

# Understanding HR analytics

01

*Arguably the most practical tool and greatest potential  
for organizational management is the emergence of predictive analytics.*

FITZ-ENZ AND MATTOX II (2014)

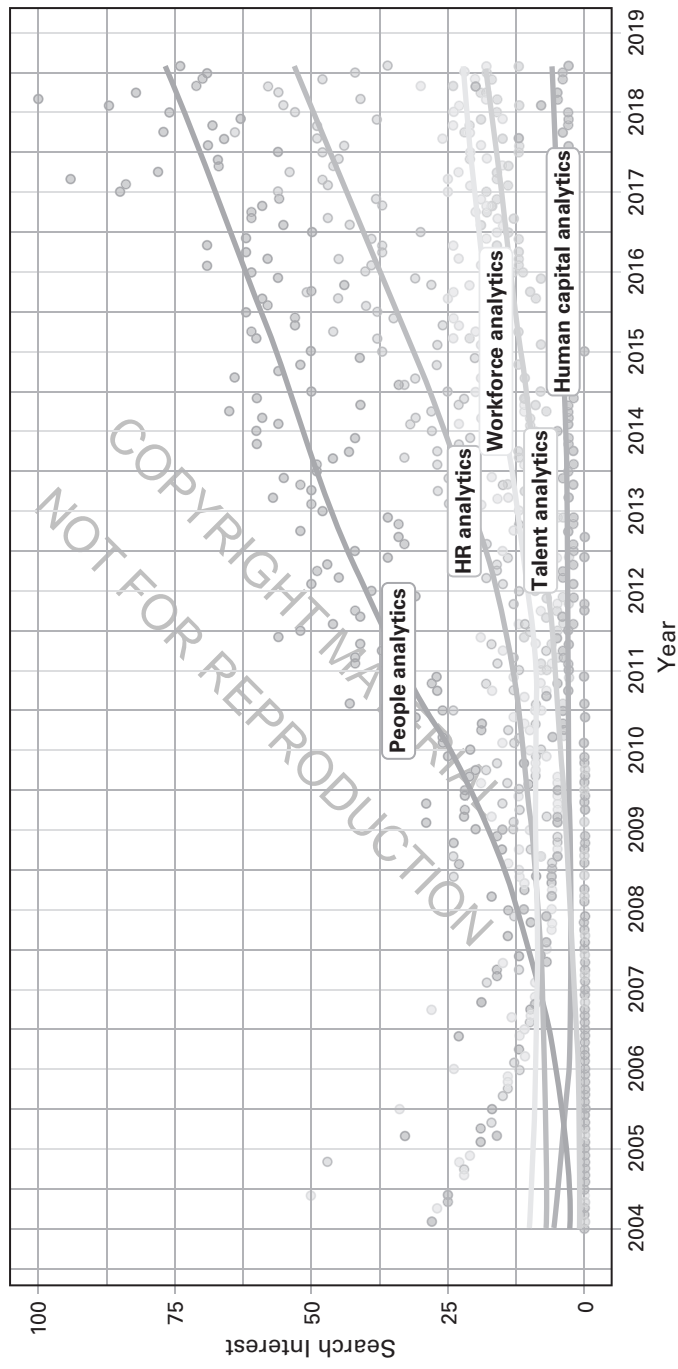
*Analytics present a tremendous opportunity to help organizations understand what they don't yet know... By identifying trends and patterns, HR professionals and management teams can make better strategic decisions about the workforce challenges that they may soon face.*

HUSELID (2014)

Since the first edition of this book was written (and published in 2016) the field of HR analytics has seemingly gone from something that was beginning to attract a great deal of interest to, what can be now be considered, an important (if not essential) aspect of what should be included in the offering of any sophisticated HR function. There has been some speculation about what is the best name for the specialism (see Edwards, 2018), with some preferring workforce analytics or people analytics to HR analytics.

Figure 1.1 shows the growth of interest in the area, based on internet searches; clearly, the plot lines are only going upwards over recent years! The key word that we can associate with the field is 'growth'! In the past few years we have witnessed a considerable growth in the number of HR analytics practitioner conferences, training courses, consultancy offerings, books (e.g. Levenson, 2015; Edwards and Edwards, 2016; Guenole et al, 2017) and academic papers (e.g. Angrave et al, 2016; Marler and Boudreau, 2017 and Kryscynski et al, 2017). The quotes at the top of this page are as relevant now as they were at the time that the earlier version of this book was published. It is becoming quite clear from the narrative, blogs and articles that are being published around HR analytics that, as a field, it is becoming an increasingly important part of the HR sphere.

