to human capital management (HCM) decisions, this may mean that someone is rejected for an interview based on the letter font used on his curriculum vitae (CV) or resumé. It might not be a conscious decision; the reviewer may just equate a particular style with professionalism. Though most would agree presentation matters, making a decision to not interview someone based on one data point, and that data point being a preference for Times New Roman over Cambria, could be considered less than ideal. This matters because the sum total of all the small and large HCM decisions *will* make or break an organization. Who we hire and promote, how we compensate and motivate people, the type of training they receive—these decisions have a direct and identifiable impact on the success of the organization.[4]

Though there is an ongoing debate about just how rational we really are,[5] there is agreement that we are often pushed toward acting irrationally,[6] even when rational action would lead to the best outcomes. I conduct empirical research, and the research questions that interest me evolve around this question: What works at work? For example, does giving employees more decision-making authority lead to better firm performance? Does the executive compensation plan provide an incentive to actually improve performance?

One topic on which I have done a fair amount of research is the granting of stock options to nonexecutive employees.[7] From the perspective of standard rational economic theory, this is really a foolish thing to do. Economic theory would say that granting stock options to anyone other than the top few employees is about as sensible as burning the options. The primary theoretical lens used to justify granting company shares to employees is called *agency theory,* and although it provides a very good rationale for the granting of stock options to executives, it provides a very poor one for granting to nonexecutives.[8] Based on agency theory, there is no reason to expect giving stock options to nonexecutive employees will motivate them to work harder, smarter, or longer, because their individual efforts have very little impact on the share price. However, surprisingly, initially even to me, giving stock options to nonexecutive employees seems to do just that. We have repeatedly found evidence that giving stock options to a broad set of employees (in some cases, everyone in the firm) increases productivity and other performance outcomes.[9] So, this would argue that in this instance, employees are not acting as one would expect econs to act. Instead of making people work harder because they think their work can move the share price, they appear to be working harder because of some completely different reason.

A detailed exploration of what is driving those behaviors is beyond our scope here, but it may be that broad-based stock options create a culture of engagement. Stock options may go some way toward establishing a workplace where there is an attitude that we are all in this together, and maybe this is what causes employees to work harder, smarter, longer, or more collaboratively.[10] What this means is that when we are attempting to predict how people are *actually* going to respond, the rationale model is not of much use. (Like it or not, our default assumption is often that people will respond rationally.) It also means that our *predictive models* need to incorporate new findings from behavioral economics, psychology, and neuroeconomics.

In an interview conducted in the *Sloan Management Review,* Thomas Davenport, who, along with Jeanne Harris, has written extensively on analytics, said that he thought many great tools were being underutilized.[11] In the article, Davenport went on to say that not only was he referring to structured and unstructured data but also to the insights on decision making that could be found in the "wisdom of crowds," "behavioral economics," and "neuroscience." This section explores a number of the factors that impact the quality of our decision making.

1.1.1 Intuition Versus Analytical Thinking

The fact that we do not decide rationally is not to suggest that there is anything wrong with the way our brains work; after all, it is our minds that came up with things like language, the written word, chocolate-covered peanuts (significant and important things). Daniel Kahneman's, notion of thinking fast and slow and Thayler and Sunstein's System 1 and System 2 cover the important characteristics of how we think. Thinking fast is essentially making decisions based on intuition, and thinking slow, as the name implies, refers to making decisions based primarily on analytical evaluation. Kahneman also uses the terms *System 1* and *System 2* thinking. System 1 thinking is our intuition—those thoughts, feelings, impressions, associations, and preparations for action that all happen automatically and fast (for example, chatting with friends or brushing our teeth). System 2 thinking, reflective thinking, is by contrast slow and deliberate, thoughtful and effortful. This is the type of thinking we engage in when rule-based logic is required or when, for example, we are completing our taxes or learning a new skill. Examples of situations where we think fast include the following:[12]

- Detect that one object is more distant than another
- Detect hostility in a voice
- Understand simple sentences

At other times, our thinking needs to slow considerably, as in the following examples:[13]

- Teaching someone a new skill
- Filling out a survey
- Checking the validity of a complex logical argument

Basing decisions solely on intuition can be problematic. Making hiring, promotion, and bonus decisions based on gut instinct carries with it the potential for including a lot of bias and incomplete information. The fact is that most workforce management decisions are rife with potential biases, and making these decisions with the assistance of analytics can help eliminate many of these biases. This is not to say that there is no place for "expert" intuitive knowledge. The use of stock options is an example. Based purely on a rational model of decision making, no firm would ever issue stock options to anyone other than the two or three top employees who may have the power to move the share price.