**Figure 1.1** Plot of internet search interest of HR analytics subject words from 2004–18 (graph produced by Paul Van der Laken, 2018, p.18)



There have been calls by some to ensure that the HR function moves away from introducing ‘copycat practices’ to ‘promoting practices and advising the organization’s leadership’ through an assessment of available data and research linked to the particular issue at hand (Rousseau and Barends, 2011); HR analytics, with its natural emphasis on relying on data and research to help answer business questions, helps to answer this call. The reality is that, even though many HR professionals may have a conceptual understanding of what HR analytics might involve, very few people have the relevant competencies to be able to actually carry out sophisticated predictive HR analytics. Whilst more skilled analytic experts are moving into the HR analytic field, and the importance of analytics competencies for the function is now being recognized (Kryscynski et al, 2017), there is some way to go before the HR profession has the necessary level of analytic competency to fully utilize the potential of HR analytics. This book aims to help people develop these competencies and to demystify what may (for many) currently be hidden behind the ‘magic curtain’ of HR analytics. The book hopes to metaphorically pull back both curtains and give potential analysts a foundation of tools to tie them securely to the wall. Before we go on to discuss and help demystify HR analytics, it is important to define our terms and set out our stall as to what we mean by ‘predictive HR analytics’.

## Predictive HR analytics defined

We define ‘predictive HR analytics’ as: ‘the systematic application of predictive modelling using inferential statistics to existing HR people-related data in order to inform judgements about possible causal factors driving key HR-related performance indicators. The results of this modelling can be used (where appropriate) to make tangible predictions about particular results or people outcomes’.

Put simply, we take the sophisticated statistics and quantitative analyses techniques that scientists use to predict things (such as what may cause heart disease or what might help to cure cancer) and apply them to the information we hold about people in organizations. This enables us to test statistical models and predict things such as what might drive high performance or what might cause an employee to leave the organization. Furthermore, where appropriate, we can also then apply these predictive models to make tangible predictions about particular results or outcomes (eg employee or organizational behaviour) that we might expect to find, given certain conditions.

Being able to apply predictive statistical models to HR-related data requires some knowledge of statistics and the capability (and experience) to understand and interpret meaning behind results that analyses are telling us. At the moment (as discussed

in various places within this book), very few HR functions actually utilize the statistical analytical techniques that are available to them. More often than not, whilst HR metrics and HR analytics teams do (at the moment) process and report on vast amounts of people-related data, very few apply statistical techniques that enable predictive inferences to be made. This is as much the case now (2019) as it was at the time of the previous edition of this book (2016).

It is worth noting here that predictive modelling is sometimes associated with computational data science techniques linked to big-data analyses and machine learning. However, many techniques underlying such applications rely on the statistical techniques that we present in this book, for example regression analyses that produce algorithms to make predictions (see Chapter 10). As the statistical techniques presented here cover a wide array of possible techniques that an HR analytics expert might use, understanding these statistical tools and how they apply to HR data provides a deep foundational basis for any budding HR analytics professional.

## Understanding the need (and business case) for mastering and utilizing predictive HR analytic techniques

HR information and management information (MI) teams currently spend considerable time and effort producing descriptive report after descriptive report – monitoring them, comparing them across geographical boundaries and over time periods, but often doing very little else with the report other than producing it – again and again. Descriptive HR reports usually produced by MI teams will generally only present a picture or ‘snapshot’ of what is occurring in the organization at that particular time. Whilst there is little doubt that these reports are useful to the business in ensuring that managers understand what is going on within the organization, there is a real limit to what these reports can tell us. Descriptive reports do very little more than describe what is happening; they lack the capability to help understand and account for *why* things are happening in the organization. Furthermore, when running these reports, the analysts generally fail to interrogate the data fully for other possible explanatory factors (which can help clarify why something might be happening). They also tend to fail to test or check the degree to which their data might be robust and valid. Furthermore, descriptive reports do not in any way help us to make predictions about what we might find in the future. It is this ability that differentiates predictive HR analytics from the analysis currently carried out by the majority of HR MI teams.

Experts such as Bersin (2012) outline the importance of using predictive analytics to help organizations predict and understand the performance of a person (or indeed a group of people) based on available historical data. Once that sufficient people-related data has been collected over time, it is then possible to analyse patterns and trends based on this historical data. As quoted in the epigraph to this chapter, in 2014 Huselid argued: ‘Analytics present a tremendous opportunity to help organizations understand what they don’t yet know... By identifying trends and patterns, HR professionals and management teams can make better strategic decisions about the workforce challenges that they may soon face.’ Predictive HR analytics therefore offers the opportunity to help model and analyse historical data and interrogate patterns in order to help understand causal factors and do exactly what Bersin and Huselid are suggesting is important.

Knowing what has happened in our organization and having evidence for why things have happened, in particular what the drivers are of certain behaviours within our organization, will undoubtedly help us to make better decisions. For example, if we can identify predictors of things like high performance, productivity increases, staff retention, higher employee and team engagement, then this information gives managers a good steer as to what strategic activities to invest in to help lever important employee outcomes.

## Human capital data storage and ‘big (HR) data’ manipulation

To be able to realize the potential of predictive HR analytics all of us are reliant upon what current and historical data is available. Predictive HR analytics relies completely on good data; we cannot look for patterns in data when the available data is limited and sketchy. Thus the success of HR analytics is completely reliant on the availability of good people-related information. As we discuss in Chapter 2, increasingly HR functions are not necessarily faced with the problem of there being a lack of data available – they are often faced with the problem that there is too much data to know what to do with. Much has been talked about in the popular and practitioner press about ‘big data’ (we discuss this in Chapter 2). Thus a challenge often faced by an HR analytics team is what to do with all the people-related HR data that is available. Once we have sufficient HR-related data, one of the biggest challenges is getting that data into the right format for analysis (we walk through an example of this in Chapter 2).

Useful HR-related data is made up of many different types of information and might include the following:

- skills and qualifications;
- measures of particular competencies;
- training attended;
- levels of employee engagement;
- customer satisfaction data;
- performance appraisal records;
- pay, bonus and remuneration data.

It takes time and considerable manipulation of data files to make sure that the models run are appropriate to the type of data available, so Chapter 2 talks more about systems and data, and Chapter 3 will help you to determine which models to run for which circumstance. Ultimately, the data available (and the data that is missing) is the key determining factor on what kind of analysis can be carried out and what business questions can be answered. The other important factor is respect for the ‘head space’ required to be able to fully engage with the data, the analysis, and what it all means for the organization.

## Predictors, prediction and predictive modelling

By definition, central to the idea of ‘predictive’ HR analytics is that something can be ‘predicted’. One of the critiques sometimes posed at predictive HR analytics is that the ‘predictive’ part is very rarely realized. Obviously, if the future was known by an organization then this would be extremely useful and managers would be able to make strategic decisions in order to exploit it. Presumably this is one of the reasons why ‘predictive analytics’ as a term has become so popular. However, in terms of analytics, there are a number of ways that we can use the term ‘predictive’ and it is worth distinguishing this at the start so that we can be comfortable with our use of the term in this book (and indeed the title of the book!).

One of the ways that we (and others) use the term ‘prediction’ is related to the idea of identifying ‘predictors’ or potential ‘causal’ factors that help explain why a particular feature or measure shows variation (eg why performance levels vary amongst employees). As we explain in Chapter 3, some of the analytic techniques that we use aim to explore relationships between many different types of data (or variables) in order to identify ‘predictors’ of some important HR outcome (such as employee performance or staff turnover). This type of analysis is used to identify trends and relationships between multiple factors with the hope of obtaining information that suggests the possible causes of variation in the phenomenon that we are hoping to predict. Assuming that we find a range of significant features of our people-related data where variation is associated (in a unique way) with an increase

or decrease in what we hope to account for, we can say that we have found potential ‘predictors’. In this context one can also refer to these predictors as potential ‘drivers’ of our outcome. Importantly, the use of the word ‘predictors’ here implies that we seek out and have found potential ‘causes’ of variation on the feature we are trying to predict (see Chapter 12 for our discussion of causality and challenges of assuming that relationships found in data imply ‘causality’). Almost all of our case study chapters (Chapters 4–9) utilize analytics that relate to this form of the word ‘prediction’.