Silicon Valley, the undisputed epicenter of worldwide technological innovation, was one of the first to recognize how broadly distributed stock options could help motivate and retain employees.[14] In fact, some say that stock options provide the fuel that powers Silicon Valley.[15] Frankly, Silicon Valley might never have existed (and so some of the world's greatest innovations might not have happened) if those making HCM decisions had thought like econs and assumed everyone else did too.

What you want to keep in mind here is that although there is a critical role for intuition (that is, paying attention to your gut), it is almost always advisable to temper decisions with analytics. Generally speaking, many of the decisions associated with HCM have considerable potential for bias. Consequently, the ideal approach is one that combines the best analytics with well-seasoned human expertise.

1.1.2 Poor Intuitive Statisticians

Another critical realization is that we are really lousy statisticians. In the introduction to his book, Kahneman recounts the story of the first research project that he and Tversky undertook. They wanted to determine how good we are as intuitive statisticians. So, they developed and administered a survey at a meeting for the Society of Mathematical Psychology; participants included those who had authored statistical textbooks.[16] Even those with years of training and expertise were not good at predicting the probability of an event. Those with substantial training in statistics were prone to accept research that was based on small sample sizes and also gave a hypothetical graduate student inaccurate advice regarding the number of observations she would have to collect. This matters because we are constantly accessing the probability of an event occurring (for example, the probability that an employee will perform as expected, the likelihood that a specific compensation approach will promote desirable outcomes). Fortunately, there is a fix, or at least a fairly robust solution. Data coupled with a good idea of the factors influencing an outcome, along with some pretty straightforward statistics, will go a long way toward predicting a likely outcome.

1.1.3 Understanding Human Nature

In a book about advanced analytics, it might strike you as odd that I will also be emphasizing the critical role that human intuition plays in decision making. I emphasize this because a number of constraints apply to advanced analytics when attempting to *predict* how people are actually going to act. Take, for example, stock options. Any model that expects rational behavior would expect no incentive effect associated with their use. (For example, individuals should not work longer, harder, or smarter.) However, that is not what we observe. People do actually work much harder. The more we understand how people think and act and what is important and what motives them, the greater the likelihood that we can accurately *predict* behaviors. Much new evidence from the natural and social sciences helps us better understand human nature; the same holds true for the humanities. For instance, experimental philosophy is empirically testing many basic assumptions about how we experience and relate to the world.[17] We delve into the implications of these new findings in subsequent chapters.

1.1.4 Biases and Decisions

One of the most critical factors influencing our decision making is our own biases. These are not something that we are generally even consciously aware of. However, they adversely impact our decisions making. A number of biases are especially troublesome when making HCM decisions, including the following:[18]

- **Confirmation bias:** This bias causes us to ignore evidence that undermines a preconceived idea. For instance, we may be convinced that someone is the person for the job even after much evidence to the contrary.

- **Anchoring:** We have a tendency to focus on data points that we consider to be especially telling. For instance, when making hiring decisions, college grade point average may weigh heavily, even though it has not been shown to be a good predictor of job performance.

  Anchoring refers to our tendency to weigh this one data point too greatly when making decisions.

- **Loss aversion:** This bias refers to our tendency to weigh potential losses greater than potential gains. We come by this bias honestly; there is an evolutionary advantage to focus on potential threats (hungry predators) rather than focusing on long term planning.