A second use of the term in the context of ‘predictive HR analytics’ is the use of ‘predictive modelling’. Here, we take features and findings of our analysis (for example, where we identify a series of factors that were related to variations in staff productivity or sales), then we apply our model to help demonstrate or ‘predict’ what would happen to our key outcome variable (eg staff productivity or sales) if we could do something to change or adjust the key drivers that we have identified. We demonstrate this use of the word ‘prediction’ in Chapter 10.

Finally, a third use of the term ‘prediction’ that we can use in the context of ‘predictive HR analytics’ is that we can translate the findings from our ‘predictive models’ where we identified ‘predictors’ of variation in our particular outcome variable (eg staff productivity or sales) and use the resulting model to ‘predict’ how current or future employees (or teams) may behave (eg staff productivity or sales) in the future. We also demonstrate this use of the word ‘prediction’ in Chapter 10 where we show how, through identifying patterns and trends in existing data, you can apply a particular algorithm to newly collected information so as to provide evidence-based predictions of possible future behaviour that can help managers to make a decision.

Importantly, this book can help provide a ‘walk-through’ and demonstrate to students of HR analytics how they can apply statistics in order to fully utilize all aspects of the promise that the term ‘predictive HR analytics’ implies.

## **Current state of HR analytic capabilities and professional or academic training**

As mentioned, the field has moved on considerably since the previous edition of this book; there now seems to be a much greater availability of HR/people analytics training providers that service the professional HR community. In 2016 there was an obvious scarcity of this, but a number of academic institutions are now including HR/people analytics modules in their teaching. There has also been a general growth in data analytics and business analytics academic programmes available.

We discussed previously how HR training provision generally does not tend to include either intermediate or advanced level quantitative analyses; ultimately, there are no general expectations that HR should include analytics, and it is often the case that students can get to an HR Masters level without having ever been trained in statistics. Certainly, the vast majority of people who enter the HR profession (in the UK at least) do not have the required skills to be able to carry out any sophisticated predictive HR analytics. The level of analytic skills that HR graduates possess will often be dependent upon the degree that they studied at undergraduate level; for example, an undergraduate degree in a traditional discipline such as economics, mathematics or psychology would have statistics as a substantial part of the degree content. Within many countries, even when students have come from a business or management degree, such students can often sidestep statistics (almost) completely. Up until 2018, HR may have been seen by some students as a 'safe haven' from numbers. In addition to this, many HR professionals move into HR without formal academic training and are unlikely to have had any formal training in statistics. If we take the UK as an example and we look at the competency requirements for membership into the Chartered Institute of Personnel and Development (CIPD) up to and before 2018, even with advanced-level module expectations there was very little requirement that candidates develop numerical abilities (let alone statistical abilities). At the time of writing, the authors have been informed that the CIPD is preparing a new set of professional standards and quantitative skills will be included in this to a greater degree.

Recent research, however, is beginning to show how important analytic competencies are in the HR profession. Kryscynski et al (2017) showed a positive relationship between ratings of analytic competencies and ratings of performance from a number of stakeholders. However, Minbaeva (2017) reports on a Deloitte (2015) survey that indicated 75 per cent of companies surveyed indicated 'human capital analytics' was important for business performance but only 8 per cent had strong capabilities. A recent CIPD survey of the state of HR analytics in the profession showed considerable geographical variation in HR capabilities with advanced analytics, with only 21 per cent of UK respondents stating that they had confidence in conducting advanced analytics (and only 6 per cent indicating that they use these regularly).

In terms of how an HR team gets the competencies required to conduct advanced analytics, there is a debate about how best to set up an HR analytics offering/team (Rasmussen and Ulrich, 2015; Edwards, 2018) and often data scientists/quantitative scientists who do not originate from the field of HR are an important resource to draw upon to include in the HR analytics team. This is mainly because HR specialists rarely have the requisite skills, even though there is a perceived need for the HR profession to have these capabilities. This skills/capability gap is, however, something



that this book hopes to do something about! Whether the HR professional is a generalist, a specialist in one particular area (such as talent, diversity or engagement), or the head of HR for a large multinational organization, the ability to identify and understand trends and patterns, to take bias and gut instinct out of decision making, and to predict organizational challenges is something that will set them apart in becoming a credible, high-performing HR professional (helping the organization to be more successful). This competence gap needs to be addressed if the HR profession is to fully exploit the opportunities that Huselid is alluding to in the quote at the beginning of this chapter.