- **Status quo:** This bias is the tendency to go along with the status quo or the default option.[19]

- **Framing:** You can find an excellent example of framing in an article by Paul J. H. Schoemaker and J. Edward Russo.[20] Managers were asked what how they would respond to the following situation:

"Assume you are the vice president of manufacturing in a Fortune 500 company that employs over 130,000 people with annual sales exceeding $10 billion. Due to the recession as well as structural changes in your industry, one of your factories (with 600 employees) is faced with either a complete or partial shutdown. You and your staff carefully narrowed the options to either:

A. Scale back and keep a few production lines open. Exactly 400 jobs will be lost (out of 600).

B. Invest in new equipment that may or may not improve your competitive position. There is a 1/3 chance that no jobs will be lost but a 2/3 chance all 600 jobs will be lost.

Financially, these options are equally attractive (in expected rate of return). The major difference is the effect of the decision on the plant workers, who have stood by the company for many hard years without unionizing. Which option would you choose if these were your only alternatives?"

The exercise is repeated and this time the options are slightly reworded.

A. "Scale back and keep a few production lines open. Exactly 200 jobs will be saved (out of 600 threatened by layoff).

B. Invest in new equipment that may or may not improve your competitive position. There is a 1/3 chance all jobs will be saved but a 2/3 chance that none of the 600 jobs will be saved."[21]

Tellingly, when "framed" in the first example, most managers choose option A. When framed by the second, most managers choose the opposite.

These and other biases that are discussed in later chapters all serve to undermine the quality of many decisions generally and HCM decisions specifically.

1.1.5 Big Data and Information Overload

We are in the age of very, very big data. Just how big? Pretty big. Table 1.1 describes various quantities of bytes.[22]

Table 1.1 Byte Measurements

Name	Value
Kilobyte (KB)	10^3
Megabyte (MB)	10^6
Gigabyte (GB)	10^9
Terabyte (TB)	10^{12}
Petabyte (PB)	10^{15}
Exabyte (EB)	10^{18}
Zettabyte (ZB)	10^{21}
Yottabyte (YB)	10^{24}

The amount of data in "big data" is simply staggering. There are roughly one billion transistors per person and four billion cell phone users.[23] According to Gartner, the amount of information is growing at 59% annually,[24] and much of this information is unstructured data in the form of video, social media, blogs, and so on. There is simply too much information for our brains to process adequately. The brain itself can be thought of as a tremendous data producing mechanism, given that it contains 85 to 100 billion neurons and produces roughly 300,000 petabytes of data each year.[25] For some time now, we have had more information than we can process, and the ongoing exponential increase in information (information explosion) exacerbates this situation. One place where computers have us beat is in processing tremendous amounts of information very, very fast.

1.1.6 The Problem with Certitude

During dinner once with a former colleague and her husband, *Raiders of the Lost Ark* came up as we were talking about movies. We started discussing the scene in which Marian (played by Karen Allen) won a drinking game in the bar she owned. My former colleague was absolutely certain that the person she drank under the table was Indiana Jones (Harrison Ford). *Raiders of the Lost Ark* was one of my favorite movies, so I knew differently. I told her that it was actually some otherwise unknown local, not Indy. So certain that she was right, she said that she would bet her house it was Jones. The words of some wise sage popped into my head: "If someone offers you a perfectly good house, take it." So, I took the bet, and we headed down to the local video rental store. However, I was starting to have mixed feelings about actually taking their house, so I told them that I would be happy to let them off the hook and drop the bet. This elicited some pretty dodgy accusations about my stomach for betting. So, as long as they insisted.... Before watching the movie, I asked my former colleague (who is extremely bright and one of the top academics in her field) what she considered to be the probability of her being correct. She said 99.9999%. In other words, she was sure that she was right, really sure. Anyone who has seen the movie and remembers that scene will know that I won a house. In case you are interested, I let them stay in their home, but I was not above occasionally asking whether they were taking good care of my property. I am not sharing this story to spotlight my movie knowledge. Instead, I want to point out that just because we really, really think we are right does not mean that we necessarily are. And trust me, I have been guilty of this more than once.

1.1.7 Advanced Analytics Does Not Care Who It Annoys

Unfortunately, some in positions of authority have fragile egos or are primarily concerned with advancing their own agenda rather than dealing with actual facts. Hiring yes men and yes women is simply a losing proposition. Warren Buffett, for instance, goes out of his way to seek out people to tell him that he is wrong, and many (if not all) successful organizations never become self-satisfied. One of the big advantages of advanced analytics is that it is entirely immune to big egos, group think, and the loudest getting their way.

Evolution has favored those who are good at advancing an argument, whether or not the argument is based on fact, and so we come by our opinionated natures honestly. The challenge arises when the focus shifts from getting to the truth of the matter to winning the argument instead. Of course, we hope, those who are right win. Unfortunately, though, the evidence indicates that this is not always the case. The April 2011 issue of the *Journal of Behavioral and Brain Sciences* was devoted to the theory of argumentative reasoning.[26] The theory holds that we developed rationality not as a result of our desire to pursue philosophical and scientific insight and to develop a superior morality, but rather we developed it to win arguments. When it comes to winning arguments, what matters is certitude—knowing, or at least projecting, that you are certain you are right. Those skilled at winning arguments are advancing arguments rather than looking for the truth. All too often, therefore, "cherry picking" of the facts takes place. Here is where more sophisticated analytical models can play a critical role.

Philip Tetlock convincingly advises that we should consider expert advice with caution. Over a 20-year period, Tetlock followed the forecasts of 284 experts who were professional predictors of political and economic trends. He asked them to rate the probability of three different possible outcomes: no change in the current situation or either an increase or decrease in a factor like economic growth. He discovered that the experts with many years of experience and Ph.D.s were roughly as accurate as dart-throwing monkeys.[27] This is in no way meant to disparage the advice of all experts; after all, forecasting the future is a difficult thing. However, it is sensible to view most prognostications cautiously.

In his book *Streetlights and Shadows*, the psychologist Gary Klein, states the following:

> I am saddened to see ineffective decision-support systems that are designed in accordance with ideology rather than observation. If we try to balance the human as hazard model with the human as hero model, and to balance the automatic, intuitive system with the reflective, analytical system, we should have more of a chance to create decision-support systems that will get used.[28]

The tools and processes discussed in the rest of this book will attempt to just that: combine both the intuitive and analytical to provide us with the best possible decision.

1.1.8 Types of Decision Making

Hoch and Kunreuther propose three different levels from which decision making can be viewed:[29]

- **Normative:** The normative approach holds, for example, that we would be better served by making decisions based on rationality.
- **Descriptive:** The descriptive level describes what we actually observe about how decisions are made.
- **Prescriptive:** Prescriptive recommendations focus on improving decision making.

Much decision science research and work is tied to formal mathematical models. Recently, however, cognitive approaches to decision making have been a focus. This discussion adopts a *prescriptive* approach to our evaluation of the various factors that impact decision making and the technologies that can influence desirable outcomes.

1.2 Rise of the Machines: Advanced Analytics and Decision Making

According to Gartner, Inc., the term *advanced analytics* is defined as follows:[30]

> As analysis of structured and content (such as text, images, video, voice) data using sophisticated quantitative methods (such as statistics, descriptive and predictive data mining, simulation, and optimization) to produce insights that traditional approaches to BI such as query and reporting are unlikely to discover. It is frequently applied to make decisions, solve business problems and identify opportunities by providing better forecasts, causal understanding, pattern identification, process and resource optimization, and assisting with scenario planning process.

The challenge is that although substantial gains wait, very few firms actually utilize advanced analytics. Only 13% of organizations utilize predictive analytics, and only 3% use prescriptive analytics, such as optimization and simulation.[31] To this list, I want to add *actionable recommendations,* such as provided by machine learning and expert systems.

Recently, the focus on HCM metrics has gone a long way toward establishing the relationships between variables of interest (for example, training initiatives) and performance outcomes (for example, employee turnover by division).[32] Advanced analytics provides a deepening of the tools associated with business intelligence, with a focus on predicting and prescribing the optimal course of action. These techniques are increasingly being used in functions like operations, finance, and marketing and can have the same impact within human resources.

According to Gartner, this will matter.[33]

> Pervasive, advanced analytics will become necessary for leading organizations that want to gain competitive advantage.
>
> The explosion of data volume, and its variety and velocity, will enable new, high-value advanced analytic insights and use cases.
>
> Lack of skills will be a critical inhibitor to adoption and deriving value from advanced analytics.
>
> Embedding collaboration and social capabilities in advanced analytic applications will facilitate higher quality and more transparent decision making.