Importantly, one of the key aims of this book is to help educate HR students and practitioners so as to help have a positive impact on the profession as a whole by adding to the quantitative literacy of people within it. Of course, in trying to achieve this aim, we will always be confronted with the phenomenon of many people having an automatic ‘off switch’ when it comes to statistics. This is no doubt why books out there have titles such as *Statistics for people who think they hate statistics* and *Statistics without tears*, etc. We argue, and truly believe, that having a strong quantitative analytic capability and knowledge of statistics will provide a firm foundation for any HR professional. Thus, mastering the HR metric by learning to carry out predictive HR analytics will fundamentally strengthen the skillset of the profession.

## Business applications of modelling

Almost all of the analyses presented in this book will have significant business implications and application; sometimes this is obvious and sometimes this requires a careful consideration of the results of the models tested. One of the things that the HR analytics team will need to be able to do, as a matter of course, is to be able to translate analysis findings to potential business applications. We discuss this in Chapter 10 where we give some examples of translating our predictive models to specific applications. However, we only touch the surface of presenting examples of ways in which the analytics in this book could be translated to specific business applications. Importantly, any HR analytics team should instil a mentality of always looking to answer the ‘So what?’ question (one that they will inevitably be asked when presenting their analytic results). The analytics team need to be always on the lookout for how their findings could be translated to useful practice knowledge, and whether any particular knowledge gained can help to strengthen and steer the organization’s people strategy.

## HR analytics and HR people strategy

In learning and applying the methods outlined in this book, it should become obvious to the analytics team that it is possible to use analytical models to help steer, adjust and even drive business strategy. Ultimately the analytics approaches recommended can provide evidence-based pointers for practice and can help take some emotion and gut instinct out of ‘people’ decision making. Methods such as those described in all of the case study chapters should be able to help highlight key strategic factors to focus on when dividing a people strategy plan, and the methods outlined in Chapter 9 (monitoring the impact of people interventions) will assist the HR function in tracking and monitoring the success of their people plan (providing opportunities for reflection and adjustment to the plan). We discuss how to use predictive models to improve performance, turnover and hiring decisions – essential areas of HR on which the success of the function is measured. Hopefully the methods discussed in this book will assist HR analytics teams and their organizations to make sound, evidence-based people decisions that will help the organization to prosper – and, in doing so, value the HR function.

### Becoming a persuasive HR function

*The development of HR’s strategic role has been an evolution...*

*The next step in the evolution is for HR professionals, and particularly senior HR professionals, to develop what we call analytic literacy.*

HUSELID AND BECKER (2005: 279).

As you work through this book, you will begin to understand the opportunities that can open up for answering business questions, even those that have not been asked yet! We believe that this ‘analytic literacy’ will help transform the HR function. An HR function that fully utilizes predictive HR analytics capabilities will be more credible because the function will be able to present robust ‘hard’ evidence to show that it has a good understanding of what makes its people tick, along with knowledge of who is likely to perform well, who is likely to leave, which parts of the organization are showing race or gender bias, which candidates are likely to be successful in the organization, and which interventions had a significant impact on the organization and which did not. The function will be able to carry out substantial ‘what if’ scenario modelling to help build solid business cases that help the organization to make decisions around whether particular investments are likely to be worthwhile, and what the return on those investments are likely to be.

By systematically going through this book and the exercises provided, any developing HR analytics team should have increased their capabilities and learnt many things that will help them to become *Masters of the HR Metric*.