There is an ever-increasing need for data scientists—those who understand statistics, computer science, and data modeling and analysis. More effective HR decisions can be made when these skills are used to assist with the full spectrum of HR tools.

1.2.1 Advanced Analytics

As mentioned previously, we can improve our decision making. Metrics and analytics have long been used to assist decision making, and as computing power increases (along with our understanding of behavior), our tools are becoming more powerful as we develop models that more accurately predict outcomes.

Figure 1.1 provides an overview of a hierarchy of analytics. Level I is an organization's use of basic metrics to obtain information such as headcount, employee turnover, and even some simple statistics such as the use of means and averages. Next is Level II, which is characterized by correlations. This consists of determining whether and when variables move relative to one another. For example, as employee morale goes up, what happens to employee turnover? Of course, correlations do not mean causation; however, they do suggest a possible relationship. Level III shows a focus on establishing causation and on predictions of what will happen next (anything from who will make a good employee to whether a specific payment package will promote the intended organizational outcomes).

Advanced analytics can aid in establishing causation, which is generally thought of as the holy grail of analytics. That is, does the intervention we put in place have a direct impact on the bottom line? For instance, does the new compensation approach increase employee productivity, reduce employee turnover, and ultimately impact sales and profitability? This can then be used not only to justify expenditures but also to make determinations about what policy, practice, or intervention is advantageous to use in the future.

Advanced analytics can be thought of in two parts. Part one attempts to predict what will occur. As discussed in the previous section, this requires a broad understanding of how individuals and groups will react. Part two, and the primary focus of this book, is about optimization. The focus here is not about what a decision *will* be, but rather what it *should* be.

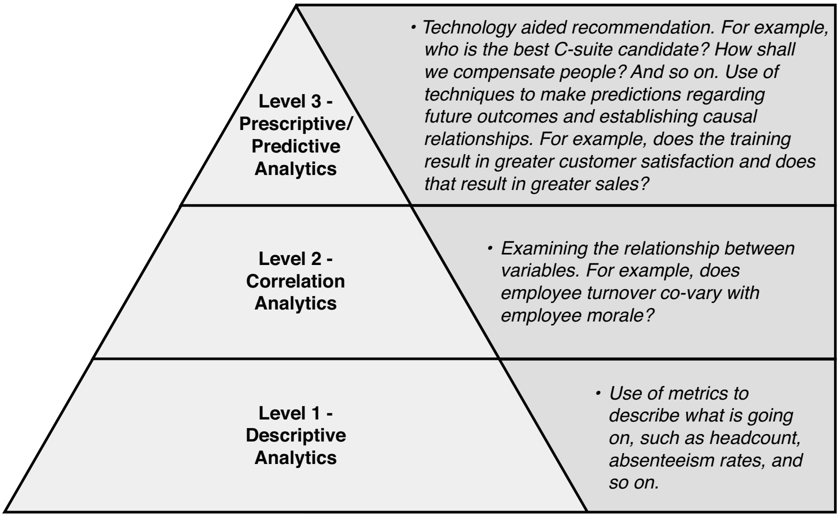

Figure 1.1 Hierarchy of analytics

It is a good thing that these tools are becoming more available, because according to a 2010 survey by IBM, there is a real need for HCM decisions to move toward higher levels of prediction and causation.[34] That survey found that advanced analytics were rarely used for activities such as evaluating workforce performance, retaining valued talent, and developing future leaders. Nowhere, on any of these HR issues reviewed, did more than a quarter of the organizations actually engage in advanced analytics. One of the least used analytical processes is the use of collaboration across the organization. Only 5% of the firms interviewed used advanced analytics along with collaboration and knowledge sharing.

HR has nothing to feel bad about. It is estimated that only 3% of firms use any form of advanced analytics. However, it is projected that the use of analytics will grow substantially over the coming years.[35] This book covers each of these three perspectives of decision making:[36]

- **Descriptive:** What happened and what is happening?
- **Predictive:** What will happen? What might happen?
- **Prescriptive:** What should happen? What is the best course of action?

1.2.2 Predicting Outcomes

Recently, the Sundem-Tierney equation has been updated. You may be wondering what exactly the Sundem-Tierney equation is used for. Basically, it predicts how long the marriages of celebrities will last. As one of the authors proclaims, tongue in cheek, "One of great unsolved mysteries in social science."[37]

The Sundem-Tierney Celebrity Marriage Longevity Equation

$$\sqrt{\frac{NYT}{ENQ}\frac{(Ah+Aw)}{(Sc+5)}Md\left[\frac{Md}{(Md+2)}\right]T^2}$$

Where:

NYT = The number of times the wife's name been mentioned in the *New York Times*

ENQ = The number of times the wife's name has been mentioned in the *National Enquirer*

Ah = Age in years of the husband

Aw = Age in years of the wife

Md= Number of months the couple dated before marriage

Sc= Number of scantily clad photos from the top five photos found during a Google image search of her name

T = Time in years for which you want to calculate the percentage chance the couple will still be married

This equation represents a revision of the old equation, and it turns out that this one is a much more robust predictor of the duration of celebrity marriages. For example, the equation accurately predicts that Jennifer Lopez's marriage to Ojani Noa (her first husband, a relationship that most people don't even know about) would not last very long (it lasted 13 months), but it predicts a 71% chance that Prince William and Kate Middleton will make it 15 years or longer.

Many become nervous when they hear things like "model building" or "optimization," but this does not need to be so intimidating. There is nothing intimidating about listing the factors that go into making the best decision. Getting all the best and required data might not always be especially easy, but determining the *determinants* (the factors influencing an outcome) can actually be rather fun and interesting. Take, for example, the following equation; it is attempting to determine the likelihood of marital bliss. By Robyn Dawes, this model predicts the likelihood of the survival of a marriage.[38]

Frequency of Lovemaking – Frequency of Quarrels

See, nothing at all boring about predictive modeling. As you might imagine, having a negative number associated with this equation is not a good thing. Because of the availability of the necessary data, predictions such as these are becoming more and more common and found across many facets of life. Predicting compatibility is the task organizations such as Match.com and eHarmony attempt to do. Dawes formula is a simple one that essentially attempts to serve the same function as the ones developed by these dating services. They are both attempting to identify a list of factors that will predict the success of relationships. In the case of eHarmony and Match.com, this also consists of information on emotional, cognitive, and social attributes, physical activity, personality characteristics, education, geography, and so on.

One more:

Runs Created = (Hits + Walks) × Total Bases / (At Bats + Walks)

Some of you might recognize this formula. William James, the founder of sabermetrics, developed it. If this is not familiar to you, maybe you remember the book *Moneyball*, by Michael Lewis, or the movie by the same name starring Brad Pitt. James's sabermetrics is the underlying approach used to predict success at getting on base, and this is exactly what the formula predicts: a hitter's ability to get on base. It did not worry about exactly how he got there. As a matter of fact, the formula takes into consideration those who walk as well as those who get hits.[39]

Making predictions is something that we do all the time. Will a stock price go up or down? Will your friends get married? Will this person make a good employee or a good executive? What kind of professional experiences will assist them in becoming better employees?

Within the broad area of decision support systems, a variety of different models are used to aid in decision making.[40] The relevant variables when "modeling" HCM decisions include all those factors that influence the outcome you are interested in. For example, what might be some of the causes of employee turnover? This decision will be influenced by, among other things, a number of the following factors:

- Employee morale and satisfaction
- Labor market conditions
- Relationship with direct reports

Another example is workforce planning, which seeks to accurately forecast future employment needs. Again, a number of factors may influence the best decision about the type and number of employees needed, including the following:

- Business strategy and objectives
- Current workforce quantity and competencies
- Required workforce quantity and competencies

In later chapters, we will evaluate factors influencing the ideal job candidate for your situation and the optimal compensation structure. Determining these factors is where expert knowledge and experience comes in, and when these are combined with the right analytics, you are on your way to making much better decisions.