## References

- Angrave, D, Charlwood, A, Kirkpatrick, I, Lawrence, M and Stuart, M (2016) HR and analytics: Why HR is set to fail the big data challenge, *Human Resource Management Journal*, 26, pp 1–11
- Bersin, J (2012) *The HR Measurement Framework*, Bersin and Associates Research Report, November
- Edwards, M R (2018) HR metrics and analytics, in *E-HRM: Digital approaches, directions and applications*, ed M Thite, Routledge, Abingdon, UK
- Edwards, M R and Edwards, K (2016) *Predictive HR Analytics: Mastering the HR metric*, Kogan Page, London [Online] [www.koganpage.com/PHRA](http://www.koganpage.com/PHRA)
- Fitz-enz, J and Mattox II, J R (2014) *Predictive Analytics for Human Resources*, Wiley, New Jersey
- Guenole, N, Ferrar, J, and Feinzig, S (2017) *The Power of People: Learn how successful organizations use workforce analytics to improve business performance*, London, Pearson FT Press
- Huselid, M A and Becker, B E (2005) Improving human resources' analytical literacy: Lessons from moneyball, in *Future of Human Resource Management*, ed D Ulrich, M Losey and S Meisinger, John Wiley and Sons, New York
- Huselid, M (2014) [accessed 30 November 2015] The corporate mirror, *D'Amore-McKim School of Business* [Online] <http://www.damoreckimleadersatworkblog.com/corporate-mirror-looking-big-data-analytics-workforce-management/#sthash.4qx5y7F3.dpuf>
- Kryscynski, D, Reeves, C, Stice-Lusvardi, R, Ulrich, M and Russell, G (2017) Analytical abilities and the performance of HR professionals, *Human Resource Management*, Online First, DOI: 10.1002/hrm.21854
- Levenson, A (2015) *Strategic Analytics: Advancing strategy execution and organizational effectiveness*, Berrett-Koehler Publishers, Oakland, CA
- Marler, J H and Boudreau, J W (2017) An evidence-based review of HR analytics, *The International Journal of Human Resource Management*, 28 (1), pp 3–26
- Minbaeva, D B (2017) Building credible human capital analytics for organizational competitive advantage, *Human Resource Management*, Online First, DOI: 10.1002/hrm.21848
- Rasmussen, T and Ulrich, D (2015) Learning from practice: How HR analytics avoids being a management fad, *Organizational Dynamics*, 44, pp 236–42
- Rousseau, D M and Barends, E G R (2011) Becoming an evidence-based HR practitioner, *Human Resource Management Journal*, 21, pp 221–35
- Van der Laken, P (2018) *Data-driven human resource management: The rise of people analytics and its application to expatriate management*, PhD Thesis, Tilburg University

## Further reading

CIPD [accessed 30 November 2015] Talent analytics and big data : The challenge for HR

[Online] <http://www.cipd.co.uk/hr-resources/research/talent-analytics-big-data.aspx>

CIPD (2018) People Analytics: Driving Business Performance With People Data: A Global Survey of Multiple Professional Perspectives on People Data and People Analytics, June 2018 [Online]

<https://www.cipd.co.uk/knowledge/strategy/analytics/people-data-driving-performance>

Holley, N [accessed 30 November 2015] Big data and HR: The Henley Centre for HR

Excellence, *Henley Business School* [Online] [http://www.henley.ac.uk/html/hwss/files/](http://www.henley.ac.uk/html/hwss/files/Henley-Centre-for-HR-Excellence-Big-Data-Research-paper.pdf)

[Henley-Centre-for-HR-Excellence-Big-Data-Research-paper.pdf](http://www.henley.ac.uk/html/hwss/files/Henley-Centre-for-HR-Excellence-Big-Data-Research-paper.pdf)

IBM [accessed 30 November 2015] Analytics: The new path to value, *IBM and MIT Sloan*

*Review* [Online] [http://www-935.ibm.com/services/uk/gbs/pdf/Analytics\\_The\\_new\\_path\\_](http://www-935.ibm.com/services/uk/gbs/pdf/Analytics_The_new_path_to_value.pdf)

[to\\_value.pdf](http://www-935.ibm.com/services/uk/gbs/pdf/Analytics_The_new_path_to_value.pdf)

KPMG [accessed 30 November 2015] People are the real number: HR analytics has come of

age [Online] [https://www.kpmg.com/GR/en/IssuesAndInsights/ArticlesPublications/](https://www.kpmg.com/GR/en/IssuesAndInsights/ArticlesPublications/Documents/workforce-analytics-download.pdf)

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