1.2.3 Improper Linear Models: Combining Expert Intuition with Analytics

The work of Robyn Dawes provides an excellent justification and argument for the use of expert expertise combined with the use of advanced analytics. Analytics can be used to develop a comprehensive list of factors that ultimately promote performance, or make a good employee, or any number of different decisions, and the experts can use their expertise to develop the weightings for the various factors.

In his article "The Robust Beauty of Improper Linear Models in Decision Making," Dawes remarkably concluded that a simple algorithm is accurate enough to compete with regression analysis and, frankly, much better than the opinion of an expert. Consider, for example, the *Apgar test.* In 1953, Dr. Virginia Apgar, an anesthesiologist, was asked how she would assess the health of a newborn. She wrote down five variables (respiration, reflex, muscle tone, color, and heart rate) and assigned a score of 0, 1, or 2 depending on the strength of the variable. A baby with a score of 4 or less needed immediate attention, and a baby with a score of 8 or more was pink, crying, and good to go. This simple algorithm has certainly saved the lives of thousands of babies over the years.[41]

Yes, this is a simple algorithm, but identifying which variables are important is not so simple. Picking the important variable that predicted newborn health was done by someone who had very deep practical experience and research. Dr. Virginia Apgar was born in 1909 in Westfield, New Jersey, and was educated at Mount Holyoke College and Columbia University College of Physicians and Surgeons (CUCPS), where she graduated in 1933 and finished her residency in 1937. She went on to become the first woman to become a full professor at CUCPS, in 1949. Dr. Apgar had 20 years of experience around newborns when she developed her test. She had considerable *expert* knowledge through observation, study, experience, research, and practical experience to establish those five variables. Could there be other (better) ones? Maybe. Could, perhaps, respiration be the most important and color the least at predicting the well-being of the newborn? These are exactly the types of questions that deep analytics can answer.

This approach is further supported by Stephen Hoch in the summary of his chapter, "Combing Models with Intuition to Improve Decisions":[42]

> Most decisions have three stages: (1) variable identification, (2) variable valuation, and (3) information integration into an overall evaluation. Experts are good at the first two stages but are plagued by inconsistency in stage three. By outsourcing stage three to a mechanical model, the quality of decisions can be enhanced. By carefully combining human experts, statistical models, and new data-mining tools, we can improve the quality of forecasts and other decisions.[43]

We'll be using this exact approach when modeling our decisions: an expert determining the importance of factors coupled with analytics.

1.2.4 Artificial Intelligence and Machine Learning

What exactly is meant by the term *artificial intelligence* (AI) garners a significant amount of discussion. Machine learning and expert systems are both forms of AI. There is also natural language and the neural nets and other AI tools. As the name suggests, natural language refers to the capability of machines to understand and act on spoken language. Neural nets are computer systems that mimic the human brain. For our purposes, I will focus on machine learning and sophisticated expert systems (sometime referred to as Deep Q&A expert systems). Both have substantial scope for assisting with the decision making within HCM and elsewhere.

According to Yaser S. Abu-Mostafa, a Professor of electrical engineering and computer science at Cal Tech and the co-author of the book *Learning from Data*, at its most basic, machine learning can be defined as follows:

> At its simplest, machine learning algorithms take an existing data set, comb through it for patterns, then use these patterns to generate predictions about the future.[44]

Machine learning has been utilized within a number of different functions, including finance, marketing, and operations (and in HR, but less so). It is generally associated with the ability, as the name implies, to learn (mostly through trial and error). An example is in gaming settings, where the system can learn by playing the game over and over. This is one of the reasons that machine learning can be used effectively for chess or Jeopardy!; they are games that are repeated. Within HR, there is also repetition; we hire computer programmers again and again, we design and deliver compensation repeatedly, and we put our high-potential employees through executive development programs. All of these activities can be refined through utilizing machine learning.

The following list describes a few instances of when machine learning can be applied to HR decisions:

- Identify professional experience, educational attainment, personal characteristics, and other life experiences associated with superior job performance
- Use social media to obtain information on the success of a specific recruitment approach
- Identify factors associated with voluntary turnover of high-potential candidates
- Predict future workforce skills and quantity

The applications of machine learning are many, but there are also potential drawbacks. Machine learning relies primarily on the use of an algorithm as it trolls through a dataset looking for instance the "ideal" candidate or the ideal pay package. Again, according to Abu-Mostafa,[45] it is not always easy to actually name or identify the attributes that have been identified. In addition, many decisions associated with HCM may need to be explicitly defined or backed out of. An employee (or potentially the courts) may question how a specific decision was arrived at. This might not always be easy to determine when using machine learning. Machine learning tends to use algorithms to do the work. Algorithms are a predetermined set of factors that need to be evaluated to arrive at some required output. An example is calculating payroll; this takes into consideration hours worked, overtime, tax, and other deductions.

Whereas machine learning focuses on the use of algorithms, expert systems utilize heuristic approaches. Heuristic approaches generally follow a set of rules to arrive at some conclusion or recommendation. Expert systems make it possible to see how a decision was made.

1.3 Human and Machine: The Ideal Decision-Making Team

We are in luck because machines happen to be very good at exactly what we are not so good at. Gartner, the information technology consulting and research firm, produces a series of research notes that cover a wide range of topics related to information technology and associated topics and disciplines. The company occasionally issues what they refer to as "maverick" research, which is research that pushes the technological and social envelope on a topic. One such research note,"Judgment Day, or Why We Should Let Machines Automate Decision Making,"[46] was written by Nigel Rayner. They believe that we are at a point at which more and more decisions will be automated and the decisions taken by machines will be better than ones made by humans.

In their recent book *Race Against the Machine,* Erik Brynjolfsson and Andrew McAfee of MIT provide some insight into the question of our relationship to technology. There has long been a question about whether technology will replace us or complement us. This is a question that has been around since the first machine was built. The position taken in *Race Against the Machine* is that our decisions can be far superior if we leverage those aspects of machines that *complement* our own facilities. Brynjolfsson and McAfee discuss the 1997 loss of Garry Kasparov to IBM's Deep Blue supercomputer. The media seized on to the win by Deep Blue; discussed much less was the fact that the best chess champions were actually teams of humans using computers. According to Kasparov, a strong human player using a standard laptop was able to beat Hydra, a supercomputer designed for chess.[47] CEOs find that data-driven decisions provide the greatest potential for long-term value creation.[48] This really is the crux of the matter: developing and utilizing technologies that compensate for our weaknesses and accentuate our strengths.

Are some HCM decisions best addressed through advanced analytics? The fact is that these new and developing tools could aid with nearly all decisions. Table 1.2 describes some of the important HCM decisions and how advanced analytics can assist.

Table 1.2 HCM Decision Framework

HCM Decision	Challenges to Optimal Decision Making	Advanced Analytical Tool
Alignment with organizational objectives	Tremendous variation of situations and potential policies and practices	Machine learning/expert systems
Workforce planning	Broad scope of pertinent information	Simulation and predictive analytics Machine learning/expert systems
Selection	Biases	Predictive analytics Machine learning/expert systems
Performance management	Biases	Predictive analytics Machine learning/expert systems
Compensation	Biases Large data sources	Machine learning/expert systems
Collaborative decision making	Data overload	Predictive analytics/expert systems

1.3.1 A Word About AI Tools

A number of different AI software applications are available from various AI vendors. In addition, many different open source and commercially available tools can assist with decision making. I am going to be primarily using a sophisticated expert system called Expert Maker, which includes a broad range of AI tools. You can find these tools on this book's website: DecisionAnalyticsInc.com.

Depending on your level of interest, you might want to consider a number of open source and commercially available tools, including

Python, R, Octave, WEKA, MATLAB, Apache Hadoop, and vendors (including the usual suspects SAS, IBM, Oracle, and SAP) that are developing ever-more sophisticated AI tools in their business intelligence and other offerings. In addition, some smaller companies and start-ups are doing very interesting things. I profile a few in later chapters. There is much more to say about this, so I encourage you to visit the website (DecisionAnalyicsInc.com) to find more information. I also strongly recommend that if you do not know how to code, learn. There are great online resources available to help you with this (Codeacademy, Code/Racer, MIT OpenCourseWare, Coursera, among others).

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